Investor Behaviour: An Examination of Investor Sentiment and Cognitive Dissonance

by

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Abstract

This thesis seeks to examine the roles of investor sentiment and cognitive dissonance on investor behaviour. The objectives of this thesis are: first, to investigate the impact of the interaction of investor sentiment with culture on momentum and post-earnings-announcement-drift by way of cognitive dissonance in international markets; second, using investor sentiment and analyst recommendations to examine how cognitive dissonance affects institutional herding in the U.S. financial market.

The effect of investor sentiment, culture as well as cognitive dissonance is examined for the two anomalies, momentum and post-earnings-announcement-drift. The investigation is carried out both across a wide range of countries and in two distinct culture groups. We investigate these issues by building on a specific behavioural model and by bringing together arguments from psychology and the cross-culture literature in relation to investor sentiment, culture and the notion of cognitive dissonance. We propose that cognitive dissonance will be evident when private or public news contradicts investors' sentiment. This will cause a slow diffusion of such news being incorporated into stock prices, resulting in return continuation and people in different cultures experiencing different degrees of cognitive dissonance and in different situations. The empirical findings suggest that cognitive dissonance is a key driver in explaining these two anomalies across countries and in the two distinct cultures.

The interaction of investor sentiment and analyst recommendations on institutional herding is investigated by using two commonly used herding measures in the micro-level in the U.S. It suggests that cognitive dissonance is an important driver for institutional herding by taking account of the interaction between the two factors. Cognitive dissonance will be evident when analyst recommendation revisions conflict with sentiment, causing institutions to herd differently in the current and subsequent periods. The two herding measures allow us to capture different aspects of herding in the two periods and to gain better insights into spurious and intentional herding.

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1 Introduction

1.1 Background and Motivation

Under traditional finance theories, market participants are assumed to be rational and markets are informationally efficient (Fama, 1970). Stock prices should be unpredictable since the market should reflect all available information. If stock prices deviate from their fundamental values, rational arbitrageurs should be able to eliminate such a mispricing very quickly. In past decades, numerous anomalies and puzzles have been raised by empirical studies, which contradict the efficient market hypothesis (Fama, 1970) and traditional finance theories are difficult to explain such phenomena. Examples include post-earnings-announcement-drift (Bernard and Thomas, 1990), stock price momentum in the medium horizon (Jegadeesh and Titman, 1993), mean reversion in the long run (Debondt and Thaler, 1985) and institutional herding (Lakonishok et al., 1992). In order to explain various financial market anomalies and puzzles, researchers have extended their research domain to market participants' behaviour based on psychology and sociology and attribute variations of asset prices to the extent of investors' non-rational behaviour. This research is known as Behavioural Finance, involving theoretical modelling of investor psychological biases and empirical investigation of investor decision making system. Investor sentiment, which is one of the pillars of behavioural finance, refers to erroneous beliefs or psychological biases such as overconfidence, self-attrition bias and conservatism. The sentiment may be treated as the non-rational evaluation of asset characteristics (Shleifer, 2000; Baker et al., 2008). In general, investor sentiment can be described as waves of optimistic and pessimistic sentiment- at least from time to time (Baker and Wurgler, 2007).

This thesis contributes to the behavioural stream using investor sentiment in explaining financial market phenomena through its interaction on cognitive dissonance. In particular, the first two empirical chapters investigate the effect of investor sentiment and cognitive dissonance on two anomalies, momentum and post-earnings- announcement-drift in different cultures using data across a wide range of countries. The study is first motivated by the fact that those anomalies appear to provide the biggest challenge to the efficient market hypothesis (Fama, 1998) and although the evidence for these anomalies is extensive, it is not found for all international markets. While cultural individualism has been shown to be of relevance to these anomalies, to date it is not clear why cultural factors might influence the level of returns. Invest sentiment has been offered to explain momentum and post-earnings-announcement-drift (e.g. Antoniou et al., 2013; Livnat and Petrovits, 2009). Based on the premise that culture serves as an informal institution to regulate investor behaviour (e.g. investor sentiment), we expect culture to influence investor trading decisions and, in turn, momentum and post-earnings-announcement-drift anomalies. We seek to address these issues by bringing together arguments from the psychology and cross-culture literature regarding the difference in relation to sentiment and its impact on cognitive dissonance since sentiment might interact with other market features differently across cultures. In addition to examining the impact of cognitive dissonance on momentum (PEAD) in 40 (34) countries with differing levels of individualism, we pay particular attention to the impact of the difference in cultures between the east and west, allowing us to gain better insights into the impact of cognitive dissonance on how investors process information in the two distinct cultures. Building on Hong and Stein (1999) and recognising Westerners' (Easterners') belief in continuation (reversal), we propose cognitive dissonance arises in different circumstances and to differing degrees in the two cultures, resulting in it being a key driver of the anomalies. Results support our hypotheses, suggesting sentiment and culture interact to impact cognitive dissonance, explaining differences in the anomalies across countries.

In the third empirical chapter, we proceed to investigate the joint effect of investor sentiment and analyst recommendations on another financial phenomenon, institutional herding. The study is motivated by the fact that the two factors, investor sentiment and analyst recommendations, have been shown to be prominent in affecting institutional herding. We propose that institutional investors may experience cognitive bias (e.g. cognitive dissonance) when processing analyst information (e.g. analyst recommendations) and sentiment related indicators. In particular, cognitive dissonance may be evident when the two factors do not suggest similar price movements. In turn, in a same period, institutional investors may herd strongly in response to the arrival of information strongly in the absence of cognitive dissonance, resulting in stronger within-period herding. On the other hand, when cognitive dissonance is evident, in order to resolve such uncertainty, institutional investors may be more likely to follow the trades of others in the subsequent period, resulting in stronger adjacent-period herding. Two micro-level herding measures are employed in the study to help us capture within- and adjacent-period herding and different aspects of institutional herd behaviour, allowing us to gain better insights into intentional and spurious herding.

1.2 Thesis Contribution

The main contribution of this thesis is that it provides the first investigation of the interaction between investor sentiment and another prominent factor in financial market anomalies by way of cognitive dissonance. In the first two empirical chapters, we address the importance of investor sentiment in affecting the level of stock returns in different cultures. A number of studies show that people's behaviour depends to a large extent on their cultural background (e.g. Douglas and Wildavsky, 1982; Guiso et al. 2006). People are not able to change their ethnicity, race or family history, and only can alter their country or religion with difficulty (Becker, 1996). Due to such difficulties, culture will have a significant impact on their behaviour throughout their lifetimes.

Chui et al. (2010) first link the cultural effect to momentum profits and a subsequent study by Dou et al. (2015) show the effect of culture on post-earnings-announcement-drift. However, to date it is not clear why cultural factors might influence the level of returns and both studies do not link sentiment to culture. We believe that research on culture and sentiment is promising since an individual response to sentiment may be influenced by their cultural background. We tackle these issues by examining the interaction of investor sentiment and culture on two anomalies, bringing together arguments from psychology and cross-culture literature in relation to sentiment, culture and the notion of cognitive dissonance. We propose that cognitive dissonance may be a major driver of the two anomalies, with the interaction of sentiment and culture causing this phenomenon to arise in different circumstances and to differing degrees in the west and the east. While previous studies of the two anomalies have examined the roles of sentiment and culture independently, to date no study has examined their joint impact or considered the implications of their interaction on cognitive dissonance and momentum and PEAD. Results suggest that cultural differences relating to individualism impact on the level and extent of the two anomalies, while cultural biases concerning continuation and reversal drive the differences in relation to the two anomalies across western and ESEA markets. Thus, our analysis suggests that cognitive dissonance is a major determinant of prior empirical findings relating to both momentum profits and PEAD.

The third chapter focuses on the effect of investor sentiment, analyst recommendations and cognitive dissonance on institutional herding. The study contributes to the literature in two important ways. First, while previous studies have examined the impact of analyst recommendations and sentiment on mutual fund herding separately, to the best of our knowledge, this is the first study to investigate the individual and joint effects of the two factors on institutional herding. Second, we examine the effect of both factors on institutional herding over multi-periods using both within-period (Lakonishok et al., 1992) and adjacent-period (Sias, 2004). This allows us to capture different aspects of institutional herd behaviour. Our results from using two herding measures allow us to gain greater insights into intentional and spurious herding. Using the LSV measure, we find institutional investors tend to herding strongly in the presence of optimistic sentiment and for stocks with downgrades, which are consistent with prior literature (Brown et al., 2013; Liao et al., 2013). However, using the Sias measure, we find adjacent period herding is stronger following pessimistic periods and such herding is mainly driven by institutions following the trades of others. In examining the interaction between investor sentiment and analyst recommendations on institutional herding, we propose that in the presence of cognitive dissonance, within-period herding will be dampened but adjacent-period herding arising from institutions following the trades of others will be prominent since when investors experience cognitive dissonance, they are more likely to trade with delay and to resolve such uncertainty and, hence they are more likely to follow the trades of others in the subsequent period. Overall, the results are consistent with our expectations. At last, the results of subsequent stock returns following institutional herding using both herding measures show that there is only weak evidence of return reversals, suggesting that information-based herding plays a key role in driving institutional herding by considering the interaction of analyst recommendations and investor sentiment.

1.3 Structure of the Thesis

The remainder of the thesis consists of 5 chapters organised as follows:

Chapter 2 reviews the relevant literature on five central research themes, including investor sentiment, cognitive dissonance, momentum, post-earnings-announcement- drift and institutional herding. Investor sentiment is introduced first, including the role of psychology and behavioural based models, empirical evidence of the effect of investor sentiment on investor behaviours and stock markets, and is followed by the introduction to cognitive dissonance, which is a central theme throughout all three empirical chapters. The last three themes start with empirical evidence, construction and measurement of each anomaly, followed by possible explanations.

Chapter 3 empirically studies the interaction of investor sentiment and culture on cognitive dissonance and the extent of momentum profits. The study uses a framework in the spirit of the behavioural model of Hong and Stein (1999). It is undertaken in an international setting, allowing us to gain better insights into the extent of how psychological biases of investors (e.g. cognitive dissonance) impact on momentum profits across cultures.

Chapter 4 studies the interaction of investor sentiment and culture as well as the impact of cognitive dissonance in relation to post-earnings-announcement-drift. The study also uses the same framework as the previous empirical chapter.

Chapter 5 investigates the interaction of analyst recommendations and investor sentiment on institutional herding. The examination of institutional herding is conducted using two different micro-level herding measures. Institutional herd behaviour is analysed under different levels of analyst recommendations and under different sentiment states as well as the impact of the interaction of the two factors by way of cognitive dissonance.

All three empirical chapters develop previously untested hypotheses, undertake detailed empirical analyses and several robustness tests.

Chapter 6 presents the conclusion, which provides a summary of the thesis, draws implications and offers directions for future research.

2 Literature Review

This chapter presents reviews of the five central themes of the thesis. The first two sections, 2.1 and 2.2, introduce investor sentiment and the theory of cognitive dissonance. Sections 2.3 and 2.4 document the evidence and causes of momentum profits and post-earnings-announcement-drift, respectively, and are followed by a discussion of institutional herding.

2.1 Investor Sentiment

2.1.1 Efficient Market Hypothesis (EMH)

An efficient market is defined as a market in which asset prices always fully reflect all available information (Fama, 1970). When information related to the fundamental value of an asset arrives, the asset price should react instantaneously and move to a new fundamental value. In an efficient market, it should be impossible for investors to generate consistent profits in a systematic way. There are three arguments for the EMH. The first argument is associated with investor rationality. In an efficient market, investors are assumed to be fully rational where they value each asset based on its fundamental value. This implies that the asset price is adjusted to a new value when new information about fundamentals arrives. The second argument of the EMH presents that even if there are some irrational investors in the market, the market still can be efficient because their trades are independent and random and cancel each other out without affecting prices. The third argument of the EMH refers to arbitrage. The arbitrage argument shows that even if there are some mispriced assets in the market due to correlated trades, such mispricing will be corrected by the arbitrageurs who will short overpriced assets and buy underpriced assets (Shleifer, 2000). Such an arbitrage opportunity will be exploited very quickly.

The challenge to the first EMH assumption concerns the rationality of economic agents. In traditional finance theories, market participants are assumed to be fully rational in processing information. Sentiment is not considered in rational behaviour of economic agents. Hayek (1952) argues that no one can be fully knowledgeable, and the limitation of knowledge may unavoidably lead to mistakes when investors make trading decisions regardless their rationality. Kahneman and Tversky (1973) state that when investor make decisions under uncertainty, they may deviate from the Bayesian updating system in updating information. In behavioural finance studies, bounded rationality has been introduced. Sentiment such as mood and emotion has been considered in the process of the decision making system. Thus, market participants cannot always behave fully rationally.

The challenge to the second EHM assumption concerns the direction of trades of irrational investors. Some studies suggest that irrational investors may trade in the same direction rather than independently and randomly because people are subject to the same psychological biases (e.g. overconfidence and conservatism) and show the same “irrational” preferences (see, for example, Kahneman and Tversky, 1979). Therefore, investors may form their beliefs and make trading decisions in a way which is subject to the same cognitive bias, resulting in highly correlated investment decisions. In such a case, their trades would impact stock prices in the same direction instead of cancelling each other out. In the literature, irrational investors are typically referred to as individual/retail/unsophisticated investors and rational investors are referred to as institutional/sophisticated investors. However, institutional investors have an incentive to herd due to reputational reasons, which may destabilise the market. Under such a premise, the second EMH argument would be violated.

The challenge to the third EHM assumption concerns the effectiveness of arbitrage. First, arbitrageurs are assumed to be fully rational and not subjective to cognitive biases. DeLong et al. (1990a) suggest that arbitrageurs face noise trader risk to eliminate stock mispricing. Noise trader risk refers to the view that irrational investors will cause prices to deviate even further after the arbitrageurs place their position. This would bring losses to arbitrageurs who will not be able to maintain their position. Consequently, arbitrageurs will take this into account and will not take the position. Hence, arbitrage is limited under such a case. Second, Delong et al. (1990b) point out that rational investors, such as feedback traders, will strengthen the effect of sentiment traders instead of eliminating the effect. For example, feedback traders will make profits by trading in the same direction as sentiment traders. Third, Delong et al. (1991) suggest that irrational traders can exist and dominate the market in the long run so that rational arbitrageurs face great risk in arbitraging mispricing over a long horizon. Shleifer and Vishny (1997) argue that such long-term arbitrage will force them to liquidate their position before prices revert to the fundamental value. Thus, the arbitrage is also limited. The empirical evidence of the challenge is further discussed in section 2.3.4.1.

2.1.2 Empirical Challenges to EMH

The benchmark null hypothesis of the EMH is that investors cannot forecast asset returns with any measures of risk (e.g. beta). This implies it is impossible to make consistent profits using fundamental risk factors. Hong and Stein (2007, p109) state that “any other form of predictability would represent a profitable trading rule and hence a free lunch to investors”. There are many empirical studies that challenge EMH and are difficult to rationalise by risk factor models e.g. post-earnings announcement-drift (Ball and Brown, 1968), the contrarian strategy (DeBondt and Thaler, 1985), momentum (Jegadeesh and Titman, 1993) and the value-glamour phenomenon (e.g. Fama and French, 1992; Lakonishok et al., 1994). Almost all these studies have been explained by using behavioural explanations involving short-run underreaction and long-run overreaction by less rational investors. Underreaction may be due to a gradual information flow (Hong and Stein, 1999), conservatism and anchoring biases (Edwards, 1968; Barberis et al. 1998) and the disposition effect (Frazzini, 2006). Overreaction may result from positive feedback trading (Hong and Stein, 1999), overconfidence and self-attrition bias (Daniel et al., 1998), representative heuristics (Barberis et al., 1998) and herding behaviour due to information cascades (Bikhchandani et al., 1998). However, Fama (1998) argues the EMH still holds since overreaction is as common as underreaction. The argument seems to be unconvincing because underreaction and overreaction occur under different circumstance (Sewell, 2010) and appear to allow investors to make consistent excess returns.

2.1.3 Investor Sentiment and Behavioural Finance

Behavioural finance is a research stream which studies the impact of psychology on the behaviour of investors and how such behaviour subsequently influences the market. A key argument in behavioural finance is that the existence of behavioural biases (investor sentiment) among individual/irrational investors will affect stock prices only if limits to arbitrage hold which prohibit rational investors from exploiting any mispricing. Thus, investor sentiment is one of the most important foundations of behavioural finance. In reality, investors, especially individual investors, make trading decisions not only based on relevant information, but also based on their psychological biases, emotions and the opinions of others. Thus, it is important to learn which, and how, psychological biases have a significant influence on investors' decision-making. The role of investor sentiment may be the key to answering this question.

2.1.3.1 Sentiment: How Investors Form Their Beliefs

Rational agents are efficient and unbiased and update information through a Bayesian updating system. However, irrational investors are behaviourally biased and have erroneous beliefs.[1] McDougall (1926, p. 164) argues that "According to social psychology, sentiment is an organized system of emotional dispositions centered about the idea of some object. The organization of the sentiment in the developing mind is determined by the course of experience; that is to say, the sentiment is a growth in the structure of the mind that is not natively given in the inherited constitution. The growth of the sentiments is of the utmost importance for the character and conduct of individuals and of societies". Thus, sentiment refers to the emotion and cognitive bias of an individual.

In the perspective of behavioural finance, individuals' emotion affects and biases their decisions. Emotional bias is a mental state originated spontaneously instead of through conscious effort, for example, overconfidence/overoptimism. Cognitive bias refers to the conscious reasoning process, and thus cognitive bias can be originated from faulty reasoning, hence better information and suggestion can often correct it. Cognitive biases include overconfidence, representativeness, availability, anchoring and adjustment (Tversky and Kahneman, 1974). There are some theoretical models incorporating psychological biases to examine the relationship between investor sentiment and asset returns. Three main models have attracted widespread attention in the literature.

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[1] Extensive studies in the literature classify professional traders and institutional investors as rational agents and retail/individual investors as irrational investors. However, a number of articles document that professionals are far from bias free (Barberis and Thaler, 2003; Shefrin, 2000).

First, Barberis et al. (1998) propose a model of investor sentiment i.e. how investors form their beliefs. They show that conservatism bias in isolation might lead to underreaction, causing investors to underweight new information, which will be slowly incorporated into prices, but once the information is fully reflected in the prices there is no further predictability about stock returns. Further, they present a model that combines the “conservatism bias” with the “representative heuristic” (Tversky and Kahneman, 1974) to show how investors form their beliefs. The “representative heuristic” refers to people being likely to justify an uncertain event or sample due to it being similar to the parent population and ignoring the laws of probability in the process. They discuss that the “representative heuristic” may lead investors to mistakenly predict that firms with current extraordinary growth will continue to persist in the future. The combined theory can lead stock prices to deviate from their fundamental value and cause long horizon negative returns for stocks with consistently high returns in the past. Their model is in line with delayed overreaction, consistent with positive feedback trading causing market prices to deviate from fundamental values.

Daniel et al. (1998) present an alternative model which is consistent with short-term momentum and long-term reversal effects. They argue that investors are characterised by “overconfidence” and “self-attribution” biases. When subsequent public information arrives, investors will asymmetrically update confirming and disconfirming news. The informed traders attribute the performance of the ex-post winners to their selection skills and that of the ex-post losers to bad luck. Thus, investors overestimate the precision of their signals for these stocks, suggesting that the arrival of confirming news increases their overconfidence and disconfirming news dampens it. Based on their increased overconfidence due to “self-attribution” bias, investors push up the price of winner stocks above fundamental values. The delayed overreaction leads to momentum profits followed by subsequent reversals to the fundamentals, since the overreaction would be realised eventually.

Finally, Hong and Stein (1999) propose an alternative model which is also in line with short-term momentum and long-term reversals effects. The model is based on initial underreaction to information, followed by a subsequent overreaction. It assumes that private information diffuses slowly over time, resulting in positive serial correlation in returns. There are two types of investors in their model, newswatchers and momentum traders, who trade on different sets of information. The newswatchers only have private information, but ignore past price changes, while momentum traders ignore the private information and only trade on the past price changes. The underreaction caused by news watchers and subsequent positive serial correlation in returns attracts the attention of momentum traders who will overreact to the positive serial correlation in returns, thus resulting in momentum profits. Lower risk aversion on the part of the momentum traders leads to greater delayed overreaction. Stock prices finally revert to fundamental values, resulting in returns reversals.

2.1.3.2 Empirical Evidence of Investor Sentiment and the Stock Market

Investor sentiment has received much attention by researchers since 1990 and has been regarded as "controversial" because it contradicts the traditional finance theory. Keynes (1936, p. 154) mentions that "market is subject to waves of optimistic and pessimistic sentiment, which are unreasoning and yet in a sense legitimate where no solid basis exists for a sound calculation."

Sentiment generally refers to the mood of investors. To date, there is no single universal definition for investor sentiment. The existing definitions of investor sentiment in the literature range from investors erroneous beliefs to model-specific psychological biases. In early studies, sentiment has been linked to speculative bubbles (Smidt, 1968), biased expectations about stock prices (Zweig, 1973) and noise (Black, 1986). Since 1990, investor sentiment has become more and more popular since the pioneering study of behavioural finance by De Bondt and Thaler (1985): two supported the cognitive bias of overreaction to unexpected and dramatic news, which results in predictable mispricing of stocks. DeLong et al. (1990a) refer to sentiment as people's formation about expected cash flows and risks that are not rationalised by existing explanations. Shleifer (2000) states that sentiment reflects the common investors' judgment mistakes by a large number of investors, instead of uncorrelated random mistakes. Baker and

Wurgler (2006) refer to it as the propensity of investors to speculate which describes waves of optimism and pessimism. Brown and Cliff (2004, p2) argue that “sentiment represents the expectations of market participants to a norm: a bullish (bearish) investor expects returns to be above (below) average”. In Lee et al. (1991) it represents the difference in asset valuation between rational and irrational investors.

In addition, investor sentiment refers to the view that investors form erroneous beliefs. That can happen due to two reasons: (1) individuals update their beliefs based on information about fundamentals in an unsystematic way. (2) they update their beliefs in a systematic way but use noisy signals which are not related to fundamentals. For example, people who are overconfident in picking stocks and will update information in a different way from Bayesian updating. They would underreact to public information and overreact to private information (Daniel et al. 1999).

The role of investor sentiment has been examined in a wide range of areas within finance and a number of key studies are discussed as follows. Solt and Statman (1988) first use the Bearish sentiment index to proxy investor sentiment. The proxy, which is published by Investor Intelligence, is the ratio of the number of bearish advisors to the total number of advisors and is used as a contrary indicator. Advisors become more bullish after a DJIA increases over the past four weeks and vice versa. They show that the bearish sentiment index has no predictive power in forecasting future stock prices.

Clarke and Statman (1998) show that the sentiment of newsletter writers has no predictive power for future returns but past returns and volatility of these returns do influence sentiment. High returns in the short run of four weeks are correlated with a movement of newsletter writers from bearishness to bullishness. High returns in the long run up to 52 weeks are related to “nervous bullishness”- a movement of newsletter writers from bearish to both bullish and the correction. Lee et al. (2002) confirm their findings and show that using the sentiment index by Investor Intelligence, the change in sentiment is positively correlated with excess returns. The bullish (bearish) shifts in sentiment result in downward (upward) revisions in volatility and higher (lower) future excess returns.

Brown and Cliff (2004) use both institutional and individual investor sentiment. Individual sentiment is proxied by the sentiment survey run by the American Association of Individual Investors (AAII) and institutional sentiment is measured by the survey of Investor Intelligence (II). They find that investor sentiment and market contemporaneous returns are highly correlated and market returns can predict future sentiment, but sentiment does not predict future market returns. In addition, they show that institutional sentiment is more strongly correlated with large stock returns, suggesting that sentiment is not only limited to individuals.

A subsequent study by Brown and Cliff (2005) uses Investor Intelligence to forecast market returns over the next 1-3 years. They find investor sentiment is negatively correlated with long term returns, suggesting that optimism is related to stock overvaluation and low subsequent returns as the price adjusts to its intrinsic value. They suggest that institutional investors tend to adjust their sentiment by considering the sentiment of individual investors.

Schmeling (2007) uses institutional and individual sentiment in his study to proxy for smart money and noise trader risk, respectively. He finds that institutional sentiment positively predicts future market returns over intermediate horizons but individual sentiment negatively forecasts future stock market returns. The finding relating to individual sentiment is consistent with the argument that overoptimism of individual investors pushes the market far away from its fundamental value and eventually it is corrected, resulting in market return reversals. He also shows that institutional investors take into account the expected level and changes of individual sentiment which is a proxy for noise trader risk. Specifically, when institutional investors recognise market prices have been driven far away from fundamental value, such deviation has to be corrected eventually. Thus, expected returns of institutional investors should be decreased (increased) with a higher level of optimistic (pessimistic) sentiment of individual investors. On the other hand, in the short run, when institutional investors recognise that individual investors may drive market prices even further above (below) the intrinsic value, institutional investors become more optimistic (pessimistic) as the sentiment of individual investors becomes even more optimistic (pessimistic) (see, e.g. Shleifer, 2000).

Moreover, Baker and Wurgler (2006) construct a composite sentiment measure by extracting the common factors of the sentiment proxies and examine investor sentiment in the stock market. They use six sentiment proxies: trading volume, the divided premium, the closed-end fund discount, the number of IPOs, the first-day returns on IPOs and the equity share in new issues. To mitigate the effect of macroeconomic conditions from each of the variables, they regress each variable on six macroeconomic indicators: growth in industrial production, real growth in durable, nondurable and service consumptions, growth in employment and an NBER recession indicator. They find that the sentiment effect is more pronounced for stocks that are difficult to value and hard to arbitrage.

In a study that examines post-earnings-announcement drift and accruals in relation to investor sentiment, Livnat and Petrovits (2009) find that good news (bad news) earns significantly higher (lower) abnormal returns following pessimistic (optimistic) sentiment periods and low (high) accruals earns significantly higher (lower) abnormal returns following optimistic (pessimistic) sentiment periods. This suggests that if news contradict sentiment, investors underreact to the conflicting information. In the same spirit, Mian and Sankaraguruswamy (2012) examine the relation between investor sentiment and the sensitivity of stock prices to earnings announcements and find that investors react strongly to good news (bad news) during optimistic (pessimistic) periods, in particular the reaction is much stronger for bad news during pessimistic periods, consistent with the argument that the incremental cash flows embedded in bad news are more uncertain, risky and difficult to value than those embedded in good news. In addition, the effect of sentiment is more pronounced for the earnings announcement of small stocks, young stocks, high volatility stocks and the stocks which are difficult to arbitrage.

McLean and Zhao (2009) link investor sentiment with real investment and find that investor sentiment has a positive effect on both investment and external finance and show that operational efficiency decreases in high sentiment periods, but rises in low sentiment periods.

A study by Schmeling (2009) uses the Consumer Confidence Index and examines the relation between investor sentiment and cross-sectional stock returns in 18 industrialised countries and shows that future stock returns are lower in the majority of countries during high sentiment periods. The sentiment negatively forecasts future stock market returns. They also show that the sentiment effect is more pronounced for small and growth stocks and for countries with less market integrity.

There is also evidence of investor sentiment in relation to different financial anomalies. Stambaugh et al. (2012) examine the effect of investor sentiment on a number of anomalies. They find that long-short strategies of these anomalies are much more profitable in high sentiment periods, since during optimistic periods mispricing is more prevalent as stocks become overall overpriced and it is costly to short sell due to limits to arbitrage. The profits are mainly attributed to the short legs and sentiment has no impact on the long legs of the strategies. This is because during high sentiment periods, short-legs become more overpriced than long legs, since an anomaly itself represents mispricing and due to limits to arbitrage, short leg results in underperformance. During pessimistic periods, long legs will be unlikely to become underpriced due to it not being costly to buy stocks.

Yu and Yuan (2011) show that there is a positive relation between market expected returns and conditional volatility during pessimistic periods whereas the relation disappears during optimistic periods suggesting that the market is less rational during optimistic periods because of higher participation by noise traders during such periods. Antoniou et al. (2013) confirm the findings of Yu and Yuan (2011) and find that the CAPM model is effective in pricing covariance risk during pessimistic periods but not effective during optimistic periods, which is consistent with the notion that noise traders tend to be active during optimistic periods and inactive during pessimistic periods.

A recent study by Antoniou et al. (2013) investigates the role of sentiment and cognitive dissonance in explaining momentum profits. They find that momentum profits arise only under optimism and that news that contradicts investors' sentiment causes cognitive dissonance, resulting in slow diffusion of such news being incorporated into stock prices and momentum profits. Individual investors rather than institutional investors are reluctant to sell loser stocks under optimism. Momentum profits are only significant during optimism since losers are underpriced, which is due to short-selling constraints impeding arbitraging of loser stocks. They also show that long run reversal also only occurs under optimism. This is consistent with Hong and Stein (1999) that momentum traders strengthen the price continuation, and subsequently prices revert to fundamental value.

2.1.4 Conclusion

To conclude, in the last two decades, numerous anomalies and puzzles have proved difficult to explain by traditional finance theories. In order to explain the various market anomalies, scholars have extended their research to the perspective of the behavioural domain – studying the market participant from psychology and sociology. Investor sentiment is one of its important foundations, providing an alternative theory of how investors behave in financial markets and the impact on stocks prices and has been shown to be important in many areas of finance. We will therefore consider it more fully in this thesis. However, unlike most prior studies, we will consider sentiment within the extent of cognitive dissonance on market anomalies. Thus, we pay special attention to investor sentiment in all three empirical chapters.

2.2 Cognitive Dissonance

2.2.1 Introduction of Cognitive Dissonance

Festinger (1957) first introduced the concept of cognitive dissonance, which refers to individuals holding two or more contradictory cognitions at the same time. The cognitions include beliefs, individual behaviour and information. It occurs many areas in our life. For example, consider a scenario in which a man who has a strong value on being environmentally responsible just bought a new car that he late finds does not get great gas mileage. Thus, there are two conflicting beliefs. The first belief is that it is important for the man to take care of the environment and the second belief is that he is driving a car which is not environmentally-friendly. When dissonance is evident, to resolve such discomfort, investors may avoid any information likely to generate dissonance and become reluctant to react to such information.

Festinger (1957) defines cognitive dissonance using the mathematical equation as

$$M=D/(D+C) \tag{2.1}$$

Where M is the magnitude of dissonance experienced by investors;
D is total cognitions which are dissonant from a referent cognition;
C is the sum of cognitions that are consonant with the same referent cognition.

Festinger (1957) argues that when people experience cognitive dissonance, they seek to find a way to reduce it by means of seeking new information. The framework of cognitive dissonance involves a four-step process of dissonance arousal and reduction. The first step is that a cognitive discrepancy occurs. Second, people experience dissonance and feel discomfort. Third, they are motivated to seek to reduce cognitive dissonance. Fourth, cognitive dissonance may be reduced by means of seeking new information.

Goetzmann and Peles (1997) examine the role of cognitive dissonance in mutual fund investors. They suggest that individual investors may experience cognitive dissonance in making a mutual fund purchase decision. Some researches document that investor dollars are invested more rapidly in winning funds (mutual funds with good performance) than outflows from losing funds (mutual funds with poor performance). Goetzmann and Peles suggest that investors are slow to quit past losing funds since they are reluctant to recognise they made a bad investment decision.

Darrat et al. (2002) examine the role of index futures trading in spot market volatility. They find that index future trading cannot attribute to the observed volatility in the spot markets. Instead, they find strong evidence that volatility in the future markets is itself an outgrowth of a turbulent spot market. Their findings are consistent with cognitive dissonance theory. This is because as the spot market itself becomes more volatile, investors are more likely to try to reduce cognitive dissonance in which they made wrong investment decisions. Thus, investors increasing engage in more hedging activities, not only to reduce perceived risk from spot market, but also to avoid future pain of regret.

Prast and Vor (2005) argue that due to cognitive dissonance, information filtering by investors provides a plausible explanation in which the exchange rate of the euro against US dollar fell although there is a convergence in the growth rates of the two regions. Specifically, due to cognitive dissonance, investors react differently to good and bad news. In euro area, they don't much attention to favourable euro news compared to the bad news. However, they pay great attention to good US news compared to the bad news. Such an asymmetric pattern may explain why the convergence of economic growth differential between two areas did not cause the appreciation of the euro.

According to Kindlegerger (2000), cognitive dissonance is a significant factor in affecting herding in financial markets. Argentesi and Lutkepohl (2009) find the evidence of cognitive dissonance in relation between stock market performance and acquiring information. They argue that when investors experience cognitive dissonance, in order to reduce it, they prefer to ignore the information that contradicts to the market performance. They find that when stock market performs well, investors purchase more newspapers whereas when market performs bad, the sale of newspapers decreases. Their findings are consistent with the argument of cognitive dissonance.

Antoniou et al. (2013) have linked cognitive dissonance to the momentum puzzle. They argue that newswatchers experience cognitive dissonance in processing the arrival of new information when the news contradicts their sentiment states. This implies that bad (good) news diffuses slowly during optimistic (pessimistic) periods. In other words, investors are reluctant to trade such stocks when the sentiment is optimistic, resulting in stronger momentum profits.

A recent study by Chang et al. (2016) use brokerage data and experiment to examine cognitive dissonance in the disposition effect both within and across asset classes. They find evidence that cognitive dissonance is a driver of the disposition effect. They argue that, in the case of stocks, investors experience cognitive dissonance when faced with losses and the belief that they made good decisions. Cognitive dissonance provides the basis for an overall reluctance to realize losses and more willing to realize gains where no cognitive dissonance experienced. However, in case of funds, investors can resolve such cognitive dissonance by blaming fund managers. Thus, delegated stocks will exhibit a weaker disposition effect or reverse disposition effect if the effect of delegation is large enough.

2.2.2 Conclusion

To conclude, cognitive dissonance has been shown to be of importance in other disciplines. To date, there are only a few studies examining cognitive dissonance in the finance discipline. Thus, we will bring together investor sentiment interacting with other factors and the theory of cognitive dissonance to examine financial anomalies. In the first two empirical chapters, we examine the effect of cognitive dissonance and culture on momentum profits and post-earnings-announcement-drift. Cognitive dissonance is expected to be evident when private or public information contradicts investors' sentiment and such phenomena may be different across different cultures. In the third empirical chapter, we examine cognitive dissonance in relation to institutional herding, since cognitive dissonance may be evident when the two factors (sentiment and analyst recommendation revisions) conflict with each other and in turn influence institutional herd behaviour.

2.3 Momentum Profits

2.3.1 Introduction

A substantial literature documents and examines the profitability of momentum strategies, since the seminal work of Jegadeesh and Titman (1993) - simply buying asset winners with high recent returns and selling asset losers with low recent returns during past 3 to 12 months and holding a zero-cost portfolio for the subsequent 3 to 12 months results in an especially profitable investment strategy which is robust to sub-sample periods. A number of subsequent studies find that momentum strategies are consistently profitable throughout many countries worldwide beyond the U.S (e.g. Chui et al., 2010) and across different asset classes including bonds, currencies, and commodities (Menkhoff et al. 2012; Asness et al. 2013).

While equity momentum is an established empirical fact, there are numerous explanations that have been documented in the literature to explain momentum profits and various factors have been examined to be important in determining momentum profits, but the sources of momentum profits are still unresolved. Jegadeesh and Titman (1993, 2001) argue that the momentum effect is difficult to explain by standard asset pricing models (e.g. Fama-French three-factor and CAPM models). Consequently, researchers have proposed various explanations for momentum profits which can be classified as (i) additional systematic risk explanations, (ii) cognitive biases or behavioural explanations and limits to arbitrage. However, researchers have not reached a consensus of a generally accepted explanation for momentum profits yet, and Jegadeesh and Titman (2011) suggest that risk is insufficient to explain the phenomenon.

2.3.2 The Momentum Evidence around the World

Jegadeesh and Titman (1993) focus on the performance of medium-term trading strategies that buy past winners and sell past losers in the U.S equity markets with formation and holding periods between three and 12 months. Specifically, the strategy selects stocks on the basis of stock returns over the past J months and holds them for K months. At the beginning of each month t, stocks are sorted into portfolio deciles based on their past J-month cumulative returns in ascending order. The portfolio with the highest returns is called the “winner” decile and the portfolio with the lowest returns is called the “loser” decile. The strategy takes a long position in the winner portfolio and a short position in the loser portfolio, held for K months. To increase the power of the test, overlapping portfolios are constructed. Specifically, a new position at time t is initiated and the position for both winners and losers that are initiated at time t-K is closed. Thus, every month, 1/K of stocks are revised in the winner and loser portfolios. Momentum returns for a given month are the equally weighted average returns on K portfolios in that month. To mitigate bid-ask spread and lead-lag effects, they skip a formation period month t since both bid-ask spread (Jegadeesh and Titman, 1995) and lead-lag effects (Lo and MacKinlay, 1990) can contribute to short-term contrarian profits. The zero investment strategies that buy and sell the same amount of securities in winner and loser deciles earn abnormal returns.

Numerous studies have showed evidence of momentum (Galariotis, 2014). Subsequent studies have examined momentum strategies in different countries around the world. Rouwenhorst (1998) finds that momentum strategies are profitable in European stock markets and the returns on momentum portfolios across European countries are highly correlated with the returns on the U.S momentum portfolios, suggesting that momentum profits are subject to a common factor across countries. Griffin et al. (2003) further extend the sample to 39 countries in examining the momentum effect and find momentum profits are significantly positive in most of the countries. Chui et al. (2010) find that momentum strategies are profitable throughout the world except in Asia (e.g. Japan). In addition, the profitability of momentum strategies on the basis of stock market indices across countries are examined by Chan et al. (2000) and their results show that momentum profits are both statistically and economically significant.

2.3.3 Rational Explanations for Momentum Profits

Numerous risk-based explanations have been put forward to explain momentum profits after Jegadeesh and Titman (1993) first discovered the momentum effect. However, the existing risk-based theories are still unconvincing, since none of the risk factors can fully explain momentum profits.

Earlier evidence suggested that momentum profits are difficult to explain by either the CAPM or the Fama-French 3-factor model (Fama and French, 1996; Jegadeesh and Titman, 2001). Researchers may attribute momentum profits to delayed reaction of stock prices to some common factors, including both systematic- and unsystematic risk factors. Intuitively, if stock prices react to common information with some delay, investors should be able to use the current common information to predict future stock prices and create a profitable trading strategy. Jegadeesh and Titman (1993) suggest that momentum profits are unlikely to arise from delayed reaction of stock prices to a market component. If momentum profits are attributed to market realisations, the realisations should be positively serial correlated. They find that serial covariance of 6-month returns of an equally weighted index is negative, suggesting that the market component does not contribute to momentum profits. Second, they examine whether momentum profits are due to lead-lag effects of the market component. If momentum profits do arise from the lead-lag effects of the market component, then larger market component realisations imply larger momentum profits. They regress momentum profits on the square of 6-month value weighted market returns in the previous period and find that the coefficient is negative, indicating that the lead-lag effects of the market component do not contribute to momentum profits. Thus, the evidence indicates that stock prices may react to non-market components, resulting in momentum profits.

The evidence above has shown that the market component cannot be used to explain momentum profits. Jegadeesh and Titman (1993) suggest that non-market factors do contribute to momentum profits. Moskowitz and Grinblatt (1999) analyse industry momentum, which can be used to fully capture the performance of traditional momentum strategies. In their portfolio formation, they rank stocks on the basis of past 6-month industry returns and form value weighted industry portfolios. They show that high momentum industry portfolios earn higher returns than low momentum industry portfolios. To examine whether industry momentum can explain traditional momentum, they use the random industry strategy to perform the test. Specifically, each firm in the winner and loser industry portfolios is substituted by other random firms that are not in the same industry, but have the same ranking in another industry. Thus, the stocks in the new portfolios have a similar level of past returns to that in the initial industry portfolios. They find that the random industry momentum strategy earns almost zero profits, suggesting that the industry factors can sufficiently explain traditional momentum returns. However, Grundy and Martin (2001) re-examine the performance of the industry momentum strategy (Moskowitz and Grinblatt, 1999) by skipping a month to avoid microstructure issues and find that both the industry strategy and the random industry strategy earn insignificant profits.

Some researchers also link momentum profits to macroeconomic factors, but evidence has proved to be rather challenging. To examine whether momentum profits depend on the state of the economy, some economic variables have been used to predict time-series momentum profits. These findings estimate monthly time-series regressions of the momentum profits (MOM_t) on conditional state variables as follows:

$$MOM_t = \gamma 0 + \beta 1 * STATE_{t-1} + \varepsilon_t \qquad (2.2)$$

Chordia and Shivakumar (2002) and Cooper et al. (2004) show that momentum premiums are related to macroeconomic state variables. Chordia and Shivakumar (2002) first find that commonly used macroeconomic variables for measuring market conditions can predict time-series momentum profits. However, Cooper et al. (2004) find that the lagged 3-year market returns can serve as a good predictor in forecasting momentum profits and the macroeconomic variables used by Chordia and Shivakumar (2002) fail to explain momentum profits in the presence of either standard price screens or skipping a month return. The macroeconomic variables also cannot explain the fact that momentum profits are positive and significant following positive market returns (UP market) in the findings of Cooper et al. (2004).

Momentum profits are likely to be procyclical and cross-sectional dispersion in stock returns can explain momentum profits where a higher return dispersion implies lower momentum profits according to Stiver and Sun (2010). Return dispersion is measured as the standard deviation of 100-disaggregate-portfolio returns formed on size and BM equity ratios over the previous three months. They find that the cross-sectional dispersion in stock returns that can serve as a market state variable contains incremental information of the current state of the economy and the countercyclical nature of aggregate return volatility and the dispersion in conditional market betas. Their regression results indicate that the return dispersion effect subsumes the predictive power of macroeconomic factors in Chordia and Shivakumar (2002) and that of market state variables in Cooper et.al. (2004). Furthermore, Wang and Xu (2010) find that market volatility combined with market states can predict momentum profits. In their regression analysis, they show that market volatility subsumes the predictive power of market returns and macroeconomic factors, with the predictive power of market volatility centring on losers. In particular, momentum profits are especially low during negative market and high volatility states.

The growth rate of industrial production (MP) is a priced risk factor in standard pricing models, which can explain more than half of momentum profits (Liu and Zhang, 2008). They document that MP loads temporarily more heavily on winners than losers and the duration of the expected growth spread roughly matches the duration of momentum profits, suggesting that MP plays an important role in driving momentum profits. The liquidity risk is also shown to be important in explaining momentum profits (Pastor and Stambaugh, 2003). Recently, Asness et al. (2013) examine value and momentum premiums jointly and find a strong correlation between value and momentum profits across different asset classes. They find that exposure to funding liquidity risk can be only identifiable when examining value and momentum jointly across markets, providing a partial explanation for the correlation structure.

In addition, earnings momentum strategies earn sizable profits where they construct a zero-investment portfolio that is long the highest earnings surprise portfolio and short the lowest earnings surprise portfolio (Chordia and Shivakumar, 2006). Not surprisingly, price momentum and earnings momentum are positively correlated. The Fama-French three-factor model is extended to include earnings (price) momentum-based zero investment portfolios as a systematic factor to explain the payoff of the price (earnings) momentum strategies. They find that earnings momentum cannot be explained by the systematic factor of price momentum, whereas price momentum is primarily driven by the systematic component of earnings momentum. Since earning momentum portfolios, which are well diversified, are unlikely to contain any firm-specific news, such as earnings surprises, the source of price momentum is unlikely to be due to firm-specific factors. They also find that earnings momentum is correlated with macroeconomic variables even after controlling for the Fama-French three factors, suggesting that it contains fundamental macroeconomic information, which possibly explains why it captures price momentum (see Chordia and Shivakumar, 2002).

Moskowitz et al. (2012) find that the time-series of momentum strategies across different asset classes earn significant abnormal returns and the time-series momentum profits across different classes are highly correlated, suggesting that time-series momentum strategies are affected by a common component that does not exist in the underlying assets themselves. They also find that the time-series momentum profits are significantly correlated with cross-sectional momentum profits across different asset classes. Both findings are consistent with the findings of Asness et al. (2013) who also suggest a common component among traditional momentum strategies across different asset classes.

To conclude, evidence from the above studies suggests that momentum profits are not generally rationalised by rational explanations, since none of the macroeconomic risk factors or non-market components can fully explain momentum profits. The findings are consistent with the findings of Jegadeesh and Titman (2011) that momentum profits cannot be fully explained by risk factors.

2.3.4 Behavioural Finance

Since the momentum effect is difficult to rationalise by standard asset pricing models, researchers have moved the research into behavioural domains to explain the phenomenon. Shleifer (2000) argues that financial markets may not be efficient and the momentum effect is a strong phenomenon that contradicts the efficient market hypothesis. According to Shleifer (2000), irrational investors with different cognitive biases matter in determining momentum profits i.e. investor sentiment is important in explaining the momentum effect. In the previous section 2.1.3, it is argued that the existence of behavioural biases (investor sentiment) among individual investors will affect stock prices only if limits to arbitrage holds, which prohibits rational investors from exploiting the mispricing. Limits to arbitrage and investor sentiment are two main foundations of behavioural finance, which are discussed in detail as follows.

2.3.4.1 Limits to Arbitrage

Arbitrage refers to the fact that arbitrageurs buy underpriced stocks and sell overpriced stocks to earn risk-free returns. The stock prices consequently revert to their fundamental values. However, due to limits to arbitrage, rational investors are not able to exploit anomalies in the market, such as the momentum anomaly. Barberis and Thaler (2003) show there are several issues that formalise the possibilities of limits to arbitrage.

First, transaction impediments, including short-selling constraints and high implementation costs, affect limits to arbitrage. Large mutual fund managers find it difficult to short sell stocks and in some extreme cases, shares that are mispriced are not available to borrow. Transaction costs have been used to explain momentum profits (Lesmond et al. 2004; Li et al. 2009). Lesmond et al. (2004) show that momentum profits can be fully explained by transaction costs, suggesting that transaction costs impede investors to arbitrage. However, Li et al. (2009) find that six out of the nine momentum strategies produce positive and significant profits even after accounting for transaction costs, which is inconsistent with the findings of Lesmond et al. (2004). Their findings suggest that the results of Lesmond et al. (2004) are subject to a specific sample and a particular momentum strategy. A study by Badreddine et al. (2012) tests momentum strategies on optioned stocks which are classified as highly liquid and lower short sell stocks. The momentum strategies on such stocks are profitable, which is consistent with the findings of Jegadeesh and Titman (1993), suggesting that short sell constraints are not the main driver for momentum profits.

The role of idiosyncratic risk is also documented in the literature to explain the momentum and long-term reversal effects. Arena et al. (2008) find that with the exclusion of stocks in the lowest NYSE size decile and stocks with prices under $5, higher idiosyncratic volatility stocks imply higher momentum profits and the momentum loser effect is the strongest in the highest idiosyncratic risk tercile whereas the momentum winner effect is not different across portfolio terciles. Brav et al. (2010) also use idiosyncratic risk to explain momentum profits and sort firms into idiosyncratic risk quintiles and value weight their returns. They find that losers have especially low returns and do not find evidence of higher returns for high idiosyncratic winners, which is consistent with the findings of Arena et al. (2008). McLean (2010) obtains similar results to those of Arena et al. (2008) in excluding such stocks that have high idiosyncratic risk from the sample and suggests that Brav et al.'s (2010) empirical design asymmetrically undervalues the influence of high idiosyncratic risk momentum firms that may contribute to momentum profits. He shows that idiosyncratic risk plays an important role in preventing arbitrage in the long-term reversal effect, whereas the momentum effect is not related to idiosyncratic risk, suggesting that transaction costs are enough to prevent arbitrageurs from wiping out momentum profits. The possible explanation for Mclean (2010) is that arbitrageurs with longer investments horizons of 1 year or more have a better chance of recovering their transaction costs in reversal portfolios than in momentum portfolios.

Second, it is impossible to find a close substitute for mispriced assets. Arbitrageurs cannot hedge their position in the mispriced asset if there is an adverse change in fundamental value of the asset. Lastly, De Long (1990a) shows that noise trader risk is also an important factor for limits to arbitrage. Arbitrageurs face noise trader risk, which causes the mispricing to become even worse before it corrects. The arbitrageurs cannot maintain their position and receive margin calls so they have to liquidate a part of their position. The situation becomes even worse if they trade with others' capital.

To sum up, limits to arbitrage have been seen to be important in preventing rational investors from exploiting momentum profits. This would prevent rational investors from exploiting the mispricing. In the next section, empirical evidence of behavioural biases of individual investors is discussed in relation to momentum profits.

2.3.4.2 Behavioural Explanations

Numerous behavioural arguments have been put forward to try to explain the momentum puzzle, both from a theoretical perspective and in terms of empirical analysis. For example, behavioural based theoretical models have been developed by Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999) based on either psychological biases (e.g. overconfidence, representativeness and self-attribution bias) or bounded rationality within a heterogeneous trader model. These models were discussed in details in section 2.1.3.1.1. However, other possible behavioural explanations have been examined.

Firm-specific characteristics have been linked to momentum profits. Intuitively, if the momentum anomaly arises due to stock prices inefficiently reacting to information that relates to the firm, the firm-specific characteristics, which are used as proxies of various types or the quality of firm information, are related to momentum profits. Hong et al. (2000) find that momentum strategies are much more profitable among stocks with small market capitalization and low analyst coverage, which is consistent with the behavioural model of Hong and Stein (1999). Since stocks with low analyst coverage refer to the stocks that have less public information, investors may react more slowly to such information. Further, there is always more private information associated with stocks that have less public information. Investors may overreact more strongly to more private information as suggested by Daniel et al. (1998). Lee and Swaminathan (2000) show that momentum profits are larger for stocks with higher trading volume. Intuitively, stocks with higher trading volume have lower transaction costs and can be traded more easily than stocks with lower trading volume. Such stocks are also associated with more public information, resulting in larger differences in investor opinions for these stocks. It indicates that analysing the fundamental value of these stocks by investors would be difficult. Psychological biases suggest that people are likely to be more overconfident about their ability to choose the stocks that are hard to value. Thus, overconfidence suggested by Daniel et al. (1998) can contribute to momentum profits. Another possible explanation is that stocks with higher trading volume attract more attention and thus are likely to be involved in positive feedback trading strategies (buy past winners and sell past losers) introduced by De Long et al. (1990b).

Zhang (2006) explores the role of information uncertainty in the momentum anomaly. He hypothesises that investors only underreact to public information and will underreact more strongly when the information is more uncertain due to the psychological bias of overconfidence. He finds that greater information uncertainty implies relatively lower future stock returns following bad news and comparably higher future stock returns following good news, suggesting that information uncertainty delays information incorporation into stock prices. In his study, analyst forecast revisions and accumulated returns in the past 11 months are used to distinguish good news from bad news, firm size, firm age, analyst coverage, dispersion in analyst earnings forecasts, stock volatility and cash flow volatility are used as proxies for information uncertainty. The evidence indicates that market reaction is incomplete, since good news predicts relatively higher future returns and bad news predicts relatively lower future returns. The stronger information uncertainty implies larger market inefficiency, suggesting that investors will underreact more strongly to the new information in the case of greater information uncertainty.

According to Avaramov et al. (2007), the momentum effect is more prominent for low-grade firms and is insignificant for stocks with a credit rating from AAA to BB, suggesting that the momentum effect persists only among firms with high credit risk regardless of firm size. They also find that momentum payoffs should be higher during the recession when credit risk is a major concern. Further, Agarwal and Taffler (2008) point out that Avaramov et al. (2007) do not examine whether credit rating can fully capture the performance of momentum strategies. They show that distress risk factors can explain a large part of momentum profits, which is consistent with the findings of Avaramov et al. (2007). Sagi and Seascholes (2007) show that momentum strategies are more profitable among firms with higher revenue growth volatility, lower cost and more valuable growth options than the traditional momentum strategies.

A study by Verardo (2009) shows similar results to the findings of Zhang (2006) by using only one factor from Zhang (2006), which is dispersions in analyst forecasts, but interprets her results differently by emphasising that investors' heterogeneity of beliefs is an important driver of momentum profits. Her study tests an empirical relation between differences in investor opinions and stock return continuations in the cross-section of U.S. stocks to disentangle the effect of disagreement from the effects of prior uncertainty and information uncertainty. The predictive cross-sectional regressions show that heterogeneity of beliefs has a significantly positive impact on stock return continuations after controlling for a stock's visibility, the speed of information diffusion, uncertainty about fundamentals, information precision, and stock volatility.

Furthermore, there are other behavioural theories that have been linked to the momentum effect. The disposition effect has been documented to explain momentum profits by many researchers due to underreaction to market information. Grinblatt and Han (2005) show that prospect theory combined with mental accounting can explain a large part of momentum profits. Prospect theory (PT) refers to the concave function (risk averse) in the domain of capital gains and convex function (risk loving) in the domain of capital losses and both gains and losses are separated by a reference point. Mental accounting (MA) provides a basis for decision makers to set the reference point to determine capital gains and losses. The intuition behind PT/MA is that the demand function is different from a standard utility function in the way that winners are less desirable than losers, other things staying the same. They use average cost basis as a proxy for the reference point and use the gap between current stock market price and the reference price as a proxy for the capital gains (losses), which is a good indicator of future returns. The model is in line with the empirical evidence of the disposition effect.

George and Hwang (2004) show that the "anchoring effect" can explain a significant part of momentum profits. Specifically, the 52-week high price level is a good indicator for predicting future returns. Intuitively, when good news has pushed stock prices to exceed or near the 52-week high, investors are reluctant to buy such stocks even if new information confirms stock prices to increase. The information eventually spreads, and the prices increase, resulting in stock return continuations. Similarly, when bad news has pushed stock prices far away from the 52-week high price level, traders are reluctant to sell such stocks even if negative shocks imply a price fall. The information eventually prevails, and the stock prices decline. Thus, traders' unwillingness to revise their portfolios depends on the 52-week high price level and the greatest reluctance is at the price level which is nearest and farthest from the 52-week high. Their argument confirms the disposition effect. There are notable similarities between the two different explanations for momentum profits above. Taken together, both are consistent with the disposition effect and confirm that momentum profits are due to underreaction to market information.

There are other factors that are important in determining momentum profits. For example, Cooper et al. (2004) which is discussed earlier find that momentum profits only exist in the UP market, which is consistent with the behavioural models of Daniel et al. (1998) and Hong and Stein (1999). Intuitively, Daniel et al.'s (1998) model suggests that the aggregate confidence level should increase following an UP market since investors would attribute good performance of stocks to their stock selection skills due to "self-attribution" bias and Hong and Stein's (1999) model suggests that risk aversion would decrease following market gains, resulting in a stronger delayed overreaction.

Asem and Tian (2010) extend the findings of Cooper et.al. (2004) to analyse the market continuation in the same state versus transition to a different state. Their finding is consistent with the behavioural model of Daniel et al. (1998) who show that confirming information will strengthen investors' overconfidence and disconfirming information will dampen it due to the "self-attribution" bias. Specifically, momentum profits will be higher when the market continues in the same state than when market transitions to a different state.

In addition, Kelsey et al (2010) examine the role of market uncertainty measured by Knightian uncertainty to explain momentum profits and find that momentum profits are more likely to arise during high market uncertainty, which is consistent with the findings of Zhang (2006). In their study, Knightian uncertainty refers to the circumstances in which the objective probabilities are unknown or imperfectly unknown and it occurs when the quality of the information is bad or when the market is characterized by a lack of information or when there is a high disagreement of investor opinions. Furthermore, Hameed et al. (2008) show that informed trading is an important factor in determining momentum profits and Bloomfield et al. (2009) find that momentum profits only arise when there are only informed traders in the markets.

There is also evidence to indicate that culture is an important factor in determining momentum profits across countries. Chui et al. (2010) first link the cultural effect to momentum profits worldwide and find that the individualism index which is related to overconfidence and self-attribution biases can explain momentum profits across countries. Their findings suggest that individuals in different cultures process information differently and are subject to different psychological biases.

Recently, Antoniou et al. (2013) investigate the role of investor sentiment on momentum profits. They find momentum profits only arise under optimism and show that news that contradicts investor sentiment cause cognitive dissonance that slows the diffusion of such news being incorporated into stock prices, resulting in momentum profits. They also find that retail investors rather than institutional investors are reluctant to sell loser stocks under optimism. Momentum profits are only significant during optimism, since losers are under-priced, which is due to the short-selling constraint impeding arbitrage of loser stocks. They also show that long-run reversals also only occur under optimism. The evidence is consistent with Hong and Stein (1999) where momentum traders would strength the price continuation and subsequently, prices revert to its fundamental value.

Antoniou et al. also state "This raises the question of whether the asymmetric momentum pattern we have documented for the United States, where individualistic attitudes are considered to be higher than in other cultures, gains support in countries characterized by less individualism. Exploration of this issue would seem to be an interesting area for future research." (Antoniou et al. 2013, pages 273-4). We believe that research on the interaction of culture and sentiment on cognitive dissonance will be promising, since individual proneness to sentiment may be influenced by investors' cultural background. A cross-cultural psychology literature suggests that people experience cognitive dissonance across cultures. Miller (1984) was the first to argue that cultural differences may lead to different expression of psychological biases. She examines the difference between holistic (Asian and Indian) and agentic (Western European and North American) cultures. In holistic cultures, people view the self in relation to others and emphasise more on harmonious social relationships. People from agentic cultures emphasise more on their own decisions and actions.

In a subsequent seminal paper, Markus and Kitayama (1991) analyse the cultural differences between collectivist and individualistic cultures. Individualistic cultures are concerned with self-integrity and emphasise more on their own attitudes and behaviours. In contrast, collectivist cultures are concerned with group-relationship and social harmony. Markus and Kitayama argue that cognitive dissonance is a strong phenomenon in western or individualistic cultures. In such cultures, people express their opinions purely based on their own judgment whereas the expression of opinions in collectivist cultures is only a part of self-judgement but also includes expressions that influence the degree of harmony within a group.[2] Given such evidence, we argue that investors in individualistic cultures will experience much stronger cognitive dissonance than in collectivist cultures and test such a hypothesis in relation to momentum profits in the first empirical chapter.

2.3.5 Conclusion

To conclude, under the efficient market hypothesis, momentum profits should be fully exploited because there is so much "smart money". The momentum effect has existed for many years and both rational and behavioural theories have been proposed to explain it. However, none of the theories can fully explain momentum profits. As suggested by Jegadeesh and Titman (2011), risk factors are insufficient to capture the full performance of momentum strategies and behavioural explanations seem to be promising for further research. The evidence of behavioural models and empirical findings show

[2] Other experimental studies include Heine and Lehman (1997), Spencer-Rodgers et al. (2010) and references in these papers.

that investor sentiment (Shleifer, 2000) which refers to people having different cognitive biases plays a crucial role in determining momentum profits. Recently, investor sentiment (Antoniou et al., 2013), specifically whether individuals are optimistic or pessimistic (different beliefs) about the current situation, and cultural effects have attracted much attention in the behavioural domain. Chui et al. (2010) first link cultural effect to momentum profits. However, to date it is not clear why cultural factors might influence the level of returns and their study does not link sentiment to culture. None of the researchers has examined the interaction between investor sentiment and other factors in determining momentum profits. Thus, our first empirical chapter will focus on the interaction between sentiment and cultural effects to examine the momentum effect.

2.4 Post-Earnings-Announcement-Drift

A substantial literature documents the effect of post-earnings-announcement-drift (hereafter, PEAD) since the work of Ball and Brown (1968) – stocks with high positive earnings surprises tend to have high abnormal returns and stocks with large negative surprises continue to earn low returns. According to the semi-strong version of the efficient market hypothesis, available information should be incorporated into stock prices immediately when news is announced. However, PEAD is an anomaly that is not in line with market efficiency. Fama (1998, page 304) states that "Which anomalies are above suspicion? The post-earnings-announcement drift… has survived robustness checks, including an extension to more recent data…" The efficient market hypothesis proposes that all available information to the market should be reflected in stock prices. Once new information is available, stocks prices should be adjusted to the information immediately. However, evidence suggests stocks prices following good news continue to drift upwards and those following bad news continue to drift downwards and the drift lasts up to several months. The phenomenon is not only confirmed in the U.S but also found in the UK (see e.g. Hew et al., 1999; Liu and Strong, 2003), in Finland (Booth et al., 2005), in China (Truong, 2011) and in international markets (Dou et al., 2015; Griffin et al, 2005; Hong et al., 2001; Hung et al., 2014). There are two main measures of earnings surprises to quantify new information about earnings including the standardised unexpected earnings and the analyst forecast based measure. The standardised unexpected earnings model is based on a univariate time-series earnings forecasting model, which may ignore other potential variables that could matter in affecting expected earnings. Many studies such as Brown and Rozeff (1978), Collin and Hopwood (1980) and O'Brien (1988) have compared the measurement of analyst forecasts based models with the unexpected earnings model, suggesting that the analyst forecasts based model is superior to the other because analysts use different information in their forecasts. Thus, the analyst forecasts based measure is employed in the second empirical chapter.

2.4.1 Evidence of PEAD

The PEAD effect has survived for decades and has been found both in developed and emerging markets. Stocks with positive earnings will drift upwards after the announcement up to several months and stocks with negative earnings surprise will drift downwards. Ball and Brown (1968) first documented PEAD of good and bad news firms and the drifts lasted up to two months. Their sample covers the period 1957 to 1965, including 261 firms but the sample does not include young stocks or firms that do not report on December 31 and that do not have data availability on Compustat, the CRSP tapes and the Wall Street Journal. They construct two models for expectation of income and test market reaction when the forecasts prove to be incorrect. They measure residual of net income and earnings per share using a time-series regression model and earnings per share using a naïve model. The residuals of net income and earnings per share exhibit drift behaviour. A subsequent study by Jones and Litzenberger (1970) examines two samples from Compustat. The first sample covers 510 firms from 1962 to 1965 and the second one includes 618 firms from 1964 to 1967. They only observe drift for positive surprises, but not for negative surprises, suggesting that unfavourable earnings would cause investors to sell stocks more rapidly than favourable earnings. A subsequent study by Latane et al. (1977) examines 975 standardised unexpected earnings and the drift is observed for both positive and negative earnings surprises.

A review paper by Ball (1978) shows not only evidence of PEAD, but also explains PEAD due to a systematic experimental error, market inefficiency and private costs of information processing, and failure of the two-parameter model. While most of the early studies on PEAD have suffered from several limitations including small sample, sample selection biases and risk measurement error, there are a number of subsequent studies on PEAD, confirming its profitability.

Foster et al. (1984) carry out a study using 56000 observations from 2,053 firms spanning from 1974 to 1981 on Compustat. They find the drift of positive and negative earnings surprises is persistent over the sample period and show that firm size is negatively correlated with the drift, but is positively correlated with the sign and magnitude of the earnings surprise. In addition, they find that earnings forecast error and firm size alone explain 81% and 61% of the variation in PEAD, respectively and there are no drifts when earnings are scaled by the absolute value of earnings and scaled by the standard deviation of the forecast error. Bernard and Thomas (1990) use quarterly data over the period from 1974 to 1986 including 84,792 firms from NYSE/AMEX and 15,475 firms from NASDAQ. They find the drift is prominent in the first three months and almost disappears beyond three months. The drift is positively correlated with the magnitude of the unexpected earnings and the absolute value of the drift is negatively correlated with firm size. A subsequent study by them uses a new methodology to examine PEAD in which they transform the earnings surprise into coded quintiles based on their ranking in each accounting period and scale the coded scores from 0 to 1 to eliminate outliers and potential non-linearities. They conclude that PEAD is due to underreaction to earnings information.

The extensive studies of PEAD in the following period in the U.S markets are: Albarbanell and Bernard (1992); Ball (1992); Bhushan (1994); Mendenhall (2004) and Battalio and Mendenhall (2007). All of these studies confirm the existence of PEAD. Hew et al. (1996) examine PEAD in the UK stock market. Their results are consistent with the findings from the U.S., but the drift lasts for a longer period after the earnings announcement. Evidence of PEAD can also be found in international markets. Dou et al. (2015) find significant positive earnings momentum profits for 30 out of the 41 countries examined, including for Canada, the U.S and most of the major western European markets and all ESEA markets except Singapore. In contrast, Hong et al. (2003) examine 11 markets around the world and find significant profits from exploiting earnings momentum profits for all of the western markets in their sample and only one (Hong Kong) of six ESEA markets. Griffin et al. (2003)

find that earnings momentum strategies are on average profitable in all countries but one American market, one Asian market, and one European market.

2.4.2 Explanations for PEAD

A number of studies have been documented to explain PEAD. There two main streams in the existing explanations of PEAD: 1) behavioural explanations: investor underreaction, analyst underreaction and biased information processing; 2) Misspecification of risk.

2.4.2.1 Behavioural Explanations

The most frequent and accepted explanation of PEAD in the literature is underreation to earnings surprises. This argues that investors and analysts underreact to new information, resulting in such news incorporating slowly into stock prices. These behavioural explanations include analyst underreaction, investor underreaction and biased information processing.

2.4.2.1.1 Analyst Underreaction

A number of studies suggest that analyst earnings forecasts are not efficient (see e.g. Lys and Sohn, 1990; Abarbanell, 1991; Ali et al., 1992). Abarbanell and Bernard (1992) examine whether analysts are biased in forecasting earnings. They show that forecast errors are positively correlated with previous earnings change. The intuition behind the finding is that analysts forecast earnings with caution and are unlikely to believe the earnings will continue to rise. If earnings continue to rise, the forecast will be smaller than the actual earnings. Thus, this results in analysts' underreaction to the earnings change in the previous time period. However, the underreaction of analyst forecasts can only explain at most half of PEAD and the authors conclude that analyst behaviour is only a partial explanation for PEAD.

2.4.2.1.2 Investor Underreaction

Investors are participants in stock markets and are influenced by analysts' forecasts. PEAD may be due to investors' overdependence on analysts. In a review paper, Lev and Ohlson (1982) describe PEAD as an unwavering belief in market efficiency. Bernard and Thomas (1989) agree with the hypothesis that markets adjust slowly to earnings information and conclude that risk factors are insufficient to explain PEAD. Bernard and Thomas (1990), Wiggin (1991), Bartov (1992) and Rangan and Sloan (1998) also support this hypothesis. However, Hirshleifer et al. (2003) find that investor underreaction is not sufficient to explain PEAD. They examine how investors respond to extreme quarterly earnings surprise and the relation between trades from individuals and subsequent abnormal returns. They find there is no relation between individual behaviour and PEAD.

2.4.2.1.3 Biased Information Processing

Another possible explanation of PEAD is biased information processing. PEAD may be due to biased research model design, bias in sample selection and bias in estimating abnormal returns (see e.g. Ball, 1992; Bushan, 1994; Rangan and Sloan, 1998; Jacob et al., 1999). In a review paper by Ball (1992), he discussed two possible explanations for PEAD:1) the market is inefficient; 2) the market is truly efficient but measurements of PEAD are incorrect. This may be due to bias estimating returns, expected returns, quarterly earnings information, transaction costs, liquidity, overestimated t-statistics or market inefficiency. Bhushan (1994) also states that transaction costs with heterogeneity of investors in processing information would result in PEAD. Rangan and Sloan (1999) show that the findings of PEAD in Bernard and Thomas (1989) may be due to research design biases. Jacob et al. (2000) provide further support in which PEAD results in Bernard and Thomas (1989) could be because of the models they used.

2.4.2.2 Misspecification of Risk

Risk attracted much attention from researchers in an early stage in misspecification of asset pricing models as explanations for PEAD. For example, Ball (1978) and Foster et al. (1984) suggest that PEAD is due to unspecific risk besides systematic risk from CAPM and reject the possibility of a specific time period or inefficient market explanation. Chordia et al. (2009) and other researchers (see e.g. Ball, 1992; Battalio and Mendenhall, 2006) suggest that PEAD is due to other risk premia besides beta risk, which are measured inaccurately or fail to be identified. Bhushan (1994) suggest there is a positive relationship between transaction costs and the magnitude of PEAD. Sadka (2006) and Ng et al. (2008) examine transaction costs proxied by bid-ask spread and commission in explaining PEAD.

2.4.3 Conclusion

To conclude, the PEAD effect has existed for many years and both rational and behavioural theories have been put forward to explain it. However, none of the theories can sufficiently explain PEAD. Recently, investor sentiment (e.g. Mian and Sankaraguruswamy, 2012) has attracted much attention in the behavioural domain. Dou et al. (2015) show that the cultural effect seems to be an important driver for PEAD across countries, but they did not link culture to investor sentiment. We believe that research on culture and sentiment will be promising, since culture has a significant impact in investors' behaviour. Given the difference in behaviour between individualism and collectivism, Markus and Kitayama (1991) argue that cognitive dissonance is a unique phenomenon in western or individualistic cultures, which is discussed in Section 2.3.4. If cognitive dissonance is a major driver in affecting investors processing public information (resulting in PEAD), it is expected that investors in individualistic and collectivist cultures experience different degrees of cognitive dissonance. To date, no researcher has examined the interaction between investor sentiment and the cultural effect on cognitive dissonance and the extent of the variation of PEAD. Thus, our research will focus on the interaction between sentiment and cultural effects to explain PEAD by way of cognitive dissonance in the second empirical chapter.

2.5 Institutional Herding

A number of studies in the literature document that investors are influenced by other investors' trading actions, thus resulting in herding. Banerjee (1992) suggests that herding occurs when individuals may ignore their own private information and imitate the actions of others by following the decisions of other individuals. Devenow and Welch (1996) and Sciubba (2002) suggest that herding behaviour is a series of correlated behaviours among individuals. Chang et al. (2000) suggest that herding is a process by which market participants make their investment decisions based on collective actions, suppressing their own beliefs. Patterson and Sharma (2007) suggest that such behaviour is due to the fact that investors trade the same securities over the same period of time or when investors trade as other investors do and ignore their private information.

2.5.1 Herding Measures in Financial Markets

To understand the empirical literature, it is necessary to be aware of the different measures of herding. Herding measures are classified into two main streams: micro-level herding measures and aggregate price and market activity herding measures. There are two commonly used herding measures in micro-level studies. The first micro-level herding measure is from the model of Lakonishok et al. (1992; thereafter, LSV).[3] According to the LSV metrics, herding is measured as the tendency of institutional investors to buy or sell a particular security relative to what they would do if they trade randomly over the same period of time. The intuition behind the LSV measure is that if herding takes place, there is a tendency of investors to disproportionally buy or sell a single stock. The second micro-level herding measure is Sias (2004; hereafter, Sias) model. He argues that if herding takes place, there is a positive correlation between the proportion of institutions buying in the current quarter and the proportion of institutions buying in the last quarter. The Sias herding consists of two components, institutional investors following their own trades and institutional investors following other institutional investors' trades. The key difference between the LSV and Sias herding measures is that while the former examines indirectly cross-sectional temporal dependence within a period, the latter tests directly whether institutional investors follow each others' trades in the subsequent period. Two measures may allow us to capture different aspects of herding since the LSV measure captures institutional herding within a period whereas the Sias measure captures how institutional investors following each others' trades in the subsequent period. By using both measures, we will be able to gain better insights into the extent to which herding is intentional or spurious.

In addition, the two most commonly used measures in return-based work are by Christie and Huang (1995) and Chang et al. (2000). Christie and Huang (1995) argue that investors tend to suppress their own beliefs and join the crowd during the periods of extreme market movements, indicating that herding is more likely to occur during periods of extreme market movements. Therefore, in the presence of herding, average stock returns would not deviate far away from market returns and thus, return dispersions should be

[3] The LSV model (1992) has been widely used in the herding literature. (e.g. Grinblatt et al., 1992, Wermers, 1999)

relatively low. In the spirit of Christie and Huang (1995), Change et al. (2000) argue that if investors are likely to follow market behaviour during periods of large price movements, then the increase and linear relation between return dispersions and the market return will no longer hold, i.e. there is a non-linear relation between return dispersions and the market return. In other words, if investors are likely to herd during periods of extreme market movements, there should be a negative non-linear relation between stock return dispersions and the market return.

Thus, two different types of herding (the micro-level and return-based models) investigate different aspects of herd behaviour in financial markets. The micro-level herding measures employ proprietary data to directly measure herding of a specific investor type (i.e. institutional investors or individual investors) whereas return-based herding using stock market data cannot distinguish herding of specific investor types. Thus, the two micro-level herding measures are employed in our study in examining institutional herding.

2.5.2 Evidence of Institutional Herding

In an early study, Lakonishok et al. (1992) do not find strong evidence of pension fund managers' herding and positive feedback trading. Grinblatt et al. (1995) examine momentum trading and herding behaviour in the mutual fund industry, using the LSV herding measure, and find strong evidence of momentum trading, but not herding. Wermers (1999) finds weak evidence of mutual fund herding in the average stock level, using the LSV herding measure, but finds strong herding in trades of small stocks and in trading by growth-oriented funds.

Sias (2004) finds strong evidence of institutional trading by examining the tendency of institutional investors to follow each others' trades in the same securities over adjacent periods and shows that institutional investors tend to engage in momentum trading but little of the herding is contributed by the momentum trading. Sias also finds that institutional herding does not drive prices away from fundamental values and suggests that the findings are consistent with information cascades. Institutional herding is also found in American Depositary Receipts (ADRs): Li and Yung (2004) show that there is a significantly positive relationship between changes in institutional ownership and ADR returns even after controlling for momentum. A more recent study by Choi and Sias (2009) uses the Sias herding measure in examining institutional industry herding and documents that institutional investors herd in industries. Celiker et al. (2015) find strong evidence of mutual funds herding within an industry by using both LSV and Sias measures and argue that herding is related to industry momentum trading.

There are also numerous studies examining institutional herding in non-US markets. The studies in a single market include: Germany (Walter and Weber, 2006; Kremer and Nautz, 2013); Hong Kong (Zhou and Lai, 2009); Japan (Kim and Nofsinger, 2005); Korea (Choe et al, 1999; Kim and Wei, 2002); UK (Wylie, 2005). All of these studies except for Japan (Kim and Nofsinger, 2005) and Korea (Choe et al, 1999) use the LSV herding measure, with the exceptions using their own designed herding measure. Results suggest that herding is more pronounced in smaller stock markets. For example, Wylie (2005) shows the evidence of fund manager herding in the smallest- and largest-capitalisation stocks aggregated by industry and the level of herding is similar to that of U.S mutual fund managers. Kim and Nofsinger (2005) find institutional herding is weaker in Japan than in the U.S but when herding occurs, it has a significant impact on price movements in both markets. They argue that the phenomenon depends on economic conditions. Walter and Weber (2006) find strong evidence of mutual fund manager herding and positive feedback trading and suggest that herding is driven by unintentional herding as a consequence of changes in benchmark index compositions. Recently, Holmes et al. (2013) use the Sias (2004) herding measure and monthly institutional holding data for the Portuguese stock market and examine herding under different market conditions, suggesting that herding is intentional, due to reputational reasons. Choi and Skiba (2015) examine institutional herding in 41 countries, using the Sias herding measure, and find that herding is more prevalent in more information transparent markets, suggesting that such herding behaviour tends to be driven by investigative herding. They also find that price adjustment is faster in markets with less information asymmetry.

2.5.3 Causes of Herding

Recent studies note that even institutional investors exhibit herding behavriour (Grinblatt et al., 1995; Lakonishok et al., 1992; Holmes et al., 2013; Sias, 2004; Wermers, 1999; Wylie, 2005). There are four theoretical explanations for herding behaviour among institutional investors: (1) information cascades. Investors may infer private information from prior trades of better-informed investors and mimic their actions, ignoring their own private information (Banerjee, 1992; Bikhchandani et al., 1992); (2) reputational herding. Managers ignore their own private information and decide to herd in order to retain or build their reputation (Scharfstein and Stein, 1990). Trueman (1994) investigates whether herding of analysts is due to reputational reasons and analysts tending to release forecasts that are similar to others' forecast instead of revealing their privation information; (3) investigative herding. Investors may herd together because they receive correlated private information from analysing the same indicators, such as analyst recommendations (Froot et al., 1992; Hirshleifer et al., 1994); (4) institutional investors may herd into stocks with specific characteristics (Falkenstein, 1996; Gompers and Metrick, 2001;).

A review study by Bikhchandani and Sharma (2000) documents that herding behaviour can be either spurious or intentional. Spurious herding takes place when institutional investors trade stocks based on their specific characteristics such as higher liquidity (Falkenstein, 1996) or when institutional investors face similar information sets or analyse the same indicators (Hishleifer et al., 1994) or when investment professionals who have similar education backgrounds and professional qualifications interpret informational signals similarly. In contrast, intentional herding results from imitating the trading actions of other investors, because they infer information from the prior trading activities. The explanations for intentional herding can be attributed to informational and reputational herding which are discussed above.

Theoretical models of intentional herding typically assume that there is not enough reliable information in the market so that investors are less certain about their own beliefs or trading decisions and tend to follow the trades of others, resulting in herding. In contrast, in the case of spurious herding, investors face similar public information and react to the information and end up with similar trading decisions.

Kremer and Nautz (2013) find that the type of herding in the stock market in

Germany is spurious herding i.e. caused by similar reactions to public information and trading signals. They use high-frequency data from the period 2006-2009 and find that herding is more pronounced in the largest and most liquid stocks. Holmes et al. (2013) examine institutional herding in the Portuguese stock market and investigate whether such herding is intentional by analysing the herding under different market conditions, suggesting that herding is primarily driven by reputational reasons.

It is important to distinguish among different causes and types of herding behaviour to investigate whether such behaviour leads to market inefficiency or not. This is not an easy task since there is a large number of factors which may affect investors' trading behaviour and decision-making system. Lakonishok et al. (1992) and Sias (2004) examine institutional herding on stocks by size. Therefore, one would expect that strong herding in small-capitalization stocks would result from intentional herding where investors infer information from each others' trades (e.g. information cascades) and spurious herding tends to be evident in large capitalization stocks, since information is more reliable and available for large stocks (e.g. investigative herding). They find information cascades herding is more pronounced for small stocks. Choi and Sias (2009) show similar findings in small stocks.

If herding is driven by positive feedback trading, such behaviour is defined as spurious herding (Froot et al. 1992; Wermers et al., 1999; Sias, 2004). The evidence of feedback trading on institutional herding is quite mixed. Lakonishok et al. (1992) find little evidence of herding and feedback trading in large stocks and strong evidence in small stocks. Sias (2004) find that little of the herding is attributed to positive feedback trading. In contrast, Grinblatt et al. (1995) document that momentum trading contributes to herding.

There are some external factors in determining institutional herding. For example, Brown et al. (2013) find that analyst recommendation is an important driver for mutual fund herding in the US. Specifically, mutual funds tend to herd into stocks with consensus upgrades and herd out of stocks with consensus downgrades. The effect of analyst recommendation revisions on mutual fund herding is much stronger for downgrades than for upgrades. They also find that such herding is due to reputational reasons. Liao, Huang and Wu (2011) show that individual investor sentiment is a key determinant in explaining subsequent mutual fund herding behaviour which is consistent with the sentiment countering hypothesis, suggesting that investors tend to sell stocks following optimistic sentiment periods.

2.5.4 Herding and Subsequent Stock Returns

A number of studies document the relation between institutional demand and stock returns. Spurious herding can be an efficient outcome if it is caused by the response to fundamental values which speeds up price adjustments and stabilises the market (Lakonishok et al., 1992). If herding is intentional, it may also stabilise stock prices if the type of herding is informational cascades (Sias, 2004). The herding due to informational cascades will not result in subsequent return reversals. However, herding can be inefficient if it is not based on fundamentals. The herding which includes reputational herding, characteristic herding, and fads isbelieved to increase market inefficiencies and thus may market prices deviate far from fundamentals. The subsequent return reversals can be observed by the impact of such herding. For example, spurious herding resulting from momentum trading can drive prices away from fundamental values and prices should be reversed subsequently. There is mixed empirical evidence on the relation between institutional herding and subsequent stock returns. Lakonishok et al. (1992) and Sias (2004), who use quarterly data, do not find return reversals following institutional herding. However, Puckett and Yan (2008) and Brown et al. (2014), who use high-frequency data, find that return reversals follow herding.

2.5.5 Conclusion

Herd behaviour generally refers to a group of investors trading in the same direction or tending to follow the trades of others into or out of securities over the same period of time. Numerous studies suggest that analyst recommendations are valuable to institutional investors and Brown et al. (2013) suggest that they are more likely to herd in (out of) analyst upgrades (downgrades). Given the importance of investor sentiment as discussed in section 2.1, to date, none of the researchers has examined the interaction of investor sentiment and analyst recommendations in determining institutional herding. It is important to understand how analyst recommendations and individual sentiment interact in affecting institutional herding. We propose that cognitive dissonance may be a key driver in affecting institutional herding by taking account of the two prominent factors. it will be evident when the two factors do not suggest similar price movements. Both the LSV and Sias measures will be employed in the study to capture different aspects of institutional herd behaviour in the presence or absence of cognitive dissonance, since the LSV measure allows us to examine institutional herding based on the two factors within a period, whereas the Sias measure captures how institutional investors herd by following each others' trades in the subsequent period.

2.6 Conclusion

Numerous studies have shown that traditional finance theories have limited power in explaining market puzzles. Researchers have extended their research to develop behavioural studies of how market participants actually behave in financial markets. In order to explain market anomalies, psychological biases are incorporated in modelling investor behaviour.

Given the importance of investor sentiment as discussed in the section 2.1, the heart of the thesis focuses on the interaction of investor sentiment and cognitive dissonance in explaining market anomalies. Specifically, none of the previous research examines the interaction between culture and sentiment. Thus, in the first two empirical chapters, we examine the effect of investor sentiment on momentum profits and PEAD in different cultures, since investors' proneness to sentiment is affected by their cultural backgrounds. Investors with distinct cultural backgrounds will be expected to interpret information differently (Otoo, 1999). The interaction is expected to impact on cognitive dissonance which will be evident when private (momentum) or public information (PEAD) contradicts investors' sentiment, resulting in a slower diffusion of the news incorporating into stock prices. In other words, investors' cultural background might influence the investor proneness to cognitive dissonance, resulting in the distinct effect of momentum and PEAD in different cultures. In the third empirical chapter, the interaction between investor sentiment and analyst recommendation revisions on institutional herding is investigated. We consider that institutional investors analyse analyst recommendations and individual sentiment in making their trading decisions. It is argued that cognitive dissonance may impact on institutional herding if the two factors (analyst recommendations and investor sentiment) conflict with each other.

3 Culture and Investor Sentiment: The Impact of Cognitive Dissonance on Momentum Profits

3.1 Introduction

A substantial literature documents and examines the profitability of momentum strategies since the seminal work of Jegadeesh and Titman (1993). Numerous arguments have been put forward to try to explain the anomaly, both from a theoretical perspective and in terms of empirical analysis. The explanations have been discussed in detail in Section 2.3. For example, behavioural based theoretical models have been developed by Daniel et al. (1998), Barberis et al. (1998) and Hong and Stein (1999) based on either psychological biases (e.g. overconfidence, representativeness, self-attribution bias) or bounded rationality within a heterogeneous trader model. In terms of empirical evidence, examples include the role of market state (Cooper et al., 2004), macroeconomic risk (Chordia and Shivakumar, 2002, Liu and Zhang, 2008), international rather than national risk (Fama and French, 2012, Asness et al., 2013), culture (Chiu et al., 2010), sentiment (Antoniou et al., 2013), and arbitrage risk (Mendenhall, 2002), among others. However, despite this work, the reasons for the existence of momentum profits are still not clear. In this chapter, we seek to examine whether culture, sentiment and cognitive dissonance can explain this anomaly using data across a wide range of countries. We pay particular attention to the impact of differences between western and East and South East Asian (henceforth ESEA) cultures.[4]

Our work is motivated by the fact that while the evidence for momentum profits is extensive, it is not found for all international markets. There is general agreement that price momentum strategies are profitable in many western markets (see for example, Jegadeesh and Titman (1993) and Antoniou et al. (2013) for the U.S., Rouwenhorst (1998) for 12 European countries and Griffin et al. (2005) and Chui et al. (2010) for 40 and 41 markets worldwide respectively, with both including the U.S., Canada and a wide range of western European markets. However, the same is not true for ESEA markets. For example, Griffin et al. (2005) find that momentum "profits are

[4] For simplicity, we will use the terms ESEA, east and eastern interchangeably when referring to these countries.

highly significant in all regions except for Asia… It is interesting to note that momentum profits for Asia are decidedly weaker than those around the world, particularly for Europe.” (2005, page 2522). Insignificant momentum profits are found for all ESEA countries in the sample. Similarly, Chui et al. (2010) find momentum returns to be insignificantly different from zero for China, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, Taiwan and Thailand, although they are significant for Hong Kong, in contrast to the findings of Griffin et al. (2005). Chui et al. (2010) also show that culture as measured by Hofstede’s individualism index, is positively related to momentum profits.

While cultural factors have been shown to be relevant to momentum profits, to date it is not clear *why* cultural factors might influence the level of returns, particularly in relation to the differences between western and ESEA countries. It is this issue, which we seek to address by bringing together arguments from the psychology literature regarding differences in relation to views of change between eastern and western cultures, sentiment and the notion of cognitive dissonance. Spencer-Rodgers et al. (2010, pages 297-8) state “The culture and cognition literature… has characterized East Asian thought as emphasizing *holistic thinking* and Western thought as emphasizing *analytical thinking*… holistic thinkers predict… greater change and more cyclical patterns of change, rather than stability or gradual linear change… [and are] more comfortable with and accepting of contradiction”. In contrast, analytical thinkers are more likely to predict that current patterns will persist and will be less comfortable with contradiction. As Ji et al. (2001, page 450) state “The view that things change from one extreme to the other extreme has long been popular in the East, whereas notions of linearity and irreversibility continue to be dominant in the West.” These differences suggest that people from the two cultures will have different expectations about continuation or reversal in stock prices.

Furthermore, while sentiment has been shown to be of relevance to anomalies (see for example, Antoniou et al., 2013; Stambaugh et al., 2012), to date its interaction with culture has not been investigated. This is important since during optimistic or pessimistic periods, cultural expectations will cause investors to experience cognitive dissonance in different cases, affecting their responses to news. For example, in relation to winner stocks, an investor from ESEA who believes in reversal will experience cognitive dissonance in the presence of optimistic sentiment, whereas investors from the west will not, given their belief in continuation. Using a framework in the spirit of Hong and Stein's (1999) heterogeneous trader model, we take account of the differences in views of cognition between the west and the east and examine how these interact with investor sentiment and develop specific hypotheses in relation to difference in momentum profits between the two cultures.

The hypotheses are examined in relation to culture, sentiment and momentum using data from 40 countries worldwide. The consumer confidence index is employed as a proxy for investor sentiment and the individualism index is used as a proxy for culture. We first perform a portfolio analysis and find that momentum profits are only prominent in high individualistic cultures during optimistic periods, which provides clear evidence of the interaction between sentiment and culture on momentum profits. The interaction on momentum profits are examined in a multivariate regression setting while controlling for other determinants that can potentially explain differences in momentum profits across countries. First, we control for variables measuring the effect of speed of information flow and information uncertainty since Zhang (2006) suggests that these variables are able to capture momentum profits. We also control for information efficiency proxies which measure the development of financial markets and institutional quality, because a more highly integrated market facilitates the flow of information and reduces trading costs (see e.g. Chui et al., 2010). Furthermore, macroeconomic factors are also controlled for since previous studies show the effect of macroeconomic factors on momentum profits (see e.g. Cooper et al., 2004 and Griffin et al., 2003). The regression results show that sentiment and, culture as well as their interaction are all highly significant even after controlling for the above explanatory variables. In the robustness tests, we also consider an alternative measure for the individualism index which comes from GLOBE. The regression analysis is re-estimated using the alternative measure and we find that the relationship between the interaction (between sentiment and individualism) and momentum profits still holds.

The analysis is then focused in relation to the argument of cognitive dissonance on the five largest markets in each of the east and west and we find that momentum profits are only significant in western culture countries during periods when sentiment is optimistic. In all five western countries, momentum profits under optimism are primarily driven by the underperformance of loser stocks, whereas the insignificant momentum profits during pessimistic periods are due to the returns to loser stocks not being of the sign consistent with momentum, suggesting that cognitive dissonance for loser stocks is a key driver of momentum profits in the presence of optimistic sentiment. In contrast, there is no clear difference in momentum profits between sentiment states for ESEA markets. Overall, the results are consistent with our specific hypotheses and provide strong support to the importance of cognitive dissonance in explaining differences in momentum profits across cultures.

To consider the possibility that the results may be driven by economic risk factors, we re-estimate Fama-French 5-factor adjusted momentum returns (Fama and French, 2015) across different sentiment states in both western and ESEA countries and find that the results are robust. To ensure that the results are not driven by a particular sentiment index, we consider an alternative index of investor sentiment (Baker et al., 2012). We construct the alternative sentiment index for each of the ten countries and re-estimate the portfolio analysis for momentum returns in western and ESEA markets across different sentiment states. The findings are qualitatively similar to the previous findings. Furthermore, the basic results in the chapter also survive a number of sensitivity tests, including using an alternative momentum strategy, different cut-offs for investor sentiment using 40% instead of 30%, and an alternative methodology of defining optimistic and pessimistic states from Stambaugh et al. (2012).

The study contributes to the literature in three ways. First, the study provides the first examination of the interaction between sentiment and culture on momentum profits in markets around the world. Second, while Chui et al. (2010) show that culture is relevant to momentum profits, to date it is not clear why cultural factors might influence the level of returns. We tackle this issue by bringing together arguments from the psychology literature regarding the differences in relation to views of change between western and ESEA cultures, sentiment and the notion of cognitive dissonance and find that the resulting difference of cognitive dissonance across western and

ESEA cultures can provide a better understanding of differences in momentum profits between the two cultures. Third, we advance the momentum literature by showing that the momentum effect is different across sentiment states in international markets and re-address the fundamental question of whether momentum profits still exist in markets around the world, while using recent data.

The remainder of the chapter is organized as follows: section 3.2 discusses issues relating to culture, sentiment and cognitive dissonance and develops testable predictions concerning momentum and how the phenomenon differs between western and ESEA markets. Section 3.3 presents the data and methodology and is followed by section 3.4 the main empirical analysis. Robustness tests are undertaken in section 3.5, which is followed by a conclusion.

3.2 Cultural Bias, Information-Based Traders and Feedback Traders: Hypothesis Development

3.2.1 Individualism, Sentiment and Momentum

Antoniou et al. (2013) examine the impact of cognitive dissonance on momentum by considering the role of investor sentiment. For the U.S. market they show that momentum profits are evident only in the presence of optimistic sentiment and attribute this to cognitive dissonance. In discussing Chui et al.'s (2010) findings that momentum profits are more marked in countries where individualism is more prevalent they state "This raises the question of whether the asymmetric momentum pattern we have documented for the United States, where individualistic attitudes are considered to be higher than in other cultures, gains support in countries characterized by less individualism. Exploration of this issue would seem to be an interesting area for future research." (Antoniou et al. 2013, pages 273-4). In the first part of our analysis, we seek to address this issue by considering the interaction of sentiment and culture on momentum profits.

While previous studies have examined separately the impact of cultural variables and sentiment on momentum profits, to date no study has investigated the joint impact of these factors and the way they impact cognitive dissonance. Therefore, before we go on to consider arguments relating to specific differences between investors from the west and the east, we consider more general arguments relating to cognitive dissonance and concepts of individualism versus collectivism. In the psychology literature, individualism and collectivism have been related to the concepts of independent and interdependent self-construal. As Cross et al. (2011, page 143) point out "Markus and Kitayama (1991) proposed that Europeans and Americans construe the self as fundamentally individual and separate from others, and they labeled this the *independent self-construal…* In contrast, Markus and Kitayama (1991) pointed out that the Japanese tend to construe the self as fundamentally connected to others and defined by relationships with others, which they labeled the *interdependent self-construal*". Subsequent to the work of Markus and Kitayama (1991), these concepts have been strongly associated with the notions of individualism and collectivism (particularly in relation to considering differences between people from western and East Asian cultures).[5]

The concept of self-construal is important for considering cultural differences and how individuals from different cultural backgrounds will view a particular situation. Individuals with strong independent self-construal place great value on self-integrity and are likely to be strongly affected by cognitive dissonance. Markus and Kitayama point out that cognitive dissonance is a strong phenomenon in western or individualistic cultures. For example, given their belief in continuation, westerners with their tendency for independent self-construal will experience, and be affected by, cognitive dissonance when faced with winner (loser) stocks and a pessimistic (optimistic) state of sentiment. In contrast people with a sense of interdependent self-construal place greater weight on the obligations and responsibilities within a group and will be less concerned with self-consistency. As such they are likely to experience weak cognitive dissonance.[6]

Using a framework in the spirit of Hong and Stein (1999), we consider differences between individualistic and collectivist cultures. Hong and Stein (1999) propose a heterogeneous trader model in which there are two types of trader, both of which are characterized by bounded rationality: newswatchers and momentum (or positive feedback) traders. The former

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[5] While Cross et al. (2011) argue that self-construal is only one aspect of individualism-collectivism, they are often treated as if they are the same.

[6] The argument of cognitive dissonance is discussed in detail in section 2.2.

base their decisions on private signals, without taking account of past or current prices. However, bounded rationality means that they cannot infer information that other newswatchers hold from movements in prices. As a result, information diffuses slowly through the newswatcher population. In contrast, momentum traders' decisions are based on past prices only. The model leads to underreaction in the short-run and long-term overreaction in relation to private news.

While culture plays no part in the Hong and Stein model, they argue "our results are attributable to the assumption that momentum traders make "simple" forecasts—i.e., they can only run univariate regressions. But even if one accepts this restriction at face value, it begs the following question: Why do *all* traders have to use the *same* single forecasting variable? Why not allow for some heterogeneity in trading styles, with different groups focusing on different predictive variables?" (Hong and Stein, 1999, page 2159). They extend their analysis to consider the possibility of contrarian traders. However, recognising that there may be "heterogeneity in trading styles" raises the question of whether cultural biases may impact on trading behaviour. We propose that cultural biases impact on both information-based investors and feedback traders.[7] Allowing for such biases for both types of investors will lead to different predictions for investors in different cultures. We argue that information-based traders are affected by sentiment and behave differently in different cultures.

In relation to cognitive dissonance, they form their trading decision on the basis of private information and are affected by sentiment. On the basis that recent price movements reflect private information diffusing slowly through this group of traders, private news being positive or negative is proxied by whether stocks are recent winners or losers. If two factors (private news and sentiment) both impact in the same direction, then there is no cognitive dissonance and investors are expected to respond to the private information without delay. However, cognitive dissonance will be evident when the two

[7] While these arguments are developed in a manner consistent with the spirit of Hong and Stein (1999), we recognise that in their model newswatchers pay no attention to past or current prices. The notion that newswatchers may trade on the basis of something in addition to private information is also presented in Antoniou et al. who "hypothesize that "newswatchers" will underreact more strongly when they receive information that contradicts their sentiment due to cognitive dissonance" (2013, page 246). Nonetheless, given the differences from Hong and Stein we refer to culturally biased information-based traders rather than using the term newswatchers.

factors do not indicate similar future price movements. In such situations, private information will, therefore, be underweighted as investors adjust their expectations in a non-Bayesian manner and continue to hold their beliefs regarding sentiment. This will result in underreaction to private information by investors. In turn, this implies that the news will diffuse slowly in the presence of cognitive dissonance, resulting in larger momentum profits.

This leads to our first hypothesis:

H1: the effect of investor sentiment on momentum profits will be more pronounced in individualistic cultures than in collectivistic cultures, since people in high individualistic cultures will experience stronger cognitive dissonance than those in low individualistic cultures.

3.2.2 Cognitive Dissonance and Momentum Profits: Western and ESEA Cultures

Again, using a framework in the spirit of Hong and Stein (1999), we now consider differences between western and eastern cultures As stated in the introduction, the cross-cultural psychology literature argues that people from western and ESEA cultures are characterized by different cognitive biases, which impacts on beliefs of change and continuity. Numerous studies show that people in East Asian and Western cultures have different beliefs that may affect their trading behaviour.

Ritsema and Karcher (1994) find that East Asian and Western European cultures have distinct views on change. The view that things change from one extreme to the other extreme has been long popular in the East whereas theories or cognitions of linearity and irreversibility have been dominant in the West (Gurevich, 1969). Peng and Nisbett (1999) show that individuals with dialectical lay beliefs, who are more often found in Japan, China, Korea and other Confucian-influenced cultures than Western European or North American cultures, are more likely to expect change and tolerate and even embrace contradiction. In the culture and cognition psychology literature, East Asians emphasise holistic thinking, while Westerners emphasise analytic thinking. Holistic thinkers are more likely to predict greater changes, and more cyclical patterns of change, rather than stability or gradual linear change, and are more comfortable with accepting contradiction. On the contrary, analytic thinkers emphasise coherence, stability and reconciliation through integration and synthesis, and are more likely to predict the current patterns to persist (Spencer-Rodgers et al. 2010).

Experimental studies support these arguments. For example, Ji et al. (2001) undertake experimental studies using Chinese and American participants and find that “Americans were more likely than Chinese to make predictions consistent with suggested trends, whereas Chinese were more likely than Americans to predict a reversal in trends.” (Page 452). Similarly, Ji et al. (2008) examine stock buy-sell decisions of North American and Chinese university students and investors within an experimental setting and find those from the west (east) had a greater tendency to predict that price trends would continue (reverse), although the differences were more marked for university students than for experienced investors.

These cultural differences appear to be deep-rooted and wide-ranging. For example, Ji (2008) examines Chinese and Canadian children aged 7-11 and again finds that the Canadians were less likely to predict change than were the Chinese. Similarly, Spina et al. (2010) find evidence that predictions of regression towards the mean are more common among Chinese participants than their Canadian counterparts in a wide range of scenarios in relation to gymnastic competition, health and weather. Given this evidence, we argue that both information-based and feedback traders are likely to be influenced by their culture. Specifically, cultural bias will make it more likely that traders from the west will have a cultural belief in continuation of price, whereas those from the east will tend to expect reversal. Furthermore, consistent with the earlier arguments about independent and interdependent self-construal, Spencer-Rodgers et al. (2010) argue investors from the east are expected to be less disturbed by, and more accepting of, contradiction than those from the west. We explore these issues by considering cognitive dissonance and examine the phenomena in relation to momentum profits.

We first consider information-based traders and the impact of cultural bias. In Hong and Stein (1999), it is assumed that information-based traders only forecast on the basis of private signals about fundamentals and news diffuses slowly through the information-based trading population. However, we argue that such traders may also be influenced by sentiment (as Antoniou et al., 2013) and by cultural bias. Specifically, based on the above arguments, western investors are assumed to believe in continuation, while ESEA investors are assumed to believe in reversal. If three factors (private news, sentiment and cultural beliefs) all impact in the same direction, then there is no cognitive dissonance and we expect traders to respond without delay to news. However, cognitive dissonance will be evident when the three factors do not suggest similar future price movements. In such situations, investors will underreact more slowly to the private information they receive. This implies that news will diffuse slowly when investors experience cognitive dissonance, resulting in larger momentum profits. Given their belief in continuation, western investors will experience no cognitive dissonance when the positive (negative) news arrives in optimistic (pessimistic) sentiment periods, but will experience cognitive dissonance otherwise. In contrast, ESEA investors expect good or bad news to mean revert, but are more comfortable with contradiction. If they experience cognitive dissonance, the cognitive dissonance will be less strong. As such these investors will experience weak cognitive dissonance in optimistic and pessimistic states for both winner and loser stocks, since the nature of the private news always contradicts their belief in mean reversion, whatever the sentiment. Exhibit 1 summarises situations in which cognitive dissonance will be experienced by the two cultural groups of information-based traders.

Exhibit 3.1: Cognitive dissonance, Private news and Sentiment

This table summarises the cognitive dissonance (CD) of winner and loser stocks experienced by the two cultural groups of investors, westerners and ESEA in optimistic and pessimistic periods.

	Westerners – belief in continuation		ESEA – belief in reversal	
	Winner stocks	Loser stocks	Winner stocks	Loser stocks
Sentiment				
Optimistic	No CD	CD	Weak CD	Weak CD
Pessimistic	CD	No CD	Weak CD	Weak CD

Now consider the impact of feedback traders. In Hong and Stein (1999), such traders are momentum or positive feedback traders. Such a view is consistent with the cultural beliefs of westerners. However, the same cannot be applied for ESEA investors. Rather, given their belief in reversal, it appears more appropriate to consider (at least some of) such investors to be negative feedback (or contrarian) traders. In other words, they will trade counter to the trades of information-based traders. In sum, this implies that any momentum effect arising from the actions of information-based traders will be accentuated in western markets by positive feedback traders, but dampened in ESEA markets by negative feedback traders.[8]

The above arguments lead to the following additional hypotheses:

H2: momentum profits will be significantly greater in western markets than in ESEA markets.

H3: For western markets, momentum returns will be driven by loser stocks in optimistic periods and by winner stocks in pessimistic periods due to cognitive dissonance. Due to it being costly to sell loser stocks, the momentum effect will be stronger during optimistic periods.[9]

H4: For ESEA markets, there will be no significant difference in momentum profits between optimistic and pessimistic states since information-based traders in each circumstance will experience weak cognitive dissonance.

In addition, given the expectation of a strong momentum effect during optimistic periods for western markets (H3), but weak effects for ESEA markets across both sentiment states:

H5: momentum profits will be greater during optimistic periods for western markets than for ESEA markets.

We examine hypotheses 2-5 for the five largest western and five largest ESEA markets for which all relevant data is available for our sample period.

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[8] As noted above, Hong and Stein (1999) find that contrarian traders have a moderate stabilising effect.

[9] The notion of if being costly to short sell (limits to arbitrage) is discussed in detail in Section 2.3.4.

3.3 Data and Methodology

3.3.1 Hofstede's Individualism Index

The Hofstede individualism index is obtained from the psychological surveys of value scores from IBM employees from Hofstede's website. The original surveys were conducted between 1967 and 1973 and covered more than 70 countries, with data being collected for the 40 countries since these countries have the largest group of respondents. In a later stage, ten new countries were added to the sample by Hofstede and the statistical method conducted in the new data sample is consistent with the data of the previous 40 countries. In 2010, Hofstede further extended his survey to 76 countries. The individualism index is derived based on the country mean scores on 14 questions about employees' attitudes toward private lives and their own work. As seen from Table 3.1, for the individualism index, the U.S has the highest level (91), followed by Australia (90) and the United Kingdom (89), while Colombia has the lowest level (13) followed by Indonesia (14) and China (20). Thus, it is clear that the sample used in this study covers a wide range of cultural attributes. Notably, only one Hofstede cultural dimension proxied by the individualism index is used in this study. This is due to two reasons: (1) it is natural to employ the individualism index in relation to cognitive dissonance, sentiment and momentum profits since the cross-cultural psychology literature suggests that cognitive dissonance is a stronger phenomenon is individualistic cultures (see e.g. Markus and Kitayama, 1991); (2) Chui et al. (2010) and Dou et al. (2015) show that there is a significant relationship between the individualism index and momentum profits and other cultural dimensions have been shown not to have such a significant relationship.

3.3.2 Stock Market Data

For the U.S market, all common stocks (share codes 10 and 11) listed in the NYSE and AMEX from the Centre for Research in Security Prices (CRSP) are used and for the other stock markets, we use all common stocks from Datastream International. We select our sample countries and stocks by applying a number of selection criteria. In the first part of the analysis we are interested in examining the joint impact of investor sentiment and culture on momentum profits. Therefore, each country in our sample is required to have

Table 3.1 Sample Stock Market Descriptive Statistics

This table shows descriptive statistics for the 40 stock markets in the sample along with scores on the individualism index. It also reports the number of firms for each country at the start and end date of the sample period. If a country has more than one major stock exchange, the name of the stock exchanges are listed in brackets. Data for the U.S market are from CRSP, while that for all other countries in the sample are from Datastream International. The stock markets in our sample are subject to the following selection criteria. (1) Each country is required to have a value for Hofstede's individualism index (IDV)) (2) Each country is required to have both stock market data and consumer confidence index data for at least five years (3) Stocks with market capitalization which are below 5% of all stocks are excluded in each month (4) Each country is required to have at least 30 stocks with available market capitalisation data in any month.

Country (Stock Exchange)	IDV	Start date	End date	No. of firms at start date	No. of firms at end date
Argentina	46	1998M7	2013M12	83	64
Australia	90	1991M1	2013M12	612	1560
Austria	55	1996M7	2013M12	107	75
Belgium	75	1991M1	2013M12	208	102
Brazil	38	2006M5	2013M12	250	242
Bulgaria	30	2007M4	2013M12	256	146
Canada	80	2002M10	2013M12	1108	906
Chile	23	2006M2	2013M12	205	156
China (Shanghai & Shenzhen)	20	1998M6	2013M12	866	2422
Colombia	13	2004M8	2013M12	71	47
Czech Republic	58	1995M10	2006M8	257	31
Denmark	74	1991M1	2013M12	218	159
Finland	63	1996M8	2013M12	123	120
France	71	1991M1	2013M12	827	563
Germany	67	1991M1	2013M12	407	682
Greece	35	1991M1	2013M12	137	144
Hong Kong	25	2000M10	2013M12	665	1231
Hungary	80	1995M07	2013M12	34	45
Indonesia	14	2002M1	2013M12	292	395
Ireland	70	1991M1	2013M12	75	30
Italy	76	1991M1	2013M12	342	265
Japan (Tokyo & JASDAQ)	46	1991M1	2013m12	1886	2387
Korea (Korea & KOSDAQ)	18	1999M9	2013M11	998	1655
Lithuania	60	2002M1	2013M12	45	30
Mexico	30	1991M1	2013M12	105	85
Netherlands	80	1991M1	2013M12	205	92
New Zealand	79	1991M1	2013M12	90	113
Norway	69	1993M4	2013M12	129	183
Poland	60	2003M2	2013M12	69	650
Portugal	27	1991M1	2013M12	114	38
Russia (Russia trading System & MICEX)	39	1999M7	2013M12	184	218
Slovenia	27	1998M7	2013M12	47	39
South Africa	65	1991M1	2013M12	398	289
Spain	51	1991M1	2013M12	142	141
Sweden	71	1996M7	2013M12	266	434
Switzerland	68	1991M2	2013M12	361	240

Thailand	20	2000M4	2013M12	366	537
Turkey	37	1991M1	2013M12	65	358
United Kingdom	89	1991M1	2013M12	1731	1288
U.S (NYSE & AMEX)	91	1991M1	2013M12	2126	1480

both stock market data and sentiment data measured by a consumer confidence index for a period of at least five years, and each country is also required to have an individualism index measure. Both domestic and foreign stocks that are listed on the major stock exchange in each country are included in the sample, but cross-listed stocks are only accounted for in the sample of their home country. Both suspended and dead stocks are included to mitigate survivorship bias.

In order to ensure that our results are not driven by small, thin-traded and illiquid stocks, several stock selection criteria are applied to our sample as follows. First, a stock with market capitalization that is below the fifth percentile in its market is excluded in any month in order to remove small and illiquid stocks (Hong et al. 2003; Chui et al. 2010). Second, if stock returns are larger (less) than 100% (-95%), the returns are set equal to 100% (-95%) to filter out stock return outliers.[10] Such a stock selection filter not only eliminate suspicious stock returns, but it also ensures that momentum profits are not driven mainly by small or illiquid stocks (Chui et al., 2010) Third, in order to have a reasonable number of stocks to form momentum portfolios, we follow Chui et al. (2010) and each country is required to have at least 30 stocks with available market capitalization data in any month. Finally, since K-month holding period returns (K=6) and past J-month cumulative returns (J=6) on each individual stock are required,[11] each stock must have a return history of a minimum of 8 months if it is delisted during the sample period.[12] Based on the above stock selection criteria, our sample consists of 40 countries.

The analysis covers the period January 1991 to December 2013 to ensure enough observations in each stock market, while using recent data. However,

[10] The stock outliers are mainly from small capitalization stocks (Ince and Porter, 2006).
[11] We use the 6-month/6-month momentum strategy in our study since it is commonly examined in momentum studies.
[12] A return history of 8 months includes 6-month formation period, one skipping month and a holding period of 1 month.

the sample period for each country is different due to data availability, as shown in Table 3.1. Table 3.1 reports summary statistics of stock markets and the individualism index for each country. It can be seen from Table 3.1 that the average sample period for all countries is approximately 15 years and the sample period varies across countries. For example, most of the developed countries have long sample periods (e.g. 23 years for the United Kingdom), whereas Bulgaria and Brazil have the shortest sample periods (approximately 6-7 years) due to data availability for their investor sentiment index. There is also considerable variation in the number of stocks across countries. For instance, at the start of the sample period, the U.S has the highest number of firms (2126) whereas Hungary has the least (34). Furthermore, the last two columns of Table 3.1 reveal that the number of firms in 16 out of the 40 stock markets has expanded over the sample period, with the number of firms listed in the stock markets of China, Hong Kong and Korea having grown the most.[13]

3.3.3 Sentiment Data

Consumer confidence indices are used as measures of sentiment in our analysis. Such indices have been discussed in detail by Lemmon and Portniaguina (2006)[14] and have been widely used for the U.S market (Fisher and Statman, 2003, Lemmon and Portniaguina, 2006, Antoniou et al., 2013) and international stock markets (Schmeling, 2009) as the proxy for investor sentiment. In addition, there are other reasons to employ this measure. First, the consumer confidence index is available for all countries in the sample and spans a reasonably long period of time. Second, although the sample period and frequency of the consumer confidence indices vary across countries, they are the only consistent measure of investor sentiment that can be comparable across countries and that are not constructed by using trading data itself (Baker and Wurgler, 2006).[15] Trading data used by Baker and Wurgler (2006) are not available for all countries in the sample.

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[13] We use the term Korea for the country of South Korea.

[14] Lemmon and Portniaguina (2006) use the consumer confidence index as a proxy for sentiment to examine the relation between small stock premiums and investor sentiment and find that consumer confidence is not strongly related to the close end fund discount which is used as a component for the investor sentiment index constructed by Baker and Wurgler (2006).

[15] Baker and Wugler (2006) constructed a sentiment measure using six proxies which consist of trading volume, the premium for dividend-paying stocks, the closed-end fund discount, the number of IPOs, the first day return of IPOs and the share of equity in new issues. The measure is the first principal component of the six proxies and their lags.

Table 3.2 Sentiment Descriptive Statistics

This table reports summary statistics for the consumer confidence index as a proxy for investor sentiment for each country, along with the source, frequency of the consumer confidence index and whether the index is seasonal adjusted or not. It also reports the number of observations (N), mean (u), minimum (Min) and Maximum (Max) for the consumer confidence index. If a series of the consumer confidence index is not seasonally adjusted, the X-12-ARIMA method is used to adjust the series, and if a series of the consumer confidence does not have in monthly frequency, it is transformed into a monthly frequency by using the last available values for months that have no data. The figures of all statistics in the table are seasonally adjusted.

Country	Source	Frequency	Seasonally Adjusted(SA)/ Non-Seasonally Adjusted(Non-SA)	N	Mean(u)	SD(σ)	Min	Max
Argentina	Datastream	Monthly	Non-SA	186	46.0	6.8	29.5	58.6
Australia	DG ECFIN	Monthly	SA	276	114.1	10.4	78.5	133.2
Austria	DG ECFIN	Monthly	SA	219	-1.19	8.0	-23	16
Belgium	DG ECFIN	Monthly	SA	276	-7.3	9.0	-26	16
Brazil	Datastream	Monthly	SA	100	112.5	7.6	94.9	128.7
Bulgaria	DG ECFIN	Monthly	SA	152	-33.8	7.7	-50.1	-13
Canada	Datastream	Monthly	SA	144	105.6	15.3	61.3	127.7
Chile	Datastream	Monthly	Non-SA	104	121.1	15.9	77.7	144.1
China	Datastream	Monthly	Non-SA	276	109.9	5.7	97	124.6
Colombia	Datastream	Monthly	Non-SA	122	20.1	9.6	-10.6	38.3
Czech Republic	DG ECFIN	Monthly	SA	228	-13.9	10.4	-35.8	3.9
Denmark	DG ECFIN	Monthly	SA	276	8.1	6.6	-8.2	19
Finland	DG ECFIN	Monthly	SA	218	13.39	5.8	-6.4	23.8
France	DG ECFIN	Monthly	SA	276	-18.7	8.9	-37	3.3
Germany	DG ECFIN	Monthly	SA	276	-9.3	9.5	-32.9	10.9
Greece	DG ECFIN	Monthly	SA	276	-38.6	16.7	-83.8	-5.8
Hong Kong	Bloomberg	Quarterly	Non-SA	168	88.9	17.1	49.7	116.4
Hungary	DG ECFIN	Monthly	SA	251	-35.35	15.1	-72.3	0.5
Indonesia	Bloomberg	Monthly	Non-SA	153	99.9	0.4	99.0	100.6
Ireland	DG ECFIN	Monthly	SA	276	-7.4	13.4	-33.1	19.1
Italy	DG ECFIN	Monthly	SA	276	-16.9	9.2	-41.5	2.5
Japan	Datastream	Monthly	SA	276	41.3	4.8	27.5	50.1
Korea	Datastream	Monthly	SA	181	99.9	1.4	96.6	102.9
Lithuania	DG ECFIN	Monthly	SA	152	-16.42	15.3	-56.1	9.2
Mexico	Datastream	Monthly	SA	153	96.7	8.6	78.6	116.3
Netherlands	DG ECFIN	Monthly	SA	276	0.8	14.2	-30.2	30.8
New Zealand	Datastream	Quarterly	Non-SA	276	100.1	1.3	96.1	102.2
Norway	Datastream	Quarterly	SA	258	19.6	12.8	-20.7	35.6
Poland	DG ECFIN	Monthly	SA	152	-22.52	10.2	-40.1	-0.5
Portugal	DG ECFIN	Monthly	SA	276	-27.8	14.7	-60.1	-0.5
Russia	Datastream	Quarterly	Non-SA	183	-13.9	12.9	-59.2	2.3
Slovenia	DG ECFIN	Monthly	SA	214	-20.92	7.3	-41.6	-4.1
South Africa	Datastream	Quarterly	SA	276	100.3	1.3	97.2	102.9
Spain	DG ECFIN	Monthly	SA	276	-14.8	11.4	-47.6	5.3
Sweden	DG ECFIN	Monthly	SA	219	9.56	8.5	-10	28
Switzerland	Datastream	Quarterly	SA	276	-13.8	20.2	-53.6	25.3
Thailand	Datastream	Monthly	SA	174	75.8	10.6	56.4	110.9
Turkey	Datastream	Monthly	SA	276	99.2	12.4	52	121.2
United Kingdom	DG ECFIN	Monthly	SA	276	-9.5	8.5	-35.2	7.1
U. S	Datastream	Monthly	SA	276	89.9	28.1	25.3	144.7

Consumer confidence index data for each country are collected from different sources. For the U.S, the Conference Board (CB) consumer confidence index is employed (Fisher and Statman, 2003; Lemmon and Portniaguina, 2006; Antoniou et al., 2013). For all European countries that are in the European Union, the data used are from the "Directorate General for Economic and Financial Affairs" (DG ECFIN) (Schmelling, 2009). For the remaining countries, data are obtained from Datastream. Since the consumer confidence index is measured differently across countries, several criteria are applied to make them consistently comparable across countries. First, if a consumer confidence index series is not seasonally adjusted, the X-12-ARIMA technique is used to adjust the series, which is used by the Conference Board to seasonally adjust the U.S consumer confidence series. Second, if a series does not have a monthly frequency, it is transformed into such a frequency using the last available values for months that have no data (Baker and Wurgler, 2006; Schmeling, 2009). The consumer confidence index for each country is not adjusted for macroeconomic variables, since previous work suggests that both adjusted and unadjusted indices yield similar results (Baker and Wurgler, 2006 and 2007; Livnat and Petrovits, 2009) and the data required for the adjustment are not available for all countries. Table 3.2 reports summary statistics of the consumer confidence index for each country. As shown in the table, the mean (and other summary statistics) of consumer confidence for each country is different. Nonetheless, it can serve as a consistently comparable proxy across countries because cutoffs in percentages (e.g. top or bottom 30%) are used to define whether the state of the current month is optimistic, mild or pessimistic. For example, the sentiment state of a given month is optimistic if the score for the consumer confidence index of that month belongs to the top 30% of the time series values of the consumer confidence index.

3.3.4 Momentum Portfolios

Momentum portfolios are formed following Jegadeesh and Titman (1993). The strategy selects stocks on the basis of stock returns over the past J months and holds them for K months. At the end of each month, securities are ranked into portfolio deciles in ascending order based on their past J-month cumulative returns.[16] The portfolio with the highest returns is in the top decile and is called the "winner" portfolio and the portfolio with the lowest returns is in the bottom decile and is called the "loser" portfolio. The strategy

[16] Ranking stocks into portfolio quintiles yields similar results that are not reported in the main body of the chapter for brevity. The results are reported in the appendix.

takes a long position in the winner portfolio and a short position in the loser portfolio, held for K months. We focus on the six-month ranking and holding period (J=K=6) momentum strategy which is commonly examined in momentum studies.[17]

To increase the power of the tests, overlapping portfolios are constructed as documented in Jegadeesh and Titman (1993). Specifically, in each month, a new position is initiated at time t and the position for both winner and loser portfolios that are initiated at time t-K is closed. Thus, we rebalance 1/K of stocks in both winner and loser portfolios, and the momentum returns for a given month is the equally weighted average return on K portfolios in that month. For example, the winner portfolio in January is equally weighted K portfolios (K=6) formed at different times, which includes the winner decile formed at the end of November based on the past returns over the previous June to November period and the winner decile formed at the end of October based on the past returns over the previous May to October period and so on up to the winner decile formed at the end of June based on the past returns over the previous January to June period. In February, the position for both winner and loser portfolios formed at the end of June is closed and the position for those formed at the end of December is initiated. Moreover, to mitigate microstructure bias issues, one month is skipped between the end of the formation period and the beginning of the holding period (Jegadeesh and Titman, 2001).

The Country-average and the composite portfolios are also formed. The country-average portfolio consists of equally weighted portfolio deciles of all countries. For example, the average momentum returns for each country are first calculated individually, which are calculated as time-series averages of momentum profits for all time periods. Momentum profits to the country-average portfolio are the equally weighted average of momentum profits for all countries. The composite portfolio is formed by putting equal weight on the portfolios of all available countries in each month. At least two countries are required in the composite portfolio at any point in time. Momentum profits to the composite portfolio in each month are calculated as the equally weighted average of momentum profits for all available countries in a given

[17] Momentum strategies with a different ranking and holding period are also examined in the robustness test. For example, J=K=12. The results are reported in the Appendix.

month. Thus, the momentum returns to the composite portfolio are calculated as the time-series average of momentum profits in the portfolio.

In order to identify the sentiment state for a specific formation month,[18] we follow Antoniou et al. (2013). First, the data of the monthly consumer confidence index for each country is collected. Second, the investor sentiment score for the specific formation month is calculated using a weighted-rolling average scheme. Specifically, portfolios are formed at the end of month t and the sentiment score for the formation month t is the sum of (3/6) multiplied by consumer confidence index score for month t, (2/6) multiplied by consumer confidence score for month t-1 and (1/6) multiplied by consumer confidence score for month t-2.[19] Then the formation month is categorised as optimistic (pessimistic) if its 3-months rolling average sentiment score ending in month t belongs to the top (bottom) 30% of the 3-months rolling average sentiment time series values, with the rest being mild states. To make sure that our results are not sensitive to the definition of sentiment states, robustness tests are carried out by using different cutoffs (e.g. 40%)[20]. To determine whether each holding month of a momentum strategy for each country is optimistic or pessimistic,[21] it is required to identify whether its corresponding formation months are optimistic or pessimistic. Since each holding month is associated with six different formation months as six overlapping formation portfolios are formed in the momentum strategy, it is necessary to identify whether the formation months as a whole are optimistic or pessimistic. If all of the formation months are classified as optimistic (pessimistic), the corresponding holding month is denoted as optimistic (pessimistic) and the rest of the months are denoted as mild. For example, the sentiment state for the holding month of January depends on the sentiment states of its six corresponding formation months in November, October, September, August, July and June.[22] If all the six formation months are optimistic (pessimistic), January is classified as optimistic (pessimistic) otherwise it is mild. Furthermore, an alternative

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[18] The formation month is the month at which the formation portfolios are constructed based on its past six-month stock returns.
[19] The sentiment data is announced with n-month lags (n=1 or 2) across countries so the data of sentiment in t, t-1 and t-2 relates to the data in month t-n, t-n-1 and t-n-2.
[20] Our results remain similar by using different cut-offs (e.g. 40%). Results are shown in the appendix.
[21] The holding month is the month at which portfolios are being held.
[22] Since one month is allowed between the holding period and the formation period in the momentum strategy, December is treated as the skipping month.

definition of investor sentiment states is used to examine the sensitivity of the results (Stambaugh et al., 2012). A high-sentiment month (optimistic) is one in which the 3-month rolling average score of the consumer confidence index in the previous month is in the top 30% of the 3-month rolling average time series values and a low-sentiment month (pessimistic) is one in the bottom 30% of the 3-month rolling average time series values, with the rest being mild states. Using this alternative definition of sentiment states yields similar results.[23]

3.4 Empirical Analysis

3.4.1 Individualism, Sentiment and Momentum Profits

3.4.1.1 Portfolio Analysis

We begin by analysing momentum profits and how these differ between optimistic and pessimistic states across 40 countries, with Tables 3.3 and 3.4 presenting results for winner, loser and momentum (winner minus loser) portfolios unconditional and conditional on sentiment, respectively. Panel A of Table 3.3 shows results by country and Panel B presents results for the country-average and the composite portfolios. Despite the sample extending to more recent years, momentum returns are in line with prior research. The third column of Panel A of Table 3.3 shows that 29 out of the 40 countries exhibit positive momentum returns, with 18 out of the 29 countries exhibiting significant momentum returns: Hungary has the largest (1.823% per month), followed by Denmark (1.481% per month), Sweden (1.465% per month) and the Netherlands (1.429% per month). In all countries, the momentum returns appear to be driven by the winner stocks, with all countries showing positive returns to this group and 35 out of the 40 being significant at the 10% or higher. However, the returns to loser portfolios are insignificantly different from zero in 25 cases, with the returns in 15 out of the 40 countries being significantly positive. Furthermore, of the five western countries included in the later analysis, all show positive momentum returns with four being significantly different from zero.[24] In contrast, only one (China) of the five

[23] Results are shown in the appendix.
[24] The exception is Canada. While this is in contrast to the findings of Chui et al. (2010), the sample periods are markedly different: Chui et al. use data for 1981-2003, whereas our sample only starts in month ten of 2002.

Table 3.3 International Momentum Profits

This table reports the average monthly returns (%) of momentum portfolios for each of the 40 countries. Each country has a different sample period. Panel A shows momentum profits for each country, along with its standard deviation. For each country, stocks are ranked into deciles based on their past 6-month cumulative returns and the winner and lose portfolios are held for 6 months. In order to increase the power of the test, overlapping portfolios are formed. The winner (loser) portfolios consist of 6 overlapping winner (loser) portfolios formed in the previous 6 months. The returns on each of the 6 overlapping winner (loser) portfolios are the simple average of returns on stocks in the winner (loser) portfolio and the return on the winner or loser portfolio is the equally weighted average return of the 6 portfolios in that month. Momentum returns are the returns of the winner portfolio minus the returns of the loser portfolio. To mitigate microstructure issues, one month is allowed between the end of the formation period and the beginning of the holding period and several stock selection criteria are applied, as discussed in detail in Table 3.1. Panel B reports momentum profits for the country-average and composite portfolios, along with their standard deviation. The country-average portfolio consists of equally weighted portfolio deciles of all countries. For example, the country-average winner portfolio is the equally weighted winner portfolios of all countries. The composite portfolios are formed by putting equal weight on the portfolios of the countries in each month. At least two countries are required in the composite portfolio at any point in time. For brevity, we only list results of winner, loser and momentum portfolios. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

Panel A. Momentum profits by country

Country	**Winner (W)**	**Loser (L)**	**W Minus L**	**Standard Deviation**
Americas				
Argentina	1.230(2.15)**	2.104(2.58)**	-0.874(-1.59)	7.28%
Brazil	1.094(1.83)*	1.294(1.48)	-0.200(-0.29)	6.56%
Canada	1.904(2.98)***	1.532(1.95)*	0.372(0.66)	6.54%
Chile	0.701(1.78)*	0.258(0.41)	0.443(0.80)	5.38%
Colombia	1.684(3.27)***	1.302(1.91)*	0.382(0.54)	7.46%
Mexico	1.950(6.54)***	1.262(2.97)***	0.688(1.84)*	6.21%
U.S.	1.530(4.16)***	0.957(1.77)*	0.573(1.69)*	6.26%
Europe				
Austria	0.712(2.17)**	0.024(0.05)	0.688(1.38)	7.21%
Belgium	1.537(5.48)***	0.805(2.02)**	0.732(1.97)**	5.89%
Bulgaria	0.072(0.11)	1.290(1.50)	-1.218(-1.46)	7.44%
Czech Republic	0.649(1.46)	0.805(1.56)	-0.156(-0.29)	6.22%
Denmark	1.391(4.99)***	-0.090(-0.20)	1.481(4.57)***	5.14%
Finland	1.296(2.93)***	0.071(0.13)	1.225(2.75)***	6.39%
France	1.163(4.12)***	0.529 (1.25)	0.634(2.07)**	5.07%
Germany	0.757(2.77)***	-0.372(-0.79)	1.129(3.13)***	5.90%
Greece	1.022(1.62)	0.722(0.97)	0.300(0.58)	8.58%
Hungary	1.794(3.12)***	-0.0290(-0.03)	1.823(2.12)**	12.7%
Ireland	1.162(2.65)***	0.807(1.06)	0.355(0.50)	11.7%
Italy	0.905(2.37)**	-0.230(-0.43)	1.135(3.20)***	5.89%
Lithuania	1.873(2.55)**	1.573(1.68)*	0.301(0.33)	10.7%
Netherlands	1.086(3.14)***	-0.343(-0.67)	1.429(3.63)***	6.53%
Norway	1.791(3.73)***	0.955(1.58)	0.836(1.96)*	7.06%
Poland	1.504(2.03)**	2.105(2.44)**	-0.601(-0.95)	7.55%
Portugal	0.781(2.43)**	1.153(2.20)**	-0.319(-0.74)	8.27%
Russia	2.408(3.77)***	3.118(4.45)***	-0.710(-1.12)	7.61%
Slovenia	0.668(1.55)	1.121(1.56)	-0.453(-0.60)	10.2%
South Africa	2.424(7.11)***	1.226(3.54)***	1.198(3.77)***	5.28%
Spain	0.984(3.01)***	0.536(1.07)	0.448(1.77)*	6.36%
Sweden	1.544(3.45)***	0.079(0.27)	1.465(3.05)***	6.90%
Switzerland	1.324(4.58)***	0.140(0.35)	1.184(3.89)***	5.04%
Turkey	3.397(3.93)***	4.511(5.06)***	-1.114(-2.40)**	7.72%
United Kingdom	1.272(4.21)***	0.059(0.16)	1.213(4.19)***	4.81%

Asia Pacific				
Australia	1.430(3.42)***	1.173 (2.34)**	0.257(0.909)	4.69%
China	2.125(2.53)**	1.204(1.28)	0.92(1.65)*	7.92%
Hong Kong	1.051(1.65)*	0.851(1.01)	0.200(0.47)	5.44%
Indonesia	1.769(3.21)***	2.423(3.65)***	-0.656(-1.22)	8.62%
Japan	0.223(0.55)*	0.424(0.83)	-0.201(-0.64)	5.21%
Korea	0.631(0.85)	0.053(0.06)	0.578(1.18)	6.41%
New Zealand	1.834(5.13)***	0.456(1.02)	1.378(3.22)***	7.11%
Thailand	1.597(2.65)***	1.263(1.81)*	0.334(0.67)	6.34%
Panel B. Country average and composite portfolios				
Country-average	1.371(13.27)***	0.981(5.86)***	0.390(3.27)***	6.22%
Composite	1.454(6.42)***	0.895(2.86)***	0.559(3.05)***	3.05%

ESEA countries have significant momentum returns.[25] Panel B of Table 3.3 reports momentum profits from implementing the momentum strategy around the world. The results in Panel B indicate momentum returns to the country-average portfolio are 0.390% per month, while those to the composite portfolio are 0.559% per month, with both being significant at the 1% level.[26] In sum, the results for the whole sample period demonstrate that momentum profits vary substantially across countries.

We now consider the results in relation to momentum profits under different sentiment states.[27] Panel A of table 3.4 shows that there are marked differences in momentum returns between optimistic and pessimistic states. During optimistic periods, all but four countries (Argentina, Czech Republic, Portugal and Slovenia) exhibit positive momentum returns. Momentum profits in 20 out of the 36 countries are positive and statistically significant at the 10% level or higher. The largest momentum profits under such a state are in Germany (3.19% per month), Lithuania (2.94% per month), Colombia (2.29% per month) and Switzerland (2.17% per month). All of these are high for monthly returns compared to Jegadeesh and Titman (1993) who find about 1.5% per month when no split is based on sentiment.[28] In contrast, during pessimistic periods, only two of the 40 countries exhibit significantly positive momentum returns (Hungary and Switzerland) and the returns in 25 out of the 40 countries are negative, with 5 out of the 25 being significantly

[25] Again this is broadly in line with Chui et al. (2010). In their study four of these five had insignificant profits, the exception being Hong Kong. However, again there is limited overlap in sample periods.
[26] The results of momentum profits around the world are consistent with Chui et al. (2010). The significant momentum returns of the country-average portfolio is primarily driven by the significant returns of European countries and the U.S due to longer sample periods.
[27] We use the 30/40/30 split described in section 3.3. The 40/20/40 cut-off is also used in the robustness tests.
[28] The higher momentum monthly returns under optimism are primarily due to the performance of the loser portfolio.

negative. The lowest momentum returns are in Argentina (-4.301% per month), Bulgaria (-3.874% per month), Norway (-3.106% per month) and Australia (-2.506% per month). The negative or insignificant momentum profits under pessimism are primarily due to the returns to loser stocks not being of the sign consistent with momentum, with the returns being positive in 39 cases (the exception being Slovenia) and significant in 21 out of the 39 countries. The differences in momentum returns between optimistic and pessimistic states are positive in 33 out of 40 cases and the difference is statistically significant in 13 cases, with 12 differences being positive and significant. Furthermore, it is worth noting the difference in results for the five western and five ESEA countries used in the later analysis. For western markets, the difference in momentum returns between optimistic and pessimistic states is positive and significant in four out of five countries, whereas for ESEA markets, such a difference is only significant in one out of five countries. Examination of Panel B shows that momentum returns are positive and significant at the 1% level for both the country-average and composite portfolios during optimistic states. In contrast, the returns are either insignificantly different from zero (composite) or negative and significant at the 10% level (country-average) under the pessimistic states. The difference in momentum profits between optimistic and pessimistic states is significant for both the country-average and composite portfolios. Taken together, the results in Table 3.4 clearly demonstrate differences in momentum profits between different sentiment states across countries. We now turn to consider the interaction between culture and sentiment and examine our first hypothesis. Table 3.5 presents results where we consider the roles of culture (as measured by the individualism index) and investor sentiment. Double sorts are undertaken on the basis of individualism and sentiment. Each country in the sample is categorised into one of three culture measure groups based on their score on the individualism index (IDV). Specifically, using the relevant index, we categorise countries into the top and bottom 30%, with the middle 40% being excluded from the analysis.[29] Results are reported for the composite portfolio based on these splits.[30] The table is divided into three panels and in each panel returns are shown for winner, loser and the momentum portfolios. Before going on to consider

[29] For brevity, we don't report results under mild state.

[30] Results for country-average portfolios are qualitatively similar and are reported in table A3.2 in the appendix.

Table 3.4 Investor Sentiment and Momentum Profits

This table reports the average monthly returns (%) of winner, loser and momentum portfolios during two sentiment states (optimistic and pessimistic) for each of the 40 countries (Panel A) and the country-average and composite portfolios (Panel B). The stocks ranked in the top decile based on the past six month cumulative returns are winner “W” stocks and those in the bottom decile are loser “L” stocks. Each month is identified as optimistic, mild or pessimistic. To identify a particular formation period as optimistic or pessimistic; the corresponding sentiment score is calculated by using the weighted average scheme as follows. The weights 3, 2 and 1 are given to the month t, t-1 and t-2. If the weighted average score of the formation month belongs to the top 30% of the time series of rolling average sentiment scores, it is defined as optimistic, whereas if the weighted average score of the formation month belongs to the bottom 30% of the time series observations, it is defined as pessimistic, with the rest being mild states. To determine whether each holding month of the momentum strategy for each country is optimistic or pessimistic, it is required to identify whether its corresponding formation months are optimistic or pessimistic. Since each holding month is associated with six different formation months as six overlapping formation portfolios are formed in the momentum strategy, it is necessary to identify whether the formation months as a whole are optimistic or pessimistic. If all of the formation months are classified as optimistic (pessimistic), the corresponding holding month is denoted as optimistic (pessimistic) and the rest of the months are denoted as mild. Panel B reports momentum profits during the two sentiment periods for the country-average and composite portfolios. The formation of the country-average and composite portfolios is described in table 3.3. For brevity, we don’t list results under mild states. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

Panel A country momentum profits and sentiment states

Country	**Optimistic**			**Pessimistic**			**Opt.-Pess.**		
	W	**L**	**Mom**	**W**	**L**	**Mom**	**W**	**L**	**Mom**
<u>Americas</u>									
Argentina	0.938	2.332	-1.394	5.233	9.534	-4.301	-4.295	-7.202	2.907
	(0.93)	(1.51)	(-1.27)	(2.78)***	(2.78)***	(-1.83)*	(-2.01)**	(-1.91)*	(1.12)
Brazil	0.968	-0.871	1.839	3.948	6.414	-2.466	-2.980	-7.285	4.305
	(1.77)*	(-1.17)	(1.97)*	(2.53)**	(3.92)***	(-1.41)	(-1.80)*	(-4.05)***	(2.18)**
Canada	1.514	0.330	1.184	1.443	3.208	-1.765	0.071	-2.878	2.949
	(0.81)	(0.17)	(0.78)	(1.81)*	(1.50)	(-1.09)	(0.04)	(-0.98)	(1.33)
Chile	-0.835	-0.944	0.109	1.973	3.207	-1.234	-2.808	-4.151	1.343
	(-1.49)	(-0.76)	(0.12)	(3.17)***	(1.51)	(-0.62)	(-3.35)***	(-1.69)*	(0.62)

Colombia	1.733	-0.558	2.291	3.401	2.381	1.020	-1.672	-2.939	1.271
	(2.27)**	(-0.41)	(2.05)**	(3.53)***	(1.88)*	(0.74)	(-1.36)	(-1.57)	(0.72)
Mexico	3.803	2.411	1.392	1.726	2.791	-1.065	2.077	-0.380	2.457
	(4.22)***	(2.38)**	(1.26)	(3.41)***	(2.03)**	(-0.80)	(2.01)**	(-0.22)	(1.42)
U.S.	1.525	-0.233	1.758	0.328	2.179	-1.851	1.197	-2.412	3.609
	(1.86)*	(-0.19)	(1.83)*	(0.25)	(1.08)	(-1.34)	(0.78)	(-1.02)	(2.14)**
Europe									
Austria	-0.831	-1.462	0.631	1.474	0.494	0.980	-2.305	-1.956	-0.349
	(-1.13)	(-1.62)	(0.83)	(1.89)*	(0.44)	(0.93)	(-2.15)**	(-1.35)	(-0.27)
Belgium	0.303	-0.353	0.656	1.881	1.610	0.271	-1.578	-1.963	0.385
	(0.38)	(-0.37)	(0.73)	(3.54)***	(1.94)*	(0.35)	(-1.66)*	(1.56)	(0.33)
Bulgaria	0.851	0.595	0.256	-0.718	3.156	-3.874	1.569	-2.561	4.130
	(0.47)	(0.36)	(0.19)	(-1.21)	(1.85)*	(-2.13)**	(0.83)	(-1.08)	(1.82)*
Czech Republic	0.113	0.675	-0.562	-0.390	0.154	-0.544	0.503	0.521	0.018
	(0.15)	(0.81)	(-0.61)	(-0.52)	(0.12)	(-0.41)	(0.47)	(0.34)	(0.01)
Denmark	1.895	0.166	1.729	2.514	4.051	-1.537	-0.619	-3.885	3.266
	(3.13)***	(0.26)	(3.81)***	(2.67)***	(2.38)**	(-1.16)	(-0.56)	(-2.14)**	(2.34)**
Finland	-1.976	-3.008	1.032	2.990	1.398	1.592	-4.966	-4.406	-0.561
	(-1.59)	(-2.62)***	(1.14)	(3.31)***	(0.95)	(1.38)	(-3.26)***	(-2.37)**	(-0.38)
France	0.712	-1.357	2.069	1.906	2.340	-0.433	-1.194	-3.697	2.503
	(0.78)	(-1.26)	(2.67)***	(3.58)***	(2.94)***	(-0.73)	(-1.13)	(-2.80)***	(2.56)**
Germany	-2.014	-5.207	3.193	2.673	1.854	0.819	-4.687	-7.061	2.374
	(-2.67)***	(-3.03)***	(2.27)**	(5.75)***	(2.95)***	(1.62)	(-5.52)***	(-3.86)***	(1.96)**
Greece	-3.544	-4.320	0.776	-1.170	1.015	-2.185	-2.374	-5.335	2.961
	(-1.03)	(-1.18)	(0.36)	(-1.56)	(0.71)	(-1.99)**	(-0.67)	(-1.36)	(1.22)
Hungary	1.509	0.089	1.420	3.504	0.189	3.315	-1.989	-0.100	-1.889

	(1.01)	(0.04)	(0.72)	(2.86)***	(0.12)	(2.73)***	(-1.03)	(-0.04)	(-0.82)
Ireland	1.225	0.541	0.684	1.262	3.143	-1.881	-0.037	-2.597	2.564
	(1.47)	(0.47)	(0.61)	(1.12)	(1.08)	(-0.61)	(-0.03)	(-0.83)	(0.78)
Italy	-0.772	-2.648	1.876	0.421	-0.117	0.538	-1.193	-2.531	1.342
	(-1.10)	(-2.19)**	(2.15)**	(0.62)	(-0.10)	(0.64)	(1.22)	(-1.47)	(1.11)
Lithuania	2.162	-0.782	2.944	2.220	2.680	-0.460	-0.058	-3.462	3.404
	(1.71)*	(-0.67)	(2.82)***	(1.50)	(1.34)	(-0.26)	(-0.03)	(-1.49)	(1.69)*
Netherland	0.879	-0.483	1.362	2.070	2.049	0.021	-1.191	-2.532	1.341
	-1.06	(-0.55)	(1.70)*	(3.82)***	(2.11)**	(0.03)	(-1.20)	(-1.93)*	(1.19)
Norway	3.019	0.903	2.116	3.234	6.340	-3.106	-0.215	-5.437	5.222
	(2.31)**	(0.84)	(2.46)**	(3.59)***	(3.36)***	(-1.99)**	(-0.14)	(-2.50)**	(2.93)***
Poland	-1.069	-2.335	1.266	4.653	5.146	-0.493	-5.722	-7.481	1.759
	(-0.54)	(-1.89)*	(1.73)*	(2.67)***	(2.35)**	(-0.28)	(-2.17)**	(-2.71)***	(0.84)
Portugal	0.107	0.969	-0.862	1.295	1.515	-0.220	-1.188	-0.546	-0.642
	(0.14)	(-0.69)	(-0.83)	(1.96)*	(1.28)	(-0.19)	(-1.18)	(-0.30)	(-0.41)
Russia	-0.365	-1.498	1.133	5.109	5.423	-0.314	-5.474	-6.921	1.447
	(-0.30)	(-1.34)	(2.04)**	(2.49)**	(3.50)***	(-0.20)	(-2.30)**	(-3.62)***	(0.85)
Slovenia	2.477	5.903	-3.426	0.581	-1.149	1.730	1.896	7.052	-5.156
	(2.41)**	(4.34)***	(-2.57)**	(0.38)	(-0.43)	(0.69)	(1.02)	(2.33)**	(-1.82)*
South Africa	3.342	1.334	2.008	3.616	3.426	0.190	-0.274	-2.092	1.818
	(6.12)***	(2.18)**	(3.76)***	(2.80)***	(3.07)***	(0.16)	(-0.20)	(-1.69)*	(1.38)
Spain	0.941	0.774	0.167	0.934	1.264	-0.330	0.007	-0.490	0.497
	(1.30)	(0.71)	(0.23)	(1.41)	(1.12)	(-0.34)	(0.01)	(-0.31)	(0.41)
Sweden	-1.566	-3.692	2.126	3.312	3.487	-0.175	-4.878	-7.179	2.301
	(-1.51)	(-2.68)***	(1.97)**	(3.08)***	(2.57)***	(-0.21)	(-3.27)***	(-3.71)***	(1.56)
Switzerland	0.798	-1.374	2.172	2.143	0.721	1.422	-1.345	-2.095	0.750

	(1.06)	(-1.67)*	(3.06)***	(4.02)***	(1.15)	(3.11)***	(-1.49)	(-2.02)**	(0.89)
Turkey	1.854	1.793	0.061	6.047	7.859	-1.812	-4.193	-6.066	1.873
	(1.15)	(1.07)	(0.12)	(2.79)***	(2.93)***	(-1.20)	(-1.56)	(-1.92)*	(1.18)
United Kingdom	0.201	-1.748	1.949	1.868	2.503	-0.635	-1.667	-4.251	2.584
	(0.16)	(-1.69)*	(2.26)**	(3.55)***	(1.99)**	(-0.68)	(1.25)	(2.48)**	(2.04)**
Asia Pacific									
Australia	1.007	-0.035	1.042	4.366	6.872	-2.506	-3.359	-6.907	3.548
	(1.00)	(-0.04)	(2.11)**	(4.30)***	(4.39)***	(-2.11)**	(-2.35)**	(-3.81)***	(2.75)**
China	3.977	2.708	1.269	1.454	2.005	-0.551	2.523	0.703	1.820
	(2.26)**	(1.12)	(0.84)	(1.01)	(1.09)	(-0.49)	(1.14)	(0.24)	(0.96)
Hong Kong	2.524	2.420	0.104	1.535	0.874	0.661	0.989	1.556	-0.557
	(1.83)*	(1.72)*	(0.18)	(1.13)	(0.48)	(0.74)	(0.51)	(0.68)	(-0.52)
Indonesia	1.792	0.762	1.030	0.195	1.499	-1.304	1.597	-0.737	2.334
	(2.49)**	(0.74)	(2.36)**	(0.14)	(0.95)	(-1.07)	(0.85)	(-0.39)	(1.99)**
Japan	-0.249	-0.984	0.735	0.766	1.288	-0.522	-1.015	-2.272	1.287
	(-0.26)	(-0.78)	(1.69)*	(0.99)	(1.26)	(-0.85)	(-0.82)	(-1.60)	(1.69)*
Korea	-1.195	-1.660	0.465	4.097	3.891	0.206	-5.292	-5.551	0.259
	(-0.61)	(-1.05)	(0.31)	(2.76)***	(1.89)**	(0.17)	(-2.16)**	(-2.14)**	(0.13)
New Zealand	0.514	-0.680	1.194	4.347	2.180	2.167	-3.833	2.860	-0.973
	(0.85)	(-0.77)	(1.72)*	(3.62)***	(1.79)*	(1.47)	(-2.85)***	(-1.90)*	(-0.59)
Thailand	1.855	1.373	0.482	4.474	4.032	0.442	-2.619	-2.659	0.040
	(1.73)*	(1.00)	(0.53)	(4.65)***	(3.75)***	(0.52)	(-1.82)*	(-1.52)	(0.03)

Panel B: Country-average and Composite portfolios

	Optimistic			Pessimistic			Opt. - Pess.		
	W	L	Mom	W	L	Mom	W	L	Mom
Country-average	1.044	-0.010	1.054	2.333	2.775	-0.442	-1.289	-2.785	1.496

	(2.67)***	(-0.02)	(5.51)***	(8.72)***	(7.71)***	(-1.85)*	(-2.72)***	(-5.03)***	(4.89)***
Composite	0.809	-0.144	0.953	2.116	1.840	0.276	-1.307	-1.984	0.677
	(2.50)**	(-0.35)	(3.72)***	(6.69)***	(4.31)***	(0.98)	(-2.89)***	(-3.37)***	(1.78)*

the role of sentiment, Panel A of Table 3.5 provides results split by individualism, but not by sentiment. There is a marked difference in momentum returns between high and low individualism cultures: while returns to winner portfolio are positive and significant in both groups, with no significant difference between the two, the returns to loser portfolio are insignificantly different from zero for high individualism culture countries, but highly positive and significant for the low individualism culture group. The net result is that momentum returns are positive and significant at the 1% level in the high group, but are insignificant in the low group, with the difference between high and low being positive and statistically significant at the 1% level. The key question is whether these findings apply under all sentiment states or are driven by differences across states.

The results in Panels B and C allow examination of this issue and to test hypothesis H1. Returns during optimistic and pessimistic periods are shown for the high individualism culture group in Panel B and those during optimistic and pessimistic periods are shown for low individualism culture countries in Panel C. For the high group, momentum profits are positive and significant under optimism, but not under pessimism, suggesting that the returns in Panel A are primarily the result of the optimistic sentiment for this group. The difference in momentum returns between optimism and pessimism is positive and significant for the high group. In contrast, momentum returns in the low group as shown in Panel C are insignificantly different from zero under both sentiment states, with the difference between states also being statistically insignificant. The results in Panels B and C also allow an examination of the differences in momentum profits between the two culture groups across optimistic and pessimistic sentiment periods. The findings provide clear evidence in favour of our first hypothesis (H1): the effect of investor sentiment on momentum profits is more pronounced in individualistic cultures than in collectivist cultures. To illustrate, momentum profits during both sentiment periods in high individualistic cultures are significantly higher than those in low individualistic cultures.[31] The higher momentum profits during optimistic (pessimistic) periods in high individualistic cultures is primarily driven by the loser (winner) stocks, suggesting investors in high individualistic cultures experience stronger cognitive dissonance than in low individualistic cultures,

[31] The difference in momentum profits across difference sentiment periods between the two culture groups are also tested.

Table 3.5 Investor sentiment, Individualism and Momentum

This table presents the average monthly returns (%) of the momentum strategy for the composite portfolios sorted by investor sentiment and Individualism index. Panel A reports momentum profits sorted by individualism. Panels B and C present momentum profits for high and low individualism levels after controlling for the effect of sentiment. At the end of each month, momentum portfolios for each country are constructed and all countries in the sample are sorted into three groups by using top (bottom) 30% cutoffs based on their individualism index. Each month is identified as optimism, mild or pessimism. The definition of sentiment states of holding period is discussed in detail in Table 3.4. Both the country-average and composite portfolios are formed in each individualism - and investor sentiment-sorted category. The formation of the country-average and composite portfolios is described in table 3.3. For brevity, we only report results of the composite portfolio.[32] The corresponding t-statistics are shown in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Composite portfolios	**Momentum portfolios**		
	Winner	**Loser**	**W-L**
Panel A. Portfolio returns and Individualism			
High IDV	1.451	0.379	1.072
	(5.69) ***	(1.09)	(4.83)***
Low IDV	1.933	1.862	0.071
	(6.16)***	(5.12)***	(0.30)
High. - Low.	-0.482	-1.483	1.001
	(-1.24)	(-2.98)***	(3.13)***
Sentiment level			
Panel B. High Individualism			
Optimistic	0.659	-0.899	1.558
	(1.45)	(-1.69)*	(3.85)***
Pessimistic	1.819	1.282	0.537
	(4.22)***	(1.77)*	(1.67)*
Opt. - Pes.	-1.160	-2.181	1.021
	(-1.85)*	(-2.46)**	(1.97)**
Panel C. Low Individualism			
Optimistic	0.650	0.377	0.273
	(1.53)	(0.80)	(0.12)
Pessimistic	1.097	1.660	-0.563
	(2.12)**	(1.99)**	(-1.03)
Opt.-Pes.	-0.447	-1.283	0.836
	(-0.67)	(-1.29)	(1.36)

resulting in a slower diffusion of good (bad) news during pessimistic (optimistic) periods in high individualistic cultures.

3.4.1.2 Regression Analysis

We next investigate the impact of sentiment, culture and their interaction on

[32] Results of the country-average portfolio are reported in the appendix.

momentum profits in a multivariate regression setting by taking account of other potential determinants of momentum that vary across countries. In particular, momentum profits are regressed on the sentiment index, individualism, the interaction variable between investor sentiment and individualism, and other control variables as in the following model:

$$Mom_{j,t} = \alpha_0 + \beta_1 * IDV_j + \beta_2 * Sent_{j,t-1} + \beta_3 * IDV * Sent + \gamma * Control \quad (3.1)$$

Where $Mom_{j,t}$ is the return on the momentum portfolio in country j in month t. IDV_j is a categorical variable that equals 1 (-1) if the value of IDV belongs to the top (bottom) 30% of values of IDV of 40 countries, otherwise 0. *Sent* is a categorical variable which equals 1 (-1) if monthly sentiment of each country belongs to the optimistic (pessimistic) group with the rest being 0. IDV*Sent is the individualism and sentiment interaction variable. Standard errors are clustered by country and time. We follow Chui et al. (2010) to include other cross-country variables that may explain cross-country variations in momentum profits. The potential variables classified as firm characteristics, financial market development, and institutional quality and macroeconomic variables are set out below.

A number of studies examine firm characteristics as proxies for the effect of the speed of information flow and information uncertainty and its effect on momentum profits. In prior research, for example, Zhang (2006) shows that firm characteristic variables are able to explain the variation in momentum profits and Lee and Swaminathan (2000) show that trading volume is important in explaining momentum profits. These firm characteristic variables are examined at the stock level (see e.g. Zhang, 2006 for U.S) and the country level (see e.g. Chui et al., 2010). The variables include the natural logarithm of market trading volume (LnTN), the natural logarithm of stock market volatility (LnV), the natural logarithm of analyst coverage (LnCov), the natural logarithm of the dispersion of analyst forecasts (LnDisp), the cash flows growth rate volatility (VolFCF), the logarithm of median firm size (LnSize) and the average price to book ratio (PB).[33]

Chui et al. (2010) suggest that more developed stock markets and better institutional quality facilitate the efficiency of information flow and reduce

[33] The detailed construction for each control variable is explained in the appendix. In addition to the variables included by Chui et al. (2010) and Griffin et al. (2003) we also include the price to book ratio in the regression since Zhang (2006) shows this firm characteristic is important in capturing the variation in momentum profits

trading costs. These variables may potentially affect momentum profits. Therefore, we include proxies to capture these effects to examine whether the relation of sentiment, culture and momentum profits can be subsumed by the efficiency of the stock market. The financial market development variables used are total private credit expressed as a ratio of credit to GDP (CREDIT) as a measure of the financial market development; the average common language dummy variable (LANG) and an index on control of capital flows (CONTRL) suggested by Chan et al. (2005), the ratio between the monthly market value of the S&P-IFC market index and the monthly market value of the S&P-IFC investable index (OPEN) as a measure of stock market openness. The institutional quality variables include the insider index (INSIDER) (a high value suggests that insider trading is less prominent), the ICRG corruption index (CORRP) (a higher value indicates a lower level of corruption), the ICRG political risk index (POLITICAL), the natural logarithm of transaction costs index (LnTRAN), and the investor protection index (PROTECTION). Griffin et al. (2003) show that macroeconomic state variables such as GDP growth rate and inflation rate are able to explain the variation in momentum profits. Following Griffin et al. (2003), the GDP growth rate (GDP) and inflation rate (Inflation) are included in the regression to examine whether the effect of sentiment and individualism on momentum profits across countries can be subsumed by macroeconomic variables.

Table 3.6 presents the results of equation (3.1). In model 1, the constant term is 0.0048, suggesting that the momentum strategy earns around 0.48% return per month when both of sent and IDV are equal to zero i.e. both sent and IDV are at a moderate level. The estimated coefficients on investor sentiment (sent) and individualism (IDV) are 0.005 and 0.0062 respectively, with both being significant at the 1% level, suggesting that the momentum effect is more pronounced during optimistic periods and in high individualistic culture countries. Specifically, momentum profits increase or decrease by 0.5% when individualism is high or low compared to moderate levels of individualism. Similarly, the momentum strategy earns more or less 0.62% returns per month when sentiment is optimistic or pessimistic compared to the mild sentiment state. In model 2, model 1 is extended by including the interaction term between sentiment and individualism and the results show that the coefficient on the interaction term is 0.0024, significant at the 10% level, suggesting that the effect of investor sentiment on momentum profits

Table 3.6 Determinants of Momentum Profits across Countries

Monthly momentum returns are regressed on the categorical individualism index (IDV), categorical sentiment (sent) variables and an interaction term between individualism and sentiment. Categorical variable of IDV index equals 1 (-1) if IDV score belongs to the top (bottom) 30% of their scores, otherwise 0. Sentiment is a categorical variable which equals 1 (-1) if monthly sentiment of each country belongs to the optimistic (pessimistic) group with the rest being 0. IDV*SENT is the individualism and sentiment interaction variable. Model (3) reports the results with control variables, including firm characteristics, financial market development, and institutional quality variables. The firm characteristics variables include the natural logarithm of market trading volume (LnTV), the natural logarithm of stock market volatility (LnV), the natural logarithm of analyst coverage, the natural logarithm of the dispersion of analyst forecasts (LnDISP), the cash flows growth rate volatility (VolFCF), the logarithm of median firm size (LnSIZE) and the average price to book ratio (PB). The financial market development variables include the total private credit expressed as ratio of GDP (CREDIT), the average common language dummy variable (LANG), the ratio between the monthly market value of the S&P-IFC market index and the monthly market value of the S&P-IFC investable index (OPEN), and an index on control of capital flows (CONTRL). The institutional quality variables include the insider index (INSIDER, a high value suggests that insider trading is less prominent), the ICRG corruption index the ICRG (CORRP), political risk index (POLITICAL), the natural logarithm of transaction cost index (LnTRAN), and the investor protection index (PROTECTION). The macroeconomic variables include the GDP growth rate (GDP) and inflation rate (Inflation) Standard errors are clustered by country and time. The corresponding t-statistics are shown in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

	(1)	(2)	(3)	(4)
Intercept	0.0048(4.96)***	0.0048(4.95)***	0.0021(3.71)***	0.0031(4.01)***
IDV	0.0050(3.88)***	0.0050(3.82)***	0.0043(3.62)***	0.0044(3.77)***
SENT	0.0062(3.71)***	0.0059(3.32)***	0.0039(2.91)***	0.0041(2.99)***
IDV*SENT		0.0024(1.81)*	0.0026(2.01)**	0.0025(2.00)***
Control variables				
LnTV			-0.0134(-1.98)**	-0.0151(-2.01)**
LnV			-0.0172(-3.91)***	-0.0191(-3.88)***
LnCov			0.0126(1.21)	
LnDISP			0.002(1.31)	
VolFCF			-0.0002(-0.61)	
LnSize			-0.0018(-2.81)***	-0.0015(2.93)***
PB			-0.0261(-1.03)	
CREDIT			-0.0563(-0.87)	
LANG			0.0182(2.03)**	0.0213(2.33)**
OPEN			-0.0745(-0.93)	
CONTRL			-0.0085(-0.41)	
INSIDER			0.0534(0.61)	
CORRP			0.0001(0.43)	
LnTRAN			0.0806(2.33)**	0.0903(2.41)**
POLITICAL			0.0010(0.21)	
PROTECTION			-0.0462(-0.58)	
GDP			-0.0001(-0.21)	
Inflation			0.0007(0.19)	
Country FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
N	8231	8231	8231	8231
R squared (%)	1.46	1.61	9.21	5.93

is indeed stronger in individualistic cultures than in collectivistic cultures. In other words, momentum profits are even higher with higher levels of both individualism and sentiment. The finding is consistent with our first hypothesis. The coefficient of the interaction term is interpreted as the momentum strategy being more profitable in high individualism cultures when sentiment is optimistic. In model 3, we further consider whether the explanatory power of independent variables can be subsumed by the control variables. The results indicate that even after controlling for other explanatory variables, individualism, sentiment and the interaction term are significant at the 5% level or higher. We notice that momentum profits decrease in market trading volume, firm size (LnSize) (1% significance level), stock market volatility (LnV) (1% significance level) and increase in common language (LANG) (5% significance level), and transaction cost (LnTRAN). Consistent with Zhang (2006) and Chui et al. (2010), momentum profits decrease in firm size (LnSize), suggesting that the momentum effect is more prominent in small firms. In contrast to Lee and Swaminathan (2000), the estimated coefficient on stock market trading volume (LnV) is negative.[34] The language variable measures the extent of the familiarity to foreign investors and the capital flow restrictions and higher value of LANG indicates that foreign investors will be able to invest more. The positive estimated coefficient of LANG suggests that the momentum effect is more prominent in less capital flow restricted countries. The positive estimated coefficient on transaction cost variables indicates that momentum profits will be higher in countries with higher costs of trading. It would be interesting to include all significant independent variables in model (4) instead of estimating all control variables to reduce collinearity. The results are qualitatively similar to those in model (3).

Overall, the findings in Tables 3.4, 3.5 and 3.6 show clear support for the first hypothesis and provide evidence that sentiment and culture interact to affect momentum profits. Given such findings, we now proceed to focus the analysis on the five largest western and ESEA markets to test the remaining hypotheses and to gain a clearer and better understanding of the role of cognitive dissonance in explaining the momentum phenomenon.Cognitive

Dissonance and Momentum Profits: Western and ESEA Cultures

We now turn to examine hypotheses 2-5 in relation to differences in behaviour between western and ESEA countries and the impact of these differences on momentum profits. We first present results relating to the ten

[34] Lee and Swaminathan (2000) examine the relation between trading volume and momentum profits at the stock level. However, we examine such a relation at the country level.

markets analysed without any split by sentiment in Table 3.7.[35] Returns to the winner, loser and momentum portfolios are shown for the ten countries separately in Panel A, while Panel B presents results for western and ESEA country-average and composite portfolios. It is clear from Panel A that all five western countries exhibit positive momentum, with the returns being significant at the 5% level or higher in four (the exception being Canada). In all cases, the momentum returns appear to be driven by the winner stocks, with all five countries showing significantly positive returns to this group. However, the returns to loser portfolio are positive in four out of the five countries, with the returns being

Table 3.7 Momentum Profits for Western and ESEA Countries

This table reports the average monthly returns (%) of winner, loser and momentum portfolios for each of the ten countries. Panel A shows the momentum profits for each country, along with its standard deviation. For each country, stocks are ranked into quintiles based on their past 6-month cumulative returns and held for 6 months and the past 6-month cumulative returns of each stock in the winner (loser) portfolios must be larger (less) than 0%. Stocks are ranked in quintiles in order to have a reasonable number of stocks. Other stock selection criteria and the formation of momentum portfolios are discussed in detail in Table 3.3. Panel B reports returns to the country-average and composite portfolios for Western and ESEA countries, along with their standard deviation. The construction of the country-average and composite portfolios is discussed in detail in Table 3.3. For brevity, we only list results of winner, loser and momentum portfolios. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

Panel A. Momentum profits by country

Country	**Winner (W)**	**Loser (L)**	**W Minus L**	**Standard Deviation**
West				
Canada	1.731(3.08)***	1.303(1.89)*	0.428(0.97)	5.09%
France	1.195(4.48)***	0.564(1.25)	0.631(2.71)***	4.27%
Germany	0.749(3.09)***	-0.127(-0.35)	0.876(3.13)***	4.59%
United Kingdom	1.204(4.29)***	0.041(0.16)	1.163(4.19)***	3.63%
U.S.	1.357(4.40)***	0.732(1.77)*	0.625(2.52)**	4.56%
East				
China	1.143(1.72)*	0.973(1.32)	0.170(0.55)	4.21%
Hong Kong	1.120(1.82)*	0.862(1.10)	0.258(0.47)	4.60%
Japan	0.627(1.93)*	0.667(1.74)*	-0.040(-0.18)	4.26%
Korea	0.880(1.29)	0.312(0.40)	0.568(1.42)	5.22%
Thailand	1.548(2.95)***	1.264(1.81)*	0.284(0.69)	5.28%

Panel B. Country-average and Composite portfolios

Portfolio	Formation	Winner(W)	Loser(L)	W Minus L

[35] Comparing the results in table 3.7 for the ten countries with those in table 3.4, we see there are some minor differences. This is due to the additional filters applied for this section of only including in our sample winner stocks that have positive returns and loser stocks which have negative returns. In addition, since in the next chapter we examine the interaction between momentum and post earnings announcement drift, stocks are ranked in quintiles in order to have a reasonable number of stocks that have earnings announcements available. However, the differences are minor and do not affect the results.

Method			
Panel B.1.Country-average Portfolio			
West	1.247(7.90)***	0.503(1.96)**	0.744(5.89)***
East	1.064(6.95)***	0.816(5.139)***	0.248(2.53)**
West-East	0.183(0.83)	-0.313(-1.04)	0.496(3.10)***
Panel B.2. Composite Portfolio			
West	1.125(4.17)***	0.314(0.93)	0.811(2.92)***
East	1.001(2.71)***	0.825(1.72)*	0.176(0.21)
West-East	0.124(0.34)	-0.511(1.67)*	0.635(1.99)**

significantly different from zero at the 10% level in two (Canada and the U.S). It is interesting to notice that for Canada, the returns to the winner portfolio are the highest but that the reason the momentum returns are insignificant is due to the high positive returns to the loser portfolio. In contrast, none of five ESEA countries show significant momentum returns. The findings in Panel A of significantly positive momentum profits in four out of the five western countries but insignificant returns for all five ESEA countries are consistent with H2 that momentum profits will be significantly greater in western markets. The hypothesis gains further support in Panel B, where momentum profits for the country-average and composite portfolios are shown for western and ESEA cultures. For the composite portfolio, while there is little and insignificant difference in returns to winner portfolio between western and ESEA markets, there is a substantial and significant difference in relation to loser returns.[36] Furthermore, for both portfolios in Panel B, momentum profits are significantly positive for the west and insignificantly different from zero for the east, with the difference between the two groups being statistically significant, providing clear support for hypothesis H2.

We next consider the impact of sentiment, with Table 3.8 showing returns to winner, loser and momentum portfolios for optimistic and pessimistic states, together with the differences between the two sentiment states for all three portfolios. Again, Panel A of Table 3.8 shows results for individual countries and Panel B for the country-average and composite portfolios. As far as the western markets are concerned as shown in Panel A, momentum profits are positive and sizeable under optimism in all five countries, with all of them being significant at the 10% percent level or higher. In contrast to the results presented in Table 3.7, returns to winner portfolios under optimism are

[36] For the country-average portfolio, there is no significant difference in returns to both winner and loser portfolios between the two culture groups.

insignificantly different from zero in three out of the five cases, with the exception (Canada and the U.S) being significant at the 10% level. The returns to the loser portfolio are negative in four out of five countries, with two out of the four being significant at the 5% level or higher, again in contrast to the results for the whole sample period in Table 3.7. For the European markets, the returns to the loser portfolio are substantially larger than to the winner portfolio, with the opposite being the case for the U.S and Canada. Thus, as hypothesised in H3, momentum returns are primarily driven by loser stocks in optimistic periods for European countries, although this is not the case for the North American Markets.

Examination of columns 4-6 for western markets shows that momentum profits are insignificantly different from zero in all five countries under pessimism, with the returns being negative in three out of five cases. The negative or insignificant momentum returns under pessimism are due to the returns to the loser portfolio not being of the sign consistent with momentum. The returns to the winner portfolio are positive in four out of the five cases under pessimism, with three out of the four being significant at the 5% level or higher, whereas the returns to the loser portfolio under pessimism are positive in all five cases, with three being significant at the 10% level or higher. The final three columns of Table 3.8 show differences in winner, loser and momentum returns between optimistic and pessimistic states. In all five cases, the differences for momentum returns are statistically significant and of the expected sign. The findings are consistent with H3: the momentum effect is stronger under optimism than pessimism for western markets.

We now turn to consider the results for ESEA markets in table 3.8. While the results for western markets showed a marked and significant difference between sentiment states, for the east there is no such clear difference, as hypothesised in H4. Table 3.8 shows that momentum returns are insignificantly different from zero in both sentiment states for all countries. There is also very little evidence of significance of return continuation to the winner or loser portfolios, with 2 out of the 10 cases being significant at the 10% level or higher. Significant return continuations are only found for winner stocks for Hong Kong during optimistic states and for those for Thailand during pessimistic states. Moreover, in all five countries the difference in momentum returns between optimistic and pessimistic periods is insignificantly different from zero, clearly supporting H4.

Panel B of Table 3.8 presents the country-average and composite results by culture groups. The results shown in this panel further confirm the findings from Panel A and are consistent with the hypotheses 3 and 4. Furthermore, the results in Panel B also allow us to directly examine H5 which states that momentum returns under optimism will be greater in western markets than ESEA markets. The figures in the third column show that both country-average and composite momentum profits are sizeable and significant in western markets during optimistic periods whereas those in ESEA markets are insignificantly different from zero. Notably, momentum profits are primarily driven by the underperformance of loser stocks. In addition, there is no such difference under pessimism between the two cultural groups. Thus, the findings are consistent with H5.

Taken together, the results presented in Tables 3.7 and 3.8 provide strong support for hypotheses 2-5. In addition to momentum profits clearly differing based on culture and sentiment as shown in Tables 3.5 and 3.6, the examination of the five western and five ESEA markets supports our argument that cognitive dissonance plays a large part in explaining the difference in momentum profits in different markets. Specifically, by taking account of the psychology literature on beliefs relating to continuation and reversal and how these differ between western and ESEA cultures, we hypothesise how the interaction between sentiment and culture will impact on momentum returns in the two culture groups. Our results are consistent with these arguments.

Table 3.8 Momentum Profits and Sentiment for Western and ESEA Countries

This table reports the average monthly returns (%) of winner, loser and momentum portfolios across sentiment states (optimistic and pessimistic) for each of the 10 countries (Panel A) and the country-average and composite portfolios (Panel B). For each country, stocks are ranked into quintiles based on their past 6-month cumulative returns and held for 6 months and the past 6-month cumulative returns of each stock in the winner (loser) portfolios must be larger (less) than 0%. Stocks are ranked in quintiles in order to have a reasonable number of stocks. Other stock selection criteria and the formation of momentum portfolios are discussed in detail in Table 3.3. The sentiment formation is discussed in detail in Table 3.4. The average monthly returns to the country-average and composite portfolios during two sentiment periods (optimistic and pessimistic) are reported in Panel B. The formation of the country-average and composite portfolios is detailed in Table 3.3. The first three columns in Panel A show the returns of winner, loser and momentum portfolios under optimism, the second three columns show the returns of the three portfolios under pessimism and last three columns show the differences in returns of these portfolios between optimism and pessimism. For brevity, we only list results of winner, loser and momentum portfolios. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Momentum profits conditional on sentiment by country

Country	Optimistic			Pessimistic			Opt.-Pess.		
	W	L	Mom	W	L	Mom	W	L	Mom
West									
Canada	1.698(1.89)*	0.382(0.52)	1.316(2.37)**	-0.194(-0.15)	0.536(0.29)	-0.730(-0.68)	1.892(1.98)**	-0.154(-0.08)	2.046(2.13)**
France	0.597(1.04)	-0.892(-1.40)	1.489(3.55)***	1.743(3.74)***	2.461(5.00)***	-0.718(-1.500)	-1.146(-2.01)**	-3.353(-3.47)***	2.207(2.96)***
Germany	-0.326(-0.68)	-1.708(-2.08)**	1.382(2.19)**	1.937(4.91)***	1.677(2.67)***	0.260(0.54)	-2.263(-4.98)***	-3.385(-4.01)***	1.122(2.01)**
United Kingdom	0.412(0.70)	-1.648(-2.64)***	2.060(2.99)***	1.335(2.38)**	1.119(1.25)	0.216(0.42)	-0.923(-1.74)*	-2.767(-3.21)***	1.844(-3.01)***
United States	0.925(1.67)*	-0.386(-0.50)	1.311(2.50)**	1.179(1.50)	2.184(1.94)*	-1.005(-1.45)	-0.254(-0.31)	-2.570(-2.01)**	2.316(2.41)**

ESEA

	Optimistic			Pessimistic			Opt-Pess.		
	W	**L**	**Mom**	**W**	**L**	**Mom**	**W**	**L**	**Mom**
China	1.622(1.23)	1.906(1.13)	-0.284(-0.31)	0.954(1.01)	1.096(1.26)	-0.142(-0.26)	0.668(0.78)	0.810(0.53)	-0.142(-0.31)
Hong Kong	2.070(1.73)*	2.035(1.76)*	0.035(0.09)	0.265(0.22)	-0.110(-0.07)	0.375(0.63)	1.805(1.71)*	2.145(1.83)*	-0.340(-0.51)
Japan	-0.627(-0.95)	-0.922(-1.33)	0.295(0.99)	0.463(0.71)	1.120(1.26)	-0.657(-1.33)	-1.090(-1.31)	-2.042(-1.61)	0.952(1.01)
Korea	-0.471(-0.38)	-1.523(-1.41)	1.052(1.32)	2.265(1.63)	2.395(1.21)	-0.130(-0.14)	-2.736(-1.63)	-3.918(-1.65)	1.182(1.01)
Thailand	0.996(1.12)	0.691(0.63)	0.305(0.44)	3.936(5.99)***	3.631(4.18)***	0.305(0.48)	-2.940(-3.78)***	-2.940(-3.51)***	0.000(0.00)
Panel B. Country-average and Composite portfolios									
Panel B.1. Country-average portfolio									
West	0.661(2.00)**	-0.850(-2.16)**	1.511(10.73)***	1.200(3.21)***	1.595(4.56)***	-0.395(-1.50)	-0.539(-0.78)	-2.445(-4.12)***	1.906(9.01)***
East	0.718(1.32)	0.437(0.60)	0.281(1.27)	1.577(2.30)**	1.626(2.55)**	-0.049(-0.26)	-0.859(-0.92)	-1.189(-1.03)	0.330(1.07)
West-East	-0.057	-1.287(1.57)	1.230(4.70)***	-0.377(-0.48)	-0.031(-0.04)	-0.346(-1.01)	0.320(0.27)	-1.256(1.97)**	1.576(4.22)**
Panel B.2. Composite portfolio									
West	0.576(1.34)	-1.011(1.98)**	1.587(4.98)***	1.336(2.91)***	1.567(2.34)**	-0.231(-0.59)	-0.760(-1.85)*	-2.578(-2.71)***	1.818(2.69)***
East	0.777(1.19)	0.267(0.41)	0.510(1.09)	1.451(2.44)**	1.388(1.78)*	0.063(0.29)	-0.674(-1.09)	-1.121(-1.52)	0.447(0.78)
West-East	-0.201(-0.24)	-1.287(-2.31)**	1.077(2.46)**	-0.115(-0.21)	0.179(0.31)	-0.294(-0.61)	-0.086(-0.21)	-1.457(2.37)**	1.371(2.01)**

3.5 Robustness tests

3.5.1 An Alternative Individualism Index

To examine the robustness of our results for 40 countries, we follow Chui et al. (2010) and collect an alternative measure of individualism from the GLOBE (Global Leadership and Organizational Behaviour Effectiveness) project. The GLOBE project is a group of researchers focusing on culture and leadership in 62 countries. In the project, there are nine cultural dimensions: Performance Orientation, Assertiveness, Future Orientation, Humane Orientation, Institutional Collectivism, In-Group Collectivism, Power Distance, and Uncertainty Avoidance. Among these dimensions, Chui et al. (2010) suggest that institutional collectivism appears to reflect the same construct as Hofstede's individualism. We collect the country scores on the GLOBE's institutional collectivism ($Indv_{GLOBE}$) dimension for our sample from House et al. (2004). To be consistent with Hofstede's individualism index, we define a new variable $Indv_{GLOBE,}$ which is equal to GLOBE's institutional collectivism times -1. Thus, a higher value of $Indv_{GLOBE}$ suggests a higher degree of individualism of the country. The two indices are highly correlated so the categorical variable of GLOBE individualism is almost identical to the categorical variable of Hofstede's individualism. We expect the coefficient on the GLOBE individualism index is qualitative similar to that of Hofstede's individualism index. The regression model shown in equation (3.1) is re-estimated, with Hofstede's individualism index being replaced with GLOBE's institutional collectivism and we find the $Indv_{GLOBE}$ coefficient to be positive and significant at the 1% level and the interaction term between individualism and sentiment remains significant at the 10% level. Overall, our results are robust regardless of whether we use the GLOBE collectivism index or Hofstede's individualism index.

3.5.2 Is It Risk?

While the evidence so far suggests that there is a marked difference in momentum profits between western and ESEA cultures conditional on investor sentiment, we have not addressed whether such findings are due to economic risk factors. We now investigate this issue by estimating the Fama and French (2015) 5-factor (thereafter, FF-5) risk-adjusted returns during

Table 3.9 Determinants of Momentum Profits across Countries and the GLOBE Individualism Measure

Monthly momentum returns are regressed on the GLOBE individualism index, the sentiment variables and an interaction term between individualism and sentiment. GLOBE individualism index, is equal to GlOBE's institutional collectivism times -1. Categorical variable of $Indv_{GLOBE}$ equals 1 (-1) if IDV score belongs to the top (bottom) 30% of their scores, otherwise 0. All other variables are defined in Table 4.5. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

	(1)	(2)
Intercept	0.0039	0.0038
	(4.13)***	(4.10)***
$Indv_{GLOBE}$	0.0041	0.0040
	(3.91)***	(3.78)***
SENT	0.0064	0.0060
	(3.54)***	(2.82)***
IDV*SENT		0.0028
		(1.83)*
Country FE	YES	YES
Time FE	YES	YES
N	8231	8231
R squared (%)	1.41	1.65

different sentiment periods. Fama and French (2015) show that the FF-5 factor model generally performs better than the FF-3 factor model in explaining different anomalies. The FF-5 risk factors are able to capture a significant part of such anomalies, such as net share issues, accruals, volatility and market β. However, the risk factors still fail to explain the momentum effect (Fama and French, 2015).

In order to estimate risk-adjusted returns, we follow Cooper et al. (2004) to form a time-series of raw returns relating to each holding month and then regress time-series returns on the FF-5 factors and a constant. Therefore, we obtain the estimated factor loadings for each portfolio and a constant. The risk-adjusted momentum returns are:

$$r_{kt}^{adj} = r_{kt}^{raw} - \sum_i \beta_{ik} f_{it}$$

Where $r_{k,t}^{adj}$ and $r_{k,t}^{raw}$ are the risk-adjusted- and raw-returns for each momentum portfolio in holding month K, in calendar month t, respectively,. f_{it} is the realization of factor i of FF-5 in calendar month t, and β_{ik} is the estimated factor loading in month K on f_{it}. We compute the FF-5 factor adjustments which are excess return of the value-weighted market index as R_m, over the 1-month T-bill return R_f as the market portfolio, the return differential between small and big firms (SMB), the difference between the returns on diversified portfolios of stocks with high and low book-to-market firms (HML), the difference between the returns on diversified portfolios of stocks with robust and weak profitability as operating profitability (OP) and the difference between the returns on diversified portfolios of stocks of low and high investment firms as Investment factors (INV).[37] We follow Fama and French (2015) to form the risk factor portfolios. The stock market data are obtained from Datastream and the accounting data are downloaded from Compustat. At the end of each June, stocks are categorised into two size groups (Small and Big) based on the median of stocks' capitalization. To calculate the HML factor, stocks are first allocated independently to three B/M groups (low, median and high) based on 30/40/30 cutoffs. The intercepts of the two sorts (size and B/M) create six value-weighted Size to B/M portfolios. The sort is taken in June of year t, B is book equity at the end of the fiscal year ending in year t-1 and M is market capitalization at the end of December of year t-1.

The Size-OP and Size-Inv portfolios are formed in the same way as the Size-B/M portfolios. The operating profitability (OP) measured with accounting data for the fiscal year ending in year t-1, is revenue minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity. Investment, INV, is the change in total assets from the fiscal year ending in year t-2 to the fiscal year ending in t-1, divided by t-2 total assets. The value factor HML is calculated as the equally weighted average of the two (Small and Big) high B/M portfolio returns minus the average of the two low B/M portfolio returns. The profitability and investment factors are calculated in the same way as that of HML apart from HML being replaced by either operating profitability (RMW) (robust minus weak) or investment (CMA) (conservative minus aggressive). The size factor SMB is calculated as the equally weighted average of the three small stock portfolio returns minus the average of the three big stocks portfolio returns.

Table 3.10 presents the FF-5 (2015) risk-adjusted momentum profits for ten markets in the east and west without any split by sentiment. In contrast to the results in Table 3.7, the momentum returns appear to be primarily driven by the loser stocks in three out of the five countries (France, Germany and the UK), with the other countries being primarily driven by the winner stocks (Canada and the U.S). Momentum profits for all five western countries

[37] The FF-5 risk factors are explained in detail in Fama and French (2015).

Table 3.10 Risk-Adjusted Momentum Profits for the Western and ESEA Countries

This table reports the risk-adjusted returns (%) of momentum portfolios for each of the ten countries. For each momentum portfolio, a time-series of raw returns is formed and is regressed on excess market return, the SMB, HML, OP and Inv factors when risk is adjusted according to the FF (2015) 5-factor model. Panel A shows risk-adjusted momentum profits for each country. For each country, stocks are ranked into quintiles based on their past 6-month cumulative returns and held for 6 months and the past 6-month cumulative returns of each stock in the winner (loser) portfolios must be larger (less) than 0%. Stocks are ranked in quintiles in order to have a reasonable number of stocks. Other stock selection criteria and the formation of momentum portfolios are discussed in detail in Table 3.3. The sentiment formation is discussed in detail in Table 3.4. Panel B reports results of the country-average and composite portfolios for Western and ESEA countries. The formation of the country-average and composite portfolios is detailed in Table 3.3. For brevity, we only list results of winner, loser and momentum portfolios. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Momentum profits by country			
Country	**Winner (W)**	**Loser (L)**	**W Minus L**
West			
Canada	0.939(2.29)**	0.775(1.53)	0.164(0.35)
France	0.319(2.21)**	-0.566(-2.27)**	0.885(3.37)***
Germany	-0.275(-1.82)*	-1.693(-5.91)***	1.418(4.82)***
United Kingdom	0.489(2.87)***	-0.696(-2.43)**	1.185(4.84)***
U.S.	0.280(2.36)**	-0.137(-0.57)	0.417(2.41)**
ESEA			
China	1.178(1.83)*	0.990(1.44)	0.188(0.50)
Hong Kong	-1.596(-4.87)***	-2.492(-5.66)***	0.896(2.32)**
Japan	-0.203(-1.52)	-0.346(-1.59)	0.143(0.56)
Korea	-0.921(-2.40)**	-1.993(-4.19)***	1.072(2.59)**
Thailand	-0.270(-0.81)	-0.446(-1.22)	0.176(0.39)
Panel B. Country-average and Composite portfolios			
Panel B.1. Country-average Portfolio			
West	0.350(1.79)*	-0.463(-1.16)	0.813(3.49)***
East	-0.362(-0.79)	-0.857(-1.37)	0.495(2.13)**
West-East	0.712(1.43)	0.394(0.53)	0.312(1.03)
Panel B.2. Composite Portfolio			
West	0.299(2.86)***	-0.643(-3.38)***	0.942(4.62)***
East	-0.073(-0.33)	-0.474(-1.85)*	0.401(1.88)*
West-East	0.372(3.11)***	-0.169(-0.71)	0.541(2.93)***

remains positive, with the returns being highly significant in four out of the five countries (the exception again being Canada), consistent with the results shown in Table 3.7. For ESEA markets, in contrast to the findings without risk adjustments in Table 3.7, risk-adjusted momentum returns in Hong Kong and Korea are significantly positive, with the other countries remaining insignificantly different from zero. In addition, returns to loser portfolios in Hong Kong and Korea reduce significantly to -2.492% and -1.993%, suggesting that significant momentum profits in both countries are primarily due to the underperformance of loser stocks.

Panel B shows the results for the country-average and composite portfolios. For both portfolios, there is a substantial difference in momentum returns between the two culture groups. In contrast to the results in Table 3.7, the magnitude of momentum returns to the country-average portfolio is similar to that without risk adjustments in Table 3.7 but the average returns to the winner and loser portfolios in western markets reduce remarkably to 0.354% and -0.463% respectively, with the returns to winner stocks at the 10% level.

Again, in contrast to the results in Table 3.7, momentum returns to the country-average portfolio in ESEA markets increase to 0.49% per month, significant at the 10% level, with the returns to loser portfolios being significantly negative. The difference in momentum profits between western and ESEA countries is 0.312%, which is insignificant. However, the difference in momentum profits between the two culture groups for the composite portfolio is highly significant, which is consistent with hypothesis 2 that states momentum profits will be significantly greater in western markets than in ESEA markets. It is observed that momentum profits are primarily driven by the underperformance of loser stocks. Overall, after adjusting for the FF-5 factors, although there are differences in raw momentum profits and risk-adjusted momentum, both raw and risk-adjusted results provide clear support to H2.

We then go on to consider whether the impact of sentiment on momentum profits in the two culture groups can be subsumed by the FF-5 risk factors. Table 3.11 shows risk-adjusted returns to winner, loser and momentum portfolios under optimism and pessimism as well as the differences between the two sentiment states for all three portfolios. Again, Panel A shows results for individual countries in the east and west and Panel B for country-average and composite portfolios. As shown in Panel A of Table 3.11, risk-adjusted momentum profits for all western countries are all significant under optimism. Risk-adjusted returns to winner portfolios are positive in four out of the five western countries, with Canada and the U.S being significant at 10% or higher and those to the loser portfolios in all five cases being negative, with three out of the five being significant at the 1% level (the exception being Canada and the U.S).[38] The findings confirm the evidence in Table 3.8 in

[38] Raw returns to the loser portfolio are significant in only two countries.

which momentum returns are primarily driven by loser stocks in optimistic periods for European markets, although this is not the case for the North American markets. Columns 4-6 of Panel A of Table 3.11 for western markets show that momentum profits under pessimism are insignificantly different from zero in France and the UK, and are significantly negative for Canada and the U.S. The insignificant or negative momentum profits under pessimism are due to returns to both loser and winner portfolios not being of the sign consistent with momentum. The risk-adjusted momentum returns for Germany under pessimism becomes significantly positive, which is inconsistent with those from Table 3.8, but for the other countries, results are qualitatively similar. The final three columns of the table show differences between optimistic and pessimistic states. In four out of the five, the differences are statistically significant and of the expected sign, with the exception being Germany. The country-average and composite results in Panel B suggest that momentum profits are only significant during optimistic periods in western countries and are primarily driven by the underperformance of loser stocks, consistent with hypothesis H3. Overall, the results in Table 3.11 for western countries are broadly consistent with those in Table 3.8 and hypothesis 3, in which the momentum effect is stronger during optimistic periods than pessimistic periods for western markets.

We now turn to consider the results for ESEA countries in Table 3.11. The results for risk-adjusted returns are overall consistent with those of raw returns in Table 3.8. In nine out of the ten cases (optimism and pessimism), momentum returns are insignificantly different from zero during both sentiment states, consistent with hypothesis 4. The country-average and composite results in Panel B of Table 3.10 confirm the findings from Panel A and are consistent with H5: momentum returns during optimistic periods will be greater in western markets than ESEA markets. Again, the pattern of momentum profits for ESEA markets in Table 3.8 remains robust to these risk adjustments.

Overall, the results of risk-adjusted returns are broadly consistent with the hypotheses and the findings using raw returns in previous sections. While

Table 3.11 Risk-Adjusted Momentum Profits Conditional on Sentiment for Western and ESEA Countries

This table reports the risk-adjusted returns (%) of momentum portfolios across sentiment states (optimistic and pessimistic) for each of the 10 countries (Panel A) and the country-average and composite portfolio (Panel B). The sample period spans Jan. 1991 to Dec. 2013. For each momentum portfolio, a time-series of raw returns is formed and is regressed on excess market return, the SMB, HML, OP and Inv factors when risk is adjusted according to FF (2015) 5-factor model. For each country, stocks are ranked into quintiles based on their past 6-month cumulative returns and held for 6 months and the past 6-month cumulative returns of each stock in the winner (loser) portfolios must be larger (less) than 0%. Stocks are ranked in quintiles in order to have a reasonable number of stocks. Other stock selection criteria and the formation of momentum portfolios are discussed in detail in Table 3.3. The sentiment formation is discussed in detail in Table 3.4. The average monthly returns on the country-average and composite portfolios during two sentiment periods (optimistic and pessimistic) are reported in Panel B. The formation of the country-average and composite portfolios is detailed in Table 3.3. The first three columns in Panel A show the returns of winner, loser and momentum portfolios under optimism and the second three columns show the returns of the three portfolios under pessimism and last three columns show the difference in returns of these portfolios between optimism and pessimism. For brevity, we only list results of winner, loser and momentum portfolios under optimism and pessimism. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Momentum profits conditional on sentiment by country

Country	**Optimistic**			**Pessimistic**			**Opt.-Pess.**		
	W	**L**	**Mom**	**W**	**L**	**Mom**	**W**	**L**	**Mom**
West									
Canada	1.341(1.84)*	-0.190(-0.30)	1.531(2.47)**	-0.558(-0.71)	1.669(1.44)	-2.227(-2.08)**	1.899(2.12)**	-1.859(-1.98)**	3.758(3.71)***
France	0.172(0.59)	-1.283(-3.04)***	1.455(3.27)***	0.292(1.27)	-0.042(-0.07)	0.334(0.62)	-0.120(-0.07)	-1.241(-2.86)***	1.121(2.75)***
Germany	-0.665(-2.38)**	-2.116(-3.57)***	1.451(2.43)**	0.159(0.47)	-1.252(-2.83)***	1.411(2.59)***	-0.824(2.43)**	-0.864(2.02)**	0.040(0.06)
United Kingdom	0.084(0.29)	-1.751(-4.58)***	1.835(4.86)***	0.251(0.73)	0.150(0.21)	0.101(0.18)	-0.167(-0.31)	-1.901(-4.73)***	1.734(4.81)***
U. S	0.532(2.85)***	-0.239(-0.50)	0.771(1.78)*	-0.336(-1.31)	0.818(1.68)*	-1.154(-1.70)*	0.868(3.07)***	-1.057(-1.98)**	1.925(4.76)***

ESEA

	Optimistic			Pessimistic			Opt-Pess.		
	W	**L**	**Mom**	**W**	**L**	**Mom**	**W**	**L**	**Mom**
China	1.034(0.80)	0.777(0.60)	0.257(0.21)	0.993(0.84)	0.573(0.45)	0.420(0.91)	0.041(0.13)	0.204(0.42)	-0.163(-0.21)
Hong Kong	-2.590(-4.74)***	-2.302(-3.68)***	-0.288(-0.59)	-1.368(-3.15)***	-1.994(-2.47)**	0.626(0.99)	-1.222(-2.05)**	-0.308(-0.57)	-0.914(-2.01)**
Japan	-0.499(-2.48)**	-0.957(-4.20)***	0.458(1.48)	-0.203(-0.84)	0.033(0.11)	-0.236(-0.50)	-0.296(-1.53)	-0.990(-4.23)***	0.694(1.71)*
Korea	-0.825(-1.04)	-2.420(-3.68)***	1.595(2.35)**	-0.600(-1.04)	-1.407(-1.31)	0.807(0.96)	-0.225(-0.27)	-1.013(-1.18)	0.788(1.23)
Thailand	-0.212(-0.43)	-0.486(-0.67)	0.274(0.34)	0.376(0.60)	0.359(0.46)	0.017(0.02)	-0.588(-0.98)	-0.845(-1.11)	0.257(0.31)
Panel B. Country-average and Composite portfolios									
Panel B.1 Country-average portfolio									
West	0.293(0.90)	-1.116(-2.85)**	1.409(8.08)***	-0.038(-0.22)	0.269(0.55)	-0.307(-0.48)	0.331(0.70)	-1.385(-6.56)***	1.716(2.82)**
East	-0.618(-1.05)	-1.078(-1.80)	0.460(1.48)	-0.160(-0.40)	-0.487(-0.95)	0.327(1.69)	-0.458(-2.12)*	-0.591(-2.51)*	0.133(0.42)
West-East	0.911(1.36)	-0.038(-0.05)	0.949(2.67)**	0.122(0.28)	0.756(1.07)	-0.634(-0.96)	0.789(1.51)	-0.794(-2.50)**	1.583(2.51)**
Panel B.2 Composite portfolio									
West	0.216(1.27)	-1.200(-4.64)***	1.416(5.01)***	-0.005(0.03)	-0.048(-0.16)	0.043(0.13)	0.221(1.29)	-1.152(-4.96)***	1.373(4.99)***
East	-0.360(-0.94)	-0.964(-2.44)**	0.604(1.20)	0.140(0.40)	-0.061(-0.14)	0.201(0.78)	-0.500(-1.17)	-0.903(-2.24)**	0.403(0.93)
West-East	0.576(1.63)	-0.236(-0.79)	0.812(2.01)**	-0.145(-0.51)	0.013(0.08)	-0.158(-0.67)	0.721(1.81)*	-0.249(-0.65)	0.970(2.41)**

every possible risk-based explanation cannot be ruled out, it is sensible to conclude that the difference in momentum profits between the two culture groups cannot be subsumed by rational risk premia as modeled in the FF-5 factor model.

3.5.1 An Alternative Sentiment Index

In this section, we examine the sensitivity of our results for ten western and ESEA countries to an alternative index for investor sentiment. The sentiment measure is constructed by Baker et al. (2012) for international markets, who suggest that investor sentiment can be captured by variables that related to investors' propensity to speculate. In contrast to the consumer confidence index which is a pure survey sentiment measure, Baker et al. (2012) sentiment measure is constructed using stock market data. Due to data availability in global markets, they construct a yearly sentiment index using four proxies: a volatility premium, the number of IPOs, the average first day IPO return and market turnover.[39] The stock market data is obtained from Datastream and IPO data is from updated version of Loughran et al. (1994) ((http://bear.cba.ufl.edu/ritter/Int2008.pdf). They also regress each of these variables against macro-economic fundamentals. The sentiment index is the 1st principal component of the residual series from the regressions. We follow their procedures to construct the sentiment index for each of five western and ESEA countries. However, each of four proxies is not adjusted for the macro series since Baker and Wurgler (2006, 2007) suggest that both adjusted and unadjusted indices yield similar results and the macro data are not available for all countries. The results in Tables 3.8 (raw returns) and 3.10 (risk-adjusted returns) are re-estimated. First, the total sentiment index coefficients for each of ten western and ESEA markets are reported as follows:

$Sent_{canada,t} = 0.448PVOL_t + 0.589NIPO_t + 0.678RIPO_t - 0.211TURN_t$;

$Sent_{France,t} = 0.66PVOL_t + 0.530NIPO_t + 0.439RIPO_t + 0.291TURN_t$;

$Sent_{Germany,t} = 0.627PVOL_t + 0.657NIPO_t + 0.393RIPO_t + 0.148TURN_t$;

$Sent_{UK,t} = 0.557PVOL_t + 0.526NIPO_t + 0.564RIPO_t - 0.309TURN_t$;

[39] Volatility premium is the log ratio of the value-weighted average market-to-book ratios of stocks with high idiosyncratic volatility (top tercile) and stocks with low idiosyncratic volatility (bottom tercile). The number of IPOs is the log number of initial public offerings over the year. The average first day returns is the average first-day returns of initial public offering over the year. The turnover ratio is measured as the detrended log market turnover with an up-to five year moving average.

$Sent_{US,t} = 0.513PVOL_t + 0.412NIPO_t + 0.536RIPO_t + 0.572TURN_t$;

$Sent_{China,t} = 0.675PVOL_t + 0.130NIPO_t + 0.298RIPO_t + 0.663TURN_t$;

$Sent_{Hong\ Kong,t} = 0.589PVOL_t + 0.599NIPO_t - 0.008RIPO_t + 0.543TURN_t$;

$Sent_{Japan,t} = 0.531PVOL_t + 0.566NIPO_t + 0.599RIPO_t + 0.200TURN_t$;

$Sent_{South\ Korea,t} = -0.309PVOL_t + 0.432NIPO_t + 0.559RIPO_t + 0.637TURN_t$;

$Sent_{Thailand,t} = 0.445PVOL_t + 0.605NIPO_t + 0.596RIPO_t + 0.286TURN_t$;

In each market, there is at least one eigenvalue of the variables that exceeds one.[40] The percentage of variance explained by the first principlal component is, in order of listed countries above, 46.7%, 43.6%, 47.5%, 43.6%, 43.1%, 37.8%, 51.9%, 47.7%, 36.5% and 50.2%. These figures are similar to the 49% reported in Baker and Wurgler (2006) for a six-factor index of U.S. sentiment and to the average 42% reported in Baker et al. (2012) for the four-factor index of sentiment in six international countries.

Tables 3.12 and 3.13 report Tables 3.8- and 3.10- equivalent momentum raw- and FF-5 risk-adjusted- returns during optimistic and pessimistic periods, using the Baker et al. (2012) sentiment measure instead of the consumer confidence index. All other calculations remain the same as those in Tables 3.8 and 3.10. As shown in Panel A of Table 3.12, raw momentum profits are positive and highly significant under optimism for all five western markets. In contrast to the findings using the consumer confidence index, momentum returns under optimism in all five cases appear to be driven by the winner stocks, with all but Germany exhibiting significantly positive returns to this group and the returns to loser portfolios in four out of the five countries being insignificantly different from zero. However, after adjusting by the FF-5 factors as shown in Table 3.13, returns to winner stocks drop substantially in all five markets and those to loser portfolios for all five countries become negative, with four out of the five to loser portfolios being significant at the 10% level or higher. It suggests that after adjusted for the FF-5 risk factors, momentum profits in western countries seem to be driven by loser stocks instead of winner stocks, consistent with H3 which states that for western markets, momentum profits are primarily driven by loser stocks when sentiment is optimistic. Furthermore, both raw and FF-5 risk-adjusted momentum profits under pessimism are insignificantly different from zero or

[40] The detailed statistics for the four sentiment proxies are not reported but are available on request.

Table 3.12 Momentum Profits and the Alternative Sentiment Index for Western and ESEA Countries

This table reports the average monthly returns (%) of momentum portfolios across sentiment states (optimistic and pessimistic) for each of the 10 countries (Panel A) and the country-average and composite portfolios (Panel B). For each country, stocks are ranked into quintiles based on their past 6-month cumulative returns and held for 6 months and the past 6-month cumulative returns of each stock in the winner (loser) portfolios must be larger (less) than 0%. Other stock selection criteria and the formation of momentum portfolios are discussed in detail in Table 3.3. Sentiment is measured using the yearly sentiment index constructed by Baker et al. (2012) using volatility premium, number and 1st-day returns in IPOs, and market turnover. The overall sentiment index is the first principal component of the four sentiment proxies. The sentiment formation is discussed in detail in Table 3.4. The average monthly returns on the country-average and composite portfolios during two sentiment periods (optimistic and pessimistic) are reported in Panel B. The formation of the country-average and composite portfolios is detailed in Table 3.3. The first three columns in Panel A show the returns of winner, loser and momentum portfolios under optimism and the second three columns show the returns of the three portfolios under pessimism and last three columns show the difference in returns of the three portfolios between optimism and pessimism. For brevity, we only list results of winner, loser and momentum portfolios under optimism and pessimism. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Momentum profits conditional on sentiment by country

Country	Optimistic			Pessimistic			Opt.- Pess.		
	W	L	Mom	W	L	Mom	W	L	Mom
West									
Canada	2.010(2.25)**	0.690(0.85)	1.320(2.62)***	3.484(4.29)***	4.579(3.34)***	-1.095(-0.98)	-1.474(-2.03)**	-3.899(-2.89)***	2.415(2.68)***
France	1.944(3.07)***	0.894(1.69)*	1.050(2.89)***	0.405(0.88)	0.390(0.49)	0.015(0.03)	1.539(2.71)***	0.504(0.76)	1.035(2.18)**
Germany	0.826(1.51)	0.047(0.08)	0.779(2.05)**	-0.265(-0.51)	-1.240(-1.32)	0.975(1.67)*	1.091(1.87)*	1.287(1.47)	-0.196(-0.13)
United Kingdom	1.450(2.86)***	0.073(0.17)	1.377(3.78)***	-0.019(-0.04)	-0.837(-0.90)	0.817(1.53)	1.469(2.91)***	0.910(1.14)	0.560(1.01)
U.S.	1.431(2.68)***	0.411(0.53)	1.020(1.97)**	1.111(1.32)	1.987(1.49)	-0.876(-1.03)	0.320(0.64)	-1.576(-1.33)	1.898(2.24)**
ESEA									

	Optimistic			Pessimistic			Opt.-Pess.		
	W	L	Mom	W	L	Mom	W	L	Mom
China	2.778(2.32)**	2.920(2.35)**	-0.142(-0.32)	1.744(1.42)	1.439(0.90)	0.305(0.47)	1.034(1.13)	1.481(1.31)	-0.447(-0.49)
Hong Kong	3.469(3.07)***	4.598(3.09)***	-1.129(-1.36)	1.527(1.79)*	0.680(0.63)	0.847(1.79)*	1.942(1.84)*	3.918(2.71)***	-1.976(-2.01)**
Japan	1.481(2.17)**	1.211(1.78)*	0.270(0.70)	-0.522(-0.79)	0.272(0.28)	-0.794(-1.46)	2.003(2.32)**	0.939(1.52)	1.064(1.71)*
Korea	3.083(2.61)***	2.602(1.92)*	0.481(0.63)	-1.655(-0.94)	-1.637(-0.76)	-0.018(-0.02)	4.738(2.99)***	4.239(2.73)***	0.499(0.83)
Thailand	3.252(3.50)***	2.966(3.12)***	0.286(0.46)	-0.478(-0.41)	-0.410(-0.25)	-0.068(-0.06)	3.730(3.71)***	3.376(3.35)***	0.354(0.61)
Panel B. Country-average and Composite portfolios									
Panel B.1 Country-average portfolio									
	Optimistic			**Pessimistic**			**Opt. - Pess.**		
	W	**L**	**Mom**	**W**	**L**	**Mom**	**W**	**L**	**Mom**
West	1.532(7.17)***	0.423(2.53)*	1.109(10.2)***	0.943(1.39)	0.976(0.92)	-0.033(-0.07)	0.589(1.05)	-0.553(-0.57)	1.142(2.45)*
East	2.813(8.00)***	2.859(5.30)***	-0.046(-0.16)	0.123(0.19)	0.069(0.13)	0.054(0.20)	2.690(3.99)**	2.790(4.19)***	-0.10(-0.19)
West-East	-1.279(-3.11)**	-2.436(-4.31)***	1.155(3.74)**	0.820(0.42)	0.907(0.77)	-0.087(-0.17)	-2.101(-2.40)**	-3.343(-2.84)**	1.242(1.91)*
Panel B.2 Composite portfolio									
West	1.664(3.91)***	0.428(1.07)	1.236(5.30)***	0.697(1.53)	0.272(0.36)	0.425(0.90)	0.967(2.01)**	0.156(0.23)	0.811(1.99)**
East	2.994(5.44)***	2.989(4.42)***	0.005(0.02)	-0.694(-1.02)	-0.770(-0.84)	0.076(0.18)	3.688(5.73)***	3.759(5.43)***	-0.071(-0.13)
West-East	-1.330(-2.68)**	-2.561(-3.34)***	1.231(5.13)***	1.391(1.79)*	1.042(1.42)	0.349(0.59)	-2.721(-2.48)**	-3.603(-5.57)***	0.882(2.43)**

Table 3.13 Risk-Adjusted Momentum Profits and the Alternative Sentiment Index for Western and ESEA Countries

This table reports the FF-5 risk-adjusted returns (%) of momentum portfolios across sentiment states (optimistic and pessimistic) for each of the 10 countries (Panel A) and the country-average and composite portfolio (Panel B). For each country, stocks are ranked into quintiles based on their past 6-month cumulative returns and held for 6 months and the past 6-month cumulative returns of each stock in the winner (loser) portfolios must be larger (less) than 0%. Stocks are ranked in quintiles in order to have a reasonable number of stocks. Other stock selection criteria and the formation of momentum portfolios are discussed in detail in Table 3.3. For each momentum portfolio, a time-series of raw returns is formed and is regressed on excess market return, the SMB, HML, OP and Inv factors when risk is adjusted according to FF (2015) 5-factor model. Sentiment is measured using the yearly sentiment index constructed by Baker et al. (2012) using volatility premium, number and 1st-day returns in IPOs, and market turnover. The overall sentiment index is the 1st principal component of the 4 sentiment proxies. The sentiment formation is discussed in detail in Table 3.4. The average monthly returns on country-average and composite portfolios during two sentiment periods (optimistic and pessimistic) are reported in Panel B. The formation of the country-average and composite portfolios is detailed in Table 3.3. The first three columns in Panel A show the returns of winner, loser and momentum portfolios under optimism and the second three columns show the returns of the three portfolios under pessimism and last three columns show the difference in returns of the three portfolios between optimism and pessimism. For brevity, we only list results of winner, loser and momentum portfolios under optimism and pessimism. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Risk-adjusted momentum profits conditional on sentiment by country

Country	**Optimistic**			**Pessimistic**			**Opt.-Pess.**		
	W	**L**	**Mom**	**W**	**L**	**Mom**	**W**	**L**	**Mom**
West									
Canada	0.891(1.09)	-0.255(-0.34)	1.146(1.80)*	2.584(3.57)***	3.085(2.89)***	-0.501(-0.51)	-1.693(-2.01)**	-3.340(-3.36)***	1.647(1.99)**
France	0.090(0.26)	-0.634(-1.65)*	0.724(2.00)**	-0.457(-1.62)	-0.787(-1.41)	0.330(0.52)	0.547(1.43)	0.153(0.31)	0.394(0.99)
Germany	-0.732(-2.71)**	-1.472(-3.16)***	0.740(1.76)*	-0.702(-2.09)**	-1.449(-2.72)***	0.747(1.23)	-0.030(-0.21)	-0.023(-0.16)	-0.007(-0.03)
United Kingdom	0.188(0.59)	-0.847(-2.39)**	1.035(2.95)***	-0.033(-0.09)	-0.140(-0.19)	0.107(0.19)	0.221(0.41)	-0.707(-1.97)**	0.928(2.71)***
U. S	0.579(2.70)***	-0.435(-1.99)**	1.014(3.43)***	-0.269(-0.83)	1.290(1.99)**	-1.559(-1.89)*	0.848(2.83)***	-1.725(-2.93)***	2.573(3.61)***

ESEA									
China	2.340(1.87)*	2.794(2.22)**	-0.454(-0.47)	-0.025(-0.02)	-0.226(-0.22)	0.201(0.50)	2.365(1.91)*	3.020(2.41)**	-0.655(-0.75)
Hong Kong	-1.876(-2.42)**	-1.662(-1.56)	-0.214(-0.24)	-1.323(-2.84)***	-2.594(-3.87)***	1.271(2.39)**	-0.553(-0.61)	0.932(1.41)	-1.485(2.13)**
Japan	-0.394(-1.71)*	-0.617(-1.87)*	0.223(0.58)	-0.313(-1.33)	0.218(0.76)	-0.531(-1.22)	-0.081(-0.12)	-0.835(-2.16)**	0.754(1.61)
		Optimistic			**Pessimistic**			**Opt.-Pess.**	
	W	**L**	**Mom**	**W**	**L**	**Mom**	**W**	**L**	**Mom**
Korea	-0.803(-1.15)	-2.036(-2.51)**	1.233(1.51)	-0.814(-0.82)	-0.432(-0.36)	-0.382(-0.37)	0.011(0.10)	-1.604(-1.76)*	1.615(1.81)*
Thailand	0.511(0.94)	0.603(0.91)	-0.092(-0.12)	-1.016(-1.74)*	-0.153(-0.20)	-0.863(-0.84)	1.527(1.89)*	0.756(1.37)	0.771(1.01)
Panel B. Country-average and Composite portfolios									
Panel B.1 Country-average portfolio									
West	0.203(0.74)	-0.729(3.74)**	0.932(11.01)***	0.225(0.37)	0.400(0.47)	-0.175(-0.43)	-0.021(-0.05)	-1.129(-1.75)	1.108(2.40)*
East	-0.044(-0.06)	-0.184(-0.21)	0.139(0.47)	-0.698(-2.96)**	-0.637(-1.27)	-0.061(-0.16)	0.654(1.18)	0.454(0.57)	0.200(0.36)
West-East	0.248(0.35)	-0.545(-1.61)	0.793(2.58)**	0.923(1.44)	1.037(1.08)	-0.114(-0.05)	-0.675(-0.95)	-1.583(-1.37)	0.908(1.72)
Panel B.2 Composite portfolio									
West	0.211(1.53)	-0.728(3.33)***	0.939(4.12)***	0.208(0.61)	0.132(0.20)	0.076(0.22)	0.003(0.08)	-0.860(-3.51)***	0.863(3.91)***
East	0.056(0.12)	-0.349(-1.03)	0.405(1.49)	-0.531(-1.49)	-0.545(-1.52)	0.014(0.10)	0.587(1.34)	0.196(0.51)	0.391(1.51)
West-East	0.155(0.71)	-0.379(2.01)**	0.534(1.98)**	0.739(1.61)	0.677(-1.59)	0.062(0.20)	-0.584(-1.42)	-1.056(3.92)***	0.472(2.31)**

significantly negative in all five western markets. Overall, the findings for western markets are consistent with H3.

We now consider the results for ESEA countries in Tables 3.12 and 3.13. Under both sentiment states, raw momentum returns are insignificantly different from zero in nine out of the ten cases (optimistic and pessimistic) as shown in Table 3.12. After controlling for FF-5 risk factors, momentum returns for all ESEA markets become insignificantly different from zero under optimism, with the magnitude of returns to winner stocks dropping remarkably in all five markets. Both raw and risk-adjusted momentum returns under pessimism remain insignificantly different from zero in four out of five ESEA markets (the exception being Hong Kong). The country-average and composite results in Panel B of Tables 3.12 and 3.13 show that there is no clear difference in momentum profits (both raw and risk-adjusted returns) between optimism and pessimism, consistent with the results using the consumer confidence index and hypothesis 4. It is also observed from Panel B of Tables 3.12 and 3.13 that for both country-average and composite portfolios, the differences in raw and risk-adjusted momentum profits between western markets and ESEA markets are significant at the 5% level or higher during optimistic states. However, there is no significant difference in both raw and risk-adjusted momentum profits between the two culture groups when sentiment is pessimistic. The findings are consistent with H5: momentum returns during optimistic periods will be greater in western markets than in ESEA markets.

Overall, the results in Tables 3.12 and 3.13 from using the alternative sentiment measure are qualitatively similar to those using the consumer confidence index as a proxy for sentiment, suggesting that the interaction of sentiment and culture affect cognitive dissonance and the extent of momentum profits regardless of the choice of investor sentiment proxy.

3.5.2 Sensitivity tests

We carry out three additional sensitivity tests to assess the robustness of the results: (1) re-estimating empirical analysis in all tables using an alternative ranking-(J) and holding (K) periods (J=K=12) as shown in Tables A3.3 to A3.5, which is also a widely researched momentum strategy in the literature; (2) a 40% cutoff for optimistic/pessimistic sentiment is used as shown in Tables

A3.6 and A3.7; (3) we follow Stambaugh et al. (2012) to identify investor sentiment periods as shown in Tables A3.8 and A3.9. Specifically, a high-sentiment month (optimistic) is one in which the 3-month rolling average score of the consumer confidence index in the previous month is in the top 30% of the 3-month rolling average time series values and a low-sentiment month (pessimistic) is one in the bottom 30% of the 3-month rolling average time series values, with the rest being mild states. The results of these tests, which are reported in the appendix, are qualitatively similar to those reported in the earlier analysis.

3.6 Conclusion

The momentum puzzle seems to be a major challenge to the efficient market hypothesis, and to date no satisfactory explanation for the anomaly has been provided. However, a mixed picture has emerged globally, with western markets showing clear evidence of momentum, but ESEA markets broadly being characterized by insignificant momentum profits. We propose that cognitive dissonance may be an important driver of the anomaly, with the interaction of investor sentiment and culture causing cognitive dissonance to arise in different circumstances and to differing degrees in the west and the east. While previous studies of the momentum anomaly have examined the roles of sentiment and culture independently, to date no study have examined their joint impact or considered the implications of their interaction on cognitive dissonance and momentum.

In this chapter, we take account of the interaction between sentiment and culture and using an approach in the spirit of Hong and Stein (1999) propose five hypotheses to explain differences across countries in relation to the profitability of the momentum strategy. In addition to examining momentum across 40 countries, we focus attention on the five largest markets in each of the west and the east, given psychological arguments and evidence about differences in self-construal in the two cultures. Specifically, we recognise that westerners have a strong tendency to believe in continuation, while those from the east expect reversal. Our results provide support to all hypotheses and provide evidence consistent with cultural biases and sentiment interacting to impact on cognitive dissonance. Results suggest that cultural biases concerning continuation and reversal are important drivers for the differences in relation to the momentum anomaly across western and ESEA markets. Results are robust to a number of additional tests and alternative specifications. By identifying how the interaction of sentiment and culture affects cognitive dissonance and the extent of momentum profits across countries, it is interesting to see how such an effect influences post-earnings-announcement-drift, since Hong et al. (2003) find that earnings momentum is stronger in the west than in the east. Thus, in the next chapter, we will proceed to investigate how the interaction affects cognitive dissonance and post-earnings-announcement-drift.

3.7 Appendix

3.7.1 Definitions of Control Variables in the Regression Analysis

Table A3. 1 Variables, Sources and Definitions in the Regression Analysis

Variable	Source	Definition
Firm characteristics		
Market trading volume (TV)	Datastream	Market trading volume for each country in each month is calculated as the market dollar trading volume of the Datastream Global index of this country scaled by the index's market capitalization in this month.
Stock market volatility (V)	Datastream	Stock market volatility for each country in each month is measured as the sum of squared return on each stock divided by the number of stocks.
Analyst coverage (Cov)	IBES	Analyst coverage (Cov) for each country in each month is the sum of average number of analysts offering one-year ahead earnings forecast for all available stocks. If there is no analyst data for a firm from IBES, then the average number of analysts is treated as zero.
Dispersion of analyst forecasts (Disp)	IBES	Arithmetic mean of standard deviation of analyst forecasts for each earnings announcement of each country in each year.
Cash flows growth rate volatility (VolFCF)	Datastream	The equally weighted average of annualized standard deviation of log free cash flow changes for each country in each year. The annualize standard deviation is measured as monthly standard deviation of log free cash follow growth $*(12)^{1/2}$.
Median firm size (Size)	Datastream	Median of firm size for each country is the median of each country's market capitalisation of Datastream global index in each year.
Price to book ratio (PB)	Datastream	Price to book ratio for each country in each year is measured as arithmetic mean of each country's market to book ratio of Datastream global index.
Financial market development variables		
Total private credit (CREDIT)	World Development Statistics Database, World Bank	Total private credit for each country in each year divided by this country's GDP
Familiarity of foreign investors (LANG)	Chan et al. (2005)	An average value of common language dummy that equals to one if two countries share a major language, zero otherwise.
Control of capital flows (CONTRL)	Chan et al. (2005)	A higher value suggests more restrictions on capital flows.
Stock market openness (Open)	S&P's Emerging Markets Database	The variable is calculated as the market capitalisation of constituent stocks in the S&P's /International Finance Corporation Investor index divided by those in the

		S&P's/International Finance Corporation global index of this country.
Insider index (INSIDER)	La Porta et al. (2006)	A lower value indicates that insider trading is more pronounced.
Corruption index (CORRP)	International Country Risk Guide (ICRG)	A lower score indicates a higher level of corruption.
political risk index (POLITICAL)	ICRG	A lower score indicates a higher political risk.
Transaction costs index (TRAN)	Chan et al. (2005)	A lower value indicates lower transaction costs.
Investor protection index (PROTECTION)	ICRG	A lower score indicates a lower level of investor protection.
Macroeconomic variables		
Inflation rate(Inflation)	IMF	Annual consumer price index changes (%) for each country in each year.
GDP growth rate (GDP)	IMF	Nominal GDP growth rate for each country in each year.

3.7.2 Country-Average Results for Table 3.5

Table A3. 2 Investor Sentiment, Individualism and Momentum for the Country-Average Portfolio

This table presents the average monthly returns (%) of momentum strategy for the country-average portfolio sorted by investor sentiment and Individualism index. Panel A reports momentum profits sorted by individualism. Panels B and C present momentum profits for high and low individualism levels after controlling for the effect of sentiment. At the end of each month, momentum portfolios for each country are constructed and all countries in the sample are sorted into three groups by using top (bottom) 30% cutoffs based on their individualism index. Each month is identified as optimism, mild or pessimism. The definition of sentiment states of holding period is discussed in detail in Table 3.4. Both the country-average and composite portfolios are formed in each individualism - and investor sentiment-sorted category. The formation of the country-average and composite portfolios is described in table 3.3. For brevity, we only report results of composite portfolio. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Country-average portfolios	**Momentum Portfolio**		
	Winner	**Loser**	**Winner-Loser**
Panel A. Portfolio returns and Individualism			
High IDV	1.400	0.373	1.027
	***(10.62)	(1.57)	***(4.31)
Low IDV	1.372	1.374	-0.002
	***(5.26)	***(3.99)	(-0.007)
High. - Low.	0.008	-0.963	0.971
	(-0.15)	*(-1.66)	***(3.24)
Sentiment level			
Panel B. High Individualism			
Optimistic	1.137	-0.390	1.527
	***(3.30)	(-1.11)	***(3.11)
Pessimistic	1.870	1.422	0.448
	*** (2.98)	(1.21)	(1.04)
Opt. -	-0.734	-1.810	1.079

Pes.			
	(-0.87)	*(1.73)	**(1.97)
Panel C. Low Individualism			
Optimistic	1.087	0.874	0.213
	(0.7)	(0.47)	(0.06)
Pessimistic	1.396	2.103	-0.707
	***(2.77)	***(2.83)	(-1.48)
Opt.-Pes.	-0.309	-1.23	0.919
	(-0.33)	**(-2.32)	(1.24)

3.7.3 Momentum Strategy with Ranking-(J) and Holding (K) Periods =12

Table A3. 3 Momentum, Investor sentiment and Individualism with Ranking and Holding Periods=12

This table presents the average monthly returns (%) of momentum strategy for the composite portfolio sorted by investor sentiment and Individualism index. Panel A reports momentum profits sorted by individualism. Panel B and C present momentum profits for high and low individualism levels after controlling for the effect of sentiment. At the end of each month, momentum portfolios for each country are constructed and all countries in the sample are sorted into three groups by using top (bottom) 30% cutoffs based on their individualism index. Each month is identified as optimism, mild or pessimism. The definition of sentiment states of holding period is discussed in detail in Table 3.4. Both the country-average and composite portfolios are formed in each individualism - and investor sentiment-sorted category. The formation of the country-average and composite portfolios is described in table 3.3. For brevity, we only report results of composite portfolio. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Composite portfolios	**Momentum portfolios**		
	Winner	**Loser**	**W-L**
Individualism level			
Panel A. Portfolio returns and Individualism			
High IDV	1.589	0.512	1.077
	***		***
Low IDV	1.933	1.643	0.290
	***	***	
High. - Low.	-0.344	-1.131	0.787
		***	**
Sentiment level			
Panel B High Individualism			
Optimistic	0.813	-0.903	1.716
	**	**	***
Pessimistic	2.131	1.613	0.518
	***	***	
Opt. - Pes.	-1.312	-2.516	1.198
	***	***	**
Panel C Low Individualism			
Optimistic	1.212	0.949	0.263

Pessimistic	2.111 **	2.443 **	-0.332
Opt.-Pes.	-0.899	-1.494 **	0.595

Table A3. 4 Momentum Profits for Western and ESEA countries with Ranking and Holding Periods=12

This table reports the average monthly momentum returns (%) for each of the ten countries. Panel A shows the individual momentum profits for each country, along with its standard deviation. For each country, stocks are ranked into quintiles based on their past 6-month cumulative returns and held for 6 months. In order to increase the power of the test, overlapping portfolios are formed. The winner (loser) portfolio consists of 12 overlapping winner (loser) portfolios formed in the previous 12 months. The Return on each of the 6 overlapping winner (loser) portfolios is the simple average of returns on stocks in the winner (loser) portfolio and the return on the winner or loser portfolio is the equally weighted average return of the 6 portfolios in that month. The momentum returns are the returns of the winner portfolio minus the returns of the loser portfolio. To mitigate microstructure issues, 1 month is allowed between the end of the formation period and the beginning of the holding period and several stock selection criteria are applied, as discussed in detail in Table 3.1. Panels B and C report the country-average and composite momentum profits for western and ESEA countries. For brevity, we only list results of winner, loser and momentum portfolios. The asterisks refer to different significant levels: *** (1%), ** (5%), * (10%).

Panel A. Momentum profits by country

Country	Winner (W)	Loser (L)	W Minus L
West			
Canada	1.413***	0.431*	0.982***
France	1.314***	0.612**	0.702***
Germany	1.021***	-0.112	1.133***
United Kingdom	0.809***	0.012	0.797***
U.S.	0.981 ***	0.179	0.802***
ESEA			
China	0.732	0.539	0.193
Hong Kong	1.350**	0.892*	0.458
Japan	0.898**	0.691*	0.207
Korea	1.212*	0.672	0.540
Thailand	1.111**	0.821*	0.290

Panel B. Country-average portfolio

	Winner(W)	Loser(L)	W Minus L
West	1.108***	0.224	0.883***
ESEA	1.061***	0.723***	0.338
West-East	0.047	-0.499*	0.546**

Panel C. Composite portfolio

West	1.412***	0.601**	0.811***
ESEA	1.012	0.798	0.214
West-East	0.400	-0.197	0.597**

Table A3. 5 Momentum Profits and Sentiment for Western and ESEA Markets with Ranking and Holding Periods=12

This table reports the average monthly returns (%) of winner, loser and momentum portfolios across sentiment states (optimistic and pessimistic) for each of the 10 countries (Panel A) and the country-average(Panel B) and composite portfolios (Panel C). For each country, stocks are ranked into quintiles based on their past 6-month cumulative returns and held for 6 months and the past 6-month cumulative returns of each stock in the winner (loser) portfolios must be larger (less) than 0%. Stocks are ranked in quintiles in order to have a reasonable number of stocks. Other stock selection criteria and the formation of momentum portfolios are discussed in detail in Table 3.3. The sentiment formation is discussed in detail in Table 3.4. The average monthly returns to the country-average and composite portfolios during two sentiment periods (optimistic and pessimistic) are reported in Panel B. The formation of the country-average and composite portfolios is detailed in Table 3.3. The first three columns in Panel A show the returns of winner, loser and momentum portfolios under optimism and the second three columns show the returns of the three portfolios under pessimism and last three columns show the differences in returns of these portfolios between optimism and pessimism. For brevity, we only list results of winner, loser and momentum portfolios. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Momentum profits conditional on sentiment by country

Country	Optimistic			Pessimistic			Opt.-Pess.		
	W	L	Mom	W	L	Mom	W	L	Mom
West									
Canada	1.512***	-0.128	1.640***	0.823**	0.678*	0.145	0.689**	-0.806*	1.495***
France	0.621***	-0.921***	1.542***	1.571***	1.901***	-0.33	-0.950***	-2.822***	1.872***
Germany	0.412	-1.489***	1.901***	1.312***	1.389***	-0.077	-0.900***	-2.878***	1.978***
United Kingdom	0.643***	-1.284***	1.927***	1.251***	1.301***	-0.05	-0.608***	-2.585***	1.977***
United States	0.732***	-0.457**	1.189***	1.143***	0.998***	0.145	-0.411	-1.455***	1.044***

ESEA

	Optimistic			Pessimistic			Opt-Pess.		
	W	**L**	**Mom**	**W**	**L**	**Mom**	**W**	**L**	**Mom**
China	1.368*	1.210*	0.158	0.787	0.413	0.374	0.581	0.797	-0.216
Hong Kong	1.783***	1.653**	0.13	0.672	0.341	0.331	1.111**	1.312**	-0.201
Japan	0.213	-0.238	0.451	0.901**	0.987**	-0.086	-0.688	-1.225***	0.537
Korea	0.289	-1.011	1.300	1.906***	1.998***	-0.092	-1.617**	-3.009***	1.392*
Thailand	0.783	0.731	0.052	2.682***	2.111***	0.571	-1.899**	-1.380**	-0.519
Panel B. Country-average portfolio									
West	0.784**	-0.856***	1.640***	1.220***	1.253***	-0.033	-0.436	-2.109***	1.673***
East	0.887*	0.469	0.418	1.390**	1.170**	0.220	-0.502	-0.701*	0.199
West-East	-0.103	-1.325***	1.222***	-0.170	0.083	-0.253	0.066	-1.408***	1.475***
Panel C. Composite portfolio									
West	0.732*	-0.912**	1.644***	1.612**	1.435***	0.177	-0.880*	-2.347***	1.467***
East	0.748*	0.562	0.186	1.675**	1.543**	0.132	-0.927*	-0.981**	0.054
West-East	-0.016	-1.474***	1.458***	-0.063	-0.108	0.045	0.047	-1.366***	1.413***

3.7.4 40% Cutoffs for Investor Sentiment

Table A3. 6 Momentum, Investor Sentiment and Individualism with 40% Sentiment Cutoffs

This table presents the average monthly returns (%) of momentum strategy for the composite portfolio sorted by investor sentiment and Individualism index. The formation of the country-average and composite portfolios is described in detail in Table 3.3. Panel A reports momentum profits sorted by individualism. Panels B and C present momentum profits for high and low individualism levels after controlling for the effect of sentiment, respectively. At the end of each month, momentum portfolios for each country are constructed and all countries in the sample are sorted into three groups by using top (bottom) 30% cutoffs based on their individualism index. Each month is identified as optimism, mild or pessimism. The definition of sentiment states of holding period is discussed in detail in Table 3.4. Both the country-average and composite portfolios are formed in each individualism - and investor sentiment-sorted category. The formation of the country-average and composite portfolios is described in table 3.3. For brevity, we only report results of composite portfolio. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Composite portfolios	**Momentum portfolios**		
	Winner	**Loser**	**W-L**
Individualism level			
Panel A. Portfolio returns and Individualism			
High IDV	1.451 ***	0.379	1.072 ***
Low IDV	1.933 ***	1.862 ***	0.071
High. - Low.	-0.482	-1.483 ***	1.001 ***
Sentiment level			
Panel B. High Individualism			
Optimistic	0.781 *	-0.871 *	1.652 ***
Pessimistic	1.543 ***	1.189 *	0.354
Opt. - Pes.	-0.762 *	-2.060 ***	1.298 **
Panel C. Low Individualism			
Optimistic	1.513 **	0.412	1.101 *
Pessimistic	2.312 **	1.437 *	0.875
Opt.-Pes.	-0.799	-1.025 *	0.226

Table A3. 7 Momentum Profits and Sentiment for Western and ESEA Countries with 40% Sentiment Cutoffs

This table reports the monthly momentum returns (%) during two sentiment states (optimistic, mild and pessimistic) for each of the 10 countries (Panel A) and the country-average portfolio (Panel B) and the composite portfolio (Panel C). Since we are not interested in the momentum profits during mild state, returns for winner, loser and momentum portfolios during optimistic and pessimistic states are reported. The stocks ranked in top decile based on past six-month cumulative return are winner "W" stocks and those in the bottom decile are loser "L" stocks. Each month is identified as optimistic, mild or pessimistic. To identify a particular formation period as optimistic or pessimistic; I calculate the corresponding sentiment score is calculated by using the weighted average scheme as follows. The weights 3, 2 and 1 are given to the month t, t-1 and t-2. If the weighted average score of the formation month belongs to the top 40% of the time series of rolling average sentiment scores, it is defined as optimistic, whereas if the weighted average score of the formation month belongs to the bottom 40% of the time series observations, it is defined as pessimistic, with the rest being mild states. The average monthly returns in percentage on country-average and composite portfolios during two sentiment periods (optimistic and pessimistic) are reported in Panel B. The formation of country-average and composite portfolios is discussed in detail in Table 3.3. The first three columns in Panel A show the returns of winner, loser and momentum portfolios under optimism and the second three columns show the returns of the three portfolios under pessimism and last three columns show the differences of returns of the three portfolios under between optimism and pessimism. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Momentum profits conditional on sentiment by country

Country	**Optimistic**			**Pessimistic**			**Opt.- Pess.**		
	W	**L**	**Mom**	**W**	**L**	**Mom**	**W**	**L**	**Mom**
West									
Canada	1.913***	0.312	1.601***	0.213	0.873***	-0.660*	1.700***	-0.561	2.261***
France	0.213	-1.213***	1.426***	1.103***	1.987***	-0.884***	-0.890***	-3.200***	2.310***
Germany	-0.301	-1.984***	1.683***	1.213***	1.761***	-0.548**	-1.514***	-3.745***	2.231***
United Kingdom	0.412	-1.010***	1.422***	1.701***	1.116***	0.585*	-1.289***	-2.126***	0.837***
United States	0.731***	-0.401*	1.132***	1.691***	1.010***	0.681*	-0.960***	-1.411***	0.451**

ESEA

	Optimistic			Pessimistic			Opt-Pess.		
	W	**L**	**Mom**	**W**	**L**	**Mom**	**W**	**L**	**Mom**
China	1.310*	1.701**	-0.391	0.783	0.791	-0.008	0.527	0.910	-0.383
Hong Kong	1.891**	1.801**	0.090	0.781	0.301	0.480	1.110**	1.500**	-0.390
Japan	-0.281	-0.101	-0.180	1.413**	1.781**	-0.368	-1.694**	-1.882**	0.188
Korea	-0.101	-1.271*	1.170	1.783**	2.871***	-1.088	-1.884**	-4.142***	2.258***
Thailand	1.212**	0.564	0.648	2.982***	2.691***	0.291	-1.770**	-2.127***	0.357
Panel B. Country-average portfolio									
West	0.594	-0.859***	1.453***	1.184***	1.349***	-0.165	-0.591	-2.209***	1.618***
East	0.806*	0.539	0.267	1.548***	1.687***	-0.139	-0.742	-1.148**	0.406
West-East	-0.213	-1.398***	1.185***	-0.364	-0.338	-0.027	0.152	-1.060**	1.212***
Panel C. Composite portfolio									
West	0.698*	-0.756**	1.454***	1.543***	1.792***	-0.249	-0.845**	-2.548***	1.730***
East	0.823*	0.531	0.330	1.213**	1.412**	-0.199	-0.670	-1.199**	0.529
West-East	0.155	-0.969**	1.124**	0.330	0.380	-0.050	-0.175	-1.349***	1.174**

3.7.5 Different Sentiment Definition by Stambaugh et al. (2012)

Table A3. 8 Momentum, Investor Sentiment and Individualism with a Different Sentiment Definition

This table presents average monthly returns (%) of momentum strategy for composite portfolios sorted by investor sentiment and Individualism index. The formation of the country-average and composite portfolios is described in detail in Table 3.3. Panel A reports momentum profits sorted by individualism. Panel B and C present momentum profits for high and low individualism levels after controlling for the effect of sentiment. At the end of each month, momentum portfolios for each country are constructed and all countries in the sample are sorted into three groups by using top (bottom) 30% cutoffs based on their individualism index. Each month is identified as optimism, mild or pessimism. The definition of sentiment states of holding period is discussed in detail in Table 3.4. Both the country-average and composite portfolios are formed in each individualism - and investor sentiment-sorted category. For brevity, we only report results of composite portfolio. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Composite portfolios	Momentum portfolios		
	Winner	**Loser**	**W-L**
Individualism level			
Panel A. Portfolio returns and Individualism			
High IDV	1.451 ***	0.379	1.072 ***
Low IDV	1.933 ***	1.862 ***	0.071 (0.30)
High. - Low.	-0.482	-1.483 ***	1.001 ***
Panel B. High Individualism			
Optimistic	0.781 *	-0.891 **	1.672 ***
Pessimistic	1.792 ***	1.212 ***	0.580
Opt. - Pes.	-1.011 **	-2.103 ***	1.092 **
Panel C Low Individualism			
Optimistic	1.633 **	1.034	0.599
Pessimistic	1.732 ***	1.828 **	-0.096
Opt.-Pes.	-0.099	-0.794	0.695

Table A3. 9 Momentum Profits and Sentiment for Western and ESEA Countries with a Different Sentiment Definition

This table reports the monthly momentum returns (%) during two sentiment states (optimistic, mild and pessimistic) for each of the 10 countries (Panel A) and the country-average portfolio (Panel B) and the composite portfolio (Panel C). Since we are not interested in the momentum profits during mild state, returns for winner, loser and momentum portfolios during optimistic and pessimistic states are reported. The stocks ranked in top decile based on past six month cumulative return are winner "W" stocks and those in the bottom decile are loser "L" stocks. Each month is identified as optimistic, mild or pessimistic. To identify a particular formation period as optimistic or pessimistic; we calculate the corresponding sentiment score is calculated by using the weighted average scheme as follows. The weights 3, 2 and 1 are given to the month t, t-1 and t-2. If the weighted average score of the holding month belongs to the top 30% of the time series of rolling average sentiment scores, it is defined as optimistic, whereas if the weighted average score of the formation month belongs to the bottom 30% of the time series observations, it is defined as pessimistic, with the rest being mild states. The average monthly returns in percentage on country-average and composite portfolios during two sentiment periods (optimistic and pessimistic) are reported in Panel B. The formation of country-average and composite portfolios is detailed in Table 3.3. The first three columns in Panel A show the returns of winner, loser and momentum portfolios under optimism and the second three columns show the returns of the three portfolios under pessimism and last three columns show the differences of returns of the three portfolios under between optimism and pessimism. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%)

Panel A. Momentum profits conditional on sentiment by country

Country	Optimistic			Pessimistic			Opt.-Pess.		
	W	L	Mom	W	L	Mom	W	L	Mom
West									
Canada	0.891**	-0.310	1.201***	2.012***	2.210***	-0.198	-1.121***	-2.520***	1.399***
France	0.542	-0.981***	1.523***	1.222***	1.792***	-0.570*	-0.680	-2.773***	2.093***
Germany	0.213	-1.984***	2.197***	0.901**	1.761***	-0.860**	-0.688**	-3.745***	3.057***
United Kingdom	0.781***	-0.990***	1.771***	1.301***	1.012***	0.289	-0.520	-2.002***	1.482***
United States	1.012***	-0.681***	1.693***	1.431***	1.782***	-0.351	-0.419	-2.463***	2.044***

ESEA

	Optimistic			Pessimistic			Opt-Pess.		
	W	**L**	**Mom**	**W**	**L**	**Mom**	**W**	**L**	**Mom**
China	0.721	0.622	0.099	1.341	1.012	0.329	-0.620	-0.390	-0.230
Hong Kong	1.210***	1.012	0.198	0.998	0.561	0.437	0.212	0.451	-0.239
Japan	0.341	0.010	0.331	1.011***	0.781**	0.230	-0.670	-0.771	0.101
Korea	0.389	0.201	0.188	1.998***	1.210**	0.788	-1.609**	-1.009*	-0.600
Thailand	1.341**	0.783	0.558	2.193***	1.341*	0.852	-0.852	-0.558	-0.294
Panel B: Country-average portfolio									
West	0.688**	-0.989***	1.677***	1.373***	1.711***	-0.338	-0.686**	-2.701***	2.015***
East	0.800*	0.526	0.275	1.508**	0.981**	0.527	-0.708	-0.455	-0.252
West-East	-0.113	-1.515***	1.402***	-0.135	0.730	-0.865	0.022	-2.245***	2.267***
Panel C: Composite portfolio									
West	0.671	-0.972**	1.643***	1.898**	1.631***	0.267	-1.227***	-2.603***	1.376***
East	0.782*	0.431	0.351	1.241**	0.939**	0.302	-0.459	-0.508	0.049
West-East	-0.111	-1.403***	1.2***	0.657	0.692*	-0.035	-0.768*	-2.095***	1.327***

4 Culture and Investor Sentiment: The Impact of Cognitive Dissonance on Post-Earnings-Announcement-Drift

4.1 Introduction

In the last chapter, we examined the interaction between culture and investor sentiment on the momentum which is one of the above suspicion anomalies (Fama, 1998). It is interesting to examine the interaction effect on the other above suspicion anomaly, i.e. Post-earnings-announcement-drift (thereafter, PEAD) which is one of the biggest challenges to the efficient market paradigm (Bernard and Thomas, 1989; Fama 1998). Numerous arguments have been put forward to try to explain the anomaly, both from behavioural and rational perspective. For example, behavioural explanations include three main streams: analyst underreaction, investor underreation and biased information processing. In terms of rational explanations, examples include macroeconomic risk, beta risk, and liquidity risk. The evidence and causes of PEAD are discussed in detail in section 2.4. However, despite this work it is not clear about the reasons for the existence of PEAD. Given the findings that sentiment, culture and cognitive dissonance are relevant to price momentum as discussed in section 3, in this chapter, we seek to investigate whether culture, sentiment and cognitive dissonance can explain this phenomenon using data across a wide range of countries. We pay particular attention to the impact of differences between western and ESEA cultures.

Our work is motivated by the fact that while the evidence for PEAD is extensive, it is not found for all international markets. Evidence of PEAD in international markets is discussed in detail in Section 2.4.2. Cultural factors, in particular, Hofstede's individualism are shown to be significantly correlated with earnings momentum profits. However, to date, it is not clear why cultural factors might impact the level of returns, particular in relation to the differences between western and ESEA countries. It is the issue which we seek to address by bringing together arguments from the psychology literature regarding differences in relation to views of change between eastern and western cultures, sentiment and the notion of cognitive dissonance. In the previous chapter, we discussed the difference between eastern and western cultures. These differences suggest that people from two cultures will have different expectations about continuation or reversal in earnings surprises. In addition, while sentiment has been shown to be of relevance to earnings momentum (see e.g. Livnat and Petrovits, 2009; Mian and Sankaraguruswamy, 2012), to date its interaction with culture has not been investigated. This is important since under optimistic and pessimistic states cultural expectations will cause investors to experience cognitive dissonance in different situations, affecting their responses to news. For example, in relation to recent good news stocks, an investor from the East who believes in reversal will experience cognitive dissonance under optimism, whereas investors from the west will not, given their beliefs in continuation.[41]

Using a framework in the spirit of Hong and Stein (1999) heterogeneous trader model, we take account of the differences between eastern and western views of cognition and how these interact with sentiment to develop specific hypotheses concerning differences in PEAD between the two culture groups.[42] We test the hypotheses in relation to sentiment and culture first using data from 34 countries worldwide. We perform portfolio analysis and find that the cumulative returns of both good and bad news are significantly higher in individualistic cultures than those in collectivistic cultures, respectively, and PEAD of good (bad) news is more prominent under pessimism (optimism). Double sorts are under taken on the basis of individualism and sentiment. The findings suggest that the effect of sentiment on PEAD for both good and bad news is much stronger in the high individualism group than in the low individualism group. We then test the interaction between culture and sentiment on PEAD in a multivariate regression setting while controlling for other determinants that can potentially explain differences in PEAD across countries. We find that individualism and sentiment indices as well as their interaction are all highly significant even after controlling for such variables.

We then focus the analysis on the five largest markets in each of the east and west and find that PEAD following good news is evident in both western and ESEA markets during pessimistic periods and is much higher in western countries. Also, PEAD following bad news during optimistic periods is much

[41] Good news stocks are defined as the top 30% of stocks with the most positive earnings surprises.
[42] We again make use of Hong and Stein's (1999) model to develop specific hypotheses on sentiment, cognitive dissonance and post-earnings-announcement drift, which are similar to those in Chapter 3.

stronger in western markets than in ESEA markets, suggesting that cognitive dissonance is more evident in western markets for good (bad) news than in ESEA markets during pessimistic (optimistic) periods. Overall, the results are consistent with our specific hypotheses and provide strong support to the importance of cognitive dissonance in explaining differences in PEAD across cultures.

To ensure that our results are not driven by a particular sentiment index, we consider an alternative index of investor sentiment (Baker et al., 2012). We construct the alternative sentiment index for each of the ten countries in the east and west and re-estimate the portfolio analysis for PEAD in both western and ESEA markets using the alternative measure. The results are robust to this alternative. Furthermore, our basic results in this chapter also survive a number of sensitivity tests, including using raw returns, an alternative measure of earnings surprises and different cut-offs for investor sentiment.

Our study contributes to the literature in three ways. First, the study provides the first examination of the interaction of sentiment and culture on PEAD of good and bad news in markets around the world. Second, while Dou et al. (2015) show that culture is relevant to PEAD, to date it is not clear why cultural factors might influence the level of returns. We tackle this issue by bringing together arguments from the psychology literature regarding the differences in relation to views of change between western and ESEA cultures, sentiment and the notion of cognitive dissonance and find that the resulting difference of cognitive dissonance between western and ESEA cultures can provide a better understanding of differences in PEAD between the two cultures. Third, we advance the PEAD literature by showing that PEAD is different across sentiment states in international markets.

The reminder of the chapter is organized as follows: in section 4.2, we discuss issues relating to culture, sentiment and cognitive dissonance and develop specific hypotheses concerning PEAD and how the anomaly differs between western and ESEA cultures. Section 4.3 presents the data and methodology. Section 4.4 shows the main empirical analysis and is followed by robustness tests. Section 4.6 concludes the chapter.

4.2 Cultural Bias, Information-Based Traders and Feedback Traders: Hypothesis Development

4.2.1 Individualism, Sentiment and PEAD

Dou et al. (2013) examine the impact of culture on earnings momentum and find that there is a significant relationship between the individualism index and earnings momentum profits. However, they do not link culture to investor sentiment. Livnat and Petrovits (2009) examine the impact of investor sentiment on earnings momentum and find that good (bad) news diffuses slowly under pessimistic (optimistic) states for the U.S market. Antoniou et al. (2013) examine the impact of cognitive dissonance on earnings surprises by taking accounting of the role of sentiment. In the first part of our analysis, we seek to investigate the interaction of culture and investor sentiment on PEAD following good and bad news.

While previous studies have examined the impact of cultural variables and sentiment on PEAD separately, to date no study has investigated the joint impact of these factors or the way they impact on cognitive dissonance. Therefore, before we go on to consider arguments relating to specific differences between investors from the west and the east, we consider more general arguments relating to cognitive dissonance and concepts of individualism versus collectivism. In section 3.2, we introduced the psychology literature relating to individualism and collectivism, which has been related to the concepts of independent and interdependent self-construal. Individuals in high individualism cultures with strong independent self-construal place greater value on self-integrity and are likely to be strongly affected by cognitive dissonance. For example, given their belief in continuation, westerners with their tendency for independent self-construal will experience cognitive dissonance when faced with good (bad) news stocks and a pessimistic (optimistic) state of sentiment. In contrast, people with sense of interdependent self-construal place greater weight on the obligations and responsibilities within a group and will be less concerned with self-consistency.

We again use the Hong and Stein (1999) model as a starting point, once more taking account of the factor that both information-based and feedback traders may be affected by cultural bias.[43] As Hong and Stein (1999) argue, investors may respond differently to public news (e.g. earnings announcements) compared to private news, given that public news becomes available to all investors at the same time. We begin by examining possible cognitive dissonance arising from combinations of the nature of earnings surprises (positive or negative) and sentiment. If two factors (public information and sentiment) are inconsistent, cognitive dissonance will be evident and investors will be slow to respond to the information. Specifically, when the new information arrives, investors will underweight such information which contradicts their sentiment and adjust their expectations in a non-Bayesian manner. Such information will be slowly incorporated into stock prices, resulting in underreaction to both good and bad news in the presence of cognitive dissonance. Given the difference between individualistic and collectivist cultures, we expect that investors in individualistic cultures will experience stronger cognitive dissonance than in collectivist cultures, resulting in stronger PEAD in individualistic culture groups.[44]

This leads to our first hypothesis:

H1: the effect of investor sentiment on PEAD following both good and bad news will be more pronounced in individualistic cultures than in collectivistic cultures, since people in individualistic cultures will experience stronger cognitive dissonance than those in collectivistic cultures.

We examine the first hypothesis in relation to individualism using a sample of 34 countries around the world.[45]

4.2.2 Cognitive Dissonance and PEAD: Western and ESEA Cultures

If investors are affected by cultural bias, they will react in a similar (but possibly less strong) manner to public news as to private news, with western investors expecting continuation of either positive or negative earnings

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[43] The Hong and Stein (1999) mode is discussed in detail in section 2.1.3.
[44] Much of this section has direct parallels with the section 3.2.2 in chapter 3, with hypotheses being very similar, given the fact that we are drawing on the same arguments in relation to PEAD as we did for price momentum.
[45] Due to the availability of earnings announcements data form IBES, only 34 countries are included in the sample in contrast to the 40 countries in chapter 3.

surprises and ESEA investors expecting reversal.[46, 47] Furthermore, we argue that such investors may be also influenced by sentiment (as Antoniou et al.,2013 argue). The implication of this interaction between sentiment and investor responses to earnings surprises in terms of cognitive dissonance will be similar as for the earlier consideration of private news (as reflected in winner and loser stocks in Chapter 3) for westerners and ESEA investors. Specifically, if all three factors (public news, sentiment and cultural beliefs) impact in the same direction, then there is no cognitive dissonance and we expected traders to respond without delay to news, which will diffuse relatively quickly. However, cognitive dissonance will be evident when the three factors do not suggest similar future price movements. In such a situation, we expect investors will respond more slowly (underreact) to the news and PEAD will be larger. Give their belief in continuation, western investors will not experience cognitive dissonance when there is positive (negative) news and the sentiment is optimistic (pessimistic), but will experience cognitive dissonance otherwise. In contrast, ESEA investors believe good or bad news will mean revert, but are more comfortable with contradiction and will, therefore, experience weak cognitive dissonance in both sentiment states for both good and bad news, since the nature of public news always contradicts their beliefs in reversion, regardless of the sentiment. Exhibit 4.1 shows expectations based on these culturally-biased responses.

Exhibit 4.1. Cognitive dissonance, public news and sentiment

This exhibit summarises the cognitive dissonance (CD) experienced by westerners and ESEA for stocks with 'good' news and stocks with 'bad' news in two different sentiment periods.

	Westerners – belief in continuation		ESEA – belief in reversal	
	Good news	Bad news	Good news	Bad news
Sentiment				
Optimistic	No CD	CD	Weak CD	Weak CD
Pessimistic	CD	No CD	Weak CD	Weak CD

The above arguments lead to the following hypotheses:

H2: for stocks with good news in western markets, PEAD will be greater

[46] Following Hong and Stein's arguments, it is reasonable to assume that (at least some) information-based traders will have little, if any, cultural bias in relation to public news. However, the initial response by these investors to earnings surprises is likely to generate a culturally-biased response from feedback traders.

[47] The cultural beliefs in continuation or reversal are discussed in detail in Chapter 3.

during pessimistic states than during optimistic states, and for stocks with bad news in western markets, PEAD will be greater during optimistic states than during pessimistic states.

H3: for ESEA markets, limited PEAD may arise under any combination of sentiment and earnings surprises. However, the extent of PEAD will be greater in western markets than ESEA markets for stocks with good news during pessimistic periods and stocks with bad news when sentiment is optimistic.

We now consider the interaction of private news, public news, cultural bias and sentiment. Specifically, we examine situations in which earnings surprises (public news) have the same direction as recent stock price movements (assumed to be driven by private news) and the interaction of this mix of public and private news with sentiment and cultural beliefs. Thus, the analysis is concerned with cases where good news arises for winner stocks and bad news occurs in relation to loser stocks. In such situations, good (bad) public news reinforces the private news and the cultural beliefs associated with winners (losers).[48, 49] For western investors the winners (losers) with good (bad) news will be expected to yield future positive (negative) returns and will induce cognitive dissonance during pessimistic (optimistic) sentiment periods. For ESEA investors, winners (losers) with good (bad) news will be expected by culturally biased investors to reverse, again leading to cognitive dissonance in each sentiment state. Exhibit 4.2 shows expectations based on these culturally-biased responses.

Exhibit 4.2. Cognitive dissonance, momentum, public news and sentiment

This exhibit summarises cognitive dissonance for winners with 'good' news and loser with 'bad' news in optimistic and pessimistic states for the two cultural groups.

	Westerners – belief in continuation		ESEA – belief in reversal	
	Optimism	Pessimism	Optimism	Pessimism
Winner with good news	No CD	CD	Weak CD	Weak CD
Loser with bad news	CD	No CD	Weak CD	Weak CD

We, therefore, have the following hypotheses:

[48] When we mention good (bad) news, we refer it to as public news.
[49] It is possible that for (at least some) information-based traders the earnings surprise rationalizes the recent price trend and, hence, the belief in continuation or reversal is less strong. However, as in the previous case, feedback traders are likely to continue to be influenced by cultural bias.

H4: for winner stocks with good news in western markets PEAD will be greater during pessimistic states than optimistic states and for loser stocks with bad news in western markets PEAD will be greater during optimistic states than pessimistic states.

H5: for ESEA markets limited PEAD may arise under any combination of sentiment, momentum and earnings surprise. However, the extent of PEAD will be greater in western markets than ESEA markets for winner stocks with good news during pessimistic periods and loser stocks with negative bad news when sentiment is optimistic.

4.3 Data and Methodology

4.3.1 Earnings Announcements

The earnings announcement and analyst forecast data are from the IBES International Summary File for all countries, except for the U.S which are from the IBES U.S Summary File. Several selection criteria are applied to reach our final data sample. First, companies must be listed on a major exchange in their home country and cross-listed companies are deleted. Second, firms must be represented in both Datastream and IBES databases for international markets and in the CRSP and IBES databases for the U.S market. The sample period varies across countries due to the availability of earnings announcement data.[50] Table 4.1 reports the descriptive statistics of stock markets and earnings announcements for each country. Our finial sample includes 37,567 stocks with earnings announcements available, 234,719 earnings announcements, and 1,451,933 forecasts in total. There is a considerable variation in the number of stocks, earnings announcements and forecasts across countries. For example, the U.S has the largest number of firms (12,100), earnings announcements (62,430) and forecasts (489,251), followed by Japan and the UK. Hungary has the least number of firms (65) and earnings announcement (359) and the Czech Republic has the least number of forecasts (2,015). It is worth noting the difference in samples for the five western and five ESEA countries used in the later analysis. The sample includes 20,445 stocks with earnings announcements available,

[50] The sample period for each country is the same in this chapter as that in chapter 3 and is shown in Table 3.1.

Table 4.1 Earnings Announcements Descriptive Statistic

The table reports descriptive statistics for the earnings announcements of 34 stock markets in the sample. It reports the name of the country and the number of firms with earnings announcements available, the number of announcements and the number of forecasts for each country. The earnings announcements data and analyst forecasts data are from the IBES International Summary File for all countries, except for the U.S which are from the IBES U.S Summary File. Several selection criteria are applied to reach our final data sample. First, companies must be listed on a major exchange in their home country and cross-listed companies are deleted. Second, firms must be represented in both Datastream and IBES databases for international markets and in CRSP and IBES databases for the U.S market.

Country	Firms	Announcements	Forecasts	Country	Firms	Announcements	Forecasts
Argentina	119	798	4,300	Ireland	124	933	3,833
Australia	1,626	9,159	48,878	Italy	558	4,121	32,975
Austria	187	1,365	7,072	Japan	2,753	33,017	123,330
Belgium	221	1,808	10,350	Mexico	264	1,546	11,148
Brazil	222	1,138	6,624	Netherlands	467	3,322	36,863
Canada	1,550	7,400	63,348	New Zealand	207	1,495	6,340
Chile	178	1,284	3,907	Norway	522	2,796	15,514
China	1,558	8,755	31,773	Portugal	131	829	5,110
Czech Republic	84	362	2,015	South Africa	682	4,262	15,725
Denmark	405	2,658	13,618	Korea	1,323	8,365	31,448
Finland	277	2,231	15,348	Spain	384	2,900	32,589
France	1,474	9,888	65,966	Sweden	849	4,560	24,343
Germany	1297	8,398	66,336	Switzerland	596	4,057	31,523
Greece	331	2187	9,387	Thailand	737	2,668	20,567
Hong Kong	1,215	7,650	54,225	Turkey	498	3,288	18,180
Hungary	65	359	2,138	United Kingdom	4,040	26,318	134,533
Indonesia	523	2,372	13,376	U. S	12,100	62,430	489,251
Total	37,567	234,719	1,451,933				

116,749 earnings announcements and 819,064 forecasts for the west and 7,586 stocks with earnings announcements available, 60,455 earnings announcements and 261,343 forecasts for the east.[51] As shown in Table 4.1, the U.S. and Japan have the largest number of companies in the west and east, respectively, while Germany and Hong Kong have the smallest population of firms in the west and east, respectively. There are six countries missing in the sample including Bulgaria, Colombia, Lithuania, Poland, Russia and Slovenia due to the non-availability of earnings announcements data. Earnings surprises (SUE) are calculated as actual earnings per share minus the last median analyst consensus forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings

[51] These figures are reported in the appendix.

announcement.[52] The measure of SUE is discussed in detail in Section 2.4.1. To examine PEAD or reversal we take the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement.[53][54] The cumulative abnormal return is computed as the buy and hold raw return of the stock minus the buy and hold return on the market index as follows:

$$PEAD_{j,y} = \prod_{t=+2}^{t=+n}(1 + r_{j,y,t}) - \prod_{t=+2}^{t=+n}(1 + rm_{j,y,t}) \quad (4.1)$$

$r_{j,y,t}$ is the raw return of stock j for day t relative to the earnings announcement y, $rm_{y,t}$ is the market return from the market index for day t relative to the earnings announcement y, and n is 60 days.

In each year, all sample stocks are sorted into deciles according to their SUE within each country. The top 30% includes stocks with the most positive earnings surprises and are defined as stocks with “good news”, while the bottom 30% contains the stocks with the most negative earnings surprises and are defined as stocks with “bad news”. Returns on these portfolios are calculated as average cumulative returns of stocks in these portfolios. For each country, we calculate PEAD of good (bad) news stocks as the mean of the cumulative abnormal returns of all firm-years observations in the top (bottom) 30% of SUE. The country-average returns for good (bad) news portfolio across all countries are calculated as the average of PEAD of all countries. For example, for each of the 34 countries, PEAD is calculated. PEAD of the country-average portfolio for the 34 countries is calculated as the mean average of PEAD of the 34 countries. Returns for the pool-average portfolio for good (bad) news are calculated as PEAD of all firm-years of all available countries in the top (bottom) 30% of SUE.

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[52] Gu and Wu (2003) suggest that the median analyst forecast is a better proxy for the market expectation of earnings compared to the mean analyst forecast. The results are qualitatively similar when the mean analyst forecast is used and are reported in the appendix.

[53] Berkman and Truong (2009) report that almost 50 percent of earnings announcements were made outside trading hours in the U.S in a recent period. They suggest that researchers should calculate PEAD from day +2 following the earnings announcement date to avoid biasing PEAD upward by any contemporaneous stock price reaction. While we do not know the proportion of after-hours earnings announcements in the international stock markets because IBES and Bloomberg do not provide a complete time stamp, we choose to be conservative in our estimations by starting on day +2

[54] We also examined the cumulative raw returns to measure PEAD. The results are reported in the appendix.

4.4 Empirical Analysis

4.4.1 Individualism, Sentiment and PEAD

4.4.1.1 Portfolio Analysis

We begin by analysing PEAD without any split by sentiment, to establish whether PEAD is still evident across countries around the world using recent data. Table 4.2 presents results for PEAD following good news and negative news, with Panel A of Table 4.2 showing results by country and Panel B presenting results for the country- and pool-average portfolios.[55] The results in Panel A show that 29 out of the 34 countries exhibiting PEAD following good news, with 22 out of the 29 countries exhibiting significant PEAD: the U.S. has the largest (5.402%), followed by Indonesia (4.998%), Greece (3.305%), and Canada (3.193%). PEAD following bad news stocks is in 21 out of the 34 countries, with PEAD for bad news in 13 out of the 21 countries being significantly negative. The largest PEAD following bad news is in Argentina (-5.737%), Norway (-3.211%), South Africa (-3.052%), and Australia (-2.556%), with all being significant at the 1% level. Furthermore, of the five western countries include in the later analysis, for good news, all but Germany exhibit significant PEAD while for bad news, all but the UK and the U.S. exhibit significant PEAD. Similarly, PEAD is significantly positive following good news in all ESEA countries except Korea, while only Korea and Thailand exhibit significant PEAD following bad news, with the other three countries showing reversal. Panel B of Table 4.2 reports results for the country- and pool-average portfolios. The results in Panel B show that PEAD to the country- and pool-average portfolios following good news is 1.468% and 2.897%, respectively, with both being significant at the 1% level. However, PEAD following bad news to the country-average portfolio is a significant -0.639% whereas the pool-average portfolio exhibits significant reversal.[56] In sum, the results for the whole sample periods demonstrate that PEAD following good and bad news varies substantially across countries.

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[55] Throughout the paper we treat positive (negative) returns in the period following good (bad) news as PEAD. Significant returns in the opposite direction will be referred to as reversal. While some of the motivating literature is based on studies of earnings momentum (profits resulting from zero-investment portfolios), given the hypotheses developed below, our focus is on PEAD, rather than earnings momentum. When we refer simply to momentum profits we are referring to price or returns momentum, in line with prior literature.

[56] The returns following both good and bad news for the pool-average portfolio is larger than that of the country-average portfolio since the formation of pool-average portfolio is weighted average across observations from all countries in the sample. The country that has more observations will place a heavier weight in the results.

Table 4.2 Post-Earnings-Announcement-Drift across Countries

This table presents post-earnings-announcement drift (%) for good and bad news stocks based on earnings surprises for the 34 countries in our sample. Panel A reports PEAD for good news stocks and bad news stocks for each of the 34 countries and Panel B reports the results for the pool- and country-average portfolios. The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and the abnormal returns are buy and hold stock returns minus buy and hold market returns. Stocks in each country are ranked on earnings surprise (SUE) from annual earnings announcements. SUE is calculated as the difference between actual earnings and the median analyst forecast, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks are ranked into deciles based on their SUE. SUE_1 consists of stocks in the bottom 30 percent of earnings surprises and SUE_3 consists of stocks in the top 30% of earnings surprises in each year in each country. These equally weighted portfolios are held for three months from day +2 after the earnings announcement. The pool-average portfolio is the mean average of all firm-year observations of the 34 countries. The country-average portfolio consists of equally weighted PEAD across the 34 countries. The t-statistics are calculated using clustered standard errors on the firm level. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A: Post-earnings-announcement-drift for each country

Country	Good news	Bad news	Country	Good news	Bad news
Americas			**Europe**		
Argentina	0.907(0.60)	-5.737(-2.83)***	Netherlands	1.368(2.78)***	-0.091(-0.13)
Brazil	2.286(3.60)***	0.855(1.01)	Norway	0.248(0.46)	-3.211(-5.15)***
Canada	3.193(9.39)***	-1.162(-2.88)***	Portugal	1.066(1.42)	2.237(1.98)**
Chile	-1.165(-1.40)	1.128(0.96)	South Africa	-0.729(-1.10)	-3.052(-4.35)***
Mexico	2.456(3.34)***	1.755(1.79)*	Spain	1.200(1.68)*	0.968(1.01)
U.S.	5.402(18.86)***	2.331(7.49)***	Sweden	0.946(2.33)**	-1.823(-4.05)***
Europe			Switzerland	0.328(0.79)	-0.579(-1.08)
Austria	1.454(1.69)*	-0.587(-0.54)	Turkey	1.986(1.89)*	-1.469(-1.27)
Belgium	1.094(1.99)**	0.046(0.69)	United Kingdom	2.011(7.40)***	0.536(1.37)
Czech Republic	1.059(0.56)	-1.421(-0.69)	**Asia Pacific**		
Denmark	-0.035(-0.06)	-1.030(-1.30)	Australia	0.473(1.08)	-2.556(-5.17)***
Finland	1.306(2.88)***	-1.072(-2.19)**	China	1.943(3.51)***	0.971(1.71)*
France	0.969(2.99)***	-1.327(-3.47)***	Hong Kong	2.616(4.31)***	1.175(1.54)
Germany	-1.131(-2.81)***	-1.872(-3.32)***	Indonesia	4.998(4.98)***	-0.240(-0.23)
Greece	3.305(3.30)***	0.836(0.76)	Japan	2.869(15.0)***	1.608(8.09)***
Hungary	0.017(0.01)	-2.687(1.67)*	Korea	-0.482(-0.68)	-2.270(-2.45)**
Ireland	2.772(1.77)*	-2.466(-1.99)**	New Zealand	1.454(2.02)**	-0.257(-0.25)
Italy	1.176(2.21)**	0.347(0.58)	Thailand	2.563(3.99)***	-2.028(-2.91)***
Pane B: Pool-average and country-average portfolios					
Pool-average	2.897(4.33)***	0.404(2.67)***	Country-average	1.468(5.68)***	-0.651(-2.11)**

We now consider the results in relation to PEAD and investor sentiment. Each month is identified as optimistic, mild or pessimistic. We calculate its corresponding sentiment score by using the weighted average scheme as follows. The weights 3, 2 and 1 are given to the month t, t-1 and t-2. If the weighted average score of the announcement month belongs to the top (bottom) 30% of the time series of rolling average sentiment scores, it is defined as optimistic (pessimistic), with the rest being mild states. Columns 1 and 4 of Table 4.3 show there is a marked difference in PEAD following good news between optimistic and pessimistic states.[57] Under pessimistic states, all but six countries (Australia, Chile, Germany, South Africa, Spain and Switzerland) show PEAD. PEAD for good news stocks during pessimistic states in 15 out of the 34 countries are significant at the 10% level or higher. The largest PEAD for good news stocks in pessimistic periods is in the U.S (9.26%), followed by Thailand (7.386%), Hong Kong (5.495%) and Canada (5.06%). In contrast, during optimistic states, 9 out of the 34 countries exhibit significant PEAD for good news stocks. The largest PEAD for good news stocks in optimistic periods is in Spain (6.317%), Portugal (4.902%), Brazil (4.394%) and Indonesia (4.353%), with all being significant at the 1% level. The difference in PEAD for good news stocks between optimism and pessimism is negative in 20 out of the 34 countries and is statistically significant in 23 cases, with 15 differences being significantly negative. The finding suggests that there is clear evidence of a slower diffusion of good news during pessimistic periods.

The results in Columns 2 and 5 of Table 4.3 allow examination of PEAD for bad news stocks under optimism and pessimism. The findings provide a remarkable difference in PEAD for bad news stocks between optimism and pessimism. During optimistic periods, all but seven countries (Brazil, China, Czech Republic, Hungary, Mexico, Portugal and Spain) exhibit PEAD. PEAD for bad news stocks in 17 out of the 34 countries in optimistic periods is significant at the 10% level or higher. The largest PEAD following bad news in optimistic periods is in the Korea (-9.63%), Finland (-6.87%) and South Africa (-4.151%). However, during pessimistic states, only 4 out of the 34 countries (Argentina, Australia, China and Germany) show significant PEAD.

[57] The magnitude of post-earnings-announcement drift (PEAD) for some countries during optimistic or pessimistic states is much larger than that without splitting by investor sentiment. However, the value is comparable to that of other studies (see, for example, Livnat and Petrovits, 2008; Antoniou et al., 2013; Dou et al., 2015). For example, Antoniou et al. (2013) find that the PEAD for bad news during pessimistic periods is 8.65% in the U.S.

Table 4.3 Post-Earnings Announcement-Drift and Investor Sentiment

This table reports post-earnings-announcement drift (%) for good news and bad news stocks during optimistic and pessimistic periods for each of the 34 countries (Panel A) and the pool-average and country-average portfolios (Panel B). The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcements and the abnormal returns are calculated as buy and hold stock returns minus buy and hold market returns. Since we are not interested in the momentum profits during mild state, only results for optimistic and pessimistic states are reported. The formation of good news portfolios and bad news portfolios is discussed in detail in Table 4.2. Each month is identified as optimistic, mild or pessimistic. We calculate its corresponding sentiment score by using the weighted average scheme as follows. The weights 3, 2 and 1 are given to the month t, t-1 and t-2. If the weighted average score of the announcement month belongs to the top (bottom) 30% of the time series of rolling average sentiment scores, it is defined as optimistic (pessimistic), with the rest being mild states. The formation of the country-average and pool-average portfolios is discussed in detail in Table 4.2. The t-statistics are calculated using clustered standard errors on the firm level. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. country momentum profits and sentiment states

Country	**Optimistic**		**Pessimistic**		**Opt.-Pess.**	
	Good news	**Bad news**	**Good news**	**Bad news**	**Good news**	**Bad news**
<u>Americas</u>						
Argentina	0.408(0.35)	-1.929(-1.09)	2.798(0.86)	-11.396(-2.04)**	-2.390(-0.68)	9.467(1.65)*
Brazil	4.394(5.374)***	1.133(1.01)	0.281(0.13)	10.131(3.83)***	4.113(3.80)***	-8.998(-3.05)***
Canada	1.109(2.19)**	-2.594(-3.96)***	5.060(7.37)***	0.384(1.50)	-3.951(-3.28)***	-2.978(-2.98)***
Chile	-0.523(-0.38)	-1.572(-0.95)	-4.287(-1.79)*	2.792(1.51)	3.764(1.32)	-4.364(-1.99)**
U.S.	1.589(3.09)***	-2.803(-5.01)***	9.260(14.91)***	8.048(11.32)***	-7.671(-9.78)***	-10.851(-13.01)***
<u>Europe</u>						
Austria	1.172(0.78)	-1.542(-0.86)	1.685(1.01)	0.715(0.38)	-0.513(-0.39)	-2.257(-1.35)
Belgium	0.387(0.36)	-0.868(-0.98)	1.582(1.67)*	2.455(1.77)*	-1.195(-1.16)	-3.323(-2.26)**
Czech Republic	3.445(1.09)	0.447(0.18)	2.244(0.67)	-5.484(-1.52)	1.201(0.47)	5.931(1.68)*
Denmark	-0.324(-0.33)	-4.127(-4.35)***	1.650(1.24)	2.125(1.04)	-1.974(-1.69)*	-6.252(-5.14)***
Finland	-1.891(-2.12)**	-6.870(-7.17)***	4.428(5.63)***	0.573(0.65)	-6.319(-6.26)***	-7.443(-8.37)***
France	-0.328(-0.60)	-2.883(-4.26)***	1.558(2.41)**	0.421(0.56)	-1.886(-3.13)***	-3.304(-4.80)***
Germany	-2.143(-3.33)***	-3.371(-4.32)***	-2.372(-3.21)***	-3.782(-4.35)***	0.229(0.21)	0.411(0.15)
Greece	-1.077(-0.71)	-2.364(-1.55)	3.590(1.89)*	1.333(0.59)	-4.667(-1.97)**	-3.697(-1.81)*

Hungary	4.199(1.54)	1.738(0.44)	1.621(0.62)	-1.999(-0.80)	2.578(1.03)	3.737(1.31)
Indonesia	4.353(3.38)***	-3.739(-2.76)***	2.273(0.92)	-2.389(-1.15)	2.080(2.15)**	-1.350(-1.16)
Ireland	1.838(0.50)	-2.827(-1.41)	1.256(0.61)	-3.124(-1.08)	0.582(0.13)	0.297(0.23)
Italy	0.834(0.71)	-2.486(-2.66)***	0.808(0.79)	1.824(1.56)	0.026(0.09)	-4.310(-3.47)***
Mexico	0.001(0.01)	0.103(0.69)	2.018(1.23)	3.384(1.88)*	-2.017(-1.73)*	-3.281(-2.12)**
Netherland	-0.725(-0.82)	-2.781(-2.09)**	3.133(2.83)***	4.823(3.13)***	-3.858(-3.13)***	-7.604(-4.93)***
Norway	0.223(0.31)	-3.210(-2.86)***	3.259(2.65)***	-0.816(-0.23)	-3.167(-2.14)**	-2.720(-2.29)**
Portugal	4.902(3.15)***	3.511(1.49)	1.366(1.09)	1.725(0.96)	3.536(1.99)**	1.786(1.01)
South Africa	0.714(0.76)	-4.151(-4.270)***	-3.190(-1.83)*	-1.594(-0.91)	3.904(2.01)**	-2.557(-1.69)*
Spain	6.317(2.93)***	0.522(0.37)	-2.033(-1.40)	-0.217(-0.11)	8.350(4.01)***	0.739(0.65)
Sweden	0.166(0.28)	-3.672(-5.74)***	2.546(2.75)***	1.957(2.14)**	-2.380(-2.37)**	-5.629(-3.27)***
Switzerland	0.686(1.01)	-0.966(-1.14)	-1.157(-1.48)	-2.212(-1.15)	1.843(1.98)**	1.246(0.78)
Turkey	0.551(0.48)	-2.026(-1.41)	1.724(0.54)	-1.204(-0.30)	-1.173(-0.43)	-0.822(-1.02)
United Kingdom	-0.006(-0.01)	-0.496(-0.95)	4.183(7.12)***	2.064(2.19)**	-4.189(-7.21)***	-2.560(-2.48)**
Asia Pacific						
Australia	1.603(1.98)**	-2.042(-2.22)**	-0.166(-0.27)	-1.543(-1.67)*	1.769(2.07)**	-0.499(-0.96)
China	2.964(1.69)*	2.059(1.71)*	0.484(0.77)	-1.759(-1.81)*	2.480(1.78)*	3.818(1.86)*
Hong Kong	-1.769(-1.43)	-3.228(-1.72)*	5.495(4.07)***	3.670(2.31)**	-7.264(-5.51)***	-6.898(-3.12)***
Japan	1.542(4.91)***	-0.959(-3.27)***	2.916(7.81)***	2.037(5.20)***	-1.374(-2.39)**	-2.996(-7.60)***
Korea	-5.923(-5.38)***	-9.360(-6.79)***	3.548(2.10)**	5.272(2.62)***	-9.471(-6.16)***	-14.632(-8.10)***
New Zealand	1.760(1.24)	-1.243(-0.58)	2.045(1.78)*	2.068(1.32)	-0.285(-0.43)	-3.311(-1.60)
Thailand	1.863(1.65)	-2.773(-2.39)**	7.386(4.65)***	-1.270(-0.79)	-5.523(-4.12)***	-1.503(-1.52)
Panel B. Pool-average and country-average portfolios						
Pool-average	0.713(3.66)***	-2.398(-10.77)***	4.133(19.81)***	2.557(10.43)***	-3.420(-11.89)***	-4.955(-13.39)***
Country-average	0.833(2.33)**	-1.713(-3.09)***	1.966(4.24)***	0.554(1.09)	-1.133(-1.86)*	-2.267(4.73)***

The difference in PEAD for bad news stocks between optimism and pessimism is negative in 25 out of the 34 countries, with the difference being significantly negative in 18 cases. The results indicate that bad news diffuses slowly during optimistic periods, resulting in higher PEAD.

It is worth noting the difference in results for the five western and five ESEA countries used in the later analysis. In the case of western markets, in four out of the five countries, PEAD following good news is significant under pessimism, with their differences between optimism and pessimism being significantly negative. In relation to bad news, PEAD under optimism is significant in four out of the five countries. Similarly, for ESEA markets, PEAD following good news under pessimism is significant in all five countries and PEAD following bad news stocks under optimism is significant in all five countries except for China.

Examination of Panel B shows that PEAD following good (bad) news is positive (negative) and significant at the 1% level under pessimism (optimism) for both country- and pool-average portfolios. The difference in PEAD following good (bad) news between optimism and pessimism is of the expected sign and significant in both country- and pool-average portfolios. Taken together, the results in Table 4.3 clearly demonstrate the difference in PEAD for good and bad news stocks between sentiment states across countries. We now turn to consider the interaction between culture and sentiment and test our first hypothesis.

Table 4.4 presents results where the roles of culture and sentiment are considered in relation to PEAD. Double sorts are undertaken on the individualism index and sentiment. Each country in the sample is categorised into one of three culture measure groups based on their scores on the individualism index (IDV).[58] Specifically, using the IDV, we separate countries into the top and bottom 30%, with the middle 40% being excluded from the analysis. Results are reported for the pool-average portfolio on these splits.[59] The table is divided into three panels and in each panel PEAD is shown for good news stocks and bad news stocks. Before going on to consider the role of sentiment, Panel A of Table 4.4 provides the results split

[58] The cut-off points are 30/40/30.
[59] The country-average results are shown in the Appendix.

by individualism only. There is a clear difference in PEAD between high and low individualism countries. Both high and low individualistic countries exhibit significant PEAD following good news whereas both high and low individualistic countries exhibit reversal following bad news, with the former being significant. Also, the magnitude of PEAD following good news and reversal following bad news in the high individualism culture group is much higher than that in the low individualism group, respectively. Specifically, PEAD for good news stocks in the high and low individualism countries is 3.876% and 1.987%, respectively, with the difference being significantly positive. Similarly, reversal for bad news stocks in the high and low individualism culture groups is 1.137% and 0.080%, with the difference being significant at the 1% level. A key question is whether these findings apply in all sentiment states or are driven by differences across the states.

The results in Panels B and C of Table 4.4 allow us to investigate this issue and to test hypothesis H1 which states that the effect of investor sentiment on PEAD following both good and bad news will be more pronounced in individualistic cultures than in collectivistic cultures, since people in individualistic cultures will experience stronger cognitive dissonance than those in collectivistic cultures. The results of PEAD in optimistic and pessimistic states are shown for high individualism countries in Panel B and Panel C shows those for low individualism countries. The findings provide clear evidence of interaction between sentiment and culture. For the high individualism group, PEAD following good news is 6.420% under pessimism, which is significant at the 1% level and the difference in PEAD following good news between optimism and pessimism is significantly negative, suggesting good news diffuses slowly under pessimism. In contrast, PEAD following good news in the low individualism group drops dramatically to 1.940% compared to that in the high group (6.420%). The evidence reveals that good news diffuses much more slowly under pessimism in the high individualism group than in the low individualism group, consistent with H1 for good news. In other words, underreaction is much stronger in the high individualism countries than in the low individualism countries. In relation to bad news, again for high individualism markets, PEAD is –2.302% under optimism, which is significant at the 1% level and the difference between optimism and pessimism is -6.980%, which is significant at the 1% level, suggesting bad news diffuses slowly under optimism for this group. For the low individualism

Table 4.4 Post-Earnings Announcement-Drift, Individualism and Investor Sentiment

This table presents the pool-average results for post-earnings-announcement drift (%) following good news and bad news sorted by investor sentiment and individualism index. The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and the abnormal returns are buy and hold stock returns minus buy and hold market returns. Each country is categorised into either the top or bottom 30% based on the individualism index score, or the middle 40% which is excluded from the analysis. The announcement month is identified as optimism, mild or pessimism. The definition of sentiment states of the announcement month is discussed in detail in Table 4.3. The formation of the pool-average portfolio is discussed in detail in Table 4.2. Panel A reports PEAD for good news and bad news stocks sorted by the individualism index. Panels B and C present PEAD for good news and bad news stocks across sentiment states in the high and low individualism culture groups, respectively. The t-statistics are calculated using clustered standard errors on the firm level. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Pool-average portfolio	PEAD	
	Good news	Bad news
Individualism level		
Panel A. Portfolio returns and Individualism		
High IDV	3.876(22.08)***	1.137(5.73)***
Low IDV	1.987(7.73)***	0.080(0.28)
High. - Low.	1.889(7.21)***	1.057(5.23)***
Sentiment level		
Panel B. High Individualism		
Optimistic	1.122(3.49)***	-2.302(-6.42)***
Pessimistic	6.420(18.02)***	4.678(10.85)***
Opt. - Pes.	-5.298(-12.13)***	-6.980(-15.31)***
Panel C. Low Individualism		
Optimistic	-0.858(-1.85)*	-1.427(-2.91)***
Pessimistic	1.940(4.67)***	-0.017(-0.13)
Opt.-Pes.	-2.798(-6.21)***	-1.410(2.78)***

group, while PEAD following bad news stocks is -1.427%, which is significant at the 1% level, its magnitude (1.427%) is smaller than that for the high individualism group (2.302%). The results in two Panels allow us to compare the difference in PEAD of good and bad news across the two sentiment states between the two culture groups. During optimistic (pessimistic) periods, the difference in PEAD following bad (good news) between the two culture groups is significant -0.875% (4.480%), suggesting that the underreaction of good (bad) news stocks under pessimism (optimism) is stronger in the high individualistic cultures than in the low individualistic cultures, consistent with our first hypothesis.[60]

[60] The difference in PEAD following both good and bad news across difference sentiment periods between the two culture groups are also tested.

4.4.1.2 Regression Analysis

We next investigate the impact of sentiment, individualism and their interaction on PEAD in a multivariate regression setting by taking account of other potential determinants of PEAD that vary across countries. In particular, we regress PEAD for good and bad news stocks on the sentiment index, individualism, the interaction variable between sentiment and individualism, and other control variables, respectively, as in the following model:

$$\mathrm{Exret}_{Good\ news,i,t} = \alpha + \beta_1 * Sent_{t-1} + \beta_2 * IDV + \beta_1 * Sent_{t-1} * IDV + \gamma * \mathrm{control} \qquad (4.2)$$

$$\mathrm{Exret}_{Bad\ news,i,t} = \alpha + \beta_1 * Sent_{t-1} + \beta_2 * IDV + \beta_1 * Sent_{t-1} * IDV + \gamma * \mathrm{control} \qquad (4.3)$$

Where $\mathrm{Exret}_{i,t}$ is cumulative returns of the good or bad news portfolio for 60 days minus the corresponding cumulative returns on the market index for country i in year t as shown in the equation 4.1. IDV_j is a categorical variable of IDV index of country j equals 1 (-1) if the IDV score belongs to the top (bottom) 30% of their scores, otherwise 0. *Sent* is a categorical variable which equals 1 (-1) if the monthly sentiment of each country belongs to the optimistic (pessimistic) group with the rest being 0. *IDV*SENT* is the individualism and sentiment interaction variable. We follow Dou et al. (2015) to use the country and time fixed effects in the regression. Standard errors are clustered by country and year. We follow Chui et al. (2010) and Dou et al. (2015) to include other cross-country variables that may explain cross-country variations in PEAD. The potential variables are classified as firm characteristics, financial market development, institutional quality and macroeconomic variables which are discussed in detail in Chapter 3.

Table 4.5 presents the results of equations (4.2) and (4.3), respectively. We first consider the results in relation to good news as shown in the first three columns of Table 4.5. In model 1, we regress abnormal cumulative returns of the good news portfolio only on the individualism index and the sentiment index and the estimated coefficients on *IDV* and *sent* are 0.04 and -0.0112, respectively, with both being significant at the 5% level. It suggests that PEAD of good news is more pronounced during periods of pessimism and in the high individualistic culture countries. In model 2, the model 1 is extended by adding the interaction variable (*IDV*Sent*) between individualism and sentiment. The result shows that the *IDV*Sent* is -0.02, which is significant

Table 4.5 Determinants of PEAD across Countries

PEAD on good and bad news portfolios are regressed on the categorical individualism index (IDV) and categorical sentiment (sent) variables, respectively. The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcements and the abnormal returns are buy and hold stock returns minus buy and hold market returns. The categorical variable of IDV index equals 1 (-1) if IDV score belongs to the top (bottom) 30% of their scores, otherwise 0. Sent is a categorical variable which equals 1 (-1) if the monthly sentiment of each country belongs to the optimistic (pessimistic) group with the rest being 0. IDV*SENT is the individualism and sentiment interaction variable. Model (3) and (6) report the results with control variables, including firm characteristics, financial market development, and institutional quality variables. The firm characteristics variables include the natural logarithm of market trading volume (LnTV), the natural logarithm of stock market volatility (LnV), the natural logarithm of analyst coverage, the natural logarithm of the dispersion of analyst forecasts (LnDISP), the cash flows growth rate volatility (VolFCF), the logarithm of median firm size (LnSISE) and the average price to book ratio (PB). The financial market development variables include the total private credit expressed as the ratio of GDP (CREDIT), the average common language dummy variable (LANG), the ratio between the monthly market value of the S&P-IFC market index and the monthly market value of the S&P-IFC investable index (OPEN), and an index on control of capital flows (CONTRL). The institutional quality variables include the insider index (INSIDER, a high value suggests that insider trading is less prominent), the ICRG corruption index the ICRG (CORRP), the ICRG political risk index (POLITICAL), the natural logarithm of the transaction cost index (LnTRAN), and the investor protection index (PROTECTION). The macroeconomic variables include the GDP growth rate (GDP) and inflation rate (Inflation). Standard errors are clustered by country and time. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

	Good news				Bad news			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.0259	0.0156	0.0323	0.274	0.0021	0.0034	0.0273	0.0131
	(3.68)***	(2.65)***	(2.91)***	(2.97)***	(2.31)**	(0.78)	(0.42)	(1.33)
IDV	0.0153	0.0255	0.0184	0.203	0.0096	0.0173	0.0149	0.0152
	(3.76)***	(3.11)***	(3.03)***	(3.05)***	(3.69)***	(3.16)***	(2.11)**	(2.61)***
Sent	-0.0192	-0.0126	-0.0125	-0.0127	-0.0285	-0.0132	-0.0101	-0.0118
	(-3.11)***	(-0.81)	(-1.62)	(-1.59)	(-4.51)***	(-2.75)***	(-2.01)**	(-2.22)**
IDV*SENT		-0.0108	-0.0101	-0.0103		-0.0123	-0.0088	-0.0099
		(-3.73)***	(-2.34)**	(-2.44)**		(-2.79)***	(-2.58)***	(-2.70)***
LnTV			-0.0065	-0.0061			-0.0021	
			(-2.39)**	(-2.31)**			(-1.22)	
LnV			0.0040	0.0054			0.0054	0.0071
			(2.13)**	(2.31)**			(1.77)*	(1.88)*
LnCov			0.0032				-0.0011	
			(1.49)				(-1.31)	
LnDISP			-0.0099				-0.0141	-0.131
			(-1.61)				(1.81)*	(1.83)*
VolFCF			0.023				-0.0101	-0.143
			(1.41)				(-2.83)***	(-2.99)***
LnSIZE			0.0014				-0.0009	
			(0.41)				(-0.91)	
PB			-0.0013				-0.0020	-0.0031
			(-0.62)				(-1.77)*	(-1.89)*
CREDIT			0.0014				0.0053	
			(0.71)				(0.67)	
LANG			-0.0137	-0.0119			0.0091	0.0103
			(-2.01)**	(-1.99)**			(2.31)**	(2.48)**
OPEN			-0.0112	-0.0135			-0.0134	-0.0141
			(-1.85)*	(-1.91)*			(-1.83)*	(-1.98)**
CONTRL			0.0014				0.0029	
			(1.32)				(1.49)	
INSIDER			-0.0106	-0.0121			-0.0150	-0.0128
			(-2.20)**	(-2.23)**			(-2.01)**	(-1.91)*
CORRP			-0.0023	-0.0018			-0.0030	
			(-1.99)**	(-1.93)*			(-1.18)	
LnTRAN			0.0014				0.0011	
			(0.71)				(0.63)	
POLITICAL			0.0179	0.0199			0.0171	0.0188
			(3.06)***	(3.71)***			(3.81)***	(3.83)***
PROTECTION			-0.0012				0.0013	

			(-0.93)				(0.91)	
GDP			-0.0121 (-1.81)*	-0.0113 (-1.71)*			-0.0152 (-1.91)*	-0.0149 (-1.90)*
INFLATION			0.0001 (0.23)				0.0003 (0.39)	
N	60,005	60,005	60,005	60,005	60,646	60,646	60,646	60,646
R squared (%)	3.21	3.43	5.86	4.14	3.24	3.50	5.96	4.31

at the 10% level, suggesting that the effect of investor sentiment on PEAD of good news is more prominent in individualistic cultures than in collectivistic cultures, consistent with our first hypothesis for good news. We further consider whether the explanatory power of independent variables can be subsumed by the control variables in model 3. The results indicate that while controlling for other explanatory variables, *IDV*, *Sent* and *IDV*Sent* are significant at the 10% level or higher. Furthermore, we notice that PEAD for good news stocks increases in stock market volatility, cash flow growth rate volatility and the level of political risk and decreases in stock market volatility, the level of common language, the level of stock market openness and the level of insider trading. In model (4), we present regressions that include only those variables that are significant at the 10% level or higher in model (3). The significance level and magnitude of those variables remain qualitatively similar to model (3).

We next turn to consider the results in relation to bad news as shown in the last three columns of Table 4.5. Similarly, in model 5, PEAD for bad news stocks is only regressed on *IDV* and *Sent* and the estimated coefficients are -0.0165 and 0.0002, respectively, with both being significant at the 5% level or higher, suggesting that PEAD for bad news stocks is significantly higher during optimistic periods and in the high individualistic culture countries. The interaction variable, *IDV*Sen*t is incorporated in model 6 and others cross-country variables are considered in model 7. The results in model 6 show that the interaction term is -0.0003, which is significant at the 1% level and *IDV* and *Sent* remain significant and of the expected sign. After controlling for other explanatory variables in model 7, IDV, Sent and IDV*Sent still remains significant and of the expected sign. In model 8, we present regressions that include only those variables that are significant at the 10% level of higher. The regression includes stock market volatility, dispersion of analyst forecasts, cash flow volatility, price to book ratio, common language dummy variable, stock openness, insider index, political risk index and GDP growth rate. The coefficients are all significant and have the same sign as those in previous regressions. The results are consistent with H1 for bad news: the effect of investor sentiment on PEAD of bad news is more pronounced in high individualistic cultures than in low individualistic cultures. There is some evidence that PEAD for bad news stocks increases in the level of common language and the level of political risk and decreases in stocks market volatility, cash flow growth rate volatility and the level of openness, with the level of openness being significant at the 10% level and other variables being significant at the 5% level or higher.

4.4.2 Cognitive dissonance and PEAD: Western and ESEA cultures

In this section, we now turn to examine hypotheses 2-5 in relation to differences in behaviour between western and ESEA countries and the impact of these differences on PEAD. We only include good news stocks with positive earnings surprises and bad news stocks with negative earnings surprises.

The analysis of PEAD for the ten countries begins without any split based on sentiment, to establish whether or not PEAD is evident in the sample countries. Table 4.6 shows PEAD for good news and bad news stocks. Results for each country are shown in Panel A and Panels B and C present results for the country- and pool-average portfolios for western and ESEA markets, respectively. In Panel A, it can be seen that in nine out of the ten countries PEAD following good news is positive and significant. The exception is Germany where returns in the post-announcement period are significantly negative (reversal). The highest returns in the western sample are the two North American markets, while in the ESEA sample Thailand and Japan have the highest PEAD. From Panel B, it is evident that in both western and ESEA markets PEAD on the pool-average portfolio is significant following good news, with the former being significantly higher.[61] As shown in Panel C, for the country-average portfolio, both western and ESEA markets exhibit significant PEAD following good news but there is no significant difference in PEAD following good news between the culture

Table 4.6 Post-Earnings-Announcement-Drift for Western and ESEA Countries

[61] Comparing the results in table 4,2 for the ten countries to those in table 4.6, we see there are some minor differences. This is due to the additional filter applied for this section of only including in our sample good news stocks that have positive earnings surprises and bad news stocks which have negative earnings surprises.

This table reports the post-earnings announcement drift (%) for the ten countries in the sample. Panel A reports PEAD for good and bad news stocks for each of the 10 countries and Panels B and C report the results for the pool-average and country-average portfolios, respectively. The drift is calculated as the cumulative abnormal returns (market-adjusted) of stocks during +2 to +60 trading days following the earnings announcement and the abnormal returns are buy and hold stock returns minus buy and hold market returns. Earnings surprises are measured as actual earnings per share minus the last median analyst consensus forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with “good” (“bad”) news. Earnings surprises for each stock in the good (bad) news portfolios must be larger (less) than 0%. Returns on these portfolios are calculated as the average of returns of stocks in these portfolios. The formation of the country-average and pool-average portfolios is discussed in detail in Table 4.2. The t-statistics are calculated using clustered standard errors on the firm level. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. PEAD by country

	Westerners-Belief in continuation		**ESEA-Belief in reversal**	
	Country		**Country**	
Good news	Canada	3.157(9.11)***	China	2.000(3.51)***
	France	0.884(2.69)***	Hong Kong	0.921(1.81)*
	Germany	-0.997(-2.27)**	Japan	2.836(13.44)***
	UK	1.885(7.11)***	Korea	1.024(2.19)**
	U.S.	6.369(16.71)***	Thailand	3.298(3.37)***
Bad news	Canada	-0.635(-1.71)*	China	0.954(1.72)*
	France	-1.514(-3.21)***	Hong Kong	-0.252(-0.43)
	Germany	-1.762(-3.28)***	Japan	1.591(8.01)***
	UK	0.283(0.93)	Korea	1.648(2.18)**
	U.S.	4.345(9.89)***	Thailand	-0.042(-0.09)

Panel B. Pool-average portfolio

	Westerners-Belief in continuation	**ESEA-Belief in reversal**	**West-ESEA**
Good news	3.942(8.43)***	2.243(3.34)***	1.699(3.01)***
Bad news	1.764(3.59)***	1.203(2.27)**	0.561(1.98)**

Panel C. Country-average portfolio

	Westerners-Belief in continuation	**ESEA-Belief in reversal**	**West-ESEA**
Good news	2.260(1.83)*	2.016(4.25)***	0.244(0.184)
Bad news	0.143(0.13)	0.780(1.95)*	-0.637(-0.54)

groups.

The picture relating to bad news is less clear cut. PEAD is significant in Canada, France and Germany, but insignificantly different from zero in the UK and there is significant reversal in the U.S. For ESEA markets, there is mixed evidence of PEAD following bad news: returns are insignificantly different from zero in Hong Kong and Thailand but there is significant reversal in China, Japan and Korea. The pooled average results in Panel B show significant reversal in both western and ESEA markets following bad news. The country-average results in Panel C show that the returns following bad news are insignificantly different from zero in western markets whereas the country-average portfolio for ESEA countries exhibit significant reversal following bad news. Thus, in both cultures there is evidence of an upward drift in prices following both good and bad news. While an upward drift is consistent with PEAD following good news, in relation to bad news the results suggest reversal in prices and a possible initial overreaction to the negative shock.[62]

We now go on to consider the hypotheses relating to PEAD by splitting our sample based on sentiment. Table 4.7 presents results for our sample countries (Panel A) and for the country- and pool-average portfolios (Panels B and C). Recall that H2 hypothesised in western markets PEAD will be greater in pessimistic states for good news and greater in optimistic states for bad news. For western markets, during optimistic periods, only Canada exhibits significant PEAD for good news, with the U.S having sizeable but insignificant PEAD and the other three European countries exhibiting reversal, with only Germany's being significant. In contrast, during pessimistic periods, four out of the five western countries show significant PEAD following good news, with Germany being the exception with significant reversal. As far as the pooled average results are concerned as in Panel B, for western markets, there is no evidence of PEAD following good news during optimistic states, but significant PEAD when sentiment is pessimistic. The country-average results in Panel C are qualitatively similar to those reported in Panel B. The results in both Panels B and C are consistent with H2 for good news. Turning to negative news in western markets, PEAD is found in all five markets during optimistic periods, with all but the UK being significant at the 1% level. However, when sentiment is pessimistic, only Germany exhibits significant PEAD, with the other four cases having positive returns, indicating reversal and possible initial overreaction. The pooled average results in Panel B confirm this pattern, with returns being significantly negative under optimism, but significantly positive when sentiment is pessimistic. The country-average results in Panel C show a similar pattern to the pooled average results in Panel B. Thus, for western

[62] The reversal in the pool-average portfolio of bad news is mainly dominated by the results of the U.S, which constitutes almost half of the sample of Western countries.

Table 4.7 Post-Earnings-Announcement-Drift and Sentiment for Western and ESEA Countries

This table reports post-earnings-announcement drift (%) for good and bad news stocks during optimistic and pessimistic states for each of the 10 countries (Panel A) and the pool-average portfolio (Panel B) and the country-average portfolio (Panel C). The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and the abnormal returns are buy and hold stock returns minus buy and hold market returns. Earnings are measured as actual earnings per share minus the last median analyst consensus forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with "good" ("bad") news. Earnings surprises for each stock in the good (bad) news portfolios must be larger (less) than 0%. The definition of sentiment states of the announcement month is discussed in detail in Table 4.3. The formation of the country-average and pool-average portfolios is discussed in detail in Table 4.2. The t-statistics are calculated using clustered standard errors on the firm level. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. PEAD by country

		Westerners-Belief in continuation			**ESEA-Belief in reversal**	
		Opt.	**Pess.**		**Opt.**	**Pess.**
Good news	Canada	1.109	5.060	China	5.797	-0.306
		(2.19)**	(7.37)***		(2.48)**	(-0.45)
	France	-0.328	1.558	Hong Kong	-1.769	5.495
		(-0.60)	(2.41)**		(-1.43)	(4.07)***
	Germany	-2.143	-2.372	Japan	1.542	2.916
		(-3.33)**	(-3.21)**		(4.91)***	(7.81)***
	UK	-0.006	4.183	Korea	-5.320	2.902
		(-0.01)	(7.12)***		(-4.97)***	(1.79)*
	U.S.	1.589	9.260	Thailand	0.942	4.979
		(3.09)***	(14.91)***		(1.02)	(1.91)*
Bad news	Canada	-2.594	0.384	China	7.947	-3.199
		(-3.96)***	(1.50)		(3.12)***	(-2.91)***
	France	-2.883	0.421	Hong Kong	-3.228	3.670
		(-4.26)***	(0.56)		(-1.72)*	(2.31)**
	Germany	-3.370	-3.780	Japan	-0.959	2.037
		(-4.32)***	(-4.35)***		(-3.27)**	(5.20)***
	UK	-0.496	2.064	Korea	-8.818	7.559
		(-0.95)	(2.19)**		(5.12)***	(3.89)***
	U.S.	-2.803	8.048	Thailand	-4.540	-0.425
		(-5.01)***	(11.32)***		(-2.89)***	(-0.43)

Panel B. Pool-average portfolio

	Westerners-Belief in continuation			**ESEA-Belief in reversal**		
	Opt.	**Pess.**	**Opt.-Pess.**	**Opt.**	**Pess.**	**Opt.-Pess.**
Good news	1.066	7.180	-6.114	0.848	2.246	-1.398
	(2.03)**	(7.91)***	(-7.03)***	(2.04)**	(3.92)***	(-2.65)***
Bad news	-2.843	5.243	-8.086	-1.374	0.993	-2.377
	(-4.89)***	(5.82)***	(-7.03)***	(-2.06)**	(1.91)*	(-2.69)***

West-ESEA

	Opt.	**Pess.**
Good news	0.218(0.41)	4.834(3.77)***
Bad news	-1.469(-2.89)***	4.250(3.21)***

Panel C. Country-average portfolio

	Westerners-Belief in continuation	**ESEA-Belief in reversal**

	Opt.	Pess.	Opt.-Pess.	Opt.	Pess.	Opt.-Pess.
Good news	0.044 (0.07)	3.538 (1.85)*	-3.494 (-1.71)	0.238 (0.13)	3.197 (3.12)***	-2.959 (-1.40)
Bad news	-2.429 (-4.86)***	1.427 (0.74)	-3.857 (-1.94)*	-1.920 (-0.69)	1.928 (1.05)	-3.848 (-1.16)

West-ESEA

	Opt.	Pess.
Good news	-0.194(-0.09)	0.341(0.15)
Bad news	-0.510(-0.31)	-0.501(-0.20)

countries, there is strong evidence of PEAD following bad news under optimism, but reversal under pessimism, with the differences being statistically significant, again consistent with H2 for bad news.

It is hypothesised (H3) that for eastern markets PEAD may be evident in any combination of earnings surprises and sentiment, but that PEAD will be less evident in ESEA countries than in western countries for good news during pessimistic periods and bad news during optimistic periods. Again, the results are consistent with the hypothesis: there is evidence in Panel A of significant PEAD in all four combinations of earnings surprises and sentiment (for example, when sentiment is optimistic and news is good (bad)), with bad news during pessimistic states showing the lowest number of countries with PEAD (only two) and three countries exhibiting reversal. Specifically, for good news stocks, two and four out of the five countries showing significant PEAD under optimism and pessimism, respectively. For bad news stocks, all but China exhibit significant PEAD under optimism, with China showing significant reversal, whereas only China shows significant PEAD under pessimism. Results in Panel B provide evidence for the hypothesis in three out of the four combinations (news interact with sentiment), with reversal for bad news when sentiment is pessimistic. While the differences in returns between optimism and pessimism are of the expected sign and significant asfor the western culture, those relating to the east are of a much smaller magnitude. The results of the country-average portfolio in Panel C are qualitatively similar to those of the pool-average portfolio in Panel B.

Consideration of differences between the western and ESEA markets show significant differences in PEAD of the pool-average portfolio (Panel B) for good (bad) news when sentiment is pessimistic (optimistic), consistent with

H3.[63] In Panel C, for the pool-average portfolio, there is strong evidence of PEAD following bad news being significant higher in western countries than in ESEA countries and significant difference in PEAD following good news under pessimism between the two culture groups. The evidence for the pool-average portfolio is consistent with H3 for both good and bad news.[64]

Therefore, the results in Table 4.7 are general consistent with the hypotheses and again suggest that cognitive dissonance and cultural differences between the west and east result in differences in the extent of the anomaly in the two culture groups.

4.4.3 Cognitive Dissonance, PEAD and Momentum Profits: Western and ESEA Cultures

Our final hypothesis relates to the extent of PEAD for stocks that are both recent momentum winners with good news and recent momentum loser stocks with bad news. These are subsets of the samples examined in Table 4.7 and can be considered to be the most extreme cases in terms of both momentum and earnings surprises. Within the Hong and Stein (1999) framework, for these stocks there is assumed to be both private news (diffusing via the actions of information-based traders and reflected in momentum) and public news (the earnings surprises). Results relating to these portfolios split by sentiment are presented in Table 4.8, with Panel A again showing findings for individual countries and Panel B those for the pool- and country-average portfolios.[65] The two hypotheses for this part of the analysis are directly analogous to the two previous hypotheses relating to earnings surprises only. Specifically, for western markets, PEAD will be greater for winner (loser) stocks with good (bad) news during pessimistic (optimistic) periods (H4); and for ESEA markets PEAD may arise under any combination of sentiment and momentum and earnings surprises, but for the

[63] While the difference is also significant for bad news when sentiment is pessimistic, this relates to reversal, rather than PEAD.
[64] The difference in PEAD following good (bad) news during pessimistic (optimistic) periods between the two culture groups is insignificant. However, the t-stats are calculated based on five figures.
[65] For some of these cells the number of observations is small, particularly for ESEA markets and there is some clustering of observations. For example, while for the western markets the smallest number of observations in any combination of sentiment and winner (loser) with good (bad) earnings news is 183, for 12 of the 20 combinations for ESEA countries the sample is below 100, with the lowest being 45 observations. In addition, for China there are 68 observations, but 62 fall within the same five-month period. As such the results on a country basis should be interpreted with caution.

two higher PEAD categories identified in relation to H5, PEAD will be lower for ESEA markets than for western market (H5). To test these hypotheses, sentiment and momentum portfolios are identified in month t and stocks with earnings announcement in month t+1 are identified. An event study is performed to examine the PEAD for winners with good news and losers with bad news.

In western markets, Panel A shows that for winners with good news, there is a mixed picture for individual countries when sentiment is optimistic: the three European countries exhibit no PEAD whereas North American markets have significantly positive returns during the post-announcement period. Winners with good news during pessimism yield significant PEAD for two out of the five markets. Examination of Panels B and C of the pool-average and country-average portfolios shows that there is clear evidence of PEAD for winners during pessimistic periods. The difference between the two sentiment states is significant at the 1% level. For loser stocks with bad news, significant PEAD is evident for all five western countries during optimistic periods, but only one country (Germany) when sentiment is pessimistic (Panel A). Indeed, the significant reversal can be seen for four out of the five western markets under pessimism. Results for both pool-average (Panel B) and country-average portfolios (Panel C) provide clear evidence of PEAD for losers with bad news when sentiment is optimistic, and significant reversal when sentiment is pessimistic, with the difference again being statistically significant. Overall, the results are consistent with H4.

As far as the ESEA markets are concerned, there is mix evidence of PEAD for winner stocks with good news during optimistic periods, with two being significantly different from zero. During pessimistic periods, three out of the five showing significant PEAD. For loser stocks with bad news, returns are negative for four out of the five countries under optimism, with two of these being significant, while all five countries show reversal under pessimism, with four being significantly different from zero. Results in Panels B and C of Table 4.8 demonstrate that PEAD is evident only for winner stocks with good news under pessimism for ESEA countries. However, while the portfolio of loser stocks with bad news generates significantly higher PEAD under optimism for the western markets than for the ESEA markets, consistent with H5, the opposite is the case for winner stocks with good news when sentiment is

Table 4.8 Post-Earnings-Announcement-Drift, Momentum and Sentiment for Western and ESEA Countries

This table reports post earnings announcement drift (%) for winner stocks with good news and losers with bad news during optimistic and pessimistic states for each of the 10 countries (Panel A) and for the pool-average portfolio (Panel B) and for the country-average portfolio (Panel C). The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and the abnormal returns re buy and hold stock returns minus buy and hold market returns. Earnings are measured as actual earnings per share minus the last median analyst consensus forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked into deciles based on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with "good" ("bad") news. The definition of sentiment states of the announcement month is discussed in detail in Table 4.3. Momentum portfolios are defined in Table 3.2. Stocks with earnings announcement in month t+1 is identified and an event study is performed to examine the post earnings announcement drift. Returns on these portfolios are calculated as average returns of stocks in these portfolios. The formation of the country-average and pool-average portfolios is discussed in detail in Table 4.2. The t-statistics are calculated using clustered standard errors on the firm level. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

		West			ESEA	
		Opt.	**Pess.**		**Opt.**	**Pess.**
Winner with good news	Canada	3.002	3.960	China	-7.160	-0.410
		(2.34)**	(3.56)***		(-1.46)	(-0.11)
	France	-0.958	-0.130	Hong Kong	-2.226	5.453
		(-1.02)	(-0.34)		(-1.43)	(3.12)**
	Germany	-1.493	0.423	Japan	1.502	6.469
		(-1.55)	(0.78)		(2.17)**	(11.2)***
	UK	0.367	2.228	Korea	-5.166	1.198
		(0.56)	(4.27)***		(-2.19)**	(1.14)
	U.S.	2.159	-0.710	Thailand	5.478	9.817
		(2.58)**	(-1.04)		(2.33)**	(5.38)***
Loser with bad news	Canada	-5.884	6.400	China	42.390	2.627
		(-6.12)***	(7.22)***		(9.67)***	(1.28)
	France	-3.495	4.771	Hong Kong	-5.955	4.316
		(-4.34)***	(5.35)***		(-2.41)**	(2.13)**
	Germany	-5.179	-4.535	Japan	-1.814	3.445
		(-5.14)***	(-2.54)**		(-2.53)**	(4.89)***
	UK	-3.495	2.818	Korea	-3.465	2.898
		(-4.12)***	(2.79)***		(-1.58)	(2.13)**
	U.S.	-5.179	9.871	Thailand	-1.886	6.259
		(-4.81)***	(6.44)***		(-0.86)	(1.99)**

Panel B. Pool-average portfolio

	Western			ESEA		
	Opt.	**Pess.**	**Opt.-Pess.**	**Opt**	**Pess**	**Opt-Pess**
Winner with good news	0.369	1.786	-1.417	-0.234	4.307	-4.541
	(0.77)	(2.97)***	(-2.88)***	(-0.17)	(3.67)***	(-3.71)***
Loser with bad news	-4.553	9.698	-14.251	0.738	3.399	-2.661
	(-4.36)***	(6.12)***	(-9.34)***	(0.69)	(2.78)***	(-2.01)**

	West-ESEA	
	Opt.	**Pess.**
Winner with good news	0.603	-2.521
	(0.91)	(-2.01)**
Loser with bad news	-5.291	6.299
	(-4.99)***	(5.12)***

Panel C. Country-average portfolio

Winner with good news	0.615	1.154	-0.539	-1.514	4.505	-6.020
	(0.71)	(1.34)	(-0.63)	(-0.66)	(2.44)**	(-2.05)*
Loser with bad news	-4.646	3.865	-8.511	5.854	3.909	1.945
	(-9.53)***	(1.61)	(-3.47)**	(0.64)	(5.97)***	(0.21)

	West-ESEA	
	Opt.	**Pess.**

Winner with good news	2.129 (0.87)	-3.351 (-1.64)
Loser with bad news	-10.500 (-2.14)*	-0.044 (-0.02)

pessimistic, which is not in line with H5.[66]

Overall, the results in relation to PEAD across the two groups of five countries are broadly consistent with expectations for hypotheses 2-5 with the exception of one group for H5. These findings are consistent with the view that differences between western and ESEA cultures and the associated impact on cognitive dissonance explain differences in PEAD across the two groups of countries.

4.5 Robustness tests

4.5.1 An Alternative Individualism Index

To examine the robustness of our results for 34 countries, we follow Chui et al. (2010) and collect an alternative measure of individualism from the GLOBE (Global Leadership and Organizational Behaviour Effectiveness) project.[67] We collect the country scores on the GLOBE's institutional collectivism ($Indv_{GLOBE}$) dimension for our sample from House et al. (2004). To be consistent with Hofstede's individualism index, we define a new variable $Indv_{GLOBE,}$ which is equal to GLOBE's institutional collectivism times -1. Thus, a higher value of $Indv_{GLOBE}$ suggests a higher degree of individualism of the country. We construct is a categorical variable of $Indv_{GLOBE}$ index of country j equals 1 (-1) if IDV score belongs to the top (bottom) 30% of their scores, otherwise 0. Our regression models shown in equations (4.2) and (4.3) are re-estimated, with Hofstede's individualism index being replaced with GLOBE's institutional collectivism.[68] The two indices are highly correlated so the categorical variable of GLOBE individualism is almost identical to the categorical variable of Hofstede's individualism. We expect the coefficient on the GLOBE individualism index is qualitative similar to that of Hofstede's individualism index. The regression

[66] A possible explanation for this finding is that the belief in reversal in relation to momentum, coupled with pessimism leads to an initial underreaction to the positive earnings surprise.
[67] The GLOBE individualism index is discussed in detail in chapter 3.
[68] The two individualism indices are highly correlated so the categorical variable of GLOBE individualism is almost identical to the categorical variable of Hofstede's individualism. We expect the coefficient on the GLOBE individualism index is qualitative similar to that of Hofstede's indidvism index.

results are shown in Table 4.9. We find the $Indv_{GLOBE}$ coefficient to be positive and significant at the 5% level and the interaction term between individualism and sentiment remains significant at the 10% level or higher. Overall, the results are robust regardless of whether we use the GLOBE collectivism index or Hofstede's individualism index.

Table 4.9 Determinants of PEAD across Countries and the GLOBE Individualism Index

PEAD on good and bad news portfolios are regressed on the GLOBE individualism index, the sentiment variables and an interaction term between individualism and sentiment. GLOBE individualism index, is equal to GlOBE's institutional collectivism times -1. Categorical variable of $Indv_{GLOBE}$ equals 1 (-1) if IDV score belongs to the top (bottom) 30% of their scores, otherwise 0. All other variables are defined in Table 4.5. Standard errors are clustered by country and time. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

	Good news		Bad news	
	(1)	(2)	(3)	(4)
Intercept	0.0118	0.0105	0.0274	0.0253
	(1.12)	(1.03)	(1.31)	(1.22)
Sent	-0.0121	-0.0113	-0.0175	-0.0171
	(-1.98)**	(-1.77)*	(-3.22)***	(-3.21)***
$Indv_{globe}$	0.0005	0.0005	0.0002	0.0002
	(2.33)**	(2.32)**	(2.11)**	(2.11)**
IDV*SENT		-0.0002		-0.0003
		(-1.71)*		(-3.44)***
COUNTRY FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
N	60,005	60,005	60,646	60,646
R squared (%)	3.20	3.42	3.22	3.51

4.5.2 An Alternative Sentiment Index

In this section, we examine the sensitivity of our results for 10 western and ESEA countries to an alternative index for investor sentiment. The yearly sentiment measure is constructed by Baker et al. (2012) for international markets, who suggest that investor sentiment can be captured by variables related to investors' propensity to speculate.[69] The results for the alternative index for each of the ten countries are presented in section 4.3. The results in Tables 4.7 and 4.8 are re-estimated using the alternative sentiment measure. All other calculations remain the same as those in Tables 4.7 and 4.8, respectively.

[69] The alternative sentiment index is discussed in detail in chapter 3.

We first consider the results of PEAD and the alternative sentiment measure in western and ESEA countries in Table 4.10. In contrast to the findings in Table 4.7, as shown in Panel A of Table 4.10, for good news, Canada, the UK and the U.S. exhibit significant PEAD when sentiment is optimistic. PEAD for good news stocks is significant under pessimism in all five western countries in contrast to the four countries showing significant PEAD in Table 4.7. As far as the pooled-average results are concerned in Panel B, while there is strong evidence of PEAD during both sentiment states, PEAD is much higher under pessimism than under optimism, with the difference in PEAD for good news stocks between the two sentiment states being significant at the 1% level. The results are consistent with those in Table 4.7 and H2. Turning to bad news in western markets, there is clear evidence of PEAD during pessimistic periods but strong reversal under optimism, consistent with the results in Table 4.7 and H2. Specifically, as shown in Panel A, PEAD is shown in all western countries, with four out of the five being significant at the 5% level or higher (the exception being the UK). However, when sentiment is pessimistic, all five countries exhibit strong reversal, with the returns being positive in all cases. Overall, the results for western countries are consistent with H2.

We now consider the results for ESEA countries in Table 4.10. There is a mixed picture of PEAD for individual country across sentiment states.[70] In contrast to the results in Table 4.7, when sentiment is optimistic, all but China exhibit significant PEAD following good news. During pessimistic periods, three out of the five ESEA countries (China, Japan and Thailand) exhibit significant PEAD for good news stocks, with the other two countries showing significant reversal. Consistent with the results in Table 4.7, the pooled average results in Panel B show that PEAD is evident for good news stocks under both sentiment periods but it is much stronger under pessimism, consistent with H3 for good news. In relation to bad news, in contrast to the findings in Table 4.7, PEAD is significant during both sentiment periods in only two out of the five ESEA countries, with the others exhibiting significant

[70] The results for each of the five ESEA countries are quite sensitive to the choice of sentiment index (especially in China, Hong Kong and Korea) since the consumer confidence and Baker et al.'s sentiment are different measures and have different frequencies. The results using the alternative sentiment index show significant reversal following bad news during optimistic periods whereas those using the consumer confidence exhibit significant PEAD in both the country-average and pool-average portfolios. The rest of the results using the alternative sentiment measure are qualitatively similar to the results using the consumer confidence index.

Table 4.10 Post-Earnings-Announcement-Drift and the Alternative Sentiment Measure for Western and ESEA Countries

This table reports post-earnings-announcement drift (%) during optimistic and pessimistic states for each of the 10 countries (Panel A) and the pool-average portfolio (Panel B) and the country-average portfolio. The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and abnormal return is buy and hold stock returns minus buy and hold market returns. Earnings are measured as actual earnings per share minus the last median analyst consensus forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with "good" ("bad") news. Sentiment is measured using the yearly sentiment index constructed by Baker et al. (2012) using volatility premium, the number of IPOs, 1st-day returns in IPOs, and market turnover. The overall sentiment index is the 1st principal component of the 4 sentiment proxies. Returns on these portfolios are calculated as average returns of stocks in these portfolios. The formation of the pool- and country-average portfolios is detailed in Table 4.2. The t-statistics are calculated using clustered standard errors on the firm level. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. PEAD by country

		Westerners-Belief in continuation		**ESEA-Belief in reversal**		
		Opt.	Pess.		Opt.	Pess.
Good news	Canada	3.761 (7.38)***	6.036 (7.47)***	China	-2.972 (-3.59)***	10.470 (7.81)***
	France	0.730 (1.21)	1.525 (2.54)**	Hong Kong	2.583 (2.18)**	-1.786 (-1.93)*
	Germany	-2.128 (-2.66)***	4.930 (5.02)***	Japan	2.658 (6.18)***	2.921 (6.82)***
	UK	0.871 (1.83)*	2.301 (3.30)***	Korea	1.963 (1.81)*	-3.205 (-3.49)***
	U.S.	4.285 (8.18)***	13.248 (17.5)***	Thailand	3.073 (2.01)**	6.486 (3.79)***
Bad news	Canada	-1.202 (-1.98)**	2.869 (2.83)***	China	-1.886 (-2.18)**	9.040 (9.05)***
	France	-2.842 (-4.30)***	1.518 (1.77)*	Hong Kong	0.794 (0.63)	-4.419 (-3.10)***
	Germany	-5.979 (-7.18)***	4.588 (3.83)***	Japan	1.432 (2.75)***	1.437 (3.16)***
	UK	-0.273 (-0.44)	0.247 (0.32)	Korea	4.900 (2.92)***	-4.189 (-2.83)***
	U.S.	-0.925 (-2.26)**	11.073 (13.08)***	Thailand	-3.160 (-1.98)**	4.268 (1.65)*

Panel B. Pool-average portfolio

	Westerners-Belief in continuation			**ESEA-Belief in reversal**		
	Opt.	**Pess.**	**Opt.-Pess.**	**Opt.**	**Pess.**	**Opt.-Pess.**
Good news	2.922 (8.32)***	9.026 (18.94)***	-6.104 (-9.33)***	1.606 (4.52)***	4.161 (11.5)***	-2.555 (-6.12)***
Bad news	-1.651 (-3.21)***	7.098 (13.11)***	-8.749 (-9.21)***	1.265 (2.77)***	2.665 (5.95)***	-1.400 (-2.89)***

West-ESEA

	Opt.	**Pess.**
Good news	1.316(3.33)***	4.865(5.31)***
Bad news	-2.916(-3.53)***	4.433(5.12)***

Panel C. Country-average portfolio

	Westerners-Belief in continuation	**ESEA-Belief in reversal**

	Opt.	Pess.	Opt.-Pess.	Opt.	Pess.	Opt.-Pess.
Good news	1.504	5.608	-4.104	1.461	2.977	-1.516
	(1.29)	(2.71)**	(-1.72)	(1.30)	(1.17)	(-0.54)
Bad news	-2.244	4.059	-6.303	0.416	1.277	-0.811
	(-2.18)**	(2.14)**	(-2.92)**	(0.30)	(0.48)	(-0.27)

West-ESEA		
	Opt.	**Pess.**
Good news	0.043(0.03)	2.631(0.80)
Bad news	-2.660(-1.53)	2.836(0.88)

reversal. The pooled average results in Panel B of Table 4.10 demonstrate significant reversal following bad news across both sentiment periods, which is inconsistent with H3 for bad news. Examination of Panel B of Table 4.10 also allows us to see the difference in PEAD between western and ESEA markets across sentiment states. The results indicate that there are significant differences in PEAD for good news announced when sentiment is pessimistic and for bad news announced during optimistic periods, consistent with H3. In sum, the results in Table 4.10 of using the alternative sentiment measure generally confirm the findings using the consumer confidence index and support our hypotheses, suggesting that the interaction of sentiment and culture affect cognitive dissonance and the extent of PEAD.[71]

We next turn to consider the sensitivity of interaction between PEAD and momentum to the alternative sentiment index. Recall that H4 hypothesised that for western markets, PEAD will be greater for winner (loser) stocks with good (bad) news during pessimistic (optimistic) periods; and H5 hypothesised that for ESEA markets PEAD may arise under any combination of sentiment and momentum and earnings surprises, but for the two higher PEAD categories identified in relation to H5, PEAD will be lower for ESEA markets than for western market (H5). Table 4.11 reports Table 4.8-equivalent results for optimistic and pessimistic periods using the alternative sentiment index. Inconsistent with the results in Table 4.8, in western markets, all countries exhibit PEAD for winners with good news during both sentiment states except for the Germany showing significant reversal during optimistic periods. Consistent with the results in Table 4.8, for losers with bad news, all

[71] The results for the country-average portfolio in Panel C are qualitatively similar to those for the pool-average portfolio in Panel B. Thus, for brevity, we only discuss the results for the pool-average portfolio in the main context.

countries exhibiting strong PEAD under optimism and significant reversal under pessimism. Consistent with the results in Table 4.8 and our hypothesis 4, results in Panel B provide evidence for the pooled sample of PEAD in all four cases: PEAD is evident for winners with good news under both sentiment but that is much higher under pessimism than under optimism, with the differences between optimism and pessimism being highly significant. In relation to losers with bad news, there is strong continuation of loser stocks with bad news under optimism but significant reversal under pessimism.

As far as ESEA markets are concerned, inconsistent with the results in Table 4.8, for winners with good news, reversals are found for China during optimistic states, Hong Kong during optimistic sentiment periods and for Korea during both states. For losers with bad news, all five countries exhibit reversal when sentiment is optimistic, with three out of the five being significant at the 1% level , which is again inconsistent with the results in Table 4.8. The other results in Panel A of Table 4.11 are qualitatively similar to those in Panel A of Table 4.8. Consistent with the results in Table 4.8, Panel B demonstrates that PEAD is evident for winner with good news during both sentiment periods and significant reversal for losers with bad news under both sentiment states. The results in Panel B also allow us to compare the difference in PEAD between western and ESEA countries during the two sentiment periods. Consistent with the results in Table 4.8 and H5, PEAD for winners with good news is significantly higher in western markets than in ESEA markets during pessimistic periods and PEAD for loser stocks with bad news is significantly higher in western markets than in ESEA markets when sentiment is optimistic.

Overall, the results in Table 4.10 using the alternative sentiment measure are consistent with the results using the consumer confider index in Table 4.7 except for bad news under optimism. The results using both sentiment measures are consistent with H2 and H3. In relation to winners with good news, the results in Table 4.11 of using the alternative sentiment measure show that there is significant PEAD for winners with good news in both western and ESEA countries under pessimism, with the former being significantly higher, consistent with H5 for winner with good news. However, the results in Table 4.8 of using the consumer confidence index show that

Table 4.11 Post-Earnings-Announcement-Drift, Momentum and the Alternative Sentiment Measure

This table reports post-earnings-announcement-drift (%) for winner stocks with good news and loser stocks with bad news during optimistic and pessimistic states for each of the 10 countries (Panel A) and the pool-average portfolio (Panel B) and the country-average portfolio. The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and abnormal return is buy and hold stock returns minus buy and hold market returns. Earnings are measured as actual earnings per share minus the last median analyst consensus forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with "good" ("bad") news. The definition of momentum portfolio and sentiment is discussed in detail in Table 3.2 and Table 4.9, respectively. Sentiment and momentum portfolios are identified in month t and stocks with earnings announcements in month t+1 are identified. Returns on these portfolios are calculated as average returns of stocks in these portfolios. The t-statistics are calculated using clustered standard errors on the firm level. Corresponding t-statistics are reported in parentheses and asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. PEAD by country

	West			ESEA		
		Opt.	**Pess.**		**Opt.**	**Pess.**
Winner with good news	Canada	5.882	6.537	China	-10.692	10.847
		(4.12)***	(5.09)***		(-11.01)***	(7.96)***
	France	1.314	0.959	Hong Kong	4.333	-2.478
		(1.62)	(1.61)		(2.25)**	(-1.81)*
	Germany	-2.619	5.959	Japan	4.982	2.624
		(-3.04)***	(4.56)***		(8.03)***	(5.84)***
	UK	1.363	1.896	Korea	-1.908	-4.751
		(2.07)**	(3.51)***		(-1.18)	(-5.39)***
	U.S.	5.466	4.067	Thailand	8.166	5.856
		(4.41)***	(3.06)***		(4.33)***	(4.34)***
Loser with bad news	Canada	-2.659	7.354	China	2.915	11.500
		(-2.79)***	(4.16)***		(3.35)***	(11.03)***
	France	-2.938	5.681	Hong Kong	0.686	-6.761
		(-3.31)***	(4.24)***		(0.39)	(-3.24)***
	Germany	-8.903	6.168	Japan	2.396	2.975
		(-7.71)***	(3.54)***		(3.73)***	(4.45)***
	UK	-3.495	2.818	Korea	8.052	-7.485
		(4.12)***	(3.01)***		(3.40)***	(-6.07)***
	U.S.	-2.496	11.323	Thailand	0.273	6.194
		(-2.96)***	(4.62)***		(0.14)	(1.67)*

Panel C. Pool-average portfolio

	Westerners-Belief in continuation			Westerners-Belief in continuation		
	Opt.	**Pess.**	**Opt.-Pess.**	**Opt**	**Pess**	**Opt-Pess**
Winner with good news	1.681	3.503	-1.822	1.906	2.342	-0.436
	(3.90)***	(8.11)***	(-3.17)***	(3.58)***	(5.83)***	(-0.49)
Loser with bad news	-3.751	6.705	-10.456	3.254	3.851	-0.597
	(4.13)***	(4.11)***	(-5.32)***	(5.24)***	(6.69)***	(-0.61)

West-ESEA

	Opt.	**Pess.**
Winner with good news	-0.225	1.161
	(-0.19)	(2.10)**
Loser with bad news	-7.005	2.854
	(-5.01)***	(2.89)***

Panel C. Country-average portfolio

	Westerners-Belief in continuation			ESEA-Belief in reversal		
	Opt.	**Pess.**	**Opt.-Pess.**	**Opt.**	**Pess.**	**Opt.-Pess.**

Winner with good news	2.281 (1.46)	3.884 (3.55)***	-1.602 (-0.84)	0.976 (0.29)	2.420 (0.86)	-1.444 (-0.33)
Loser with bad news	-4.098 (-3.37)**	6.669 (4.83)***	-10.767 (-5.86)***	2.864 (2.09)**	1.285 (0.35)	1.579 (0.40)

West-ESEA		
	Opt.	**Pess.**
Winner with good news	1.305 (0.35)	1.464 (0.49)
Loser with bad news	-6.962 (-3.77)***	5.384 (1.37)

both western and ESEA countries exhibit significant PEAD for winners with good news under pessimism, with the latter being significant higher, inconsistent with H5 for winners with good news. In relation to losers with bad news, the results using the two sentiment measures are qualitatively similar, showing that there is significant PEAD (reversal) for losers with bad news for western (ESEA) countries under optimism, consistent with H5.

4.5.3 Sensitivity tests

Three sensitivity tests are carried out to assess the robustness of the results: (1) re-estimating PEAD using mean analyst forecast in the portfolio analysis for Tables 4.3 and 4.4 as shown in Tables A4.3 to A4.7 ; (2) a 40% cut-off for optimistic/pessimistic sentiment is used as shown in Table A4.9 and A4.10; (3) Raw returns are used instead of market-adjusted returns as shown in Tables A4.11 to A4.14. The results of these tests are qualitatively similar to those reported and are reported in the appendix.

4.6 Conclusion

Post-earnings announcement drift has been documented to be one of the biggest challenges to the efficient market hypothesis and it was identified by Fama (1998) as one of the candidates for being “above-suspicion” anomalies. A mixed picture has emerged globally and the evidence in relation to PEAD is inconclusive. To date, there is no satisfactory explanation for the anomaly. We propose that cognitive dissonance may be a major driver of the anomaly, with the interaction of sentiment and culture causing the phenomenon to arise in different cases and to differing degrees in western and ESEA markets. While previous studies have examined the effect of sentiment and culture on PEAD independently, to date no study has examined their interaction effect as well as the implications of their interaction on cognitive dissonance and PEAD.

In this chapter, we investigate the interaction effect using an approach in the spirit of Hong and Stein (1999) and propose a number of hypotheses to explain the difference in PEAD across countries around the world. We first examine the impact of cognitive dissonance arising from the interaction of individualism and sentiment on PEAD in 34 countries. Subsequently, we focus attention on the five largest markets in each of the east and west, given psychological arguments and evidence in differences in beliefs concernings change in the two cultures in which westerners tend to believe in continuation while those from the east expect reversal. Our hypotheses in relation to views of change are developed using an approach in the spirit of Hong and Stein (1999).We find that in high individualism and western cultures, news diffuses much more slowly which contradicts investor sentiment states than in low individualism and ESEA cultures. We also carry out a range of robustness tests which support our main findings. Our results provide general support for our hypotheses, which is consistent with cultural biases and sentiment interacting to impact on cognitive dissonance, resulting in the difference in PEAD across countries. Thus, our analysis suggests that cognitive dissonance is a major determinant of prior empirical findings relating to PEAD.

4.7 Appendix

4.7.1 Earnings Announcements Descriptive statistics for Western and ESEA Countries

Table A4. 1 Earnings Announcements Descriptive Statistics for Western and ESEA Countries

The table reports the descriptive statistics for the earnings announcements in the east and west. It reports the name of the country and the number of firms for each country and the number of stocks that also has earnings announcements available and number of announcements for each country. The earnings announcement data and analyst forecast data are from the IBES International Summary File for all countries, except the U.S which are from the IBES U.S Summary File. Several selection criteria are applied to reach our final data sample. First, companies must be listed on a major exchange in their home country and cross-listed companies are deleted. Second, firms must be represented in both the Datastream and IBES databases for international markets and in the CRSP and IBES databases for the U.S market.

Country	**Firms**	**Announcements**	**Forecasts**
WEST			
Canada	1,550	7,400	63,348
France	1,474	9,888	65,966
Germany	1,281	10,713	65966
United Kingdom	4,040	26,318	134,533
United States	12,100	62,430	489,251
Total	20,445	116,749	819,064
ESEA			
China	1,558	8,755	31,773
Hong Kong	1,215	7,650	54,225
Japan	2,753	33,017	123,330
Korea	1,323	8,365	31,448
Thailand	737	2,668	20,567
Total	7,586	60,455	261,343

4.7.2 The Country-Average Results for Table 4.4

Table A4. 2 Post-Earnings-Announcement-Drift, Investor sentiment and Individualism for the country-average portfolio

This table presents the country-average results for post-earnings-announcement drift (%) following good news and bad news sorted by investor sentiment and individualism index. The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and the abnormal returns are buy and hold stock returns minus buy and hold market returns. Each country is categorised into the top and bottom 30% based on the individualism index score, with the middle 40% being excluded from the analysis. The announcement month is identified as optimism, mild or pessimism. The definition of sentiment states of the announcement month is discussed in detail in Table 4.3. The formation of pool-average portfolio is discussed in detail in Table 4.2. Panel A reports PEAD for good news and bad news stocks sorted by individualism. Panels B and C present PEAD for good news and bad news stocks across sentiment states in the high and low individualism culture groups, respectively. Panel D presents the difference in PEAD between the two culture groups. Asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Country-average portfolios		**PEAD**	
	Good news	**Bad news**	**Good-Bad**
Individualism level			
Panel A. Portfolio returns and Individualism			
High IDV	1.615 ***	-0.411	2.026 ***
Low IDV	1.929 ***	0.209	1.720 ***
High. - Low.	-0.314	-0.620	0.306
Sentiment level			
Panel B High Individualism			
Optimistic	1.043 **	-1.770 ***	2.813 ***
Pessimistic	2.918 ***	2.024 **	0.894
Opt. - Pes.	-1.875 **	-3.794 ***	1.919 **
Panel C Low Individualism			
Optimistic	0.135	-1.026	1.161
Pessimistic	2.352 ***	1.150	1.202
Opt.-Pes.	-2.217 **	-2.176 *	-0.041

4.7.3 SUE is Calculated by using Mean Analyst Forecast

Table A4. 3 Post-Earnings-Announcement-Drift, Sentiment and Individualism using Mean Analyst Forecast

This table presents the pool-average results for post-earnings announcement drift (%) following good news and bad news sorted by investor sentiment and individualism index. Stocks in each country are ranked on earnings surprise (SUE) from annual earnings announcements. SUE is calculated as the difference between actual earnings and mean analyst forecast, scaled by stock prices 10 days prior to the earnings announcement. Each country is categorised into the top and bottom 30% based on the individualism index score, with the middle 40% being excluded from the analysis. Each year is identified as optimism, mild or pessimism. The definition of sentiment states of the holding period is discussed in detail in Table 4.3. The formation of pool-average portfolio is discussed in detail in Table 4.2. Panel A reports PEAD for good news and bad news stocks sorted by individualism. Panels B and C present PEAD for good news and bad news stocks across sentiment states in the high and low individualism culture groups, respectively. Asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Pool-average portfolios		**PEAD**	
	Good news	**Bad news**	**Good-Bad**
Individualism level			
Panel A. Portfolio returns and Individualism			
High IDV	4.312 ***	2.001 ***	2.311 ***
Low IDV	2.014 ***	0.978 ***	1.036 ***
High. - Low.	2.298 ***	1.023 ***	1.275 ***
Sentiment level			
Panel C High Individualism			
Optimistic	1.784 ***	-2.103 ***	3.887 ***
Pessimistic	7.432 ***	6.812 ***	0.620
Opt. - Pes.	-5.648 ***	-8.915 ***	3.267 ***
Panel C Low Individualism			
Optimistic	0.879 **	-1.562 ***	2.441 ***
Pessimistic	1.783 ***	0.991 **	0.792 *
Opt.-Pes.	-0.904 ***	-2.553 ***	1.649 ***

Table A4. 4 Post-Earnings-Announcement-Drift, Investor Sentiment and Individualism using Mean Analyst Forecast

This table presents the country-average results for post-earnings announcement drift (%) following good news and bad news sorted by investor sentiment and individualism index. Stocks in each country are ranked on earnings surprise (SUE) from annual earnings announcements. SUE is calculated as the difference between actual earnings and mean analyst forecast, scaled by stock prices 10 days prior to the earnings announcement. Each country is categorised into the top and bottom 30% based on the individualism index score, with the middle 40% being excluded from the analysis. Each year is identified as optimism, mild or pessimism. The definition of sentiment states of the holding period is discussed in detail in Table 4.3. The formation of pool-average portfolio is discussed in detail in Table 4.2. Panel A reports PEAD for good news and bad news stocks sorted by individualism. Panels B and C present PEAD for good news and bad news stocks across sentiment states in the high and low individualism culture groups, respectively. Asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Country-average portfolios		**PEAD**	
	Good news	**Bad news**	**Good-Bad**
Individualism level			
Panel A. Portfolio returns and Individualism			
High IDV	1.787***	-0.512	2.299***
Low IDV	1.432***	0.319	1.113***
High. - Low.	0.355	-0.831*	1.186***
Sentiment level			
Panel B.1 High Individualism			
Optimistic	1.162**	-1.891***	3.053***
Pessimistic	2.797***	1.775**	1.022*
Opt. - Pes.	-1.635**	-3.666***	2.031***
Panel C. Low Individualism			
Optimistic	0.310	-0.910**	1.220**
Pessimistic	2.034**	1.430**	0.604
Opt.-Pes.	-1.724**	-2.340**	0.616

Table A4. 5 Post-Earnings-Announcement-Drift for Western and ESEA Countries using Mean Analyst Forecast

This table reports the post-earnings announcement drift (%) based for the ten countries in the sample. The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and abnormal return is buy and hold stock returns minus buy and hold market returns. Earnings are measured as actual earnings per share minus the mean analyst forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with “good” (“bad”) news. The t-statistics are calculated using clustered standard errors on the firm level. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. PEAD by country

	Westerners-Belief in continuation		**ESEA-Belief in reversal**	
	Country		**Country**	
Good news	Canada	3.157***	China	2.000***
	France	0.884***	Hong Kong	0.921*
	Germany	-0.9972**	Japan	2.836***
	UK	1.885***	Korea	1.024**
	U.S	5.233***	Thailand	3.298***
Bad news	Canada	-0.635*	China	0.954*
	France	-1.514***	Hong Kong	-0.252
	Germany	-1.762***	Japan	1.591***
	UK	0.283	Korea	1.648**
	U.S.	2.471***	Thailand	-0.042

Panel B. Pool-average portfolio

	Westerners-Belief in continuation	**ESEA-Belief in reversal**	**West-ESEA**
Good news	3.942%***	2.243%***	1.699%***
Bad news	1.764%***	1.203%***	0.561%**
Good-Bad	2.178%***	1.040%***	

Table A4. 6 Post-Earnings-Announcement-Drift and Sentiment for Western and ESEA Countries using Mean Analyst Forecast

This table reports post-earnings-announcement drift (%) for good and bad news stocks during optimistic and pessimistic states for each of the 10 countries (Panel A) and pool-average portfolio (Panel B). The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and the abnormal returns are buy and hold stock returns minus buy and hold market returns. Earnings are measured as actual earnings per share minus the mean analyst forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with "good" ("bad") news. The definition of sentiment states of the announcement month is discussed in detail in Table 4.3. The t-statistics are calculated using clustered standard errors on the firm level. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. PEAD by country

	Westerners-Belief in continuation			ESEA-Belief in reversal		
		Opt.	**Pess.**		**Opt.**	**Pess.**
Good news	Canada	0.959	3.435***	China	3.672**	-2.911**
	France	-0.008	0.703	Hong Kong	1.618	6.619***
	Germany	-2.466***	4.452***	Japan	1.925***	3.513***
	UK	-0.004	4.310***	Korea	-5.223***	4.084***
	U.S.	1.471***	9.077***	Thailand	1.829	4.120*
Bad news	Canada	-1.032	2.506**	China	-2.060	-3.817***
	France	-1.899***	0.050	Hong Kong	-1.190	3.266
	Germany	-3.594***	3.113***	Japan	-0.702*	2.337***
	UK	-0.556	1.819***	Korea	-9.746***	4.827***
	U.S.	-2.774***	8.251***	Thailand	-2.607*	0.668

Panel B. Pool-average portfolio

	Westerners-Belief in continuation			ESEA-Belief in reversal		
	Opt.	**Pess.**	**Opt.-Pess.**	**Opt.**	**Pess.**	**Opt.-Pess.**
Good news	0.413	6.120***	-5.707***	1.213**	3.723***	-2.510***
Bad news	-2.842***	4.213***	-7.055***	-1.213**	1.846***	-3.059***

Panel C. West-ESEA

	Opt.	**Pess.**
Good news	-0.800	2.397***
Bad news	-1.629***	2.367***

Table A4. 7 Post-Earnings-Announcement-Drift, Momentum and Sentiment using Mean Analyst Forecast

This table reports post earnings announcement drift (%) for winner stocks with good news and losers with bad news during optimistic and pessimistic states for each of the 10 countries (Panel A) and the pool-average portfolio (Panel B). The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and the abnormal returns re buy and hold stock returns minus buy and hold market returns. Earnings are measured as actual earnings per share minus the mean analyst forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with “good” (“bad”) news. The definition of sentiment states of the announcement month is discussed in detail in Table 4.3. Momentum portfolios are defined in Table 3.2. Stocks with earnings announcement in month t+1 is identified and an event study is performed to examine the post earnings announcement drift. The t-statistics are calculated using clustered standard errors on the firm level. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

		West			**ESEA**	
		Opt.	**Pess.**		**Opt.**	**Pess.**
Winner with good news	Canada	1.596**	1.052*	China	7.067***	-2.694***
	France	0.228	1.212**	Hong Kong	-0.256	5.648
	Germany	-1.350	3.242***	Japan	1.473	6.956***
	UK	-0.328	2.222***	Korea	-2.743**	-1.751
	U.S.	3.007***	1.117	Thailand	3.712**	7.543***
Loser with bad news	Canada	-2.127*	9.189***	China	22.675***	-3.270
	France	-4.638***	2.369***	Hong Kong	-2.232	8.009
	Germany	-6.470***	2.953***	Japan	-0.262	5.086***
	UK	-2.733***	2.289***	Korea	-4.843***	0.692
	U.S.	-3.894***	8.669***	Thailand	-1.250	4.337*

Panel B. Pool-average Portfolio

	Western			**ESEA**		
	Opt.	**Pess.**	**Opt.-Pess.**	**Opt**	**Pess**	**Opt-Pess**
Winner with good news	1.210 *	2.343 ***	-1.133 *	1.139	4.576 ***	-3.437 ***
Loser with bad news	-4.279 ***	6.898 ***	-11.177 ***	-0.343	4.112 ***	-4.445 ***

4.7.4 40% Cut-off for Investor Sentiment Measure

Table A4. 8 Post-Earnings-Announcement-Drift, Individualism and Investor Sentiment

This table presents the pool-average results for post-earnings-announcement drift (%) following good news and bad news sorted by investor sentiment and individualism index. The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and the abnormal returns are buy and hold stock returns minus buy and hold market returns. Each country is categorised into the top and bottom 30% based on the individualism index score, with the middle 40% being excluded from the analysis. The announcement month is identified as optimism, mild or pessimism. The sentiment state of the announcement month is defined using 40% cut-off points. The formation of pool-average portfolio is discussed in detail in Table 4.2. Panel A reports PEAD for good news and bad news stocks sorted by individualism. Panels B and C present PEAD for good news and bad news stocks across sentiment states in the high and low individualism culture groups, respectively. The t-statistics are calculated using clustered standard errors on the firm level. Asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Pool-average portfolios		PEAD	
	Good news	Bad news	Good-Bad
Individualism level			
Panel A. Portfolio returns and Individualism			
High IDV	5.540***	2.331***	3.209***
Low IDV	2.321***	0.690***	1.631***
High. - Low.	3.219***	1.641***	1.578***
Sentiment level			
Panel B High Individualism			
Optimistic	1.613***	-2.671***	4.284***
Pessimistic	8.340***	6.621***	1.719***
Opt. - Pes.	-6.727***	-9.292***	2.565***
Panel C Low Individualism			
Optimistic	0.732***	-1.793***	2.525***
Pessimistic	3.424***	1.781***	1.643***
Opt.-Pes.	-2.692***	-3.574***	0.882***

Table A4. 9 Post-Earnings-Announcement-Drift and Sentiment for Western and ESEA Countries using 40% Cutoffs for Investor Sentiment Measure

This table reports post-earnings-announcement-drift (%) for good and bad news stocks during optimistic and pessimistic states for each of the 10 countries (Panel A) and pool-average portfolio (Panel B). The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and the abnormal returns are buy and hold stock returns minus buy and hold market returns. Earnings are measured as actual earnings per share minus the last median analyst consensus forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with "good" ("bad") news. The sentiment state of the announcement month is defined using 40% cut-off points. The t-statistics are calculated using clustered standard errors on the firm level. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Individual country portfolio

	West	**Opt.**	**Pess.**	**ESEA**	**Opt.**	**Pess.**
Good news	Canada	0.963***	4.763***	China	3.112	-1.238
	France	-0.288	0.998*	Hong Kong	0.882	6.567***
	Germany	-1.973***	-2.228***	Japan	2.188***	1.002***
	UK	-1.973***	-2.228***	Korea	-5.923***	2.442
	U.S.	1.242	6.345***	Thailand	1.863	7.386***
Bad news	Canada	-2.482***	0.497	China	0.980*	-3.207***
	France	-3.081***	-3.823***	Hong Kong	-0.528	4.962***
	Germany	-3.370***	-3.782***	Japan	-0.290	1.193***
	UK	-0.009	-0.008	Korea	-9.361***	3.171
	U.S.	-2.564***	6.752***	Thailand	-2.773**	-1.270

Panel B. Pool-average portfolio

	Westerners-Belief in continuation			**ESEA-Belief in reversal**		
	Opt.	**Pess.**	**Opt.-Pess.**	**Opt.**	**Pess.**	**Opt.-Pess.**
Good news	0.782***	4.125***	-3.343***	1.806***	2.783***	-0.997*
Bad news	-2.513***	2.341***	-4.854***	-0.645	1.784***	-2.429***

Table A4. 10 Post-Earnings-Announcement-Drift, Momentum and Sentiment for Western and ESEA Countries using 40% Cutoffs for Investor Sentiment Measure

This table reports post-earnings-announcement drift (%) for winner stocks with good news and losers with bad news during optimistic and pessimistic states for each of the 10 countries (Panel A) and pool-average portfolio (Panel B). The drift is calculated as the cumulative abnormal returns of stocks during +2 to +60 trading days following the earnings announcement and the abnormal returns re buy and hold stock returns minus buy and hold market returns. Earnings are measured as actual earnings per share minus the last median analyst consensus forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with "good" ("bad") news. The sentiment state of the announcement month is defined using 40% cut-off points. Momentum portfolios are defined in Table 3.2. Stocks with earnings announcement in month t+1 is identified and an event study is performed to examine the post earnings announcement drift. Returns on these portfolios are calculated as average returns of stocks in these portfolios. The t-statistics are calculated using clustered standard errors on the firm level. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. Individual country portfolio

	West	Opt.	Pess.	Opt.-pess.	ESEA	Opt.	Pess.	Opt.-pess.
Winner with good news	Canada	1.899**	3.035***	-1.107	China	-3.514**	-1.921	-9.923***
	France	0.265	0.250	-0.222	Hong Kong	0.216	9.053***	-7.679**
	Germany	-1.019	-0.303	2.105*	Japan	0.979	4.247***	-4.967**
	UK	-0.000	3.047***	-2.283***	Korea	-3.491***	-1.356	-3.841*
	U.S.	2.107***	1.212**	1.950**	Thailand	-0.116	9.956***	-7.785***
Loser with bad news	Canada	-4.335***	3.909***	-10.403***	China	21.38***	-1.100	32.73***
	France	-3.597***	1.206	-5.249***	Hong Kong	-2.472	9.990**	-10.271***
	Germany	-4.532***	-2.926***	-0.564	Japan	-2.435**	5.012***	-5.259**
	UK	-2.553***	1.124***	-5.524***	Korea	-6.121***	0.211	-6.363***
	U.S.	-4.739**	7.771***	-14.158***	Thailand	-1.949*	2.226*	-3.216***

Panel B. Pool-average portfolio

	West				ESEA		
	Opt.	Pess.	Opt.-Pess.		Opt	Pess	Opt-Pess
Winner with good news	0.989**	1.486**	-0.497		0.213	4.335***	-4.122***
Loser with bad news	-3.780***	5.431***	-9.211***		0.895*	4.312***	--3.417**

Panel C. West-ESEA

	Opt.	Pess.	Opt.-pess.
Winner with good news	0.776*	-2.849***	3.625***
Loser with bad news	-4.675***	1.119*	-5.794***

4.7.5 PEAD is calculated using Raw Returns

Table A4. 11 Post-Earnings-Announcement-Drift, Investor sentiment and Individualism using Raw Returns

This table presents the pool-average results for post-earnings-announcement-drift (%) following good news and bad news sorted by investor sentiment and individualism index. The drift is calculated as the cumulative raw returns of stocks during +2 to +60 trading days following the earnings announcement. Each country is categorised into the top and bottom 30% based on the individualism index score, with the middle 40% being excluded from the analysis. The announcement month is identified as optimism, mild or pessimism. The definition of sentiment states of the announcement month is discussed in detail in Table 4.3. The formation of pool-average portfolio is discussed in detail in Table 4.2. Panel A reports PEAD for good news and bad news stocks sorted by individualism. Panels B and C present PEAD for good news and bad news stocks across sentiment states in the high and low individualism culture groups, respectively. The t-statistics are calculated using clustered standard errors on the firm level. Asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Pool-average portfolios		**PEAD**	
	Good news	**Bad news**	**Good-Bad**
Individualism level			
Panel A. Portfolio returns and Individualism			
High IDV	3.346***	1.511**	1.835***
Low IDV	4.250***	3.187***	1.063**
High. - Low.	-0.904*	-1.676**	0.772*
Sentiment level			
Panel B.1 High Individualism			
Optimistic	2.710***	-1.665**	4.375***
Pessimistic	4.430***	4.316***	0.114
Opt. - Pes.	-1.720***	-5.981***	4.261***
Panel C Low Individualism			
Optimistic	0.042	-1.583**	1.625**
Pessimistic	7.327***	6.634**	0.693
Opt.-Pes.	-7.285***	-8.217***	0.932*

Table A4. 12 Post-Earnings-Announcement-Drift for Western and ESEA Countries using Raw Returns

This table reports the post-earnings announcement-drift (%) based for the ten countries in the sample. Panel A reports PEAD for good and bad news stocks for each of the 10 countries and Panels B and C report the results for the pool-average and country-average portfolios, respectively. The drift is calculated as the cumulative raw returns of stocks during +2 to +60 trading days following the earnings announcement. Earnings surprises are measured as actual earnings per share minus the last median analyst consensus forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with "good" ("bad") news. Returns on these portfolios are calculated as the average of returns of stocks in these portfolios. The t-statistics are calculated using clustered standard errors on the firm level. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. PEAD by country

	Westerners-Belief in continuation		**ESEA-Belief in reversal**	
	Country		**Country**	
Good news	Canada	4.666***	China	1.361***
	France	2.089***	Hong Kong	3.981***
	Germany	0.763*	Japan	1.955***
	UK	3.197***	Korea	3.067***
	U.S.	8.562***	Thailand	5.037***
Bad news	Canada	0.521	China	-0.076
	France	-0.279	Hong Kong	2.824***
	Germany	-0.339	Japan	1.299***
	UK	1.578***	Korea	1.210
	U.S.	5.537***	Thailand	0.652

Panel B. Pool-average portfolio

	Westerners-Belief in continuation	**ESEA-Belief in reversal**	**West-ESEA**
Good news	6.024 ***	2.330 ***	3.694 ***
Bad news	3.293 ***	1.193 **	2.100 **

Table A4. 13 Post-Earnings-Announcement-Drift and Sentiment for Western and ESEA Countries using Raw Returns

This table reports post-earnings-announcement-drift (%) for good and bad news stocks during optimistic and pessimistic states for each of the 10 countries (Panel A) and pool-average portfolio (Panel B). The drift is calculated as the cumulative raw returns of stocks during +2 to +60 trading days following the earnings announcement. Earnings are measured as actual earnings per share minus the last median analyst consensus forecast before the earnings announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with "good" ("bad") news. The definition of sentiment states of the announcement month is discussed in detail in Table 4.3. The t-statistics are calculated using clustered standard errors on the firm level. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

Panel A. PEAD by country

	Westerners-Belief in continuation			**ESEA-Belief in reversal**		
		Opt.	**Pess.**		**Opt.**	**Pess.**
Good news	Canada	1.716*	5.372***	China	3.672**	-2.911**
	France	-0.271	4.509***	Hong Kong	1.618	6.619***
	Germany	-2.453***	4.582***	Japan	1.925***	3.513***
	UK	-0.470	6.347***	Korea	-5.223***	4.084***
	U.S.	5.165***	13.239***	Thailand	-2.173	15.657***
Bad news	Canada	-0.425	4.509***	China	-2.060	-3.817***
	France	-3.291***	3.621***	Hong Kong	-1.190	3.266***
	Germany	-4.254***	3.011***	Japan	-0.702*	2.337***
	UK	-0.897	3.710***	Korea	-9.746***	4.827***
	U.S.	-2.237***	11.966***	Thailand	-7.208***	13.099***

Panel B. Pool-average portfolio

	Westerners-Belief in continuation			**ESEA-Belief in reversal**		
	Opt.	**Pess.**	**Opt.-Pess.**	**Opt.**	**Pess.**	**Opt.-Pess.**
Good news	3.968***	10.885***	-6.917***	2.078***	5.225***	-3.147***
Bad news	-2.481***	9.038***	-11.519***	-1.789**	2.298***	-4.087***

Table A4. 14 Post-Earnings-Announcement-Drift, Momentum and Sentiment for Western and ESEA Countries using Raw Returns

This table reports post earnings announcement-drift (%) for winner stocks with good news and losers with bad news during optimistic and pessimistic states for each of the 10 countries (Panel A) and the pool-average portfolio (Panel B). The drift is calculated as the cumulative raw returns of stocks during +2 to +60 trading days following the earnings announcement. Earnings are measured as actual earnings per share minus the last median analyst consensus forecast before the earnings-announcement dates, scaled by stock prices 10 days prior to the earnings announcement. In each year, stocks in each country are ranked on earnings surprises. The top (bottom) 30% of stocks are defined as stocks with “good” (“bad”) news. The definition of sentiment states of the announcement month is discussed in detail in Table 4.3. Momentum portfolios are defined in Table 3.2. Stocks with earnings announcement in month t+1 is identified and an event study is performed to examine the post earnings announcement drift. Returns on these portfolios are calculated as average returns of stocks in these portfolios. The t-statistics are calculated using clustered standard errors on the firm level. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

		West			ESEA	
		Opt.	**Pess.**		**Opt.**	**Pess.**
Winner with good news	Canada	5.163***	0.222	China	8.787***	-3.700***
	France	1.089	1.223*	Hong Kong	3.734*	6.669***
	Germany	-1.949**	2.242***	Japan	0.562	5.456***
	UK	0.505	3.985***	Korea	-4.061**	6.372***
	U.S.	6.420***	3.066***	Thailand	-1.010	4.321***
Loser with bad news	Canada	1.758	12.100***	China	15.601***	-0.958
	France	-4.448***	5.045***	Hong Kong	-2.011*	10.689***
	Germany	-8.427***	2.989***	Japan	-0.154	6.186***
	UK	-1.543***	4.269***	Korea	-5.123***	8.720***
	U.S.	-1.948***	9..234***	Thailand	-4.070***	8.125***

	Western			ESEA		
	Opt.	**Pess.**	**Opt.-Pess.**	**Opt**	**Pess**	**Opt-Pess**
Winner with good news	3.121 ***	2.721 ***	0.400	2.312 ***	6.123 ***	-4.811 ***
Loser with bad news	-3.279 ***	5.860 ***	-9.139 ***	-0.913	6.131 ***	-7.044 ***

5 Analyst Recommendations, Investor Sentiment and Institutional Herding

5.1 Introduction

In the previous two empirical chapter, we investigate the impact of cognitive dissonance on the above suspicious anomalies, momentum and post-earnings-announcement-drift by examining the interaction between investor sentiment and cognitive dissonance. Given the key focus of this thesis on cognitive dissonance, we proceed to investigate the impact of cognitive dissonance on institutional herding by testing the joint effect of investor sentiment and analyst recommendations. The study is motivated by the fact that the two factors, investor sentiment and analyst recommendations, have been shown to be prominent in affecting institutional herding. We propose that institutional investors may experience cognitive bias (e.g. cognitive dissonance) when processing analyst information (e.g. analyst recommendations) and sentiment related indicators. In particular, cognitive dissonance may be evident when the two factors do not suggest similar price movements.

A growing body of literature documents that institutional investors exhibit herding behaviour. Investors may herd if they face similar information sets or may herd if they ignore their own information but instead follow actions of others. It is important to understand why herding may take place since stock prices are largely affected by institutions' behaviour. A number of studies have documented why herding might occur, including reputational reasons, information cascades, correlated information and specific characteristics (e.g. Bikhchandani et al., 1992; Froot et al., 1992). The evidence and causes of institutional herding are discussed in detail in section 2.5.

If we are to have a better understanding of herding, it is beneficial to consider what external factors may influence the behaviour of institutions in this regard. Two factors that have attracted much attention in recent years have been investor sentiment and analyst recommendations. This study investigates the interaction of these factors in determining institutional herding. Analyst recommendations are highly valuable to institutional investors, as documented in a number of studies (Merton, 1987; Brennan and Hughes, 1991; Womack, 1996; Cowen et al., 2006; Ljungqvist et al., 2007). Institutional investors use both buy- and sell-side analyst information as important inputs to their investment decisions. A recent study by Brown et al. (2013) shows that mutual funds tend to follow analyst recommendation revisions and herd into stocks with upgrades and herd out of stocks with downgrades.

In the previous chapter, we have examined the importance of investor sentiment in financial markets and in the context of investor trading behaviour.[72] A number of studies suggest that institutional investors take into account the expected level and expected change of individual sentiment (e.g. Brow and Cliff, 2004, 2005; Schmeling, 2007), suggesting that institutional investors may herd to counteract individual sentiment (Lakonishok et al. 1992; Barberis and Shleifer, 2003; De Long et al., 1990; Lee et al., 1991). Accordingly, one may expect that institutional investors will herd in their buy (sell) decisions when individual sentiment is pessimistic (optimistic). Liao et al. (2011) find evidence consistent with the sentiment countering hypothesis and show that investor sentiment plays an important role in explaining mutual fund herding and show that mutual funds only tend to counteract the optimistic sentiment of individual investors.

Previous empirical studies have highlighted the impact of analyst recommendations and individual sentiment separately on mutual fund herding. In this chapter, we examine how sentiment and analyst recommendations impact on institutional herding separately and, unlike previous studies how both factors interact in determining such behaviour. Two different measures of institutional herding have been examined in the literature based on micro data: within-period herding (e.g. Lakonishok et al., 1992, hereafter LSV) and adjacent-period herding (see, e.g. Sias, 2004, hereafter Sias).[73] Since these two measures may allow us to capture different aspects of herding, we analyse both forms here. The LSV measure captures the tendency of investors to buy or sell in a particular stock within a period. In contrast, the Sias herding measure quantifies the extent to which

[72] We use investor/individual sentiment interchangeably throughout the chapter.
[73] In this chapter, we define within-period herding as institutional herding in the same quarter and adjacent-period herding as institutional herding in the subsequent period.

institutions follow each other's trades over adjacent periods. In our setting, the LSV measure allow us to capture institutional herding behaviour arising from correlated trades, which are based on trading signals of analyst recommendations and/or investor sentiment, whereas the Sias measure captures how institutional investors follow each other's trades in such situations. By using both LSV and Sias measures, we will be able to gain greater insight into the extent to which herding responses to analyst recommendations and investor sentiment are intentional or spurious.

Using both LSV and Sias herding measures, we find that, consistent with the previous studies, institutional investors tend to herd in the direction of analyst recommendation revisions and herd more strongly for stocks with analyst consensus downgrades than with analyst consensus upgrades. The findings suggest that institutional investors believe that analyst downgrades are more informative and valuable than upgrades (Brown et al., 2013). We examine the extent to which institutional herding varies with the degree of individual sentiment. The evidence suggests that investor sentiment affects both within-period and adjacent-period herding, but in different ways. In relation to within-period herding, we propose that institutional herding may arise from correlated trading behaviour as a result of analysing individual sentiment or sentiment-related indicators (Liao et al., 2013). Using the LSV measure, we find that institutional investors will herd strongly to counter optimistic sentiment of individual investors, but there is no evidence of buy herding in the presence of pessimistic sentiment. This is consistent with stock markets being more irrational during optimistic periods (Yu and Yuan. 2012). Second, in relation to the adjacent-period herding, we hypothesise that institutional investors may herd as a result of following the trades of others under different sentiment states. When sentiment is pessimistic (optimistic), stock markets become more (less) volatile (Lee et al., 2002; Holmes et al., 2013). In the presence of pessimistic sentiment, institutional investors may forego their own information and rational analysis and follow the actions of others whom they may think have more reliable information. We expect that adjacent-period herding arising from imitating the trades of others will be stronger in the presence of pessimistic sentiment than in the presence of optimistic sentiment.[74] Results confirm the hypothesis.[75]

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[74] Herding in the subsequent periods is referred to as adjacent-period herding throughout the chapter.
[75] The sentiment countering hypothesis is also consistent with the argument above. When

We further examine the interaction between analyst recommendations and investor sentiment on institutional herding. Again, the LSV and Sias herding measures allow us to gain insights into intentional and spurious herding. First, we assume that institutional investors will analyse both analyst recommendations and sentiment-related indicators in making trading decisions. When the two factors reinforce each other, institutional investors would trade strongly in response to these factors. If institutions are trading in concert, it is expected that within-period herding will be stronger. However, herding will be lower if the two factors contradict each other.

We find that within-period herding is the strongest for stocks with downgrades when sentiment is optimistic whereas the herding is lower for stocks with downgrades (upgrades) when sentiment is pessimistic (optimistic). Second, when the two factors produce conflicting trading signals, cognitive dissonance will be evident and institutional investors will become uncertain and following the trades of others might be a means of resolving this uncertainty. Therefore, since prior trades of other institutions can be only observed in the next period, adjacent-period herding is expected to be stronger when cognitive dissonance is prominent. Consistent with the arguments, we find that institutions herd strongly for upgrades (downgrades) in subsequent periods when sentiment is optimistic (pessimistic). Lastly, prior literature suggests that if institutional herding is caused by fads, reputational reasons or characteristic herding, institutional demand should be negatively correlated with subsequent returns. However, if institutional herding is driven by information-based herding, there should be no subsequent return reversals. We find a strong relation between institutional herding and returns in formation periods and weak evidence of subsequent return reversals, suggesting that information-based models primarily drive institutional herding by taking account of the interaction of analyst recommendations and sentiment.

Previous empirical studies have highlighted that mutual funds' behaviour, as well as mutual fund herding are influenced by analyst information and

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individual sentiment is pessimistic, stock markets tend to be rational (e.g. Antoniou et al., 2015). As a result, institutional investors are less likely to counter the pessimistic sentiment of individual sentiment. We argue that institutional investors may feel more uncertain during pessimistic periods, resulting in strong herding from following the trades of others in subsequent periods.

individual sentiment. In this study, we extend these findings by evaluating how institutional investors behave in response to analyst information over different sentiment periods. Therefore, our study differs from other studies and contributes to the literature in two important ways. First, while previous studies have examined the impact of analyst recommendations and sentiment on mutual fund herding separately, to the best of our knowledge, this is the first study to investigate the individual and joint effects of the two factors on institutional herding. Second, we examine the effects of both factors on institutional herding over multi-periods using both LSV and Sias measures, which help us capture different aspects of the herding behaviour. Our results from using two herding measures allow us to gain insights into intentional and spurious herding.

The remainder of the chapter is organised as follows. Section 5.2 reviews the literature and develops our hypotheses. Data and methodology are described in section 5.3. Section 5.4 presents the main empirical results. Section 5.5 provides evidence from robustness tests. Section 6 concludes the chapter.

5.2 Hypothesis Development

A number of studies in the literature document that investors are influenced by other investors' trading actions. The literature of institutional herding is discussed in detail in section 2.5. There are two primary micro-level herding measures in the literature for examining the level of herding for a group of investors. The LSV measure captures quarterly imbalances of net buyers in a particular stock within a period. Lakonishok et al. (1992) find weak evidence of pension fund managers' herding and positive feedback trading. In contrast, the Sias herding measure quantifies the extent to which institutions follow the trades of others' over adjacent periods. Using the same institutional data over the same time period, Sias finds strong evidence of institutional herding over adjacent periods. Other studies using the LSV or Sias measure are discussed in detail in Section 2.5.

5.2.1 Analyst Recommendations and Institutional Herding

5.2.1.1 Analyst Recommendations and Within-Period Herding

A number of studies document that analyst information is highly valuable to institutional investors, which may cause them to trade in concert, resulting in herding. Merton (1987) and Brennan and Hughes (1991) suggest that analyst research may be an important input in an investor's decision to invest in a stock. Womack (1996) suggests that stock analyst recommendations have investment value to institutional investors and finds that the drift with buy recommendations is smaller and short-lived and the drift with sell recommendations is large and lasts up to six months. O'Brien and Bhushan (1990) suggest that research analysts act as information intermediaries to influence institutional ownership and Brown et al. (2013) suggest that it is costly for most small management companies to conduct comprehensive in-house research, making them especially important on the sell side. Chen and Cheng (2006) show that the quarterly change in institutional holdings is positively correlated with consensus analyst recommendations and find that there are more buyer-initiated than seller-initiated trades around favourable recommendations and more seller-initiated than buyer-initiated trades around unfavourable recommendations. Costello and Hall (2011) confirm the results for individual mutual fund portfolios and find the change in fund holdings is positively correlated with analyst recommendation revisions. Franck and Kerl (2013) document that European mutual funds rely on sell-side analyst forecasts and their holdings in stocks are positively correlated with analyst consensus forecast measures. A more recent study by Brown et al. (2013) finds that analyst recommendations are important drivers for mutual fund herding in the U.S. Specifically, mutual funds tend to herd into stocks with consensus upgrades and herd out of stocks with consensus downgrades. We expect that analyst recommendation revisions have a similar effect on institutional herding.

Hypothesis 1. Analyst recommendation revisions have a significant impact on within-period herding and the level of herding is stronger for stocks with downgrades than for stocks with upgrades.

5.2.1.2 Analyst Recommendations and Adjacent-Period Herding

We now consider the relationship between analyst recommendation revisions and adjacent-period herding. When analyst information (e.g., analyst recommendation revisions) is released, institutional investors tend to follow and capitalise on analyst information. Since the investment value of analyst research is known to be short-lived, they must respond reasonably quickly to the release of a revision. We expect that institutions will herd in the same period as the release of analyst recommendation information. Herding in subsequent periods arising from following the trades of others would be relatively weak, since if institutions only trade based on such information, there is no needs for them to follow the trades of others. This leads to our second hypothesis:

Hypothesis 2. Analyst recommendation revisions have no significant impact on adjacent-period herding.

5.2.2 Investor Sentiment and Institutional Herding

Investor sentiment may be another important factor that influences herding. Extensive evidence shows that individual investors are affected by sentiment, which affects their decision-making system and consequently, stock returns and market returns are influenced. Dreman (1979) and Friedman (1984) suggest that institutional herding can be driven by irrational psychological biases, causing prices to deviate away from fundamentals. Similarly, Schwarz (2002) suggests sentiment is a key factor in investors' decision. Baddeley et al. (2010) suggest that herd behaviour is related to emotion.

Institutional herding triggered by investor sentiment can be either spurious or intentional. We may expect that investigative herding may arise if institutional investors trade together on the basis of analysing the same sentiment-related indicators. We also expect that intentional herding may be intentional: if investors are uncertain on some occasions, they are likely to follow the trades of others. We consider each of these arguments in turn.

5.2.2.1 Investor Sentiment and Within-Period Herding

There is ample evidence (e.g. Brown and Cliff, 2004, 2005; Schmeling, 2007, Shleifer, 2000) that institutional investors take into account expected individual sentiment. Schmeling (2007) suggests that institutional investors tend to be optimistic (pessimistic) when individuals tend to be pessimistic (optimistic). Kaniel et al. (2005) suggest that both individual and institutional investors often take opposite positions of trades in which institutions and individuals are found to be informed and irrational investors, respectively (Bange, 2000; Charkravarty, 2001; Sias et al., 2006).

Lakonishok et al. (1992, p. 26) argue that fund managers may herd if they all counter the same irrational moves in individual investor sentiment. Barberis and Shleifer (2003), De Long et al. (1990), Lee et al. (1991) also make similar statements. Liao et al. (2011) find strong evidence that mutual funds engage in countering individuals' optimistic sentiment. They argue that such herding arises from institutional investors analysing the same sentiment-related indicators (investigative herding). Thus, one may argue that institutional investors tend to counteract individuals' sentiment where they will engage in buying (selling) stocks when individual investors are pessimistic (optimistic). We refer to this as the sentiment countering hypothesis. In turn, if institutional investors are acting in concert to counter individuals' sentiment, we expect stronger sell (buy) herding in the presence of optimistic (pessimistic) individual sentiment. Although this argument alone predicts symmetric herding across sentiment periods, institutional herding may be more pronounced in the presence of optimistic sentiment, since stock markets are more irrational during optimistic periods due to more irrational participants in the market (see, for example, Yu and Yuan, 2011). When sentiment is optimistic, noise/individual investors trade more aggressively and are more likely to buy stocks and underestimate risk (e.g. Karlsson et al, 2005). Sentiment traders have a greater impact on stock valuations during optimistic sentiment periods than during pessimistic sentiment periods. We expect that institutional investors will engage in herding out of stocks more strongly to counteract the optimistic sentiment of individuals. When individual sentiment is pessimistic, sentiment traders are less active in the stock market because individual investors are reluctant to take short sell positions (e.g. Barber and Odean, 2008). Hence, we expect strong sell herding during optimism sentiment of individuals. We also expect buy herding during pessimism but we are not sure of the intensity of buy herding during pessimism, which should be lower than that of sell herding during optimism, since sentiment trades are less active during pessimism than optimism.

We, therefore, state our third hypothesis as follows:

Hypothesis 3: within-period herding will be stronger during periods of individual optimism than during periods of individual pessimism and this is primarily due to sell herding during optimistic periods.

5.2.2.2 Investor Sentiment and Adjacent-Period Herding

Let us now consider the relationship between individual sentiment and adjacent-period herding in relation to intentional herding. Lee et al. (2002) find that market volatility increases (decreases) when investors become more pessimistic (optimistic). In a more volatile market, risk will be higher and imitating the trades of others might be a means of resolving uncertainty about the market environment (informational cascades) (Holmes et al., 2013). For this reason, it can be argued that when individual sentiment is low (pessimistic), institutional investors are more likely to imitate the actions of others whom they assume to have more reliable information and vice versa. Consequently, after observing prior trades of others in subsequent periods, they tend to follow the actions of others. Therefore, such herding might be more evident in subsequent periods (adjacent-period herding) when sentiment is pessimistic. Therefore, we have our fourth hypothesis as follows:

Hypothesis 4. Adjacent-period herding will be higher following pessimistic periods than following optimistic periods.

5.2.3 Interaction Effect of Analyst Recommendation and Investor Sentiment on Herding

Since both analyst recommendations and individual sentiment have been shown to be important in influencing institutional herding, it is important to understand how analyst recommendations and individual sentiment interact in affecting institutional herding. The interaction may influence the level of institutional herding by way of investigative arguments and intentional reasons. We discuss each of the two arguments in turn.

5.2.3.1 Interaction Effect on Within-Period Herding

In the case of the investigative argument, it is assumed that institutional investors make trading decisions based on analyst recommendations and individual sentiment. If both factors (analyst recommendations and individual sentiment) impact investors' trading decisions in the same direction, institutional investors would trade strongly in response to the reinforcing factors, resulting in stronger herding. In contrast, if the two factors do not suggest similar trading decisions, institutional herding will be dampened. Exhibit 5.1 presents the interaction of analyst recommendation revisions and individual sentiment on within-period herding. Panel A shows the direction of the trading signal of institutional investors based on analyst recommendations revisions or investor sentiment. For analyst recommendation revisions, institutional investors will be likely to follow the direction of analyst recommendation revisions, i.e. they tend to buy (sell) stocks with upgrades (downgrades) (H1). In relation to investor sentiment, institutional investors will be likely to counter individual optimistic sentiment and again it is not certain what the intensity of institutional trades will be when individual sentiment is pessimistic, i.e. they are more likely to engage in selling stocks when individual investors are optimistic (H3).

As can be seen from Exhibit 5.1, we expect institutional herding will be most prominent for stocks with downgrades in the presence of optimistic sentiment, since in this case, there is no cognitive dissonance as both downgrades and individual optimism suggest institutions to sell. The interaction of the two factors on the direction of herding is unclear when analyst recommendation revisions and investor sentiment suggest different trading signals. Thus, herding will be lower for stocks with upgrades (downgrades) in the presence of optimistic (pessimistic) sentiment, since the two factors conflict with each other (cognitive dissonance will be evident). In addition, since we expect buy herding during pessimism is lower than sell herding during optimism, the interaction of individual pessimism and upgrades should be less strongly than that of individual optimism and downgrades on within-period herding. We, therefore, have our fifth hypothesis.

Hypothesis 5. Within-period herding will be the most pronounced for stocks with downgrades in the presence of optimistic sentiment. Herding will be lower for stocks with upgrades (downgrades) when individual sentiment is optimistic (pessimistic) than for stocks with downgrades during optimistic periods.

Exhibit 5.1. Interaction effect of analyst recommendations and investor sentiment on within-period herding

Panel A: Direction of within-period herding			
		Upgrade (buy)	Downgrade (sell)
Optimistic	(sell)	Overall: ?	Overall: Sell
Pessimistic	(buy but less strongly than the sell during optimism)	Overall: Buy	Overall: ?
Panel B. Interaction effect on within-period herding			
		Upgrade (buy)	Downgrade (sell)
Optimistic	(Sell)	lower	Strongest
Pessimistic	(buy but less strongly than the sell during optimism)	Lower than optimism vs downgrades	lower

5.2.3.2 Interaction Effect on Adjacent-Period Herding

We next consider the relationship between the interaction effect and adjacent-period herding. We hypothesise that the interaction may influence institutional herding by way of cognitive dissonance. Cognitive dissonance will be evident when the two factors (analyst recommendations and individual sentiment) do not impact their trading decisions in the same direction. In such scenarios, institutional investors become uncertain and respond slowly to the arrival of information. In turn, they are more likely to wait until the next period to follow the trades of others. This implies stronger herding which arises from imitating the trades of others in the subsequent periods. In contrast, if the two factors impact on investors' trading decisions in the same direction, then there will be no cognitive dissonance experienced by institutional investors. We expect that they would respond strongly and quickly to the two reinforcing factors. As a result, institutional investors are unlikely to follow the trades of others in subsequent periods. Herding arising from following the trades of others will not be prominent in such cases. This is because investors will become more confident to take independent decisions and do not feel the need to follow the actions of other investors. Exhibit 5.2 summarises cognitive dissonance (CD) experienced by institutional investors for stocks with upgrades and downgrades in different sentiment periods (Panel A) and the level of adjacent-period herding in each case (Panel B). In relation to analyst recommendation revisions, institutional investors will be likely to follow the direction of analyst recommendation revisions, i.e. they tend to buy (sell) stocks with upgrades (downgrades) (H1). In relation to investor sentiment, institutional investors will be likely to counter individual sentiment, i.e. they are more likely to engage in buying (selling) stocks when individual investors are pessimistic (optimistic) (H2) and sell herding during optimism is more strongly than buy herding during pessimism.

As can be seen from Exhibit 5.2, cognitive dissonance will be evident for stocks with upgrades (downgrades) in the presence of optimistic (pessimistic) sentiment. We expect herding arising from following the trades of others in the subsequent period will be stronger in such cases. Panel A shows the CD experienced by institutional investors in each scenario. We propose that if the two factors conflict with each other, cognitive dissonance will be evident. Panel B shows adjacent-period herding in each scenario. When cognitive dissonance is evident, institutional investors become uncertain and respond slowly to the arrival of information. In turn, they are more likely to wait until the next period to follow the trades of others. This implies stronger herding arising from imitating the trades of others in the subsequent period when cognitive dissonance is evident. The notation of strong and weak represents strong and weak herding in that case, respectively. We, therefore, state our following hypothesis:

Hypothesis 6. Adjacent-period herding will be strong for stocks with upgrades (downgrades) when individual sentiment is optimistic (pessimistic) and the herding will be relatively weak for stocks with upgrades (downgrades) when individual sentiment is pessimistic (optimistic)

Exhibit 5.2 Interaction effect of analyst recommendations and investor sentiment on adjacent-period herding

Panel A. Cognitive dissonance in each case		
	Upgrade (buy)	Downgrade (Sell)
Optimistic (Sell)	CD	No CD
Pessimistic (buy and less strongly than sell)	No CD	CD
Panel B. Herding in subsequent periods		
Optimistic (Sell)	Strong	Weak
Pessimistic (buy and less strongly than sell)	Weak	Strong

5.3 Data and Methodology

5.3.1 Stock Market and Stock Recommendation Data

The stock recommendation data is obtained from Thomson Financial Institutional Brokers Estimate (I/B/E/S) U.S. The detail file and all common stocks (share codes 10 and 11) listed on the NYSE, AMEX and NASDAQ are from the Centre for Research in Security Prices (CRSP). The sample period is from December 1993 to December 2014, for which analyst recommendation data is available from November 1993 from IBES. The ratings of stock recommendation range from 1 (strong buy) to 5 (sell) and are reversed in our sample so that higher ratings represent more favourable recommendations (e.g. 5 corresponds to strong buy and 1 corresponds to sell). We follow prior literature to apply several selection criteria on the recommendation data (see, for example, Jegadeesh and Kim, 2006; Loh and Stulz, 2011). The recommendation is assumed to be outstanding if the data satisfy the following criteria:

(i) A rating should be outstanding in which it has been revised to "upgrade, downgrade, or no change" within 12 months and has not been stopped by the broker (in the I/B/E/S Stopped File) (e.g. Ljungquist, Malloy and Maston, 2009).[76]

(ii) The observations where analysts are coded as anonymous by I/B/E/S are removed since it is unable to track their recommendation revisions.

(iii) The observations of analyst initiations or re-initiations are deleted since it is unable to calculate analyst recommendation revisions for these observations.

(iv) There should be at least one analyst issuing a recommendation for the stock.

Our study focuses on recommendation revisions instead of recommendation levels since prior studies suggest that recommendation revisions are more informative than the levels (e.g. Boni and Womack, 2006; Jegadeesh and Kim, 2010). The recommendation revision is computed as the current

[76] To make sure that analyst recommendations are not stale, we only include latest analyst recommendations issued within last twelve months.

recommendation level minus the prior level by the same analyst. By doing so, recommendation revisions range between -4 and +4. For each firm, we first identify whether a particular recommendation revision by an analyst is upgrade or downgrade. Stock recommendation revision is classified as an upgrade (downgrade) if the recommendation revision is greater (less) than zero.

To measure the consensus recommendation revision for a particular stock for a given period, we follow Jegadeesh et al. (2004). We first calculate the consensus recommendation level for the current and prior periods. The current consensus recommendation level is the mean of all outstanding recommendations for a given stock and only the most recent recommendation which is issued within the last 12 months for a given analyst is included and the consensus recommendation revision is the difference between the current and the prior recommendation levels. In other words, the consensus recommendation is the difference between the sum of recommendation levels from t-4 to t and that from t-5 to t-1. Panel C of Table 5.1 summarises the number of consensus recommendations revisions based on the sign of recommendation revisions. Our sample contains 149,298 consensus recommendation revisions in total. There are 35,875, 73,638 and 39,785 stocks with consensus upgrades, no change and downgrades, respectively. It can be seen from Panel C that consensus recommendation "no change" constitutes almost half of the sample and consensus recommendations upgrades and downgrades constitute nearly one quarter of the sample each.

5.3.2 Investor Sentiment

Baker and Wurgler's (2006, 2007) monthly investor sentiment index is employed as a proxy for investor sentiment.[77,78] The index is constructed based on six proxies: trading volume, the divided premium, the closed-end fund discount, the number and first-day returns on IPOs and the equity share in new issues. To mitigate the effect of macroeconomic conditions from each of the variables, they regress each variable on six macroeconomic indicators:

[77] The data is obtained from Jeffrey Wurgler's website.

[78] We also use the Consumer Confidence index as an alternative measure of investor sentiment in our study. The results remain qualitatively similar and are reported in the robustness tests.

growth in industrial production, real growth in durable, nondurable and service consumptions, growth in employment and an NBER recession indicator. The residuals from this regression are used as the sentiment proxy. Since institutional ownership are based on quarterly holdings, we calculate the quarterly investor sentiment as the average of the monthly investor sentiment. Specifically, an equal weight is given to the prior month, to the month 2 and 3 months prior to the current month. We identify optimistic (pessimistic) sentiment periods as the quarterly investor sentiment in that quarter which belongs to the top (bottom) 30% of the time-series values.

5.3.3 Institutional Ownership

Each institutional investor's quarterly holdings are obtained from Thomson-Reuters institutional holding database, which is based on institutional investors' 13(f) filings with Securities and Exchange Commission (SEC). It is required by SEC that institutional investors with $100 million or more in assets under management file a Form 13F to report all equity positions greater than 10,000 shares or $200,000 in market value within 45 days of the end of the calendar quarter. The stock market and institutional ownership data span from September 1993 to December 2014. The institutional ownership of a stock is measured as the number of shares held by institutional investors scaled by the number of shares outstanding at the end of each quarter. We follow Sias (2004) and apply several selection criteria to institutional data. First, a manager must hold at least one stock at both the beginning and the end of the quarter. Second, a stock must be traded by at least one institutional investor during the quarter. Table 5.1 presents summary statistics for the institutional data used in the study. Panel A reports the total number of institutional investors (overall and by investor type). The first column presents the times-series average across all 84 quarters and the other columns report the results every five years. On average there are 2194 institutions trading. As seen in panel A, the number of institutions increases steadily over the sample period from a low of 1,132 in 1993 to a high 3,305 in 2014. Panel A also shows that independent advisors constitute a significant part of institutional investors and indicates that the number of institutions required to file 13F reports is primarily driven by a substantial increase in the number of independent advisors, which is consistent with Gompers and Metrick (2001) and Sias (2004). In addition, the number of independent advisors and unclassified institutions increases substantially

Table 5.1 Descriptive Statistics

This table shows descriptive statistics for the number of institutional investors, the number of stocks traded by institutional investors. For each quarter between December 1993 and December 2014 we calculate the number of institutions and the number of stocks traded by at least 1, 5, 10, 20 and 50 institutional investors and by different types of institutional investors. The table reports the time-series averages of these values for the whole sample period and every 20 quarters. The current consensus recommendation level is the mean of all outstanding recommendations for a given stock and only the most recent recommendation which is issued within the last 12 months for a given analyst is included and the consensus recommendation revision is the difference between the current and the prior recommendation levels.

Year/quarter	1993-2014 average	1993/Q4	1998/Q4	2003/Q4	2008/Q4	2014/Q4
Panel A. Number of institutional investors						
No. of Institutions in database	2,194	1,132	1,568	2,002	2,962	3,305
No. of banks	189	217	184	172	188	183
No. of insurance companies	64	74	77	62	55	50
No. of mutual funds	53	68	65	52	42	38
No. of independent advisors	1,632	698	1,156	1,309	2,318	2,677
No. of Unclassified	189	75	86	407	359	357
Panel B. No. of stocks traded by institutions						
≥1 institution	6,756	3,131	5,673	7,266	8,445	9,267
≥5 institutions	7,020	5,024	5,436	7,100	8,334	9,205
≥10 institutions	6,626	4,320	5,046	6,762	8,069	8,933
≥20 institutions	5,781	3,415	4,192	5,935	7,239	8,122
≥50 institutions	4,093	2,131	2,498	4,120	5,446	6,270
≥5 banks	5,761	2,657	4,376	6,090	7,413	8,267
≥5 insurance companies	4,361	2,431	2,810	4,586	5,631	6,348
5 mutual funds	4,349	2,236	3,113	4,617	5,549	6,229
≥5 independent advisors	6,579	3,514	5,224	6,900	8,192	9,067
≥ 5 unclassified	6,756	837	2,017	4,059	5,449	6,324

Panel C. Consensus recommendation revision categories

Consensus Recommendation Revision	Frequency	Percentage
Upgrade	35,875	24.03%
No change	73,638	49.32%
Downgrade	39,785	26.65%
Total	149,298	100%

over time whereas the number of other institution groups falls steadily over the sample period. Panel B reports the number of stocks with at least 1, 5, 10, 20 or 50 institutions as well as the number of stocks with at least five of each type of the institutional traders. On average, there are 6765, 7020, 6626, 5781 and 4093 stocks traded by at least one, five, ten and twenty institutional traders each quarter respectively, indicating that the number of traded stocks decreases steadily as the number of institutions increases. Panel B reveals that the number of stocks traded by institutional investors has increased dramatically over time in all groups of institutions. The figures are consistent with those in Sias (2004).

5.3.4 Institutional Herding Measures

There are two commonly used institutional herding measures. The first micro-level herding measure is the LSV model.[79] According to the LSV metrics, herding is measured as the tendency of institutional investors to buy or sell a particular security relative to what they would do if they trade randomly over the same period of time. The LSV herding is measured as the percentage of net buyers (investors who increase their ownership in a stock during a given period) relative to the total number of investors who trade that stock minus an adjustment factor that decreases as the number of investors active in that stock increases. The LSV herding measure, HM, is measured as:

$$HM_{it} = \left|P_{i,t} - P_t\right| - AF_{i,t} \qquad (5.1)$$

Where $P_{i,t}$ is the fraction of institution buying security k during quarter t. P_t is the cross-sectional mean average of the raw fraction of institutions buying across k securities during quarter t. The first term captures the extent to which the raw fraction of institutions buying in stock k deviates from the cross-section mean average of the raw fraction of buying. The second term is the expected value of the first term under a binomial distribution with the probability P_t. This adjustment factor $AF_{i,t}$ ensures that the LSV herding measure will be zero if all institutional investors trade independently. Lakonishok et al. (1992) compute the level of herding as the pool-average across all stocks and all periods. The higher HM is, the stronger the herding. For instance, HM=4% suggests that out of every 100 trading transactions, four more investors trade on the same side of the market over the same period of time than would be expected if all traders traded independently. The last term in Equation (5.1), $AF_{i,t}$ is an adujustment factor for security i in

[79] The LSV model (1992) has been widely used in the herding literature. (e.g. Grinblatt et al., 1992, Wermers, 1999)

quarter t, which controls for random variation around expected percentage of buys, under the null hypothesis of random and independent trading by institutional investors. It is calculated for each security-quarter by assuming the number of institutions buying security i in quarter t and following a binomial distribution with probability P_t.

To distinguish the direction of herding, herding on the buy and sell sides is analysed. The buy herding (BHM_{it}) and sell herding (SHM_{it}) are defined as follows (Wermers, 1999):

$$BHM_{it} = HM_{it} \text{ if } P_{i,t} - P_t > 0 \tag{5.2}$$

$$SHM_{it} = HM_{it} \text{ if } P_{i,t} - P_t < 0 \tag{5.3}$$

Our second empirical measure of herding at the micro-level is constructed by Sias (2004) who examines institutional herding by computing the cross-sectional correlation between institutional investors' demand this quarter and last quarter.[80] At the beginning and the end of each quarter, each institutional investor's position is calculated for each security as a fraction of the security's shares outstanding. We classify an institutional investor as a buyer if ownership of the investor in the security increases and a seller if their ownership decreases.

To analyse institutional herding, we begin by estimating a cross-sectional regression across K securities:

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t} \tag{5.4}$$

Where $\Delta_{k,t}$ is the standardised fraction of institutions buying security k in the current quarter t, $\Delta_{k,t-1}$ is the standardised fraction of institutions buying security k in the last quarter t-1 and $\varepsilon_{k,t}$ is a zero mean error term. The coefficient β_t is the cross-sectional correlation between institutional demand in the current quarter and institutional demand in the last quarter and it measures the extent to which institutional investors herd into the same security from the current quarter to the last quarter. The level of Sias herding is calculated as the time-series average of the coefficient β. The coefficient β_t consists of two components, institutional investors following their own trades and institutional investors following other institutional investors' trades. Specifically,

[80] Sias's (2004) model has been widely used in past studies (see, e.g. Choi and Sias 2009, Holmes et al. 2013)

$$
\begin{aligned}
\beta_t &= \rho(\Delta_{k,t}, \Delta_{k,t-1}) \\
&= \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})} \right] \\
&\times \sum_{k=1}^{K} \left[\sum_{n=1}^{N_{k,t}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{n,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t} N_{k,t-1}} \right] \\
&+ \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})} \right] \\
&\times \sum_{k=1}^{K} \left[\sum_{n=1}^{N_{k,t}} \sum_{m=1, m\neq n}^{N_{k,t-1}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t} N_{k,t-1}} \right]
\end{aligned}
\tag{5.5}
$$

Where K is number of securities, D is a dummy variable equal to one (zero) if trader n is a buyer (seller) of security k in quarter t, Raw is the raw fraction of the number of institutions buying security k during quarter t, $\sigma(\mathrm{Raw}\Delta_{k,t})$is its cross-sectional standard deviation across K securities, $\overline{Raw\Delta_t}$ is the cross-sectional mean average of raw fraction of the number of institutions buying in quarter t, $N_{k,t}$ is the number of institutional traders trading security k during quarter t, $D_{m,k,t-1}$ is a dummy variable if trader m (m≠n) is a buyer of security k during quarter t-1. All other lag variables are defined similarly. The level of Sias herding is calculated as the time-series average of coefficient β.

Sias (2004) measures herding without distinguishing the direction of herding. Following a number of previous studies (e.g. Grinblatt et al., 1995; Wermers, 1999; Wylie, 2005), we further analyse buy herding (following each other into securities) and sell herding (following each other out of securities) to examine whether institutions buy or sell stocks when herding, where in Eq. (4) buy herding is measured as institutions that bought the security k in the last quarter t-1 ($Raw_{k,t-1}$>0.5) and sell herding is measured as institutions that sold the security k in the last quarter t-1 ($Raw_{k,t-1}$<0.5).

The key difference between the LSV and Sias herding measures is that while the former looks indirectly for cross-sectional temporal dependence within a period, the latter test directly whether institutional investors follow each other's trades in the subsequent period. The two measures allow us to capture different aspects of herding since the LSV measure captures institutional herding based on the trading signal of individual sentiment and analyst recommendations within a period whereas the Sias measure captures how institutional investors following each others' trades after the interaction of the two factors. By using both measures, we will be able to gain better insights into the extent to which herding is intentional or spurious.

5.4 Empirical Analysis

This section reports the empirical evidence on how investor sentiment and analyst recommendation revisions interact in affecting institutional herding using the previously established LSV and Sias herding measures over the sample period. We first report institutional herding on stocks with analyst recommendations available, and then examine herding under analyst recommendation revisions and under different investor sentiment periods separately. Lastly, we investigate how both factors interact in influencing institutional herding.

5.4.1 Institutional Herding Evidence

5.4.1.1 Evidence of Within-Period Herding

Analysis begins by examining whether institutions herd in stocks with analyst recommendations available using the LSV herding measure. Table 5.2 reports the average level of LSV herding as defined in equation (5.1) and Wermer's (1999) buy- and sell-herding measure as defined in equation (5.2) and (5.3) for stocks traded by at least 1, 5 and 20 institutional investors. The results reported related to the pooled average of herding for all stocks over the sample period. The three respective mean levels of aggregate herding are 3.763%, 3.534%, and 3.099% for stocks traded by at least 1, 5 and 20 institutional investors, with all being significantly different from zero at the 1% level. The figures are consistent with the findings of Brown et al. (2013) and Wermers (1999) for mutual funds. It is interesting to notice that herding decreases monotonically as trading activity by institutional investors increases, suggesting that stocks traded by large numbers of institutions are generally large value stocks and show lower levels of herding (Wermers, 1999). Moreover, sell herding is significantly stronger than buy herding, suggesting that institutions herd more strongly on the sell-side than the buy-side, which is consistent with the findings of Brown et al. (2013) for mutual funds.

5.4.1.2 Evidence of Adjacent-Period Herding

In this sub-section, we examine whether institutions herd in stocks using the Sias herding measure as defined in equations (5.4) and (5.5). The results reported relate to the average coefficients over the 84 quarters regressions. Table 5.3 reports the average of the estimates of the coefficient β and its two components i.e. institutions following their own trades and following the trades of others. As can be seen from Panel A of Table 5.3, the β is estimated to be a significant 36.884%, 37.247%, and 35.915% for the cases in which there are at least 1, 5 and 20 active institutions, respectively. These figures

Table 5.2 Evidence of Within-Period Herding

This table shows the mean level of LSV aggregate, buy and sell herding measures for stock quarters where there are at least 1, 5, 20 institutional investors during the 1993-2014 period. The aggregate LSV herding measure HM, for each stock-quarter is defined as $HM_{it} = \left|P_{i,t} - P_t\right| - AF_{i,t}$, where $P_{i,t}$ is the fraction of number of buyers to the total number of traders during quarter t, P_t is the cross-sectional mean average of fraction of buyers across k securities in quarter t and $AF_{i,t}$ is an adjustment factor ensures the measure will be zero if no herding occurs. The buy herding is measured as HM_{it} conditional on $P_{i,t} - P_t > 0$ and the sell herding is measured as HM_{it} conditional on $P_{i,t} - P_t < 0$. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

	At least 1 institutions	At least 5 institutions	At least 20 institutions
Aggregate Herding	0.03763(81.13)***	0.03534(71.31)***	0.03099(69.87)***
Buy herding	0.02934(37.31)***	0.02934(35.91)***	0.02806(29.88)***
Sell Herding	0.04633(41.33)***	0.04171(39.27)***	0.03420(32.18)***
Buy-Sell	-0.01699(-7.18)***	-0.01237(-6.64)***	-0.00614(-2.38)**

are all more than twice as large as those of Sias (2004). This is not surprising since that our sample is restricted to stocks with analyst recommendations available. The results provide strong evidence that herding takes place for stocks with analyst recommendations during the sample period. The component that arises from institutions following the trades of others constitutes a significant portion of the β (accounting for almost 80% of the β), indicating that there is strong evidence of institutions following the trades of others and relatively little evidence of institutions following their own trades.

We then partition the average of β and its two components into two parts, namely the Sias buy and sell herding as defined in section 5.5.4 where in Eq. (5.4) buy herding is measured as institutions that bought the security k in the last quarter t-1 ($Raw_{k,t-1}$>0.5) and sell herding is measured as institutions that sold the security k in the last quarter t-1 ($Raw_{k,t-1}$<0.5). The results for

Table 5.3 Evidence of Adjacent-Period Herding

This table reports the mean level of the Sias total, buy, and sell herding where there are at least 1, 5, 20 institutional investors during the 1993-2014 period. The Sias measure is the cross-sectional correlation in adjacent periods. The correlation is partitioned into two parts, cross-sectional correlation due to funds following their own trades and due to funds following the trades of others. The total correlation and two partitions are further divided into two parts, buy herding (institutions buy in quarter t-1) and sell herding (institutions sell in quarter t-1). Panel A presents the average correlation, the contribution of institutions following their own trades and the contribution of institutions following the trades of others. Panel B and C present the average correlation and two components for buy and sell herding, respectively. Panel D shows the difference in the average correlation and two components between buy- and sell-herding. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

	At least 1 institutional investors	At least 5 institutional investors	At least 20 institutional investors
Panel A. Total cross-sectional correlation			
Average coefficient	0.36884(31.12)***	0.37247(33.12)***	0.35915(33.27)***
Institutions following their own trades	0.07676(13.27)***	0.06306(12.98)***	0.05635(11.90)***
Institutions following the trades of others	0.29208(25.34)***	0.30941(25.68)***	0.30280(27.13)***
Panel B. Contribution of Buy			
Average coefficient	0.19243(28.60)***	0.19600(28.91)***	0.19731(29.31)***
Institutions following their own trades	0.04005(12.31)***	0.03318(12.01)***	0.03096(11.78)***
Institutions following the trades of others	0.15238(20.54)***	0.16282(22.35)***	0.16635(22.98)***
Panel C. Contribution of Sell			
Average coefficient	0.17209(20.10)***	0.17283(21.57)***	0.16321(19.80)***
Institutions following their own trades	0.03581(10.37)***	0.02926(9.88)***	0.02561(9.13)***
Institutions following the trades of others	0.13628(18.34)***	0.14357(19.56)***	0.13760(17.21)***
Panel D. Buy-Sell			
Average coefficient	0.02035(1.53)	0.02318(1.99)**	0.03410(2.03)**
Institutions following their own trades	0.00423(2.12)**	0.00392(3.12)***	0.00535(4.13)***
Institutions following the trades of others	0.01612(1.51)	0.01926(3.77)***	0.02875(3.98)***

the Sias buy- and sell-herding show a similar pattern to the aggregate adjacent-period herding. To illustrate, as can be seen from Panel B of Table 5.3, the β of buy herding is estimated to be a significant 19.243%, 19.6%, and 19.731% for the cases in which there are at least 1, 5 and 20 active institutions, respectively. Similarly, the β of sell herding is estimated to be a significant 17.209%, 17.283%, and 16.321% for the cases in which there are at least 1, 5 and 20 active institutions, respectively. The component that arises from institutions following the trades of others contributes to a significant portion of the β, suggesting strong evidence of institutions following the trades of others. The results in Panel D reveal that buy herding is significantly stronger than sell herding when there are more than five institutions. The difference between buy- and sell-herding is statistically different from zero at the 5% level, suggesting institutions herd more strongly on the buy-side than the sell-side in the subsequent period.

5.4.2 Analyst Recommendation Revisions and Institutional Herding

In this section, we investigate whether analyst recommendation revisions affect institutional herding. Specifically, during each quarter, each stock is classified as an upgrade, no change or downgrade stock according to its level of consensus analyst recommendation revisions. We then compute the mean level of herding separately for stocks with upgrades, no change, and downgrades.

5.4.2.1 Analyst Recommendation Revision and Within-Period Herding

We first examine the effect of analyst recommendation revisions on within-period herding. Recall that H1 hypothesised that analyst recommendation revisions have a significant impact on within-period herding and the level of herding stronger for stocks with downgrades than for stocks with upgrades. Table 5.4 reports the mean level of LSV herding measures (aggregate, buy and sell) for stocks with upgrades, no change and downgrades as well as the difference in herding between upgrades and downgrades, respectively. The average level of sell herding is statistically higher than that of buy herding in all analyst recommendation revision groups, suggesting that institutional investors herd more strongly on the sell side, which is consistent with the findings of Brown et al. (2013). As can be seen from the first row of Table 5.4, the mean level of aggregate herding for upgrades and downgrades is 3.133% and 3.573%, respectively, with both being significant at the 1% level. The difference in aggregate herding between upgrades and downgrades is 0.44%, which is statistically significant at the 5% level, indicating institutions herd more strongly on downgrades, consistent with hypothesis 1.

The mean level of buy herding for upgrades and downgrades is 2.773% and 2.727%, respectively, indicating there is no meaningful difference in herding between upgrades and downgrades on the buy-side. In contrast, the average

Table 5.4 Analyst Recommendations and Within-Period Herding

This table presents the average levels of the LSV herding under different analyst recommendation revisions (upgrades and downgrades) and the difference between upgrades and downgrades. The LSV herding measures (aggregate, buy and sell) are defined in Table 5.2. The consensus recommendation revision is the difference between the current and the prior recommendation levels and the current consensus recommendation level is the mean of all outstanding recommendations for a given stock and only the most recent recommendation which is issued within last 12 months for a given analyst is included. The consensus upgrades, downgrades and No Change are defined as the value of the consensus revision is higher than, less than and equal to zero, respectively. For brevity, we only report results for stocks with upgrades and downgrades. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

	Upgrade	Downgrade	Up. - Down.
Aggregate herding	0.03133(69.03)***	0.03573(57.87)***	-0.00440(-2.13)**
Buy herding	0.02773(86.20)***	0.02727(86.76)***	0.00046(0.87)
Sell herding	0.03517(70.38)***	0.04362(90.75)***	-0.00845(-6.18)***
Buy. - sell.	-0.00744(-7.98)***	-0.01635(-13.13)***	0.00891(-8.91)***

level of sell herding for stocks with upgrades and downgrades is 3.517% and 4.362%, respectively, indicating investors herd more strongly for downgrades on the sell-side. The evidence is consistent with the findings of Brown et al. (2013) and supports the view that investors herd more strongly to sell stocks with consensus downgrades. By and large, the difference in aggregate herding between upgrades and downgrade primarily arises from sell herding rather than from buy herding.

5.4.2.2 Analyst Recommendation Revisions and Adjacent-Period Herding

We next turn to consider the relation between analyst recommendation revisions and adjacent-period herding. It is hypothesised (H2) that analyst recommendation revisions have no significant impact on adjacent-period herding. Table 5.5 reports the results for adjacent-period herding (aggregate, buy and sell) for stocks with upgrades, downgrades, and no change as well as the difference in herding between upgrades and downgrades. As can be seen from table 5.5, the average estimates of the coefficient β and its two components are slightly higher for stocks with downgrades than stocks with upgrades but there is no meaningful difference between them. For example, as shown in Panel A, the coefficients β of aggregate herding for upgrades and downgrade is estimated to be a significant 36.847% and 37.541%, respectively. However, the difference in β between upgrades and downgrades is estimated to be an insignificant 0.694%, consistent with H2.

This can happen for a few reasons. First, when analyst information arrives in period t-1, institutional investors tend to herd in response to such information reasonably quickly because the investment value of analyst research is short-lived (Brown et al., 2013). As a result, the Sias measure may not capture such herding in the subsequent period t. Second, investors feel no needs to follow the trades of others when analyst information releases. Therefore, there is no significant difference in the Sias herding between upgrades and downgrades. It can be seen from panel B that the β of buy herding for upgrades and downgrades is estimated to be a significant 19.369% and 17.759%, respectively. However, the difference in buy herding for upgrades and downgrades is insignificant. Panel B also reveals that the components arising from following their own trades and the trades of others for stocks with upgrades are slightly larger than those for stocks with downgrades but the differences are also insignificant. Similarly, in Panel C, the β and its two components of sell herding for stocks with upgrades are slightly smaller than those for stocks with downgrades but the differences are insignificant. Furthermore, we can observe from Panel C that for stocks with upgrades, the β and its two components for buy herding are significantly larger than those for sell herding whereas for stocks with downgrades, the β and its two components for sell herding are significantly larger than those for buy herding. The findings suggest that institutions herd more strongly for stocks with upgrades on the buy-side than the sell-side but they herd more strongly for those with downgrades on the sell-side than the buy-side.

In sum, the findings of adjacent-period herding suggest that there is no significant difference in herding between upgrades and downgrades. The evidence reveals that analyst recommendation revisions have an insignificant effect on adjacent-period herding if institutions herd by following others' trades. In addition, we find that buy (sell) herding is stronger than sell (buy) herding for stocks with upgrades (downgrades) in the subsequent period. To capture herding in response to analyst information within the same period, the LSV herding measure in the previous section is able to examine the relation between immediate institutional herding and analyst recommendation revisions. The results show that within-period herding (measured by LSV) is much

Table 5.5 Analyst Recommendations and Adjacent-Period Herding

This table presents the Sias herding levels under different analyst recommendation revisions (upgrades and downgrades). The Sias herding measures (aggregate, buy and sell) and their components are defined in Table 5.3. The consensus recommendation revision is the difference between the current and the prior recommendation levels and the current consensus recommendation level is the mean of all outstanding recommendations for a given stock and only the most recent recommendation for a given analyst is included. The consensus upgrades, downgrades and No Change are defined as the value of the consensus revision is bigger, smaller and equal to zero, respectively. For brevity, we only report results for stocks with upgrades and downgrades. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

	Upgrade	Downgrade	Up. – Down.
Panel A. Total cross-sectional correlation			
Average coefficient	0.36847(29.78)***	0.37541(30.41)***	-0.00694(-0.99)
Institutions following their own trades	0.06065(12.33)***	0.05594(11.26)***	0.00470(0.81)
Institutions following the trades of others	0.30783(22.90)***	0.31947(23.11)***	-0.01164(-1.34)
Panel B. Contribution of Buy			
Average coefficient	0.19396(25.71)***	0.17759(22.71)***	0.01637(1.38)
Institutions following their own trades	0.03192(7.81)***	0.02646(6.29)***	0.00546(1.34)
Institutions following the trades of others	0.16204(17.98)***	0.15113(16.49)***	0.01091(1.41)
Panel C. Contribution of Sell			
Average coefficient	0.17441(17.53)***	0.19831(24.29)***	-0.02390(-1.61)
Institutions following their own trades	0.02871(7.25)***	0.02955(8.01)***	-0.00084(-0.34)
Institutions following the trades of others	0.14570(16.13)***	0.16876(18.19)***	-0.02306(1-.63)
Panel D. Buy-Sell			
Average coefficient	0.01955(2.13)**	-0.02072(-2.31)**	0.04027(2.46)**
Institutions following their own trades	0.00322(3.11)***	-0.00309(-2.71)***	0.00631(3.45)***
Institutions following the trades of others	0.01633(1.99)**	0.01763(1.96)**	-0.0013(-0.34)

stronger for stocks with downgrades than stocks with upgrades. It suggests that the effect of analyst recommendation revisions has a significant impact on within-period herding if institutions herd based on recommendation revisions, whereas recommendation revisions have no significant impact on adjacent-period herding if the herding is primarily driven by following the trades of others in the subsequent period.

5.4.3 Investor Sentiment and Institutional Herding

Previous empirical studies suggest that individual sentiment might influence institutional herding (Laknoishok et al., 1992; Barberris and Shleifer, 2003; De Long et al.; 1999; and Shleifer, 2000). Liao et al. (2011) examine the relationship between mutual fund herding and investor sentiment. They find strong evidence that mutual funds engage in sell herding in stocks with high individual sentiment, suggesting that rational investors tend to counteract optimistic sentiment of individual investors. In this section, we examine whether investor sentiment affects institutional herding using both herding measures.

5.4.3.1 Investor Sentiment and Within-Period Herding

It is hypothesised (H3) that within-period herding will be stronger during periods of individual optimism than during periods of individual pessimism and this is primarily due to sell herding during optimism periods. We first employ Baker and Wurgler's (2007) sentiment index to identify the sentiment quarter in the current quarter t as optimistic, mild or pessimistic. The sentiment in quarter t is estimated by the quarterly sentiment value in t-1 which is calculated as the average of the monthly investor sentiment and optimistic (pessimistic) sentiment periods are defined as the value of the index in that quarter belongs to the top (bottom) 30% of the time-series value.

Table 5.6 reports the mean level of the within-period herding (aggregate, buy and sell) in optimistic and pessimistic sentiment periods as well as the difference between the two sentiment periods. Generally, sell herding is significantly stronger than buy herding across both sentiment periods. The mean levels of aggregate herding in optimistic and pessimistic periods are 4.171% and 3.546%, respectively, and the difference between the two sentiment periods is significantly different from zero at the 1% level, suggesting that institutional investors herd more strongly in optimistic periods. The average levels of buy herding following optimistic and pessimistic periods are 3.267% and 2.988%, respectively, with the difference between optimism and pessimism is significant at the 10% level. Furthermore, the difference in sell herding between optimistic and pessimistic sentiment is 0.878%, which is significantly different from zero at the 1% level, suggesting that higher aggregate herding during optimistic periods arises primarily from

Table 5.6 Investor Sentiment and Within-Period Herding			
This table presents the average levels of the LSV herding under different investor sentiment periods (optimistic and pessimistic). The LSV herding measures (aggregate, buy and sell) are defined in Table 5.2. The Baker and Wurgler (2007) sentiment index is used to identify optimistic and pessimistic investor sentiment quarters. The quarterly investor sentiment index is calculated as the average of the monthly investor sentiment index over the quarter and optimistic (pessimistic) sentiment periods are defined as the value of the index in that quarter belongs to the top (bottom) 30% of the time-series value. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).			
	Optimistic	Pessimistic	Opt. - Pess.
Aggregate herding	0.04171(89.34)***	0.03546(86,22)***	0.00625(8.22)***
Buy herding	0.03267(76.89)***	0.02988(62.18)***	0.00280(1.77)*
Sell herding	0.05124(73.24)***	0.04246(62.89)***	0.00878(11.33)***
Buy. - sell.	-0.01856(-17.13)***	-0.01258(-16.14)***	-0.00598(-10.33)***

sell herding rather than buy herding. In sum, the findings are consistent with hypothesis 3 and provide support to the findings of Liao et al. (2011) in which institutional investors tend to herd to counteract optimistic sentiment of individual investors.

5.4.3.2 Investor Sentiment and Adjacent-Period Herding

Baker and Wurgler's (2007) sentiment index is used to identify the sentiment quarter in the prior quarter t-1 as optimistic, mild or pessimistic. We partition the time-series estimates of β into three groups representing optimism, mild and pessimism and then take the time-series average of coefficient β in each sentiment group. Recall that H4 hypothesised adjacent-period herding will be higher following pessimistic periods than following pessimistic periods. Table 5.7 reports the Sias herding measures (aggregate, buy and sell) following optimistic and pessimistic quarters as well as the difference in all herding measures between the two sentiment periods. There is a marked difference in adjacent-period herding across sentiment periods.

As can be seen from Panel A of Table 5.7, the average of the estimates of β following optimistic and pessimistic periods are 36.006% and 41.721%, respectively, and the difference is significantly different from zero at the 5% level. We observe from the last column of Panel that the components resulting from institutions following the trades of others following optimistic and pessimistic periods are 28.894% and 37.407%, respectively, and the difference between the two figures is 8.513%, which is statistically significant

Table 5.7 Investor Sentiment and Adjacent-Period Herding

This table presents the Sias herding levels under different investor sentiment periods (optimistic and pessimistic). The Sias herding measures (aggregate, buy and sell) and their components are defined in Table 5.3. The Baker and Wurgler's (2007) sentiment index is used to identify optimistic and pessimistic investor sentiment quarters. The quarterly investor sentiment index is calculated as the average of the monthly investor sentiment index over the quarter and optimistic (pessimistic) sentiment periods are defined as the value in that quarter belongs to the top (bottom) 30% of the time-series value. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

	Optimistic	Pessimistic	Opt.- Pess.
Panel A. Total cross-sectional correlation			
Average coefficient	0.36006(18.11)***	0.41721(21.25)***	-0.05715(-2.43)**
Institutions following their own trades	0.07111(11.63)***	0.04314(9.00)***	0.02797(4.77)***
Institutions following the trades of others	0.28894(15.67)***	0.37407(16.32)***	-0.08513(-4.13)***
Panel B. Contribution of Buy			
Average coefficient	0.21510(15.26)***	0.19972(19.12)***	0.01538(1.46)
Institutions following their own trades	0.04248(9.64)***	0.02065(6.89)***	0.02183(6.13)***
Institutions following the trades of others	0.17262(12.77)***	0.17917(13.43)***	-0.00645(-1.01)
Panel C. Contribution of Sell			
Average coefficient	0.13944(16.20)***	0.20702(17.37)***	-0.06758(-6.23)***
Institutions following their own trades	0.02754(7.13)***	0.02140(6.12)***	0.00614(4.13)**
Institutions following the trades of others	0.11190(14.22)***	0.18562(16.11)***	-0.07371(-8.61)***
Panel D. Buy-Sell			
Average coefficient	0.07566(7.19)***	-0.00730(-1.24)	0.08296(7.43)***
Institutions following their own trades	0.01494(4.13)***	-0.00075(-0.21)	0.01570(4.11)**
Institutions following the trades of others	0.06072(7.01)***	-0.00655(-1.11)	0.06726(6.01)***

at the 1% level. The results suggest that institutional investors herd more strongly following pessimistic periods than following optimistic periods, consistent with hypothesis 4. The evidence indicates that when sentiment is pessimistic, institutional investors become more uncertain about making trading decisions and tend to wait until the next quarter to follow the actions of other investors, whereas when sentiment is optimistic, investors do not feel the need to imitate the actions of others and make trading decisions independently as the sentiment countering hypothesis suggests that way. Moreover, as shown in the second row of Panel A, the components resulting from funds following their own trades following optimistic and pessimistic periods are 7.111% and 4.314%, respectively, with the difference being a significant 2.797%, suggesting that institutions are more likely to herd by following their own trades following optimistic periods than following pessimistic periods.

Panels B and C report adjacent-period buy- and sell-herding following optimistic and pessimistic periods, respectively. As can be seen from Panel B of Table 5.7, the average of β of buy herding following optimistic and pessimism periods are 21.510% and 19.972%, respectively, with the difference being insignificantly different from zero. The components resulting from institutions following the trades of others following optimistic and pessimistic periods are 17.262% and 17.917%, respectively, and again, the difference is insignificantly different from zero. However, the difference in components resulting from institutions following their own trades between the two sentiment periods is a significant 2.183%, suggesting institutions herd more strongly to buy by following their own trades following optimistic periods than following pessimistic periods. We observe from Panel C that, the average of β of sell herding following optimistic and pessimistic periods are 13.944% and 20.702%, respectively, and the difference is estimated to be a significant 6.758%. It suggests that institutional investors herd more strongly on the sell side following pessimistic periods than following optimistic periods. The component resulting from institutions following their own trades is significantly higher following optimistic periods than that following pessimistic periods whereas the component resulting from institutions following the trades of others is significantly lower following optimistic periods than that following pessimistic periods. The evidence suggests that higher sell herding following pessimistic periods is primarily driven by institutions following the trades of others.

In sum, we find strong evidence that adjacent-period herding is significantly stronger following pessimistic periods than following optimistic periods, which is consistent with H4 and the notion that institutional investors feel the need to follow the trades of others when the market is more volatile. We also find that adjacent-period sell herding is stronger following pessimistic periods than following optimistic periods but there is no significant difference in buy herding between the two sentiment periods.

5.4.4 Analyst Recommendations, Investor Sentiment and Institutional Herding

We now turn to the main part of the analysis to consider the interaction of analyst recommendation revisions and investor sentiment on within-period and adjacent-period herding.

5.4.4.1 Analyst Recommendations, Investor Sentiment and Within-Period Herding

This section investigates how analyst recommendation revisions and investor sentiment interact in influencing within-period herding using the LSV measure. To examine the interaction, we double sort the data sample on consensus recommendation revisions and investor sentiment quarters. Specifically, during each quarter, we classify a stock as an upgrade, no change or downgrade stock based on the consensus analyst recommendation revisions and then categorise each quarter as optimistic, mild or pessimistic according to the quarterly value of sentiment. The level of within-period herding is calculated as the pool-average of estimates in that category.

Table 5.8 shows the results for the LSV herding measures (aggregate, buy and sell) double sorted by analyst recommendation revisions and investor sentiment. Before discussing specific results, hypothesis 5 states that within-period herding will be the most pronounced for stocks with downgrades (upgrades) in the presence of optimistic (pessimistic) sentiment and herding will be lower for upgrades (downgrades) when sentiment is optimistic (pessimistic). The results in Panel A provides clear support for this hypothesis except from the strong within-herding for stocks with upgrades during pessimistic periods. Panel A reveals that there is clear evidence that the average level of herding is higher during optimistic periods than during pessimistic periods across both recommendation revision groups, but the effect of consensus recommendation revisions on institutional herding is only prominent during optimistic periods. To illustrate, the average levels of herding for upgrades and downgrades during optimistic periods are 3.515% and 3.945%, respectively, with the difference being statistically significant at the 10% level, indicating that institutional investors herd more strongly for

Table 5.8 Analyst Recommendations, Investor Sentiment and Within-Period Herding

This table reports the mean level of the LSV herding measures (aggregate, buy, and sell) double sorted by consensus analyst recommendation revisions and investor sentiment during the 1993-2014 period. The consensus recommendation revision is the difference between the current and the prior recommendation levels and the current consensus recommendation level is the mean of all outstanding recommendations for a given stock and only the most recent recommendation for a given analyst is included. The consensus upgrades and downgrades refer to when the value of the consensus revision is bigger, smaller and equal to zero, respectively. The LSV herding measures (aggregate, buy and sell) are defined in Table 5.2. The Baker and Wurgler's (2007) sentiment index is used to identify optimistic, mild and pessimistic investor sentiment quarters. The quarterly investor sentiment is calculated as the average of the monthly investor sentiment proxy over the quarter and optimistic (pessimistic) sentiment periods are defined as when value in that quarter belongs to the top (bottom) 30% of the time-series value. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

	Upgrade	Downgrade	Up. - Down.
Panel A. Aggregate Herding measure			
Optimistic	0.03515(71.22)***	0.03945(75.22)***	-0.00429(-1.79)*
Pessimistic	0.03023(60.37)***	0.03232(62.33)***	-0.00209(-1.45)
Opt.- Pess.	0.00493(8.15)***	0.00713(9.13)***	-0.00220(-1.51)
Panel B. Buy herding			
Optimistic	0.03190(60.37)***	0.02987(57.89)***	0.00203(1.03)
Pessimistic	0.02927(52.34)***	0.02729(49.23)***	0.00198(1.21)
Opt.- Pess.	0.00263(1.47)	0.00258(1.43)	0.00006(0.08)
Panel C. Sell herding			
Optimistic	0.03908(77.21)***	0.04744(81.34)***	-0.00836(-9.22)***
Pessimistic	0.03149(61.34)***	0.03796(77.23)***	-0.00646(-7.38)***
Opt.- Pess.	0.00759(7.29)***	0.00948(9.78)***	-0.00189(-1.61)
Panel D. Buy - Sell herding			
Optimistic	-0.00718(-8.01)***	-0.01757(-11.45)***	0.01039(9.45)***
Pessimistic	-0.00223(-1.48)	-0.01067(-6.34)***	0.00844(4.99)***
Opt.- Pess.	-0.00495(-4.19)***	-0.00690(-3.89)***	0.00195(1.48)

stocks with downgrades in the presence of optimistic sentiment. In contrast, the average levels of herding for upgrades and downgrades in the presence of pessimistic sentiment are 3.023% and 3.232%, with the difference being insignificantly different from zero.

The evidence suggests that institutional investors are more likely to follow analyst recommendation revisions-in particular downgrades during optimistic periods than during pessimistic periods. Furthermore, we observe from Panel A that herding is the strongest for stocks with downgrades when sentiment is optimistic, which is consistent with H5 and our cognitive argument in which if there is no cognitive dissonance experienced by investors (as both optimism and downgrades suggest them to sell as shown in Exhibit 5.1), they will react strongly to the two factors. Moreover, we find that herding is the weakest for stocks with upgrades in the presence of pessimistic periods. We also find that the average levels of herding for stocks with upgrades during optimistic periods and for stocks with downgrades during pessimistic periods are lower than that for stocks with downgrades during optimistic periods. The findings are consistent with our argument as shown in Exhibit 5.1: If cognitive dissonance is experienced (upgrades vs optimism and downgrades vs pessimism), herding will be lower.

To investigate the impact of consensus recommendation revisions and investor sentiment further, we partition the aggregate herding into buy and sell herding as shown in Panels B and C, respectively. As can be seen from Panel B, there is no significant difference in buy herding between the two revision groups and the two sentiment periods. In contrast, as can be seen from Panel C, the pattern of sell herding results shows a marked difference across sentiment and recommendation revision groups. Specifically, the average level of sell herding is 4.744% for stocks with downgrades in the presence of optimistic sentiment, which is significantly higher compared to that for stocks with downgrades during pessimistic periods (3.796%) and that for stocks with upgrades during optimistic periods (3.908%). The evidence reveals that institutional investors herd most strongly to sell downgrade stocks during optimistic periods. This is due to both optimism and downgrade suggesting them to sell so they will react strongly to two reinforcing signals. The evidence reveals that the higher herding for stocks with downgrades during optimistic periods arises primarily from the sell side than the buy-side.

In sum, the reported findings in Table 5.8 provide evidence consistent with our hypothesis 5 and suggest that institutional investors are most likely to herd for stocks with downgrades during pessimistic periods and such herding is primarily driven by sell herding.

5.4.4.2 Analyst Recommendations, Investor Sentiment and Adjacent-Period Herding

In this section, we investigate how analyst recommendation revisions and investor sentiment interact in influencing adjacent-period herding. To examine such an interaction, we double sort the data sample on consensus recommendation revisions and investor sentiment. Specifically, during each quarter, we classify a stock as an upgrade or downgrade stock based on the consensus analyst recommendation revisions and then estimate the Sias herding coefficient and its two components for each of the revision groups in each quarter. We then categorise each quarter as optimistic, mild or pessimistic and calculate the time-series average of herding coefficients and their two components in different sentiment periods.

Recall that H6 hypothesised that adjacent-period herding from following the trades of others will be stronger for upgrades (downgrades) when individual sentiment is optimistic (pessimistic). Table 5.9 shows the results for the Sias herding measures (aggregate, buy and sell) double sorted by analyst recommendation revisions and investor sentiment as shown in Panels A, B and C, respectively. The overall pattern of the results shows clear differences across recommendation revision and individual sentiment groups.

As can be seen from Panel A, for stocks with upgrades, the coefficient β for aggregate herding is 37.136% following optimistic periods, which is slightly larger than that following pessimistic periods (36.593%), although the difference is insignificantly different from zero. In contrast, for stocks with downgrades, the average of coefficients β of aggregate herding for stocks with downgrades following optimistic and pessimistic periods are 36.784% and 41.981%, respectively, with the difference being a significant 5.196%, indicating institutional investors herd more strongly for downgrade stocks following pessimistic periods, consistent with hypothesis 6. The evidence in Panel A reveals that the relatively higher herding values for stocks with upgrades following optimism and for stocks with downgrades following pessimism are consistent with H6 and our cognitive dissonance argument: if cognitive dissonance is evident (upgrade vs optimism and downgrade vs pessimism), investors are more likely to wait to trade until the next period and follow the trades of others, resulting in stronger adjacent-period herding in those two cases. The relatively lower herding values for stocks with upgrades during optimistic periods and for stocks with downgrades during pessimistic periods are also consistent with H6 and our argument that if cognitive dissonance is experienced by institutional investors (upgrades vs optimism and downgrades vs pessimism), herding will be lower.

We observe from the second row from Panel A that the coefficients β of buy herding for stocks with upgrades following optimism and pessimism are

21.742% and 17.630%, respectively, with the difference being significant at the 5% level, suggesting that institutions are more likely to herd to buy stocks with upgrades following optimistic periods than following pessimistic periods. However, for stocks with downgrades, there is no significant difference in buy herding between optimism and pessimism. Moreover, as can be seen from the third row from Panel A that the coefficients β of sell herding for stocks with upgrades following optimism and pessimism are 15.104% and 18.158%, with the difference being significantly different from zero at the 5% level, suggesting that institutions are more likely to herd to sell following pessimistic periods even for stocks with upgrades. Similarly, the coefficients β of sell herding for stocks with downgrades following optimism and pessimism are 14.858% and 21.139%, with the difference being statistically significantly at the 1% level, suggesting that institutions are more likely to sell for stocks with downgrades following pessimism than following optimism. Moreover, buy herding is the strongest for stocks with upgrades in the presence of optimistic sentiment whereas as shown in the third row of Panel A, sell herding is the strongest for stocks with downgrades in the presence of pessimistic sentiment. The results reveal that when cognitive dissonance is evident in these cases (upgrades vs optimism and downgrades vs pessimism), institutional investors are more likely to herd in the direction of analyst recommendation revisions. The evidence suggests that when institutions experience cognitive dissonance between the two factors, analyst recommendation revisions appear to be dominant.

Panels B and C of Table 5.9 allow us to examine whether adjacent-period herding in such cases is primarily driven by the portion of institutions following the trades of others. There is clear evidence that adjacent-period herding in each case is primarily driven by following the trades of others and the pattern of the component of following the trades of other as shown in Panel C is similar to that of aggregate adjacent-period herding as shown in Panel A but the results in Panel B shows a different pattern to those in Panel A. To illustrate, as shown in Panel B, for stocks with both upgrades and downgrades, aggregate herding is significantly stronger following optimism than following pessimism for both revision groups. The results in the second and third row of Panel B show that the component of aggregate herding resulting from institutions following their own trades is primarily driven by that of buy herding since buy herding is significantly stronger than sell herding in all cases. The evidence suggests that institutions are more likely to herd to buy stocks by following their own trades following optimism regardless of analyst recommendation revisions. Furthermore, as can be seen from the first row of Panel C, there is an insignificant difference in herding from institutions following the trades of others between optimism and pessimism for stocks with upgrades whereas the portions resulting from institutions following the trades of others for downgrades following optimistic and pessimistic periods are 31.438% and 39.761%, respectively, and the difference is 8.324%, which is statistically significant at the 1% level. The evidence suggests that strong adjacent-period herding for stocks with downgrades following pessimistic periods as shown in Panel A is primarily driven by institutions following the trades of others for stocks. The results in the second row of Panel C reveal that for stocks with upgrades, there is no significant difference for buy herding between optimistic and pessimistic periods. In contrast, the results in the third row of Panel C suggest that institutions tend to herd to sell both upgrade and downgrade stocks following pessimism rather than following optimism.

In sum, the results in Table 5.9 provide strong evidence that adjacent-period herding from following the trades of others is stronger for downgrades when individual sentiment is pessimistic, consistent with hypothesis 6. In addition, the results in Table 5.9 reveal that investors tend to imitate the trades of others to buy (sell) stocks with upgrades (downgrades) following optimistic (pessimistic) periods than following pessimistic (optimistic) periods.

Table 5.9 Analyst Recommendations, Investor Sentiment and Adjacent-Period Herding

This table reports the average levels of the Sias aggregate, buy, and sell herding measure double sorted by investor sentiment and consensus analyst recommendation revisions during the 1993-2014 period. The Sias measure is the cross-sectional correlation in the current and previous quarters. The correlation is partitioned into two parts, cross-sectional correlation due to funds following their own trades and that due to funds following the trades of others. The total correlation and two partitions are further divided into two parts, buy herding (institutions buy in quarter t-1) and sell herding (institutions sell in quarter t-1). The Sias herding measures (aggregate, buy and sell) are discussed in detail in Table 5.3. The consensus recommendation revision is the difference between the current and the prior recommendation levels and the current consensus recommendation level based on the mean of all outstanding recommendations for a given stock, with only the most recent recommendation for a given analyst included. The consensus upgrade or downgrade refer to when the value of the consensus revision is bigger or smaller than zero, respectively. The Baker and Wurgler's (2007) sentiment index is used to identify optimistic, mild and pessimistic investor sentiment quarters. The quarterly investor sentiment is calculated as the average of the monthly investor sentiment proxy over the quarter and optimistic (pessimistic) sentiment periods are defined when the value in that quarter belongs to the top (bottom) 30% of the time-series value. For brevity, the mild results are not reported. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

		Optimistic			Pessimistic			Opt. – Pess.	
	Upgrade	Downgrade	Up. – Down.	Upgrade	Downgrade	Up. – Down.	Upgrade	Downgrade	Up. – Down.
Panel A. Total correlation									
Aggregate herding	0.37136(21.34)***	0.36784(19.88)***	0.00352(1.33)	0.36593(20.81)***	0.41981(22.89)***	-0.05388(-2.04)**	0.00543(-0.71)	-0.05197(-2.03)**	0.05740(2.31)**
Contribution of buy	0.21742(16.12)***	0.21642(15.88)***	0.00100(0.13)	0.17630(16.71)***	0.20065(17.23)***	-0.02435(-1.66)*	0.04112(1.98)**	0.01577(1.03)	0.02535(1.67)*
Contribution of sell	0.15104(15.37)***	0.14858(16.16)***	0.00246(0.47)	0.18158(17.11)***	0.21139(18.11)***	-0.02981(-1.75)*	-0.03054(-1.97)**	-0.06281(-2.71)***	0.03227(1.78)*
Buy- Sell	0.06638(3.12)***	0.067842(3.34)***	-0.00146(-0.21)	-0.00528(-0.51)	-0.01074(-1.03)	0.00546(1.43)	0.07166(2.71)***	0.07857(3.11)***	-0.00691(-0.49)
Panel B. Institutions following their own trades									
Aggregate herding	0.05296(11.33)***	0.05347(11.13)***	-0.00051(-0.13)	0.01936(6.18)***	0.02219(7.17)***	-0.00283(-1.12)	0.03360(3.88)***	0.03128(3.39)***	0.00232(0.43)
Contribution of buy	0.03101(8.31)***	0.03146(8.38)***	-0.00045(-0.11)	0.00933(5.77)***	0.01061(5.89)***	-0.00128(-0.78)	0.02168(3.17)***	0.02085(2.81)***	0.00083(0.09)
Contribution of sell	0.02154(6.22)***	0.02160(6.16)***	-0.00006(-0.06)	0.00961(4.21)***	0.01118(5.91)***	-0.00157(-0.56)	0.01193(2.75)***	0.01042(2.68)***	0.00151(0.12)
Buy- Sell	0.00947(3.18)***	0.00986(2.67)***	-0.00039(-0.31)	-0.00028(-0.09)	-0.00057(-0.19)	0.00029(0.14)	0.00975(2.65)***	0.01043(2.64)***	-0.00068(-0.07)
Panel C. Institutions following the trades of others									
Aggregate herding	0.31839(16.21)***	0.31438(15.10)***	0.00401(0.65)	0.34657(17.11)***	0.39761(18.99)***	-0.05104(-2.01)**	-0.02818(-1.26)	-0.08323(-3.71)***	0.05505(2.14)**
Contribution of buy	0.18641(12.41)***	0.18496(12.98)***	0.00145(0.21)	0.16698(11.08)***	0.19004(13.07)***	-0.02306(-1.65)*	0.01943(1.38)	-0.00508(-0.31)	0.02451(1.61)
Contribution of sell	0.12950(10.34)***	0.12699(10.14)***	0.00251(0.31)	0.17198(13.80)***	0.20021(15.09)***	-0.02823(-1.71)*	-0.04248(-2.19)**	-0.07322(-3.11)***	0.03074(1.81)*
Buy- Sell	0.05691(3.57)***	0.05797(3.13)***	-0.00106(-0.24)	-0.00500(-0.16)	-0.01017(-0.71)	0.00517(0.47)	0.06191(2.41)**	0.06814(2.51)**	-0.00623(-0.31)

5.4.5 Regression Analysis

In the previous section, portfolio analysis is performed in examining the interaction of the two factors on institutional herding. We next investigate the impact of the two factors and their interactions on institutional herding in a multivariate regression setting by taking account of other potential determinants of institutional herding. The goal of this analysis is to investigate the interaction of the two factors on institutional herding and to disentangle such effect from the impact of other variables.

5.4.5.1 Regression Analysis on Within-Period Herding

In this subsection, we investigate the relationship between within-period herding and the interaction of the two factors while controlling for various stock characteristics as in the following model:

$$HM = \alpha_0 + \alpha_1 Sent_{t-1} + \alpha_2 Rev_t + \alpha_3 Sent\_Rev_t + \alpha_4 Strong_{buy} + \alpha_5 Strong_{sell} + \alpha_6 SUE + \alpha_7 MV_{t-1} + \alpha_8 Sent_{t-1} + \alpha_9 CUM_{t-1} + \alpha_{10} CUM_{t-2,t-5} \quad (5.6)$$

$$BHM = \alpha_0 + \alpha_1 Sent_{t-1} + \alpha_2 Rev_t + \alpha_3 Sent\_Rev_t + \alpha_4 Strong_{buy} + \alpha_5 Strong_{sell} + \alpha_6 SUE + \alpha_7 MV_{t-1} + \alpha_8 Sent_{t-1} + \alpha_9 CUM_{t-1} + \alpha_{10} CUM_{t-2,t-5} \quad (5.7)$$

$$SHM = \alpha_0 + \alpha_1 Sent_{t-1} + \alpha_2 Rev_t + \alpha_3 Sent\_Rev_t + \alpha_4 Strong_{buy} + \alpha_5 Strong_{sell} + \alpha_6 SUE + \alpha_7 MV_{t-1} + \alpha_8 Sent_{t-1} + \alpha_9 CUM_{t-1} + \alpha_{10} CUM_{t-2,t-5} \quad (5.8)$$

Where HM is the aggregate LSV herding measure, BHM is the buy herding measure and SHM is the sell herding measure. The independent variable $Sent_{t-1}$ is the Baker and Wurgler sentiment index in quarter t-1 and its coefficient is expected to be positive to be consistent with the argument that institutional investors counteract individual sentiment strongly when sentiment is optimistic. The second independent variable Rev_t is the consensus analyst recommendation revisions in quarter t and its coefficient is expected to be negative be consistent with the hypothesis that herding is stronger for stocks with downgrades than those with upgrades. The third independent variable $Sent_{t-1}* Rev_t$ is an interaction term and its coefficient is expected to be negative since herding is expected to be stronger for downgrades in the presence of optimistic sentiment. The fourth (fifth) independent variable $Strong_{buy}$ ($Strong_{sell}$) equals 1 if the recommendation revision equals 0 and the consensus recommendation is a strong buy (strong sell) in quarter t-1. We use time fixed effects to consider the dynamics of institutional herding. In order to control for potential serial correlation in the residuals, we cluster heteroskedasticity-robust standard errors by firm level.

We follow several empirical studies to include the following potential variables that may influence institutional herding and subsume the power the interaction effect of the two factors (see, for example, Brown et al., 2013; Liao et al., 2011). As for control variables, SUE is the standardised unexpected earnings surprises, which is measured as the unexpected earnings for the most recent quarter relative to earnings four quarters prior, divided by its standard deviation over the prior six quarters.[81] We take account of SUE since institutions may herd in response to earnings information as opposed to analyst recommendation revisions or investor sentiment. MV_t is defined as the market value for stock i in quarter t and its coefficient is expected to be negative since fund managers tend to herd more on small stocks (e.g. Lakonishok et al., 1992; Wermers, 1999). BM_t is the logarithm of book to market ratio for stock i during quarter t-1 and its coefficient is expected to be positive since herding is expected to be stronger among growth stocks (e.g. Wermers, 1999). $Cum_{i,t-1}$ and $Cum_{i,t-2,t-5}$ are the prior quarter returns and the cumulative 12-month returns before the prior quarter, respectively. We include such two variables since the previous literature suggests that herding can be driven by momentum trading (e.g. Wermers, 1999).

Table 5.10 presents the results for equations 5.1 to 5.3. Models 1 and 2 show the results for aggregate herding (5.1). In model 1, aggregate herding is only regressed on investor sentiment, analyst recommendation revisions and t

[81] We follow Brown et al., (2013) to calculate SUE which is measured as the unexpected earnings for the most recent quarter relative to earnings four quarters prior, divided by its standard deviation over the prior six quarters. Other studies (e.g. Truong, 2011) may use different methods to measure SUE which is calculated as the the unexpected earnings for the most recent quarter relative to earnings four quarters prior, divided by stock price prior to the earnings announcement.

Table 5.10 Multivariate Regression of Determinants of Within-Period Herding

This table reports regression results of the LSV herding measure on investor sentiment and analyst recommendation revisions. HM is the aggregate herding measure, BHM is the buy-herding measure and SHM is the sell-herding measure. Sent is the Baker and Wurgler sentiment measure. Rev is the prior-quarter consensus analyst recommendation revision. Sent*Rev is the interaction term between sentiment and revision. Strong_Buy (Strong_Sell) equals 1 if the analyst revision in the current quarter is 0 and the recommendation in the prior quarter is strong buy (sell). SUE is unexpected earnings for the most recent quarter relative to earnings four quarters before, scaled by the standard deviation of earnings over the prior six quarters. MV_{t-1} is the logged market value of a given stock in prior quarter and PB_{t-1} is the logged ratio of market value to book equity in the prior quarter. Cum_{t-1} is cumulative returns of a given stock in previous quarter. $Cum_{t-2,t-5}$ is the one-year cumulative returns of a given stock before the previous quarter. All regressions include time fixed effects and standard errors are clustered at the firm level. The number of observations and the R-squared are reported at the bottom of the table. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

	HM		BHM		SHM	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0371	0.1118	0.0291	0.0853	0.0455	0.1348
	(3.17)***	(2.65)***	(2.83)***	(3.17)***	(2.88)***	(3.69)***
$Sent_{t-1}$	0.0042	0.0033	0.0023	0.0017	0.0069	0.0054
	(2.81)***	(2.69)***	(1.77)*	(1.65)*	(2.99)***	(2.78)***
Rev_{t-1}	-0.0023	-0.0002	0.0004	0.0003	-0.0045	-0.0005
	(-3.11)***	(-0.13)	(2.03)**	(0.33)	(-3.31)***	(-1.78)*
Sent*Rev	0.0002	-0.0001	0.0002	0.0001	0.0008	-0.0001
	(0.23)	(0.21)	(0.21)	(0.17)	(0.33)	(-0.11)
Strong_Buy		0.0022		0.0005		-0.0014
		(1.68)*		(1.21)		(-1.03)
Strong_Sell		-0.0006		-0.0022		0.0005
		(-0.33)		(-1.69)*		(0.39)
SUE		-0.0006		0.0004		-0.0003
		(-0.71)		(0.33)		(-0.35)
MV_{t-1}		-0.0058		-0.0043		-0.0070
		(-3.37)***		(-2.90)***		(-3.58)***
PB_{t-1}		0.0009		0.0013		0.0007
		(3.22)***		(2.77)***		(0.61)
Cum_{t-1}		-0.0025		0.0054		-0.0108
		(-2.89)***		(2.81)***		(-3.51)***
$Cum_{t-2,t-5}$		-0.0011		0.0010		-0.0042
		(-3.12)***		(2.91)***		(-3.77)***
N	156,912	156,912	80,339	80,339	76,573	76,573
R-squared	0.0153	0.1063	0.0053	0.1045	0.0233	0.1423

heir interaction term. The results show that the estimated coefficient on Sent is significantly positive, indicating that institutions herd to counteract the sentiment of individual investors, which is consistent with H3. The estimated coefficient on Rev is significantly negative, which is consistent with the notion that institutions herd more strongly for stocks with downgrades (H1). However, the interaction is estimated to be insignificant, suggesting the two factors only affect within-period herding independently, which is inconsistent with H5. In model 2, we further consider whether the explanatory power of independent variables can be subsumed by the control variables. The results indicate that after controlling for other explanatory variables, sentiment remains significant at the 1% level, but analyst recommendation revisions become insignificant.

In models 3 and 4 (5 and 6) of table 5.10, we further consider the effect of investor sentiment and analyst recommendation revisions on buy (sell) herding. Models 3/4 and 5/6 follow same format as model 1/2. The results for buy- and sell-herding indicate that Sent positively relates to both buy- and sell-herding but the effect of investor sentiment on sell herding (coefficient= 0.0069 in model 5) is much more prominent than that on buy herding (coefficient=0.0023 in model 3), suggesting that the positive effect of investor sentiment on aggregate herding (HM) primarily comes from the sell herding rather than the buy herding. The findings indicate that institutional investors tend to sell stocks when individual sentiment is high. As shown in models 3 and 5, Rev is significantly positive for buy herding whereas it is significantly negative for sell herding, suggesting that institutions herd in the same direction as analyst recommendation revisions. However, after controlling for other potential variables, Rev becomes insignificant in both buy- and sell herding regressions.

Lastly, consistent with Wermers (1999), we find that there is a significant relationship between returns momentum and within-period herding. Specifically, as shown in Models 4 and 6, we find that the coefficients on both cumulative return variables are significantly positive (negative) for buy (sell) herding. The evidence suggests that higher stock returns imply stronger buy herding and weaker sell herding. Also, consistent with prior empirical evidence, we find that institutional herding is stronger on small and growth stocks as coefficients on MV and PB are significantly negative and positive, respectively. Moreover, we find that buy herding is weaker when analysts issue consecutive strong sell recommendations as shown in model 4, suggesting that market participants view the re-confirmation of strong sell recommendations as a negative signal for buying such stocks, which acts as a dampening effect on buy herding.

In sum, the regression results of within-period herding provide strong support to H1 and H3 in which institutions are more likely to herd for stocks with downgrades and they are more likely to herd during optimistic periods than pessimistic periods. However, the insignificant coefficient of the interaction term of the two factors suggests the two factors only affect within-period herding independently, which is inconsistent with H5.

5.4.5.2 Regression Analysis on Adjacent-Period Herding

In this subsection, we follow the time-series regression analysis in Holmes et al. (2013). We regress quarterly beta (the correlation in institutional demands between two consecutive quarters) and its two components on investor sentiment, while controlling for other potential factors.[82] To examine the interaction of investor sentiment and analyst recommendation revisions, we also run the regression for stocks with upgrades and downgrades, separately.

$$\beta_t = \alpha + b_1 \mathrm{Sent}_{t-1} + \mathrm{c} * \sum Control_{t-1} + \varepsilon_{k,t} \qquad (5.9)$$

Where β_t is the estimated quarterly beta and Sent_{t-1} is investor sentiment in the previous quarter t-1. For control variables, we include quarterly stock market returns (MR) and quarterly market volatility (MVol) as potential factors in affecting institutional herding.

Table 5.11 reports results regardless of analyst recommendation revisions (Panel A) and those for stocks with upgrades (Panel B) and for stocks with downgrades (Panel C). The dependent variable in the first column of results is β_t, in the second it is that component of β_t resulting from following their own trades and in the final column it is the component of β_t relating to institutions following the trades of others. Overall, the results of the regression analysis provide strong support for our hypotheses. Specifically, as shown in Panel A, the coefficient on Sent is -0.002, which is significant at the 1% level, confirming the earlier finding (Table 5.5) that adjacent-period herding is stronger when sentiment is low. The coefficient is estimated to be 0.001 and -0.003 for the component following their own trades (the trades of others), respectively, with both being significant at the 1% level, suggesting that the negative effect of investor sentiment on aggregate adjacent-period

[82] Analyst recommendation revisions are panel data which vary across stocks and over time and the sentiment index is time-series data. The independent and control variables of the regression analysis on adjacent-period herding are different from those for within-period herding since the regression of within-period herding is panel data analysis (both panel data (analyst recommendation revisions) and time-series data (investor sentiment) can be included in the regression), whereas the regression of adjacent-period herding is time-series and only time series data (sentiment and other time series control variables can be included).

Table 5.11 Multivariate Regression of Determinants of Adjacent-Period Herding

This table reports results for the regressions of the quarterly values of beta and the two component parts of beta ('institutions following their own trades' and 'institutions following the trades of others') on the following factors: $Sent_{t-1}$ is the Baker and Wurgler sentiment index in t-1. MR_t is quarterly stock market returns and Std_t is quarterly market volatility. Panel A presents results for total herding. Panels B and C present results for stocks with upgrades and downgrades, respectively. The number of observations and the R-squared are reported at the bottom of each panel. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

	Regressand:beta	Regressand: Beta-component 'institutions following their own trades'	Regressand: Beta-component 'institutions following the trades of others'
Panel A: Total Herding			
Intercept	0.2752	0.3363	-0.0611
	(4.90)***	(2.81)***	(-1.35)
$Sent_{t-1}$	-0.0020	0.0010	-0.0030
	(-4.08)***	(2.64)***	(-5.53)***
MR_t	-0.2891	0.1081	-0.3972
	(-2.29)**	(1.76)*	(-2.98)***
Std_t	1.8694	-2.2848	4.1542
	(5.06)***	(-2.25)**	(4.71)***
N	84	84	84
R-squared	0.2411	0.3786	0.4982
Panel B: Upgrades			
Intercept	0.3500	0.0790	0.2710
	(12.34)***	(2.72)***	(6.66)***
$Sent_{t-1}$	-0.0010	0.0009	-0.0019
	(-1.79)*	(3.91)***	(-2.98)***
MR_t	-0.1221	-0.0031	-0.1189
	(-0.82)	(-0.05)	(-0.73)
Std_t	3.5131	-2.6179	6.1310
	(2.04)**	(-1.43)	(2.38)**
N	84	84	84
R-squared	0.0717	0.0531	0.1166
Panel C: Downgrades			
Intercept	0.2752	0.3238	-0.0486
	(7.11)***	(2.58)**	(-0.48)
$Sent_{t-1}$	-0.0027	0.0011	-0.0038
	(-2.31)**	(2.33)**	(-4.18)***
MR_t	-0.3475	0.1119	-0.4594
	(-2.30)**	(1.70)*	(-2.71)***
Std_t	1.3879	-2.6200	4.0079
	(3.39)**	(-2.29)**	(4.29)***
N	84	84	84
R-squared	0.1281	0.4218	0.4058

herding primarily comes from the component for institutions following the trades of others and institutional investors tend to follow their own trades when sentiment is high. The findings are consistent with the results in Table 5.5 and hypothesis 4.

Moreover, we find that the coefficient of market returns is negative and significant in all regressions except for the component following their own trades. The evidence suggests that adjacent-period herding is stronger when market returns are lower, which comes mainly from the institutions following the trades of others and institutions are more likely to follow their own trades when market returns are higher. We also find that market standard deviation is positively related to adjacent-period herding again in all regressions except for the component following their own trades, suggesting that institutions tend to herd by following the trades of others when market risk is high. The significantly negative coefficient of market standard deviation on the component that institutions following their own trades suggests that institutions are more likely to follow their own trades when market standard deviation is lower.

In Panels B and C of Table 5.11, we further consider the effect of investor sentiment on adjacent-period herding for stocks with upgrades and downgrades, respectively. The coefficient of sent for the component of β_t for stocks with upgrades and downgrades is -0.0010 (significant at the 10% level) and -0.0027 (significant at the 5% level), suggesting that the effect of investor sentiment on adjacent-period herding is much more prominent for stocks with downgrades than for those with upgrades. Institutional investors herd more strongly for stocks with downgrades when sentiment is low, which is consistent with the previous results in Table 5.9 and H6 in which adjacent-period herding from following the trades of others will be strongest for stocks with downgrades when sentiment is pessimistic, and the herding will be lower in the other three cases. Notably, the effect of investor sentiment on stocks with both upgrades and downgrades is primarily driven by institutions following the trades of others. Moreover, we find a similar pattern of results for market returns and volatility as in Panel A. Adjacent-period herding from following the trades of others will be stronger for upgrades (downgrades) when individual sentiment is optimistic (pessimistic).

Overall, the findings in Table 5.11 show general support for our hypotheses and provide clear evidence that sentiment and analyst recommendations affect adjacent-period herding. The findings in Table 5.10 provide clear evidence for H1 and H3 in which both analyst recommendation revisions and individual sentiment have significant impact on institutional herding, but the insignificant coefficient of the interaction term between the two factors suggests the two factors influence within-period herding independently.

5.5 Robustness tests

5.5.1 Herding and Subsequent Returns

Prior research has shown herding arising from different reasons will have a stabilising or destabilising effect on stock prices (e.g., Chakravarty, 2001; Grinblatt and Titman, 1989; Sias et al., 2002; Wermers, 1999). Assuming institutional herding impacts prices, previous empirical studies suggest that if institutional herding is driven by fads, reputational herding, or characteristic herding, subsequent returns should be inversely related to institutional demand (e.g., Chakravarty, 2001; Froot and Teo, 2004; Sias et al, 2006). If herding is driven by information-based herding, we expect to observe no subsequent return reversals. In our setting, since the two herding measures capture different aspects of herding, we may observe different patterns of subsequent stock returns using different herding measures (e.g., Choi and Sias, 2010; Sias, 2004; Wermers, 1999).

We begin by classifying stocks into each category based on the level of herding in different consensus analyst recommendation revision and investor sentiment groups. We form a portfolio in each group and then calculate the equally weighted average of subsequent stock returns. Columns 1 to 6 and 7 to 12 in Tables 5.12 and 5.13 report the average quarterly returns for herding under optimistic and pessimistic states, respectively. In each sentiment group, the results for subsequent stock returns under consensus upgrades and downgrades are presented. The first two columns in each category of recommendation revisions in Tables 5.12 and 5.13 report the average quarterly raw returns for buy- and sell-herding portfolios over the indicated period. The third column presents their difference and associated significance level.

5.5.1.1 Within-Period Herding and Subsequent Returns

The results reveal evidence consistent with the hypothesis that herding is driven by the interaction of analyst recommendation revisions and investor sentiment impacts prices. We first consider the results during optimistic periods. In the first two formation quarters, as shown in the third column of

Table 5.12, stocks most purchased by institutions outperform those most sold for upgrades by 8.99%, significant at the 1% level. In the subsequent quarter immediately following formation, buy-herding stocks outperform sell-herding stocks by 0.784%, which is significant at the 1% level. When examining the long-run returns during quarters 1 to 4, we find that institutional herding for stocks with upgrades does not lead to return reversals during quarters 1 to 4. Specifically, in the four quarters immediately following the herding period (Quarter 1 to 4), buy-herding stocks underperform sell-herding stocks by an insignificant 0.9%. Similarly, under analyst downgrades, we can observe from the sixth column of Table 5.12 that buy-herding stocks outperform sell-herding stocks by 10.18% and 8.78% in the first two formation and subsequent quarters during optimism, respectively, with both figures being significant at the 1% level. The findings suggest strong contemporaneous and subsequent returns following institutional herding. However, in the quarters between 1 and 4 and between 5 and 8, buy-herding stocks underperformed sell-herding stocks by 1.54%, and 1.76% respectively, with both being significant at the 5% level. The results show that institutional herding for stocks with downgrades in the presence of optimistic sentiment leads to strong return reversals during quarters 1 to 8, which is primarily driven by the sell herding as shown in the fifth column of Table 5.12. The evidence suggests within-period herding for stocks with downgrades during optimistic periods is driven by fads, reputational herding, or characteristic herding because of strong subsequent return reversals. Overall, we find a strong positive relationship between institutional herding and stock returns for stocks with upgrades and a strong negative relationship for stocks with downgrades during optimism. The evidence reveals that within-period herding for stocks with upgrades during optimism is driven by information-based herding and the herding is driven by fads, reputational herding, or characteristic herding for stocks with downgrade during optimistic periods.

We next consider the results under pessimistic states. As far as the results under pessimistic states are concerned as shown in the ninth and last columns Table 5.12, buy-herding stocks significantly outperform sell-herding stocks in the first two formation quarters under both analyst revisions. In the four quarters immediately following formation, returns to the difference portfolio (buy minus sell) are insignificantly different from zero for both revision groups. Similarly, there is no evidence of return reversals from quarter 5 to 8 and 9 to 12. In sum, although the results in the formation periods reveal a strong positive relation between institutional herding and stock returns during quarter t-1 to t+4, we find no evidence of subsequent return reversal, suggesting that herding is driven by information-based herding for both revision groups during pessimism.

In sum, the results in table 5.12 show evidence consistent with information-based herding models i.e. informational cascades and investigative herding. Since evidence of subsequent return reversals is weak, reputational herding and fads can sometimes play a role in institutional herding for stocks with downgrades when sentiment is optimistic.

Table 5.12 Within-Period Herding and Subsequent Returns

The table reports the average quarterly raw returns for buy- and sell-herding stocks double sorted by investor sentiment and consensus analyst recommendation revisions during the 1993-2014 period. The portfolio in each group is formed and returns for the portfolio is calculated as the equally weighted of subsequent stock returns. The consensus recommendation revision is the difference between the current and the prior recommendation levels and the current consensus recommendation level is the mean of all outstanding recommendations for a given stock with only the most recent recommendation for a given analyst included. The consensus upgrade, downgrade and No Change are defined as when the value of the consensus revision is bigger, smaller and equal to zero, respectively. The LSV herding measures (buy and sell) are defined in Table 5.2. The Baker and Wurgler’s (2007) sentiment index is used to identify optimistic, mild and pessimistic investor sentiment quarters. The quarterly investor sentiment is calculated as the average of the monthly investor sentiment proxy over the quarter and optimistic (pessimistic) sentiment periods are defined as where the value in that quarter belongs to the top (bottom) 30% of the time-series value. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

	Optimistic						Pessimistic					
	Upgrade			Downgrade			Upgrade			Downgrade		
	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell
Quarters t-1 to t	0.0876	-0.0023	0.0899	0.0429	-0.0589	0.1018	0.1285	0.0612	0.0673	0.1092	0.0480	0.0612
	(20.11)***	(-0.55)	(18.23)***	(11.04)***	(-14.38)***	(16.12)***	(26.78)***	(17.96)***	(15.89)***	(21.44)***	(13.34)***	(6.71)***
Quarter t+1	0.1222	0.0438	0.0784	0.0545	-0.0333	0.0878	0.0926	0.0874	0.0052	0.0305	0.0437	-0.0132
	(22.27)***	(8.12)***	(15.16)***	(11.02)***	(-7.55)***	(14.77)***	(14.41)***	(20.71)***	(0.78)	(7.01)***	(10.27)***	(-1.61)
Quarter t+1 to t+4	0.0175	0.0265	-0.0090	0.0217	0.0371	-0.0154	0.0690	0.0652	0.0038	0.0781	0.0753	0.0028
	(1.89)*	(1.91)*	(-0.10)	(2.14)**	(5.31)***	(-1.99)**	(15.03)***	(17.96)***	(0.61)	(14.66)***	(14.12)***	(0.51)
Quarter t+5 to t+8	0.0809	0.0826	-0.0017	0.0856	0.1032	-0.0176	0.0472	0.0473	-0.0001	0.0498	0.0473	0.0025
	(14.17)***	(11.38)***	(-0.05)	(12.43)***	(12.11)***	(-2.03)**	(10.71)***	(12.01)***	(-0.01)	(11.28)***	(10.98)***	(0.48)
Quarter t+9 to t+12	0.0465	0.0395	0.0070	0.0416	0.0453	-0.0037	0.0512	0.0487	0.0025	0.0573	0.0552	0.0022
	(9.33)***	(7.44)***	(0.38)	(9.31)***	(9.77)***	(-0.21)	(11.03)***	(11.51)***	(0.41)	(13.19)***	(12.65)***	(0.56)

5.5.1.2 Adjacent-Period Herding and Subsequent Returns

Table 5.13 presents the average quarterly return for each analyst recommendation revision and investor sentiment category. Consistent with previous studies, we find a strong positive relationship between institutional herding and both current and prior-quarter returns. Specifically, in the presence of optimistic sentiment, as shown in the third and sixth columns of Table 5.13, stocks purchased by institutions outperform those sold by 5.01% and 6.76% in the two formation quarters under analyst upgrades and downgrades, respectively. In the next quarter immediately following the formation, buy-herding stocks continue to outperform the sell-herding stocks by 11.32% and 13.63% following upgrades and downgrades. During quarter t+5 to t+12, however, the average quarterly return is insignificantly different from zero, suggesting there is no evidence of return reversals at longer horizons. The results suggest that adjacent-period herding for both upgrade and downgrade stocks during optimism is driven by information-based herding.

Under pessimistic states, despite there being no evidence of a relationship between institutional herding and prior-quarter returns, we find a similar pattern of the average quarterly return in the formation and subsequent periods to that when sentiment is optimistic. Specifically, as shown in the ninth and last columns, in the two formation quarters, the average quarterly return to the difference portfolio is insignificantly different from zero under both revision groups. In the first quarter immediately following formation, buy-herding stocks outperform the sell-herding stocks by 9.28% and 8.84% following upgrades and downgrades respectively. In the quarters from 1 to 12, the average quarterly return to the difference portfolio is insignificantly different from zero. Overall, although the results in the first three rows of Table 5.13 reveal a strong positive relationship between institutional herding and stock returns during t-1 to t+1, we find only weak evidence of a subsequent return reversal, suggesting that information-based herding models (informational cascades and investigative herding) play a major role in adjacent-period herding by taking account of the interaction between analyst recommendations and investor sentiment.

Table 5.13 Adjacent-Period Herding and Subsequent Returns

The table reports the average quarterly raw returns for buy- and sell-herding stocks double sorted by investor sentiment and consensus analyst recommendation revisions during the 1993-2014 period. The portfolio in each group is formed and returns for the portfolio is calculated as the equally weighted of subsequent stock returns. The consensus recommendation revision is the difference between the current and the prior recommendation levels and the current consensus recommendation level is the mean of all outstanding recommendations for a given stock, with only the most recent recommendation for a given analyst included. The consensus upgrade, downgrade and No Change are defined as where the value of the consensus revision is bigger, smaller and equal to zero, respectively. The Sias herding measures (buy and sell) are defined in Table 5.3. The Baker and Wurgler's (2007) sentiment index is used to identify optimistic, mild and pessimistic investor sentiment quarters. The quarterly investor sentiment is calculated as the average of the monthly investor sentiment proxy over the quarter and optimistic (pessimistic) sentiment periods are defined as the value in that quarter belongs to the top (bottom) 30% of the time-series value. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%).

	Optimistic						Pessimistic					
		Upgrade			Downgrade			Upgrade			Downgrade	
	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell	Buy	Sell	Buy-Sell
Quarters t-	0.0613	0.0112	0.0501	0.0256	-0.0420	0.0676	0.1102	0.0933	0.0169	0.0741	0.0698	0.0043
1 to t	(2.91)***	(0.56)	(2.71)***	(1.32)	(-1.97)**	(3.11)***	(4.21)***	(3.55)***	(1.26)	(3.18)***	(2.71)***	(0.63)
Quarter	0.1221	0.0089	0.1132	0.0769	-0.0594	0.1363	0.1212	0.0284	0.0928	0.0977	0.0093	0.0884
t+1	(4.00)***	(0.43)	(3.65)***	(3.21)***	(-2.71)***	(4.19)***	(3.86)***	(0.81)	(4.15)***	(2.68)***	(0.24)	(2.64)***
Quarter t+1	0.0266	0.0320	-0.0054	0.0340	0.0409	-0.0069	0.0630	0.0684	-0.0054	0.0595	0.0725	-0.0130
to t+4	(0.95)	(1.98)**	(-0.21)	(2.05)**	(3.87)***	(-0.31)	(2.67)***	(3.33)***	(-0.31)	(2.77)***	(3.32)***	(-0.31)
Quarter t+5	0.0793	0.0785	0.0008	0.0819	0.0972	-0.0153	0.0484	0.0442	0.0042	0.0448	0.0475	-0.0027
to t+8	(3.68)***	(2.93)***	(0.09)	(4.77)***	(5.43)***	(-1.34)	(2.10)**	(2.19)**	(0.39)	(2.23)**	(3.41)**	(-0.45)
Quarter t+9	0.0457	0.0436	0.0021	0.0490	0.0503	-0.0013	0.0483	0.0512	-0.0029	0.0443	0.0556	-0.0113
to t+12	(2.93)***	(2.67)***	(0.41)	(2.71)***	(2.88)***	(-0.11)	(2.83)***	(3.04)***	(-0.23)	(3.13)***	(2.18)***	(-0.11)

In sum, we find that both within-period and adjacent-period herding is primarily driven by information-based herding including investigative herding and informational cascades. As discussed earlier in this Chapter, the LSV measure captures the correlated trades between institutional investors within a period based on the two factors (investigative herding), whereas the Sias measure captures how institutional investors follow each other's' trades in the subsequent period (intentional herding). Thus, both the LSV and Sias measures allow us to capture aspects of investigative herding and intentional herding and provide better insights into distinguishing between investigative herding and intentional herding. Since the results of stocks' subsequent returns suggest information-based herding plays a major role in both within- and adjacent-period herding, we conclude that in our setting, within-period (adjacent-period) herding measured by the LSV (Sias) model is primarily driven by investigative herding (informational cascades).

5.5.2 An Alternative Sentiment Measure

In this section, we examine the sensitivity of our results for institutional herding to an alternative index for investor sentiment. The consumer confidence index is employed as a measure of sentiment, which has been widely used in the literature (e.g., Fisher and Statman, 2003; Lemmon and Portniaguina, 2006; McLean and Zhao, 2009; Antoniou et al., 2013). The index is constructed by the Conference Board, and is measured outside of financial markets. This survey started on a bimonthly series in 1967 and changed to a monthly basis in 1977, with data being collected from 5000 random selected households in the U.S. Five questions are asked by the survey to participants about their expectations for the economy.[83] The consumer confidence index is formed by taking the average of scores on the 5 questions. In order to mitigate the effects of macroeconomic conditions from the consumer confidence index, we regress the index on 6 macroeconomic indicators: growth in industrial production, real growth in durable, nondurable and service consumptions, growth in employment and an NBER recession indicator. The residuals from this regression are used as

[83] There are five questions in the survey as follows: 1) How would you rate present general business conditions in your area? 2) What would you say about available jobs in your area right now? 3) Six months from now, do you think that the business conditions in your area will be better, same or worse? 4) Six months from now, do you think there will be more, same, or fewer jobs available in year area? 5) Would you guess your total family income to be higher, same or lower 6 months from now?

the sentiment proxy.[84]

5.5.2.1 An Alternative Sentiment Measure and Within-Period Herding

Tables 5.14 and 5.15 reports results equivalent to Tables 5.6- and 5.8 for within-period herding results for optimistic and pessimistic periods, using the consumer confidence index in place of the Baker and Wurgler (2007) sentiment measure. All other calculations remain the same as those in the previous tables.

The evidence in Tables 5.14 and 5.15 confirms our general findings between institutional herding and sentiment using the LSV measure. We first consider the results in Table 5.14. In contrast with the results in Table 5.6, the difference in buy herding between optimism and pessimism is significant at the 5% level. Consistent with the previous results, the average levels of aggregate and sell herding are much stronger during optimistic periods than during pessimistic periods. Specifically, the average levels of aggregate herding under optimistic and pessimistic states are 4.2% and 3.682% respectively, within the difference between optimism and pessimism being statistically significant at the 1% level. The average levels of sell herding under optimism and pessimism are 4.146% and 4.657% respectively, with the difference being significantly different from zero at the 1% level. The results suggest that institutional investors herd more strongly to sell stocks during optimistic states than during pessimistic states. It also observed from the last row of Table 5.13 that the difference in sell herding is statistically higher than that in buy herding. The results are overall consistent with the findings in Table 5.6 and confirm our H3.

Table 5.15 reports the interaction of analyst recommendation revisions and investor sentiment on institutional herding using the consumer confidence index as an alternative measure for investor sentiment. As can be seen from Panel A of Table 5.15, in contrast to the previous results using the Baker and Wurgler sentiment measure, the difference in herding between upgrades and downgrades during pessimistic sentiment is significant at the 1% level. Consistent with the previous results, within-period herding is stronger for

[84] The data are downloaded from Wurgler's website: http://people.stern.nyu.edu/jwurgler/.

Table 5.14 Alternative Investor Sentiment Measure and Within-Period Herding

This table presents the LSV herding levels under different investor sentiment periods (optimistic, mild and pessimistic). The LSV herding measures (aggregate, buy and sell) are defined in Table 5.2. The consumer confidence index is used to identify optimistic, mild and pessimistic investor sentiment quarters. The quarterly investor sentiment is calculated as the average of the monthly investor sentiment proxy over the quarter and optimistic (pessimistic) sentiment periods are defined as where the value in that quarter belongs to the top (bottom) 30% of the time-series value. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%)

	Optimistic	Pessimistic	Opt.- Pess.
Aggregate herding	0.04200(78.21)***	0.03682(74.13)***	0.00518(3.13)***
Buy herding	0.03230(33.12)***	0.02815(29.80)***	0.00415(2.43)**
Sell herding	0.05214(38.13)***	0.04657(36.13)***	0.00556(3.51)***
Buy. - sell.	-0.01984(-7.22)***	-0.01842(-7.41)***	-0.00142(-1.66)*

stocks with downgrades than for stocks with upgrades during optimistic periods and the herding is stronger for stocks with both upgrades and downgrades during optimism than pessimism (H3). Notably, herding is the strongest for stocks with downgrades in the presence of optimistic sentiment, suggesting institutions are most likely to herd when both analyst recommendation revisions and investor sentiment suggest "sell" trading decisions. The results are consistent with previous results in Table 5.8 and H5.

The results of buy and sell herding in Panels B and C of Table 5.15 allow us to further investigate the interaction of within-period herding. In contrast to the previous results shown in Panel B of Table 5.8, the effect of investor sentiment on buy herding is prominent across both revision groups, with the difference in buy herding between optimistic and pessimistic states being significantly different from zero at the 10% level. Consistent with the previous results, as shown in Panel C, sell herding is stronger during optimism than during pessimism across both revision groups and is stronger for stocks with downgrades than those with upgrades across both sentiment periods. The results in Panel C also reveal that institutions herd most strongly to sell downgrade stocks during optimism, consistent with previous results and the cognitive dissonance argument.

In sum, the evidence using the alternative sentiment generally supports our results in the previous tables and confirms the hypotheses 3 and 6.

Table 5.15 Analyst Recommendations, the Alternative Investor Sentiment and Within-Period Herding

This table reports mean values of the LSV herding measures (aggregate, buy, and sell) sorted by market/individual sentiment and consensus analyst recommendation revisions during the 1993-2014 period. The LSV herding measures (aggregate, buy and sell) are defined in Table 5.2. The optimistic and pessimistic sentiment periods are classified based on the level of sentiment. The Consumer confidence index is used to identify optimistic, mild and pessimistic investor sentiment quarters. The consensus upgrade or downgrade is defined as the value of the consensus revision is bigger or smaller than zero, respectively. For brevity, the mild results are not reported but available upon requests. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%)

	Upgrade	Downgrade	Up. - Down.
Panel A. Aggregate Herding measure			
Optimistic	0.03469(61.38)***	0.04037(68.23)***	-0.00568(-2.71)***
Pessimistic	0.02959(47.23)***	0.03514(52.31)***	-0.00555(-2.12)**
Opt.- Pess.	0.00510(3.11)***	0.00522(3.19)***	-0.00013(-0.34)
Panel B. Buy herding			
Optimistic	0.03046(51.98)***	0.03001(49.33)***	0.00046(0.31)
Pessimistic	0.02704(47.31)***	0.02582(33.75)***	0.00122(0.19)
Opt.- Pess.	0.00342(1.65)*	0.00418(1.71)*	-0.00076(-0.07)
Panel C. Sell herding			
Optimistic	0.03942(60.26)***	0.04959(63.12)***	-0.01017(-7.31)***
Pessimistic	0.03251(48.31)***	0.04449(57.31)***	-0.01198(-6.41)***
Opt.- Pess.	0.00691(3.98)***	0.00509(2.91)***	0.00181(0.83)
Panel D. Buy - Sell herding			
Optimistic	-0.00895(-7.05)***	-0.01958(-9.22)***	0.01063(7.31)***
Pessimistic	-0.00547(-3.11)***	-0.01867(-6.81)***	0.01320(6.21)***
Opt.- Pess.	-0.00349(-1.61)	-0.00091(-0.14)	-0.00258(-0.91)

5.5.2.2 An Alternative Sentiment Measure and Adjacent-Period Herding

Tables 5.16 and 5.17 report results equivalent to Tables 5.7 and 5.9 for adjacent-period herding results for optimistic and pessimistic periods, using the consumer confidence index in place of the Baker and Wurgler (2007) sentiment measure. All other calculations remain the same as those in the previous tables. Table 5.16 presents the results for adjacent herding under different sentiment periods using the consumer confidence index as a proxy for investor sentiment. As can be seen from Panel A of Table 5.16, the average levels of herding following optimistic and pessimistic periods are 38.855% and 38.116%, respectively, with both being significant at the 1% level. In contrast to our previous findings, the difference in herding between optimism and pessimism is insignificantly different from zero. However, the portions resulting from institutions following the trades of following optimistic

Table 5.16 An Alternative Investor Sentiment Measure and Adjacent-Period Herding

This table presents the Sias herding levels during different investor sentiment periods (optimistic and pessimistic). The Sias herding measures (aggregate, buy and sell) and their components are defined in Table 5.3. The consumer confidence index is used as a proxy for investor sentiment. The quarterly investor sentiment index is calculated as the average of the monthly investor sentiment proxy over the quarter and optimistic (pessimistic) sentiment periods are defined as the value in that quarter that belongs to the top (bottom) 30% of the time-series value. Corresponding t-statistics are reported in parentheses and asterisks refer to different significance levels: *** (1%), ** (5%), * (10%)

	Optimistic	Pessimistic	Opt.- Pess.
Panel A. Total cross-sectional correlation			
Average coefficient	0.38855(17.32)***	0.38116(16.99)***	0.00739(0.71)
Institutions following their own trades	0.08240(10.21)***	0.03259(5.12)***	0.04981(5.23)***
Institutions following the trades of others	0.30615(14.37)***	0.34857(15.12)***	-0.04242(-4.34)***
Panel B. Contribution of Buy			
Average coefficient	0.22556(15.31)***	0.18230(12.18)***	0.04326(4.19)***
Institutions following their own trades	0.04783(7.88)***	0.01558(5.12)***	0.03225(5.99)***
Institutions following the trades of others	0.17773(11.67)***	0.16672(12.01)***	0.01101(1.14)
Panel C. Contribution of Sell			
Average coefficient	0.15720(14.78)***	0.18897(16.31)***	-0.03177(-4.16)***
Institutions following their own trades	0.03334(7.11)***	0.01616(5.19)***	0.01718(3.13)***
Institutions following the trades of others	0.12386(12.89)***	0.17281(14.61)***	-0.04895(-4.98)***
Panel D. Buy-Sell			
Average coefficient	0.06836(6.88)***	-0.00667(-0.69)	0.07503(7.14)***
Institutions following their own trades	0.01450(1.98)**	-0.00057(-0.17)	0.01507(2.03)**
Institutions following the trades of others	0.053863.86()***	-0.00610(-0.67)	0.05996(4.76)***

and pessimistic sentiment are 30.615% and 34.857%, respectively, with the difference being significantly negative, consistent with the previous results. It suggests that institutional investors are more likely to follow others' trades in the subsequent period when sentiment is pessimistic, consistent with H4. Again, consistent with the previous results, institutions are more likely to follow their own trades following optimistic sentiment. Specifically, as shown in the second row of Panel A, the portion resulting from funds following their own trades during optimistic (pessimistic) periods is a significant 8.24% (3.259%), with the difference between optimism and pessimism being statistically significant at the 1% level.

Panels B and C present the results for buy- and sell-herding under different sentiment periods, respectively. Consistent with the previous results, buy (sell) herding is much greater during optimistic (pessimistic) periods than during pessimistic (optimism) periods. To illustrate, as shown in Panel B, buy herding is estimated to be a significant 22.556% under optimistic states, compared to a significant 18.23% under pessimistic states, with the difference being significantly different from zero. The portion resulting from institutions following their own trades (institutions following the trades of others) is a significant 4.783% (17.733%) under optimistic states. The evidence suggests that institutional investors are more likely to herd to buy by following their own trades during optimistic states than under pessimistic states. In contrast, we observe from Panel C that sell herding is estimated to be a significant 15.720% and 18.897% for optimistic and pessimistic states, respectively, with the difference between the two sentiment states being significant at the 1% level. The portion resulting from following the trades of others during optimistic and pessimistic periods is a significant 12.386% and 17.281%, respectively. The evidence suggests that institutions tend to herd to sell stocks by following the trades of others during pessimistic periods. Overall, the results in Table 5.16 are consistent with the findings in previous tables and H4.

We next consider the interaction of analyst recommendation revisions and investor sentiment on adjacent-period herding using the consumer confidence index as a measure of investor sentiment. The overall pattern in Table 5.17 shows a marked difference across sub-samples. In contrast to the previous results in Table 5.9, as shown in the first row of Panel A of Table 5.17, following optimistic sentiment, aggregate herding for stocks with upgrades is slightly smaller than that for stocks with downgrades, but the difference in herding between upgrades and downgrades is insignificantly different from zero. Consistent with the previous results, following pessimistic periods, herding for stocks with downgrades is significantly higher than that for stocks with upgrades, suggesting that institutions herd more strongly for stocks with downgrades than upgrades following pessimistic periods. The evidence supports H6.

In each panel of Table 5.17, the herding coefficient is partitioned into two parts, buy- and sell- herding. Consistent with the previous results, as shown in the second row of Panel A, buy herding is the strongest for stocks with upgrades in the presence of optimistic sentiment whereas as shown in the third row of Panel A, sell herding is the strongest for stocks with downgrades following pessimistic sentiment. To illustrate, following optimistic periods, buy herding which is estimated to be a significant 24.268% for stocks with upgrades following optimism is higher than the other three cases (combination of revisions and sentiment): 23.43% for stocks with downgrade following pessimism, 18.818% for upgrades following pessimism and 19.532% for downgrades following pessimism. In contrast, following pessimistic periods, sell herding is estimated to be a significant 22.504% for stocks with downgrades, which is significantly higher than that in the other three cases (combination of the two factors). Overall, the results generally provide support to H6.

Panels B and C of Table 5.17 show the results of the herding coefficient resulting from institutions following their own trades and the trades of others, respectively. Consistent with the previous results in Table 5.9, as shown in Panel B, aggregate, buy and sell herding are significantly stronger following optimism than following pessimism, suggesting institutions are more likely to follow their own trades during optimism. Specifically, following optimism, aggregate herding resulting from funds following their own trades is a significant 5.4% (5.241%) for stocks with upgrades (downgrades) whereas following pessimistic sentiment, aggregate herding from following their own trades is a significant 1.815% (1.572%) for stocks with upgrades (downgrades), with the difference in the herding between optimism and pessimism in each of revision groups being significant at the 1% level.

Again, consistent with the previous results, in Panel C, there is clear evidence that adjacent-period herding in each case is primarily driven by institutions following the trades of others. We observe from the first row of Panel C that there is an insignificant difference in aggregate herding from following the trades of others for stocks with upgrades between optimism and pessimism, whereas there is a significant difference in the herding for stocks with downgrades between optimism and pessimism. This suggests that institutions are more likely to follow the trades of others for stocks with downgrades following pessimism than optimism. Furthermore, the results in the second and third rows of Panel C show a similar pattern to those in Panel A. Buy (sell) herding are the strongest for stocks with upgrades during optimism (for stocks with downgrades during pessimism) in any combinations of individual sentiment and analyst recommendation revisions. The evidence suggests that institutions are more likely to herd by following the trades of others in the direction of analyst recommendation revisions when they experience cognitive dissonance, which is consistent with the cognitive dissonance argument.

Overall, the results in Tables 5.16 and 5.17 using the alternative sentiment measure are qualitatively similar to those using the Baker and Wurgler sentiment measure, suggesting that the interaction of sentiment and analyst revisions affect institutional herding by way of cognitive dissonance regardless of the choice of investor sentiment proxy.

Table 5.17Analyst Recommendations, the Alternative Investor Sentiment Measure and Adjacent-Period Herding

This table reports the mean values of the Sias aggregate, buy, and sell herding sorted by institutional sentiment and consensus analyst recommendation revisions during the 1993-2014 period. The Sias measure is the cross-sectional correlation in the current and previous quarters. The correlation is partitioned into two parts, cross-sectional correlation due to funds following their own trades and that due to funds following the trades of others. The total correlation and two partitions are further divided into two parts, buy herding (institutions buy in quarter t-1) and sell herding (institutions sell in quarter t-1). The Consumer confidence index is used to identify optimistic, mild and pessimistic investor sentiment quarters. The consensus upgrades or downgrades are defined as the value of the consensus revision is bigger or smaller than zero, respectively. The asterisks refer to the level of significance: *** (1%), ** (5%), * (10%).

	Optimistic			Pessimistic			Opt. – Pess.		
	Upgrade	Downgrade	Up. – Down.	Upgrade	Downgrade	Up. – Down.	Upgrade	Downgrade	Up. – Down.
Panel A. Total correlation									
Aggregate herding	0.40997	0.42824	-0.01827	0.38394	0.42890	-0.04496	0.02603	-0.00066	0.02669
	(20.78)***	(21.27)***	(-1.09)	(19.12)***	(22.31)***	(-2.06)**	(1.37)	(-0.18)	(1.68)*
Contribution of buy	0.24268	0.23430	0.00838	0.18818	0.19532	-0.00714	0.05450	0.03898	0.01552
	(17.13)***	(16.29)***	(0.64)	(16.99)***	(17.28)***	(-0.45)	(2.04)**	(1.62)	(1.31)
Contribution of sell	0.16523	0.19104	-0.02581	0.18764	0.22504	-0.03740	-0.02241	-0.03400	0.01159
	(14.17)***	(15.59)***	(-1.38)	(16.34)***	(18.96)***	(-1.98)**	(-1.23)	(-1.97)**	(1.03)
Buy- Sell	0.07745	0.04327	0.03418	0.00054	-0.02971	0.03025	0.07691	0.07298	0.00393
	(4.12)***	(2.87)***	(2.68)**	(0.08)	(-1.98)**	(1.96)**	(2.69)***	(2.79)***	(0.28)
Panel B. Institutions following their own trades									
Aggregate herding	0.05400	0.05241	0.00159	0.01815	0.01572	0.00243	0.03585	0.03669	-0.00084
	(10.77)***	(10.11)***	(0.71)	(6.71)**	(6.01)**	(0.52)	(7.11)***	(7.22)***	(-0.16)
Contribution of buy	0.03196	0.02867	0.00329	0.00890	0.00716	0.00174	0.02307	0.02152	0.00155
	(7.19)***	(6.84)***	(1.03)	(5.11)***	(4.61)***	(0.31)	(5.19)***	(4.87)***	(0.27)
Contribution of sell	0.02176	0.02338	-0.00162	0.00887	0.00825	0.00062	0.01289	0.01513	-0.00224
	(6.13)***	(6.47)***	(-0.69)	(4.91)***	(4.91)***	(0.08)	(3.22)***	(2.68)***	(-0.45)
Buy- Sell	0.01020	0.00530	0.00490	0.00003	-0.00109	0.00112	0.01018	0.00638	0.00380
	(3.27)***	(1.98)**	(1.48)	(0.02)	(-0.19)	(0.23)	(3.11)***	(2.63)***	(0.58)
Panel C. Institutions following the trades of others									
Aggregate herding	0.35597	0.37583	-0.01986	0.36579	0.41318	-0.04739	-0.00982	-0.03735	0.02753
	(16.29)***	(17.77)***	(-1.39)	(16.34)***	(20.33)***	(-2.17)**	(-1.35)	(-6.64)***	(2.11)**

Contribution of buy	0.21071 (12.87)***	0.20563 (12.54)***	0.00508 (0.41)	0.17928 (8.99)***	0.18817 (13.05)***	-0.00889 (-0.91)	0.03143 (1.72)*	0.01746 (1.21)	0.01397 (1.51)
Contribution of sell	0.14347 (10.11)***	0.16766 (10.98)***	-0.02419 (-1.65)*	0.17877 (9.13)***	0.21679 (14.99)***	-0.03802 (-1.78)*	-0.03530 (-1.81)*	-0.04913 (-2.69)***	0.01383 (1.15)
Buy-Sell	0.06725 (3.77)***	0.03797 (1.97)**	0.02928 (1.68)*	0.00051 (0.34)	-0.02862 (-1.97)*	0.02913 (1.91)*	0.06673 (2.81)***	0.06660 (2.80)***	0.00013 (0.05)

5.6 Conclusion

This study investigates the interaction of investor sentiment and analyst recommendation revisions on institutional herding. We employ both LSV and Sias herding measures to capture different aspects of institutional herd behaviour. Consistent with Brown et al. (2013), we find that institutional investors will herd in the direction of analyst recommendations revisions and herd more strongly for stocks with consensus downgrades than those with consensus upgrades. We also find that using the LSV measure, institutional investors tend to herd strongly in the presence of optimistic sentiment, consistent with the sentiment countering hypothesis (Liao et al., 2013) and sell herding plays a major role in such herding. However, using the Sias measure, we find that adjacent period herding is stronger following pessimistic sentiment than following optimistic sentiment and such herding is primarily due to following the trades of others, suggesting that institutional investors are more likely to follow the trades of others following such sentiment periods.

The interaction of investor sentiment and analyst recommendations on institutional herding is examined and we propose that cognitive dissonance may be a key driver in affecting such herding behaviour. Interestingly, in the presence of cognitive dissonance, we find within-period herding is weaker and the herding is the strongest for stocks with downgrades during optimistic periods, whereas adjacent-period herding is much more prominent. This may be because when investors experience cognitive dissonance, they are more likely to trade with delay to resolve such uncertainty, and hence they are more likely to follow the trades of others. Lastly, the results of subsequent stock returns following institutional herding show that there is only weak evidence of return reversals, suggesting that information-based herding plays a key role in driving institutional herding by considering the interaction of analyst recommendations and investor sentiment. The LSV and Sias herding measures allow us to capture both aspects of institutional herding due to investigative herding or informational cascades. We also examine the effect of using an to the alternative sentiment measure which is the consumer confidence index. The results are qualitatively similar to those using Baker and Wurgler’s sentiment index.

6 Conclusion

6.1 Summary and Key Findings

In past decades, numerous anomalies and puzzles have been raised by empirical studies of financial markets, which contradict the efficient market hypothesis (Fama, 1970) and traditional finance theories find it difficult to explain such phenomena. Investor sentiment, which has attracted much attention in recent years, provides a theoretical foundation of how investors form their beliefs and make trading decisions in financial markets. This thesis investigates the effect of investor sentiment with other factors in explaining three phenomena, momentum, PEAD and institutional herding by way of cognitive dissonance.

The objective of this thesis is twofold. First, momentum and PEAD were identified by Fama (1998) as the candidates for being "above-suspicion" anomalies. Extensive research over the time since this statement has confirmed this view, and to date no satisfactory explanation for these anomalies has been provided. However, there is a mixed picture that has emerged globally, with western markets showing clear evidence in relation to the two anomalies, but markets in the east generally being characterised by insignificant momentum profits and findings in relation to PEAD being inconclusive worldwide. We propose that cognitive dissonance may be a major driver of the two anomalies and is arisen in different scenarios by interacting between investor sentiment and culture which is proxied by Hofstede's individualism. Using the consumer confidence index as a proxy for investor sentiment, the impact of investor sentiment on momentum and PEAD in different cultures is investigated by way of cognitive dissonance. Empirical findings show that the effect of sentiment on momentum profits is much more prominent in countries with a high individualistic culture than those with a low individualistic culture.

In addition to examining momentum (PEAD) in 40 (34) countries we focus our analysis of the two anomalies on the five largest markets in each of the West and East, given the psychological arguments and evidence about differences in views of change in these two cultures. We build on the Hong and Stein (1999) model by incorporating investor sentiment and culture and propose that cognitive dissonance is a key driver of the anomalies: differences in cultures cause this phenomenon to arise in different sentiment periods and to differing degrees in the east and west. Specifically, we recognise that westerners have a strong tendency to believe in continuation, while those from the east tend to believe in reversal. Results suggest that cultural differences relating to individualism impact on the level and extent of the two anomalies, while cultural biases concerning continuation and reversal drive the differences in relation to the two anomalies across western and ESEA markets. As a result, cognitive dissonance will be more pronounced in western than in ESEA countries, thus resulting in stronger momentum and PEAD effects in the west. Overall, the results support our arguments, suggesting that the interaction of sentiment and culture provides a better understanding of differences in the extent of the anomalies across countries.

Our results have survived a number of robustness tests including using the risk-adjusted returns, the alternative individualism index, the alternative sentiment index, the different measure of earnings surprises and the different cut-offs for investor sentiment. The first two empirical chapters contribute to the literature in several aspects. First, it is the first study to examine the interaction between investor sentiment and culture on momentum profits and post-earnings-announcement drift by way of cognitive dissonance. We address the effect of investor sentiment on the two anomalies in different cultures since the proneness of investors to sentiment is different in different cultures. Second, our analysis may offer industry professionals insights into ways to optimize their investment process. For example, our findings suggest that popular trading strategies, e.g. momentum tend to more profitable only during optimistic sentiment in high individualism countries and western countries. Third, our work contributes to the cognitive dissonance literature that aims at understanding the importance of cognitive dissonance in financial markets. Previous studies have linked cognitive dissonance to disposition effect (Chang et al., 2016), mutual fund flows (Goetzmann and Peles), spot market volatility (Darrat et al., 2002), euro-dollar exchange rate (Prast and Vor, 2005), information flows (Argentesi and Lutkepohl, 2009) and herding in financial markets (Kindlegerger, 2000). We add to this literature by investigating the role of cognitive dissonance by examining the interaction between investor sentiment and culture in a large international sample.

Second, the thesis investigates the interaction between investor sentiment and analyst recommendations on institutional herd behaviour. The investigation is conducted by using two micro-level herding measures, LSV and Sias. The LSV measure allows us to capture institutional herd behaviour based on trading signals of analyst recommendations and/or investor sentiment within a period, whereas the Sias measure captures how institutional investors follow each others' trades in the subsequent period. Using the LSV measure, we find that institutional investors will herd in the direction of analyst recommendation revisions and herd more strongly for stocks with analyst consensus downgrades than with analyst consensus upgrades. The findings suggest that institutional investors believe that analyst downgrades are more informative and valuable than upgrades, consistent with the findings of Brown et al. (2013). The extent to which institutional herding varies with the degree of individual sentiment is examined and the evidence suggests that investor sentiment affects both within-period and adjacent-period herding, but in different ways.

Using the LSV measure, we find that institutional investors will herd strongly to counter optimistic sentiment of noise traders, but no evidence of buy herding in the presence of pessimistic sentiment, consistent with the findings of Liao et al. (2013). Using the Sias measure, we find that adjacent-period herding is stronger in the presence of pessimistic sentiment than in the presence of optimistic sentiment. The herding resulting from following the trades of others contribute almost 90% of total herding, suggesting that institutions are likely to follow the trades of others to resolve their uncertainty during pessimistic periods. The interaction of investor sentiment and analyst recommendations on institutional herding is also examined. It is proposed that institutional investors may experience cognitive dissonance when analyst recommendation revisions conflict with the sentiment related indicators. In particular, cognitive dissonance may be evident when two factors don't suggest similar price movements. In turn, institutional investors may herd strongly (weakly) to the arrival of information in the absence (presence) of cognitive dissonance, resulting in stronger (weaker) within-period herding. On the other hand, when cognitive dissonance is evident, to resolve such uncertainty caused by cognitive dissonance, we find that institutional investors are more likely to follow the trades of others in the subsequent period, resulting in stronger adjacent-period herding. Thus, we find that cognitive dissonance is a key driver for institutional herding by considering the two prominent factors that influence investor trading behaviour and institutional herding.

The study reveals that cognitive dissonance is a key driver in affecting institutional herding by taking account of the two prominent factors that influence institutional herding. Institutions behave differently within the same period and in the subsequent period due to cognitive dissonance. Both LSV and Sias herding measures are employed in our study to capture different aspects of institutional herd behaviour, allowing us to gain greater insights into intentional and spurious herding. Our findings add to several streams of the literature. First The study provides the first examination of analyst recommendation revisions and investor sentiment on institutional herding. It provides insights into how institutions respond to analyst information by considering the role of investor sentiment. We examine this issue by using two different herding measures, LSV model and Sias model to capture herding in the same period and in the subsequent period. Two herding measures allow us a better understanding of spurious and intentional herding. Second, the study contributes to the cognitive dissonance literature by showing that cognitive dissonance is one of the important biases in affecting intuitional herding.

6.2 Limitations and Directions for Future Research

The first limitation of the thesis perhaps involves the measure of investor sentiment for each of the international markets in the first two chapters. The consumer confidence index is used in the study as a proxy for investor sentiment. Although the consumer confidence index has been widely used in many studies in the literature, they are obtained from different sources and some of them are not seasonally adjusted. We also construct an alternative sentiment proxy by following Baker et al. (2012) for ten western and ESEA countries but trading data used for the construction are not available for all 40 countries and the frequency of the index is yearly. The limitations of investor sentiment proxies provide one area of future research: to identify proper sentiment indicators which are more consistent across countries and suitable for high frequency (e.g. monthly).

The second limitation of the thesis relates to the measurement of cognitive dissonance. In the first two empirical chapters, we propose that cognitive dissonance may be a major driver for momentum and PEAD, but we cannot directly examine the intensity of cognitive dissonance. In particular, private (public) news may contradict sentiment states of investors, resulting in the news slowly incorporating into stock prices. If cognitive dissonance is more evident, it is expected that news will diffuse more slowly and vice versa. It would be interesting to develop a measure of cognitive dissonance to allow consideration of the discrepancy between investor sentiment and new information.

The third limitation of the first two empirical chapters to the openness of the stock market. According to Eun et al. (2015), trade or capital market openness alleviates the effect of domestic culture on stock market. Trade openness exposes people to different ideas and values and could potentially mitigate the effect of their own culture effect on their behaviours. Capital market openness allows foreign investors to invest in domestic stock markets, alleviating the influence of domestic culture on stock price behaviour. Thus, it is interesting to examine the effect of the two factors in relation to our findings since based on these arguments, we expect a weaker influence of cognitive dissonance or the cultural effect in more open to international trade and more integrated with the global stock market.

The fourth limitation relates to the third empirical chapter in relation to the type of herding. We show that both within- and adjacent-period herding are informational based herding since it is observed that stock return reversals are relatively weak following institutional herding. To distinguish such herding due to informational cascades or correlated information, further examinations should be conducted.

The fifth limitation also relates to the third empirical chapter in relation to the consensus recommendation revisions. Altinkilic and Hansen (2009) find that average recommendation revision does not produce an economically meaningful price reaction on non-firm news (e.g. earnings announcements) dates. They suggest that analyst average recommendation revisions are uninformative. Chan et al. (2005) provide evidence that there is no difference between the average stock price movement on non-recommendation days and on recommendation days. Loh and Stulz (2010) suggest that previous studies focus on average effects, they do not discuss subsets of recommendations that are influential. They find that consistent with previous studies, a large number of recommendations are uninformative. However, instead focusing on average effect of recommendation revisions, they focus on influential recommendation changes which has significant impact on stock-price and find that 12% of the recommendation changes are influential. They suggest that those influential recommendation change are more likely to come from analysts with larger leader follower ratios and more accurate forecasts. In addition, recommendations that are away from consensus and issued with earnings forecasts at the same period tend to be more influential. Therefore, due to the majority of the recommendation revisions has no significant investment value, it seems that consensus analyst recommendation revisions or average recommendation revisions are less likely to have significant impact on prices or significant value for investors when making trading decisions based the consensus recommendation revisions. It is interesting to replicate our research by replacing consensus recommendation revisions by individual’s influential recommendation revision by following Loh and Stulz (2010).

Furthermore, the first two empirical chapters focus on the interaction of investor sentiment and culture. The literature on investor sentiment shows that professionals (institutional investors) are not likely to be affected by sentiment, whereas amateurs (individual investors) are more likely to be affected by sentiment (see e.g. Lee et al., 1991). Investors are not born as professionals; it is more appropriate to argue that experience is a major factor that influences people’s proneness to sentiment. A number of studies document that younger managers behave more like inexperienced investors (Smith et al. 1988) and younger mutual fund manager exhibit trend-chasing behaviour to buy overpriced stocks compared to older fund managers (Greenwood and Nagel, 2009). Other studies document that experience has an influence on investment decisions (Camerer and Hogarth, 1999) and reduces herd behaviour (Beckmann et al., 2008). Therefore, more experienced investors may exhibit less proneness to sentiment. It would be interesting to empirically examine the effect of experience on investors: less experienced investors are expected to have more impact on financial markets during extreme sentiment states.

In the third empirical chapter, we investigate the effect of investor sentiment and analyst recommendations on institutional herding. It would be interesting to extend our findings to examine different types of institutional investors, such as mutual funds and independent advisors, since Sias (2004) suggests that mutual funds and independent advisors are most likely to experience changes in net flows in relation to their reputation. Previous literature of herding focus on pension funds (Lakonishok et al., 1992) or mutual funds (Grinblatt., 1995). Sias (2004) mentions that different types of managers face different environments (e.g. regulatory requirements and holding periods). This may affects these institutional investors herd only within classifications. Sias (2004) also proposes that if institutional herding is primarily driven by reputational reasons, they should be more likely to follow similar classified institutions than differently classified institutions. Therefore, greater herd behaviour due to reputational reasons should be found among mutual funds and independent advisors.

Bibliography

ABARBANELL, J. S. 1991. Do analysts' earnings forecasts incorporate information in prior stock price changes? *Journal of Accounting and Economics,* 14**,** 147-165.

ABARBANELL, J. S. & BERNARD, V. L. 1992. Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior. *The Journal of Finance,* 47**,** 1181-1207.

AGARWAL, V. & TAFFLER, R. 2008. Does financial distress risk drive the momentum anomaly? *Financial Management,* 37**,** 461-484.

ALI, A., KLEIN, A. & ROSENFELD, J. 1992. Analysts' use of information about permanent and transitory earnings components in forecasting annual EPS. *Accounting Review***,** 183-198.

ANTONIOU, C., DOUKAS, J. A. & SUBRAHMANYAM, A. 2013. Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis,* 48**,** 245-275.

ANTONIOU, C., DOUKAS, J. A. & SUBRAHMANYAM, A. 2015. Investor sentiment, beta, and the cost of equity capital. *Management Science,* 62**,** 347-367.

ARENA, M. P., HAGGARD, K. S. & YAN, X. S. 2008. Price momentum and idiosyncratic volatility. *Financial Review,* 43**,** 159-190.

ARGENTESI, E., LÜTKEPOHL, H. & MOTTA, M. 2010. Acquisition of information and share prices: An empirical investigation of cognitive dissonance. *German Economic Review*, 11, 381-396.

ASEM, E. & TIAN, G. Y. 2011. Market dynamics and momentum profits.

ASNESS, C. S., MOSKOWITZ, T. J. & PEDERSEN, L. H. 2013. Value and momentum everywhere. *The Journal of Finance,* 68**,** 929-985.

AVRAMOV, D., CHORDIA, T., JOSTOVA, G. & PHILIPOV, A. 2007. Momentum and credit rating. *The Journal of Finance,* 62**,** 2503-2520.

BADDELEY, M. 2010. Herding, social influence and economic decision-making: socio-psychological and neuroscientific analyses. *Philosophical Transactions of the Royal Society B: Biological Sciences,* 365**,** 281-290.

BADREDDINE, S., GALARIOTIS, E. C. & HOLMES, P. 2012. The relevance of information and trading costs in explaining momentum profits: Evidence from optioned and non-optioned stocks. *Journal of International Financial Markets, Institutions and Money,* 22**,** 589-608.

BAI, Y. 2014. Cross-border sentiment: an empirical analysis on EU stock markets. *Applied Financial Economics,* 24**,** 259-290.

BAKER, M. & WURGLER, J. 2006. Investor sentiment and the cross-section of stock returns. *The Journal of Finance,* 61**,** 1645-1680.

BAKER, M. & WURGLER, J. 2007. Investor sentiment in the stock market. *The Journal of Economic Perspectives,* 21**,** 129-151.

BAKER, M., WURGLER, J. & YUAN, Y. 2012. Global, local, and contagious investor sentiment. *Journal of Financial Economics,* 104**,** 272-287.

BALL, R. 1978. Anomalies in relationships between securities' yields and yield-surrogates. *Journal of Financial Economics,* 6**,** 103-126.

BALL, R. 1992. The earnings-price anomaly. *Journal of Accounting and Economics,* 15**,** 319-345.

BALL, R. & BROWN, P. 1968. An empirical evaluation of accounting income numbers. *Journal of accounting research***,** 159-178.

BANERJEE, A. V. 1992. A simple model of herd behavior. *The Quarterly Journal of Economics,* 107**,** 797-817.

BANGE, M. M. 2000. Do the portfolios of small investors reflect positive feedback trading? *Journal of Financial and Quantitative Analysis,* 35**,** 239-255.

BARBER, B. M. & LYON, J. D. 1997. Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of financial economics,* 43**,** 341-372.

BARBER, B. M. & ODEAN, T. 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies,* 21**,** 785-818.

BARBERIS, N. & SHLEIFER, A. 2003. Style investing. *Journal of financial Economics,* 68**,** 161-199.

BARBERIS, N., SHLEIFER, A. & VISHNY, R. 1998. A model of investor sentiment. *Journal of financial economics,* 49**,** 307-343.

BARBERIS, N. & THALER, R. 2003. A survey of behavioral finance. *Handbook of the Economics of Finance,* 1**,** 1053-1128.

BARTOV, E. 1992. Patterns in unexpected earnings as an explanation for post-announcement drift. *Accounting Review***,** 610-622.

BATTALIO, R. H. & MENDENHALL, R. R. 2006. Post-earnings announcement drift: Timing and liquidity costs.

BECKER, G. 1996. Preferences and values. *Accounting for Taste, Harvard University Press: Cambridge*.

BERNARD, V. L. & THOMAS, J. K. 1989. Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting research*, 1-36.

BERNARD, V. L. & THOMAS, J. K. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics,* 13, 305-340.

BHUSHAN, R. 1994. An informational efficiency perspective on the post-earnings announcement drift. *Journal of Accounting and Economics,* 18, 45-65.

BIDWELL III, C. M. 1979. A test of market efficiency: SUE/PE. *The Journal of portfolio management,* 5, 53-58.

BIKHCHANDANI, S., HIRSHLEIFER, D. & WELCH, I. 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of political Economy,* 100, 992-1026.

BIKHCHANDANI, S. & SHARMA, S. 2000. Herd behavior in financial markets. *IMF Economic Review,* 47, 279-310.

BLACK, F. 1986. Noise. *The journal of finance,* 41, 528-543.

BLOOMFIELD, R. J., TAYLER, W. B. & ZHOU, F. H. 2009. Momentum, reversal, and uninformed traders in laboratory markets. *The Journal of Finance,* 64, 2535-2558.

BONDT, W. F. & THALER, R. 1985. Does the stock market overreact? *The Journal of finance,* 40, 793-805.

BOOTH, G. G., KALLUNKI, J. P. & MARTIKAINEN, T. 1996. POST - ANNOUNCEMENT DRIFT AND INCOME SMOOTHING: FINNISH EVIDENCE. *Journal of Business Finance & Accounting,* 23, 1197-1211.

BRANDT, M. W., BRAV, A., GRAHAM, J. R. & KUMAR, A. 2010. The idiosyncratic volatility puzzle: Time trend or speculative episodes? *Review of Financial Studies,* 23, 863-899.

BRENNAN, M. J. & HUGHES, P. J. 1991. Stock prices and the supply of information. *The Journal of Finance*, 46, 1665-1691.

BROWN, G. W. & CLIFF, M. T. 2004. Investor sentiment and the near-term stock market. *Journal of Empirical Finance,* 11, 1-27.

BROWN, G. W. & CLIFF, M. T. 2005. Investor sentiment and asset valuation. *The Journal of Business,* 78, 405-440.

BROWN, L. D. & ROZEFF, M. S. 1978. The superiority of analyst forecasts as measures of expectations: Evidence from earnings. *The Journal of Finance,* 33**,** 1-16.

BROWN, N. C., WEI, K. D. & WERMERS, R. 2013. Analyst recommendations, mutual fund herding, and overreaction in stock prices. *Management Science,* 60**,** 1-20.

BROWN, S. J. & WARNER, J. B. 1985. Using daily stock returns: The case of event studies. *Journal of financial economics,* 14**,** 3-31.

C. GALARIOTIS, E. 2014. Contrarian and momentum trading: a review of the literature. *Review of Behavioral Finance*, 6, 63-82.

CELIKER, U., CHOWDHURY, J. & SONAER, G. 2015. Do mutual funds herd in industries? *Journal of Banking & Finance,* 52**,** 1-16.

CHAKRAVARTY, S. 2001. Stealth-trading: Which traders' trades move stock prices? *Journal of Financial Economics,* 61**,** 289-307.

CHAN, K., COVRIG, V. & NG, L. 2005. What determines the domestic bias and foreign bias? Evidence from mutual fund equity allocations worldwide. The Journal of Finance, 60, 1495-1534.

CHAN, K., HAMEED, A. & TONG, W. 2000. Profitability of momentum strategies in the international equity markets. *Journal of financial and quantitative analysis,* 35**,** 153-172.

CHAN, L. K., JEGADEESH, N. & LAKONISHOK, J. 1996. Momentum strategies. *The Journal of Finance,* 51**,** 1681-1713.

CHANG, E. C., CHENG, J. W. & KHORANA, A. 2000. An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance,* 24**,** 1651-1679.

CHANG, T. Y., SOLOMON, D. H. & WESTERFIELD, M. M. 2016. Looking for Someone to Blame: Delegation, Cognitive Dissonance, and the Disposition Effect. *The Journal of Finance*, 71, 267-302.

CHEN, H., CHONG, T. T.-L. & DUAN, X. 2010. A principal-component approach to measuring investor sentiment. *Quantitative Finance,* 10**,** 339-347.

CHEN, X. & CHENG, Q. 2006. Institutional holdings and analysts' stock recommendations. *Journal of Accounting, Auditing & Finance*, 21, 399-440.

CHOE, H., KHO, B.-C. & STULZ, R. M. 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics,* 54**,** 227-264.

CHOI, N. & SIAS, R. W. 2009. Institutional industry herding. *Journal of Financial Economics,* 94**,** 469-491.

CHOI, N. & SKIBA, H. 2015. Institutional herding in international markets. *Journal of Banking & Finance,* 55**,** 246-259.

CHORDIA, T., SADKA, R., GOYAL, A., SADKA, G. & SHIVAKUMAR, L. 2007. Liquidity and the post-earnings-announcement drift.

CHORDIA, T. & SHIVAKUMAR, L. 2002. Momentum, business cycle, and time-varying expected returns. *The Journal of Finance,* 57**,** 985-1019.

CHORDIA, T. & SHIVAKUMAR, L. 2006. Earnings and price momentum. *Journal of financial economics,* 80**,** 627-656.

CHRISTIE, W. G. & HUANG, R. D. 1995. Following the pied piper: Do individual returns herd around the market? *Financial Analysts Journal***,** 31-37.

CHUI, A. C., TITMAN, S. & WEI, K. J. 2010. Individualism and momentum around the world. *The Journal of Finance,* 65**,** 361-392.

CLARKE, R. G. & STATMAN, M. 1998. Bullish or bearish? *Financial Analysts Journal***,** 63-72.

COLLINS, W. A. & HOPWOOD, W. S. 1980. A multivariate analysis of annual earnings forecasts generated from quarterly forecasts of financial analysts and univariate time-series models. *Journal of Accounting Research***,** 390-406.

COOPER, M. J., GUTIERREZ, R. C. & HAMEED, A. 2004. Market states and momentum. *The Journal of Finance,* 59**,** 1345-1365.

COSTELLO, D. J. & HALL, J. 2011. The impact of security analyst recommendations upon the trading of mutual funds.

COWEN, A., GROYSBERG, B. & HEALY, P. 2006. Which types of analyst firms are more optimistic? *Journal of Accounting and Economics*, 41, 119-146.

CROSS, S. E., HARDIN, E. E. & GERCEK-SWING, B. 2010. The what, how, why, and where of self-construal. *Personality and Social Psychology Review*.

DANIEL, K., HIRSHLEIFER, D. & SUBRAHMANYAM, A. 1998. Investor psychology and security market under‐ and overreactions. *The Journal of Finance*, 53, 1839-1885.

DARRAT, A. F., RAHMAN, S. & ZHONG, M. 2002. On the role of futures trading in spot market fluctuations: perpetrator of volatility or victim of regret? *Journal of Financial Research*, 25, 431-444.

DE BONDT, W. F. 1991. What do economists know about the stock market. *Journal of Portfolio Management,* 17**,** 84-91.

DE LONG, J. B., SHLEIFER, A., SUMMERS, L. H. & WALDMANN, R. J. 1990a. Noise trader risk in financial markets. *Journal of political Economy,* 98**,** 703-738.

DE LONG, J. B., SHLEIFER, A., SUMMERS, L. H. & WALDMANN, R. J. 1990b. Positive feedback investment strategies and destabilizing rational speculation. *the Journal of Finance,* 45**,** 379-395.

DEVENOW, A. & WELCH, I. 1996. Rational herding in financial economics. *European Economic Review,* 40**,** 603-615.

DOU, P., TRUONG, C. & VEERARAGHAVAN, M. 2015. Individualism, uncertainty avoidance, and earnings momentum in international markets. *Contemporary Accounting Research*.

DOUGLAS, M. & WILDAVSKY, A. 1982. Risk and culture. Berkeley. *University of California Press,* 272**,** 10-15.

DREMAN, D. N. 1979. *Contrarian investment strategy: the psychology of stock market success*, Random House Incorporated.

EDWARDS, W. 1968. Conservatism in human information processing. *Formal representation of human judgment,* 17**,** 51.

FALKENSTEIN, E. G. 1996. Preferences for stock characteristics as revealed by mutual fund portfolio holdings. *The Journal of Finance,* 51**,** 111-135.

FAMA, E. F. 1970. Efficient capital markets: A review of theory and empirical work. *The journal of Finance,* 25**,** 383-417.

FAMA, E. F. 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of financial economics,* 49**,** 283-306.

FAMA, E. F. & FRENCH, K. R. 1992. The cross-section of expected stock returns. *the Journal of Finance,* 47**,** 427-465.

FAMA, E. F. & FRENCH, K. R. 1996. Multifactor explanations of asset pricing anomalies. *The journal of finance,* 51**,** 55-84.

FAMA, E. F. & FRENCH, K. R. 2012. Size, value, and momentum in international stock returns. *Journal of financial economics,* 105**,** 457-472.

FAMA, E. F. & FRENCH, K. R. 2015. A five-factor asset pricing model. *Journal of financial economics,* 116**,** 1-22.

FESTINGER, L. 1962. *A theory of cognitive dissonance*, Stanford university press.

FISHER, K. L. & STATMAN, M. 2003. Consumer confidence and stock returns. *The Journal of Portfolio Management,* 30**,** 115-127.

FOSTER, G. 1977. Quarterly accounting data: Time-series properties and predictive-ability results. *Accounting Review***,** 1-21.

FOSTER, G., OLSEN, C. & SHEVLIN, T. 1984. Earnings releases, anomalies, and the behavior of security returns. *Accounting Review***,** 574-603.

FRANCK, A. & KERL, A. 2013. Analyst forecasts and European mutual fund trading. *Journal of Banking & Finance*, 37, 2677-2692.

FRAZZINI, A. 2006. The disposition effect and underreaction to news. *The Journal of Finance,* 61**,** 2017-2046.

FROOT, K. A., SCHARFSTEIN, D. S. & STEIN, J. C. 1992. Herd on the street: Informational inefficiencies in a market with short - term speculation. *The Journal of Finance*, 47, 1461-1484.

GOETZMANN, W. N. & PELES, N. 1997. Cognitive dissonance and mutual fund investors. *Journal of financial Research,* 20**,** 145-158.

GOMPERS, P., ISHII, J. & METRICK, A. 2003. Corporate governance and equity prices. *The quarterly journal of economics,* 118**,** 107-156.

GRIFFIN, J. M., JI, X. & MARTIN, J. S. 2003. Momentum investing and business cycle risk: Evidence from pole to pole. *The Journal of Finance,* 58**,** 2515-2547.

GRINBLATT, M. & HAN, B. 2005. Prospect theory, mental accounting, and momentum. *Journal of financial economics,* 78**,** 311-339.

GRINBLATT, M., TITMAN, S. & WERMERS, R. 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *The American economic review***,** 1088-1105.

GRUNDY, B. D. & MARTIN, J. S. M. 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Financial studies,* 14**,** 29-78.

GUISO, L., SAPIENZA, P. & ZINGALES, L. 2006. Does culture affect economic outcomes? *The journal of economic perspectives,* 20**,** 23-48.

GUREVICH, A. Y. 1969. Time as a problem of the history of culture. *Voprosy Filosofii,* 23**,** 105-116.

HAMEED, A., HONG, D. & WARACHKA, M. 2008. Momentum and informed trading.

HEW, D., SKERRATT, L., STRONG, N. & WALKER, M. 1996. Post-earnings-announcement drift: some preliminary evidence for the UK. *Accounting and Business Research,* 26**,** 283-293.

HIRSHLEIFER, D., MYERS, J. N., MYERS, L. A. & TEOH, S. H. 2002. Do individual investors drive post-earnings announcement drift. *Fisher College of Business, Ohio State University, and University of Illinois at Urbana-Champaign*.

HIRSHLEIFER, D., SUBRAHMANYAM, A. & TITMAN, S. 1994. Security analysis and trading patterns when some investors receive information before others. *The Journal of Finance,* 49**,** 1665-1698.

HOLMES, P., KALLINTERAKIS, V. & FERREIRA, M. 2013. Herding in a concentrated market: a question of intent. *European Financial Management,* 19**,** 497-520.

HONG, D., LEE, C. & SWAMINATHAN, B. 2003. Earnings momentum in international markets.

HONG, H., LIM, T. & STEIN, J. C. 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance,* 55**,** 265-295.

HONG, H. & STEIN, J. C. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of finance,* 54**,** 2143-2184.

HONG, H. & STEIN, J. C. 2007. Disagreement and the stock market. *The Journal of Economic Perspectives,* 21**,** 109-128.

HUNG, M., LI, X. & WANG, S. 2014. Post-earnings-announcement drift in global markets: Evidence from an information shock. *Review of Financial Studies***,** hhu092.

INCE, O. S. & PORTER, R. B. 2006. Individual equity return data from Thomson Datastream: Handle with care! *Journal of Financial Research,* 29**,** 463-479.

JACOB, J., LYS, T. & SABINO, J. 1999. Autocorrelation structure of forecast errors from time-series models: Alternative assessments of the causes of post-earnings announcement drift. *Journal of Accounting and Economics,* 28**,** 329-358.

JEGADEESH, N. 1990. Evidence of predictable behavior of security returns. *The Journal of Finance,* 45**,** 881-898.

JEGADEESH, N. & KIM, W. 2006. Value of analyst recommendations: International evidence. Journal of Financial Markets, 9, 274-309.

JEGADEESH, N. & TITMAN, S. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance,* 48**,** 65-91.

JEGADEESH, N. & TITMAN, S. 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of finance,* 56**,** 699-720.

JEGADEESH, N. & TITMAN, S. 2011. Momentum. *Annu. Rev. Financ. Econ.,* 3**,** 493-509.

JI, L.-J. 2008. The leopard cannot change his spots, or can he? Culture and the development of lay theories of change. *Personality and Social Psychology Bulletin,* 34**,** 613-622.

JI, L.-J., NISBETT, R. E. & SU, Y. 2001. Culture, change, and prediction. *Psychological Science,* 12**,** 450-456.

JI, L. J., ZHANG, Z. & GUO, T. 2008. To buy or to sell: Cultural differences in stock market decisions based on price trends. *Journal of Behavioral Decision Making,* 21**,** 399-413.

JONES, C. P. & LITZENBERGER, R. H. 1970. Quarterly earnings reports and intermediate stock price trends. *The Journal of Finance,* 25**,** 143-148.

KAHNEMAN, D. & TVERSKY, A. 1979. Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the econometric society***,** 263-291.

KAHNEMAN, D. & TVERSKY, A. 1982. On the study of statistical intuitions. *Cognition,* 11**,** 123-141.

KANIEL, R., SAAR, G. & TITMAN, S. 2008. Individual investor trading and stock returns. *The Journal of Finance,* 63**,** 273-310.

KARLSSON, N., SEPPI, D. J. & LOEWENSTEIN, G. 2005. The'ostrich effect': Selective attention to information about investments.

KELSEY, D., KOZHAN, R. & PANG, W. 2010. Asymmetric momentum effects under uncertainty. *Review of Finance***,** rfq021.

KEYNES, J. M. 1936. The general theory of employment, money and interest. *The Collected Writings,* 7.

KINDLEBERGER, C. P. 2000. Manias, panics, and crashes: a history of financial crises. *The Scriblerian and the Kit-Cats*, 32, 379.

KIM, K. A. & NOFSINGER, J. R. 2005. Institutional herding, business groups, and economic regimes: Evidence from Japan. *The Journal of Business,* 78**,** 213-242.

KIM, W. & WEI, S.-J. 2002. Foreign portfolio investors before and during a crisis. *Journal of international economics,* 56**,** 77-96.

KREMER, S. & NAUTZ, D. 2013. Causes and consequences of short-term institutional herding. *Journal of Banking & Finance,* 37**,** 1676-1686.

LAKONISHOK, J., SHLEIFER, A. & VISHNY, R. W. 1992. The impact of institutional trading on stock prices. *Journal of financial economics,* 32**,** 23-43.

LATANE, H. A., JOY, O. M. & JONES, C. P. 1970. Quarterly data, sort-rank routines, and security evaluation. *The Journal of Business,* 43**,** 427-438.

LEE, C., SHLEIFER, A. & THALER, R. H. 1991. Investor sentiment and the closed-end fund puzzle. *The Journal of Finance,* 46**,** 75-109.

LEE, W. Y., JIANG, C. X. & INDRO, D. C. 2002. Stock market volatility, excess returns, and the role of investor sentiment. *Journal of banking & Finance,* 26**,** 2277-2299.

LEHMANN, B. N. 1990. Fads, martingales, and market efficiency. *The Quarterly Journal of Economics,* 105**,** 1-28.

LEMMON, M. & PORTNIAGUINA, E. 2006. Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies,* 19**,** 1499-1529.

LESMOND, D. A., SCHILL, M. J. & ZHOU, C. 2004. The illusory nature of momentum profits. *Journal of financial economics,* 71**,** 349-380.

LEV, B. & OHLSON, J. A. 1982. Market-based empirical research in accounting: A review, interpretation, and extension. *Journal of Accounting Research***,** 249-322.

LI, D. D. & YUNG, K. 2004. Institutional herding in the ADR market. *Review of Quantitative Finance and Accounting,* 23**,** 5-17.

LI, X., BROOKS, C. & MIFFRE, J. 2009. Low-cost momentum strategies. *Journal of Asset Management,* 9**,** 366-379.

LIAO, T.-L., HUANG, C.-J. & WU, C.-Y. 2011. Do fund managers herd to counter investor sentiment? *Journal of Business Research,* 64**,** 207-212.

LIU, L. X. & ZHANG, L. 2008. Momentum profits, factor pricing, and macroeconomic risk. *Review of Financial Studies,* 21**,** 2417-2448.

LIU, W., STRONG, N. & XU, X. 2003. Post–earnings–announcement Drift in the UK. *European Financial Management,* 9**,** 89-116.

LIVNAT, J. & PETROVITS, C. 2009. Investor sentiment, post-earnings announcement drift, and accruals.

LO, A. W. & MACKINLAY, A. C. 1990. When are contrarian profits due to stock market overreaction? *Review of Financial studies,* 3**,** 175-205.

LOH, R. K. & STULZ, R. M. 2011. When are analyst recommendation changes influential? Review of Financial Studies, 24, 593-627.

LOUGHRAN, T., RITTER, J. R. & RYDQVIST, K. 1994. Initial public offerings: International insights. Pacific-Basin Finance Journal, 2, 165-199.

LJUNGQVIST, A., MARSTON, F., STARKS, L. T., WEI, K. D. & YAN, H. 2007. Conflicts of interest in sell-side research and the moderating role of institutional investors. *Journal of Financial Economics*, 85, 420-456.

MARKUS, H. R. & KITAYAMA, S. 1991. Culture and the self: Implications for cognition, emotion, and motivation. *Psychological review,* 98**,** 224.

MCDOUGALL, W. 1926. Outline of abnormal psychology. *American Journal of Physical Medicine & Rehabilitation,* 5**,** 473.

MCLEAN, R. D. 2010. Idiosyncratic risk, long-term reversal, and momentum.

MCLEAN, R. D. & ZHAO, M. Investor sentiment and real investment. The 2010 Annual Meeting of the Academy of Behavioral Finance & Economics, 2010. 68.

MENDENHALL, R. R. 2002. Arbitrage risk and post-earnings-announcement drift.

MENKHOFF, L., SARNO, L., SCHMELING, M. & SCHRIMPF, A. 2012. Currency momentum strategies. *Journal of Financial Economics,* 106**,** 660-684.

MERTON, R. C. 1987. A simple model of capital market equilibrium with incomplete information. *The journal of finance*, 42, 483-510.

MIAN, G. M. & SANKARAGURUSWAMY, S. 2012. Investor sentiment and stock market response to earnings news. *The Accounting Review,* 87**,** 1357-1384.

MILLER, J. G. 1984. Culture and the development of everyday social explanation. *Journal of personality and social psychology,* 46**,** 961.

MOSKOWITZ, T. J. & GRINBLATT, M. 1999. Do industries explain momentum? *The Journal of Finance,* 54**,** 1249-1290.

MOSKOWITZ, T. J., OOI, Y. H. & PEDERSEN, L. H. 2012. Time series momentum. *Journal of Financial Economics,* 104**,** 228-250.

NG, J., RUSTICUS, T. O. & VERDI, R. S. 2008. Implications of transaction costs for the post–earnings announcement drift. *Journal of Accounting Research,* 46**,** 661-696.

O'BRIEN, P. C. 1988. Analysts' forecasts as earnings expectations. *Journal of accounting and Economics,* 10**,** 53-83.

O'BRIEN, P. C. & BHUSHAN, R. 1990. Analyst following and institutional ownership. *Journal of Accounting Research*, 55-76.

OTOO, M. W. 1999. Consumer sentiment and the stock market.

PÁSTOR, Ľ. & STAMBAUGH, R. F. 2003. Liquidity risk and expected stock returns. *Journal of Political economy,* 111**,** 642-685.

PATTERSON, D. & SHARMA, V. 2007. Did Herding Cause the Stock Market Bubble of 1998-2001? : Citeseer.

PENG, K. & NISBETT, R. E. 1999. Culture, dialectics, and reasoning about contradiction. *American psychologist,* 54**,** 741.

PRAST, H. M. & DE VOR, M. P. 2005. Investor reactions to news: a cognitive dissonance analysis of the euro–dollar exchange rate. European *Journal of Political Economy*, 21, 115-141.

RANGAN, S. & SLOAN, R. G. 1998. Implications of the integral approach to quarterly reporting for the post-earnings-announcement drift. *Accounting Review***,** 353-371.

RITSEMA, R. & KARCHER, S. 1994. I ching. *Rockport, MA: Element Books*.

RITTER, J. R. 1991. The long-run performance of initial public offerings. *The journal of finance,* 46**,** 3-27.

ROUWENHORST, K. G. 1998. International momentum strategies. *The Journal of Finance,* 53**,** 267-284.

SADKA, R. 2006. Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics,* 80**,** 309-349.

SAGI, J. S. & SEASHOLES, M. S. 2007. Firm-specific attributes and the cross-section of momentum. *Journal of Financial Economics,* 84**,** 389-434.

SCHARFSTEIN, D. S. & STEIN, J. C. 1990. Herd behavior and investment. *The American Economic Review***,** 465-479.

SCHMELING, M. 2007. Institutional and individual sentiment: Smart money and noise trader risk? *International Journal of Forecasting,* 23**,** 127-145.

SCHMELING, M. 2009. Investor sentiment and stock returns: Some international evidence. *Journal of empirical finance,* 16**,** 394-408.

SCHWARZ, N. 2000. Emotion, cognition, and decision making. *Cognition & Emotion,* 14**,** 433-440.

SCIUBBA, E. 2002. Relative performance and herding in financial markets. *Performance measurement in finance: firms, funds and managers. Oxford. S***,** 285-328.

SEWELL, M. 2010. Behavioural Finance, University of Cambridge. working paper.

SHILLER, R. J., FISCHER, S. & FRIEDMAN, B. M. 1984. Stock prices and social dynamics. *Brookings papers on economic activity,* 1984**,** 457-510.

SHLEIFER, A. 2000. *Inefficient Markets: An introduction to behavioural finance*, OUP Oxford.

SHLEIFER, A. & VISHNY, R. W. 1997. The limits of arbitrage. *The Journal of Finance,* 52**,** 35-55.

SIAS, R. W. 2004. Institutional herding. *Review of financial studies,* 17**,** 165-206.

SIAS, R. W., STARKS, L. T. & TITMAN, S. 2006. Changes in institutional ownership and stock returns: Assessment and methodology. *The Journal of Business,* 79**,** 2869-2910.

SMIDT, S. 1968. A new look at the random walk hypothesis. *Journal of Financial and Quantitative Analysis***,** 235-261.

SOLT, M. E. & STATMAN, M. 1988. How useful is the sentiment index? *Financial Analysts Journal***,** 45-55.

SPENCER-RODGERS, J., WILLIAMS, M. J. & PENG, K. 2010. Cultural differences in expectations of change and tolerance for contradiction: A decade of empirical research. *Personality and Social Psychology Review*.

SPINA, R. R., JI, L.-J., GUO, T., ZHANG, Z., LI, Y. & FABRIGAR, L. 2010. Cultural differences in the representativeness heuristic: Expecting a correspondence in magnitude between cause and effect. *Personality and Social Psychology Bulletin,* 36**,** 583-597.

STAMBAUGH, R. F., YU, J. & YUAN, Y. 2012. The short of it: Investor sentiment and anomalies. *Journal of Financial Economics,* 104**,** 288-302.

STIVERS, C. & SUN, L. 2010. Cross-sectional return dispersion and time variation in value and momentum premiums.

TRUEMAN, B. 1994. Analyst forecasts and herding behavior. *Review of financial studies,* 7**,** 97-124.

TRUONG, C. 2011. Post-earnings announcement abnormal return in the Chinese equity market. *Journal of International Financial Markets, Institutions and Money,* 21**,** 637-661.

VERARDO, M. 2009. Heterogeneous beliefs and momentum profits. *Journal of Financial and Quantitative Analysis,* 44**,** 795-822.

WALTER, A. & MORITZ WEBER, F. 2006. Herding in the German mutual fund industry. *European Financial Management,* 12**,** 375-406.

WANG, K. Q. & XU, J. 2015. Market volatility and momentum. *Journal of Empirical Finance,* 30**,** 79-91.

WERMERS, R. 1999. Mutual fund herding and the impact on stock prices. *The Journal of Finance,* 54**,** 581-622.

WIGGINS, J. B. 1991. Do misperceptions about the earnings process contribute to post-announcement drift. *Manuscript (Cornell University, Ithaca, NY)*.

WOMACK, K. L. 1996. Do brokerage analysts' recommendations have investment value? *The journal of finance*, 51, 137-167.

WYLIE, S. 2005. Fund manager herding: A test of the accuracy of empirical results using UK data. *The Journal of Business,* 78**,** 381-403.

YU, J. & YUAN, Y. 2011. Investor sentiment and the mean–variance relation. *Journal of Financial Economics,* 100**,** 367-381.

ZHANG, X. 2006. Information uncertainty and stock returns. *The Journal of Finance,* 61**,** 105-137.

ZHOU, R. T. & LAI, R. N. 2009. Herding and information based trading. *Journal of Empirical Finance,* 16**,** 388-393.

ZWEIG, M. E. 1973. AN INVESTOR EXPECTATIONS STOCK PRICE PREDICTIVE MODEL USING CLOSED‐END FUND PREMIUMS. *The Journal of Finance*, 28, 67-78.