COGNITIVE BIASES, STYLE INVESTING, AND STOCK RETURN PREDICTABILITY

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ABSTRACT

COGNITIVE BIASES, STYLE INVESTING, AND STOCK RETURN PREDICTABILITY

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This dissertation consists of three distinct essays. In the first essay, "Does Credit risk explain market's participants 'cognitive biases - Evidence from Anchoring Bias in Analysts' Earnings Forecasts", using anchoring bias in analysts' earnings forecasts, I examine the relation between credit risk and market participants' cognitive biases. Recent findings indicate that analysts suffer from anchoring bias as they anchor their earnings per share (EPS) forecasts on the industry median without making sufficient adjustment. I show that the profitability of anchoring bias based trading strategies concentrates in the worst-rated stocks, especially around credit rating downgrades, suggesting that analysts exhibit stronger cognitive biases when making earnings forecasts for firms with the greatest credit risk. Furthermore, I discover that credit risk can even explain the effect of anchoring on analysts' forecast errors and future stock returns, highlighting the importance of credit risk for studies on market participants' cognitive biases and stock market anomalies. My findings have broad implications for psychology-based asset pricing theory.

In the second essay, "Investor Sentiment and Style Investing", I examine the implications of investor sentiment for style investing. I hypothesize that when investor sentiment is high, there are more style "switchers" who allocate funds based on a style's relative past performance, leading to a stronger impact of style investing on asset prices. Consistent with my hypothesis, this study has two main findings. First, style returns have predictive power for future stock

returns following high levels of sentiment but not low levels of sentiment. By focusing on the high-sentiment periods, style investing significantly affects the predictability of stock returns even during the early period of 1965-1987, and the significance of style investing increases during the later period of 1988-2014. Second, the correlation between past style returns and future stock returns can explain variation in momentum profits following high levels of sentiment but not low levels of sentiment. The profitability from the comovement-momentum based strategy under high sentiment is mainly driven by overpricing of losers socks due to short selling constraints. My findings highlight the important role of investor sentiment in pricing financial assets.

In the third essay, “Style Investing and IPO return predictability”, using a sample of 7,524 IPOs during 1975-2013, I find a strong evidence that an IPO stock’s past style returns can predict both IPO underpricing and post-IPO returns. I determine the style of each IPO stock based on its size and book-to-market ratio immediately after IPO. I find that IPO stocks’ past style returns are positively related to IPO underpricing and negatively related to post-IPO returns over 3-, 6-, and 12-month horizons. Moreover, the style return in the IPO month is negatively related to post-IPO returns up to three years. These findings underscore the empirical importance of style investing.

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CHAPTER 1

INTRODUCTION

It is well documented in the psychology literature that human beings suffer from a number of cognitive biases. While many studies have found that cognitive biases play an important role in the capital market, we do not fully understand the conditions under which market participants are more likely to suffer from cognitive biases. A better understanding of this issue has significant implications for behavioral finance and asset pricing theories.

This dissertation consists of three behavioral finance essays which are related to cognitive biases, style investing, and stock return predictability. The first essay examines the relationship between credit risk and market participant's cognitive biases. Specifically, I investigate the anchoring bias in analyst's earnings forecasts. The main findings of the first essay greatly enhance our understanding of the profound effect of credit risk on the market participants' cognitive biases, especially anchoring bias in analysts' earnings forecasts. The second essay examines the relationship between investor sentiment and style investing; both are important behavioral finance subjects that have received great attention from academics and practitioners. The second essay helps us better understand how investor sentiment contributes to stock return predictability. The third essay connects style investing with IPO stock returns. I find that style investing has a significant impact on IPO stocks' return predictability. The main finding of the third essay is novel in the IPO literature and helps explain some other puzzling results documented in previous studies.

Avramov et al. (2013) find that credit risk can explain a number of asset pricing anomalies. The first essay examines the hypothesis that market participants exhibit stronger cognitive biases when valuing firms with greater credit risk. This hypothesis is conceptually motivated by the argument that higher credit risk is associated with higher uncertainty surrounding a firm (Avramov et al., 2009b). Cognitive biases may occur when "people assess the probability of an uncertain event or the value of an uncertain quantity" (Tversky and Kahneman, 1974). Intuitively, when the event or quantity is more uncertain, individuals are more likely to suffer from cognitive biases. Using investor-level data, Kumar (2009) confirms that individual investors exhibit stronger behavioral biases when stocks are harder to value. In the first essay, I focus on a specific setting to examine my hypothesis on the relation between credit risk and market participants' cognitive biases. I choose to study stock analysts as they are stock valuation professionals whose opinions may influence other market participants. I focus on anchoring bias, which is well documented to exist in the financial market. A number of studies have examined the role of anchoring bias in the financial market. For example, George and Hwang (2004), Kaustia, Alho, and Puttonen (2008), Campbell and Sharpe (2009), Baker, Pan, and Wurgler (2012), Li and Yu (2012), Wilson (2012), Cen, Hilary, and Wei (2013), Chang, Luo, and Ren (2013), and Dougal, Engelberg, Parsons, and Van Wesep (2015).

Tversky and Kahneman (1974) introduce the concept of anchoring bias: "in many situations, people make estimates by starting from an initial value that is adjusted to yield the final answer. The initial value, or starting point, may be suggested by the formulation of the problem, or it may be the result of a partial computation. In either case, adjustments are typically insufficient." Empirically, Cen, Hilary, and Wei (2013) (henceforth CHW) find that analysts suffer from anchoring bias when making earnings per share (EPS) forecasts. Specifically, analysts anchor their forecasts on the industry norm: when a firm's forecast earnings per share (FEPS) is below (above) the industry norm (i.e., the anchor), analysts make insufficient downward (upward) adjustments away from the industry norm, and these firms subsequently experience abnormally low (high) stock returns. CHW measure analysts' anchoring by how far a stock's FEPS is above its industry norm. In other words, anchoring is measured as the signed distance between a stock's FEPS and its industry norm. I will refer to this measure as anchoring. They find that anchoring is positively related to forecast errors, earnings surprises, stock returns, and the probability of a stock split. The trading strategy of buying high anchoring stocks and selling low anchoring stocks achieves a statistically significant and economically large profit that cannot be explained by known risk or style factors.

Following my argument earlier, conceptually, I expect analysts to be more vulnerable to anchoring bias when making EPS forecasts for stocks with greater credit risk, as higher credit risk is associated with higher uncertainty surrounding a firm. Additionally, I examine whether credit risk has more explanatory power for future stock returns than anchoring bias in analysts' EPS forecasts, because credit risk not only captures the uncertainty about a firm's future *earnings*, but it also captures the uncertainty about other important factors for asset pricing such as the cost of equity capital. Merton (1974) develops a structural model of default risk in which firm equity is a call option whose strike price is the face value of debt. Therefore, default risk captures the uncertainty about not only future earnings and growth rates, but also the cost of equity. In contrast, the anchoring bias in analysts' EPS forecasts is related to only one of the several important factors for asset pricing (i.e., future *earnings*). Specifically, I examine whether credit risk can explain the effects of anchoring on forecast errors, earnings surprises, stock returns, and stock splits.

Using a sample of U.S. firms rated by Standard and Poor's (S&P) from January 1986 to December 2014, I find that the effect of analysts' anchoring on forecast errors, earnings surprises, stock returns, and stock splits exists mainly among firms with the greatest credit risk. I show that the profitability of anchoring bias based trading strategies concentrates in the worst-rated firms around rating downgrades.

My first essay makes several contributions. First, it increases our understanding about market participants' cognitive biases. By focusing on the anchoring bias in analysts' EPS forecasts, I show that analysts exhibit the strongest cognitive biases for stocks with the greatest credit risk. My findings have important implications for the behavioral finance literature. It is likely that credit risk may also explain market participants' other cognitive biases (e.g., mental accounting, loss aversion, overconfidence). I leave this for future research. Second, my finding that the credit rating effect can subsume the effect of the anchoring bias highlights the importance of credit risk in asset pricing. In particular, I stress the importance of controlling for credit risk in studies on market participants' cognitive biases and stock market anomalies. Last but not least, my finding has important implications for the puzzling negative relation between credit risk and stock return (e.g., Dichev, 1998; Vassalou and Xing, 2004; Campbell, Hilscher, and Szilagyi, 2008; Avramov, Chordia, Jostova, and Philipov, 2009b). I propose that a fruitful area of future research is to explore the interrelationships between credit risk, cognitive biases, and stock returns.

In the second essay of my dissertation, I relate the style investing to investor sentiment. The effect of investor sentiment on asset prices is one of the most contentious issues in financial economics. While numerous studies have provided evidence to the debate (e.g., Lee, Shleifer, and Thaler, 1991; Ritter, 1991; Brown and Cliff, 2005; Baker and Wurgler, 2006, 2007; Lemmon and Portniaguina, 2006; Kaplanski and Levy, 2010; Yu and Yuan, 2011; Baker, Wurgler, and Yuan, 2012; Stambaugh et al., 2012; Yu, 2013; Huang, Jiang, Tu, and Zhou, 2016; Chou, Hsieh, and Shen, 2016), this study seeks to better understand the specific mechanisms through which investor sentiment affects asset prices. For example, Stambaugh et al. (2012) find that investor sentiment plays an important role in 11 asset-pricing anomalies. However, they do not discuss the exact mechanism through which investor sentiment affects each anomaly. They expect future research to "develop a richer understanding of how sentiment plays a role in pricing financial assets." I take a step in this direction by showing that sentiment affects the extent to which style investing affects asset prices. A richer understanding of how sentiment drives asset prices away from their fundamental values is important for both market participants and policy makers.

In the style investing model of Barberis and Shleifer (2003), there are two kinds of investors: "switchers" and "fundamental traders." Switchers allocate funds based on different investment styles' relative past performance: the styles that have performed well in the past attract more funds from the styles that have performed poorly; these fund inflows (outflows) positively (negatively) affect stock prices. Due to several reasons discussed in Barberis and Shleifer (2003), fundamental traders are unable to push prices back to fundamental values quickly. An empirical prediction of Barberis and Shleifer's (2003) model is that a style's past return can predict the future return of a stock that belongs to the style. To provide empirical evidence for the style investing argument, Wahal and Yavus (2013) estimate Fama-Macbeth regressions of individual stock returns on the past returns of the style to which the stock belongs. They find a significant and positive coefficient on the style's past return. The evidence that past style return can predict future stock return is consistent with the prediction of Barberis and Shleifer (2003).

In the second essay, I test two hypotheses. The first hypothesis is the return predictability hypothesis. I hypothesize that when investor sentiment is high, investors are more likely to suffer from a cognitive bias that leads to extrapolative expectations, which induces the irrational behaviors of switchers who allocate funds based on a style's relative past performance. Therefore, the positive relation between the past style return and future stock return would be stronger following high levels of sentiment. The return predictability hypothesis that the predictive power of past style returns for future stock return is greater following high sentiment. I test my empirical prediction using the stock return regression framework examined in Wahal and Yavuz (2013). I expect the positive coefficient on past style return to be larger following high levels of sentiment.

Second, my second hypothesis is the momentum profit predictability hypothesis. The second hypothesis also has important implications for the drivers of momentum. Specifically, I expect a greater impact of comovement on momentum profits following high levels of sentiment. My second hypothesis based on both the theoretical predictions of Barberis and Shlleifer (2003) and the empirical evidences provided by Wahal and Yavus (2013). There are many rational and behavioral hypotheses for momentum. For example, see Conrad and Kaul (1998), Berk, Green, and Naik (1999), Johnson (2002), and Sagi and Seasholes (2007) for rational explanations and Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), Daniel, Hirshleifer, and Subrahmanyam (2001), and Barberis and Shleifer (2003) for behavioral explanations.

Style investing generates momentum through the mechanism of comovement of a stock with its style (Barberis and Shleifer, 2003). Empirically, Wahal and Yavuz (2013) use the contemporaneous correlation between a stock's return and its style's return to explain the variation in momentum profits. Specifically, after sorting all stocks into comovement terciles, they find that a momentum portfolio that buys winners and sells losers in the high comovement tercile have higher returns than a momentum portfolio that buys winners and sells losers in the low comovement tercile. Their findings suggest that style investing drives momentum through comovement of a stock with its style, confirming the prediction by Barberis and Shleifer (2003). As modelled in Barberis and Shleifer (2003), switchers' style investing behaviors are irrational. According to my central assumption that investor sentiment drives investors' irrational behaviors, I expect investor sentiment to affect the degree to which style investing contributes to momentum. My second hypothesis states that the comovement of a stock with its style, which is generated by style investing, can explain the variation in momentum profits following high levels of sentiment.

The second essay has several contributions. First, it provides more insight into the mechanism through which investor sentiment affects the predictability of stock returns. Specifically, I examine the relation between investor sentiment and style investing. An important assumption underlying my study is that investor sentiment drives investors' irrational behaviors. In the style investing model of Barberis and Shleifer (2003), some investors can be irrational as they make investment decisions solely based on past style performance. I expect investor sentiment to affect the aggregate irrational investing behaviors among investors. Consequently, I expect investor sentiment to make a difference to the impact of style investing on asset prices. Second, my second essay provides strong evidence that style investing is a behavioral phenomenon that is partially derived by investor sentiment. The results help to answer the open question raised by Wahal and Yavus (2013) in their conclusion whether rational or stock-specific behavioral biases are responsible for the predictability in stock returns.

Style investing has become more important over time. Examples of recent studies that have examined style investing include Barberis and Shleifer (2003), Teo and Woo (2004), Chen and Bondt (2004), Froot and Teo (2008), and Wahal and Yavuz (2013). However, I am not aware of any study that examines whether style investing affects IPO stock returns. The objective of the third essay is to fill this gap in the literature.

In the third essay, I hypothesize that the past return of a style to which an IPO stock belongs can predict the IPO stock returns, which include both the IPO stock's first-day return (i.e., underpricing) and post-IPO returns. Specifically, if some investors buy IPO stocks in the aftermarket on the first trading day based on the IPO stock's past style return, then I would expect the past style return to be positively correlated with the IPO stock's first day return. Similarly, I can also expect the past style return to be correlated with the IPO stock returns in the immediate aftermarket, over intermediate horizons, or even in the long run. However, it is an empirical question whether the past style return is positively or negatively correlated with the post-IPO stock returns. On the one hand, if investors continue to buy the IPO stocks in the aftermarket by extrapolating the past style return for the IPO stock, then I would expect a positive correlation between the past style return and the IPO stock's future return. On the other hand, if investors' buying trend reverses soon after the IPO stock's immediate aftermarket, then I would expect a negative correlation between the past style return and the IPO stock's future returns. In other words, it is an empirical question when the price trend reverses after the IPO stock starts to trade. To examine this issue, I measure post-IPO stock returns over 3 months, 6 months, 12 months, 24 months, and 36 months. I find a new predictor of IPO stock returns, the pre-IPO style return, i.e., the pre-IPO return of the style which the IPO stock belongs to. I find that not only can the pre-IPO style return predict the IPO underpricing; pre-IPO style return can also predict post-IPO 3-month, 6-month, and 12-month stock returns. Moreover, the style return in the calendar month of the IPO has predictive ability for the IPO stock's one-, two-, and three-year returns.

CHAPTER 2

DOES CREDIT RISK EXPLAIN MARKET'S PARTICIPANTS COGNITIVE BIASES?- EVIDENCE FROM ANCHORING IN ANALYSTS' EARNINGS FORECASTS

ABSTRACT

Using anchoring bias in analysts' earnings forecasts, I examine the relation between credit risk and market participants' cognitive biases. Recent findings indicate that analysts suffer from anchoring bias as they anchor their earnings per share (EPS) forecasts on the industry median without making sufficient adjustment. This study shows that the profitability of anchoring bias based trading strategies concentrates in the worst-rated stocks, especially around credit rating downgrades, suggesting that analysts exhibit stronger cognitive biases when making earnings forecasts for firms with the greatest credit risk. Furthermore, I discover that credit risk can even explain the effect of anchoring on analysts' forecast errors and future stock returns, highlighting the importance of credit risk for studies on market participants' cognitive biases and stock market anomalies. These findings have broad implications for psychology-based asset pricing theory.

Keywords: Cognitive biases; Behavioral finance; Asset pricing anomalies; Credit rating; Financial distress; Anchoring bias; Analysts' forecast errors

Chapter 2

Does Credit Risk Explain Market Participants' Cognitive Biases?

-Evidence from Anchoring Bias in Analysts' Earnings Forecasts

2.1 Introduction

It is well documented in the psychology literature that human beings suffer from a number of cognitive biases. While many studies have found that cognitive biases play an important role in the capital market, we do not fully understand the conditions under which market participants are more likely to suffer from cognitive biases. A better understanding of this issue has significant implications for behavioral finance and asset pricing theories.

Partly motivated by recent findings that credit risk can explain a number of asset pricing anomalies (e.g., Avramov et al. 2013), I examine the hypothesis that market participants exhibit stronger cognitive biases when valuing firms with greater credit risk. This hypothesis is conceptually motivated by the argument that higher credit risk is associated with higher uncertainty surrounding a firm (Avramov et al., 2009b). Cognitive biases may occur when "people assess the probability of an uncertain event or the value of an uncertain quantity" (Tversky and Kahneman, 1974). Intuitively, when the event or quantity is more uncertain, individuals are more likely to suffer from cognitive biases. Using investor-level data, Kumar (2009) confirms that individual investors exhibit stronger behavioral biases when stocks are harder to value.[1]

In this study, I focus on a specific setting to examine my hypothesis on the relation between credit risk and market participants' cognitive biases. Among market participants, I

[1] There are two main differences between Kumar (2009) and my study. First, Kumar (2009) finds that investors' behavioral biases are correlated with such valuation uncertainty proxies as idiosyncratic volatility, volume turnover, and firm age. In contrast, I discover that credit rating has strong explanatory power for cognitive biases. Second,

choose to study stock analysts as they are stock valuation professionals whose opinions may influence other market participants. Regarding cognitive biases, I focus on anchoring bias, which is well documented to exist in the financial market.[2] Tversky and Kahneman (1974) introduce the concept of anchoring bias: "in many situations, people make estimates by starting from an initial value that is adjusted to yield the final answer. The initial value, or starting point, may be suggested by the formulation of the problem, or it may be the result of a partial computation. In either case, adjustments are typically insufficient."

In particular, Cen, Hilary, and Wei (2013) (henceforth CHW) find that analysts suffer from anchoring bias when making earnings per share (EPS) forecasts. Specifically, analysts anchor their forecasts on the industry norm: when a firm's forecast earnings per share (FEPS) is below (above) the industry norm (i.e., the anchor), analysts make insufficient downward (upward) adjustments away from the industry norm, and these firms subsequently experience abnormally low (high) stock returns. CHW measure analysts' anchoring by how far a stock's FEPS is above its industry norm. In other words, anchoring is measured as the signed distance between a stock's FEPS and its industry norm. I will refer to this measure as anchoring. They find that anchoring is positively related to forecast errors, earnings surprises, stock returns, and the probability of a stock split. The trading strategy of buying high anchoring stocks and selling low anchoring stocks achieves a statistically significant and economically large profit that cannot be explained by known risk or style factors.

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while Kumar (2009) examines individual investors' disposition effect, I focus on the anchoring bias in analyst forecasts.

[2] A number of studies have examined the role of anchoring bias in the financial market. For example, George and Hwang (2004), Kaustia, Alho, and Puttonen (2008), Campbell and Sharpe (2009), Baker, Pan, and Wurgler (2012), Li and Yu (2012), Wilson (2012), Cen, Hilary, and Wei (2013), Chang, Luo, and Ren (2013), and Dougal, Engelberg, Parsons, and Van Wesep (2015).

Following my argument earlier, conceptually, I expect analysts to be more vulnerable to anchoring bias when making EPS forecasts for stocks with greater credit risk, as higher credit risk is associated with higher uncertainty surrounding a firm. Furthermore, I examine whether credit risk has more explanatory power for future stock returns than anchoring bias in analysts' EPS forecasts, because credit risk not only captures the uncertainty about a firm's future *earnings*, but it also captures the uncertainty about other important factors for asset pricing such as the cost of equity capital.[3] In contrast, the anchoring bias in analysts' EPS forecasts is related to only one of the several important factors for asset pricing (i.e., future *earnings*). Specifically, I examine whether credit risk can explain the effects of anchoring on forecast errors, earnings surprises, stock returns, and stock splits.

Using a sample of U.S. firms rated by Standard and Poor's (S&P) from January 1986 to December 2014, I find that the effect of analysts' anchoring on forecast errors, earnings surprises, stock returns, and stock splits exists mainly among firms with the greatest credit risk. I show that the profitability of anchoring bias based trading strategies concentrates in the worst-rated firms around rating downgrades. Furthermore, once I adjust for credit risk, the anchoring-return relation disappears even among the worst-rated firms. To the best of my knowledge, I are the first to report that the effect of analysts' anchoring bias can be subsumed by the credit risk effect.

The study's results are robust to various portfolio sorts and regression analyses. First, I sort all the rated stocks into five quintiles based on their credit ratings; within each credit rating quintile, I further sort the stocks into five quintiles based on the anchoring measure. While CHW find that analysts' anchoring is positively related to forecast errors, earnings surprises, stock

[3] Merton (1974) develops a structural model of default risk in which firm equity is a call option whose strike price is the face value of debt. Therefore, default risk captures the uncertainty about not only future earnings and growth

returns, and stock split ratios, I discover that these positive relations are statistically significant only for the two worst-rated quintiles. Furthermore, by progressively excluding the worst-rated firms from the sample, I find that the anchoring bias based trading strategy becomes unprofitable after excluding the stocks rated BB-D, which account for less than 7% of the total market capitalization of all rated firms or less than 44% of all rated firms. While the worst-rated stocks are small stocks overall, I confirm that the effect of credit risk on the anchoring bias effect is independent of the effect of firm size.

My second methodological approach is to run the Fama and Macbeth (1973) cross-sectional regression of forecast errors, earnings surprises, or stock returns on the measure of analysts' anchoring and credit rating, controlling for other known characteristics that may affect the dependent variables. I also estimate a logit regression for the probability of a stock split. I find that once credit rating is controlled for, the analysts' anchoring variable is no longer a significant predictor in these regressions. Taken together, I conclude that the ability of the analysts' anchoring to predict forecast errors, earnings surprises, stock returns, and the probability of a stock split is attributable to the predictive power of credit rating.[4]

Avramov et al. (2009b) find that during credit rating downgrade periods, the uncertainty about a firm's fundamentals increases sharply and stock prices of the worst-rated stocks decline considerably. Motivated by this finding, I examine how rating downgrades affect the analysts' anchoring bias effect. After excluding the periods of rating downgrades from the sample, I form the 5 by 5 credit rating- and analysts' anchoring- sorted portfolios again. I find that the anchoring effects on forecast errors and stock returns are no longer significant for any of the credit rating quintile. Using an event-time approach, I further find that analysts' anchoring, forecast errors,

rates, but also the cost of equity.

[4] I are not aware of any other study that reports the negative effect of credit risk on the probability of a stock split.

and stock returns of the worst-rated stocks, but not the best-rated stocks, decrease significantly during periods of rating downgrades.

My study makes several contributions. First, this study increases our understanding about market participants' cognitive biases. By focusing on the anchoring bias in analysts' EPS forecasts, I show that analysts exhibit the strongest cognitive biases for stocks with the greatest credit risk. My findings have important implications for the behavioral finance literature. It is likely that credit risk may also explain market participants' other cognitive biases (e.g., mental accounting, loss aversion, overconfidence). I leave this for future research.

Second, my finding that the credit rating effect can subsume the effect of the anchoring bias highlights the importance of credit risk in asset pricing. In particular, I stress the importance of controlling for credit risk in studies on market participants' cognitive biases and stock market anomalies. My finding is consistent with the idea that people are more likely to suffer from cognitive biases in more uncertain situations. As default risk captures valuation uncertainty, my results suggest that high credit risk is an important condition under which market participants exhibit strong cognitive biases.

Last but not least, my finding has important implications for the puzzling negative relation between credit risk and stock return (e.g., Dichev, 1998; Vassalou and Xing, 2004; Campbell, Hilscher, and Szilagyi, 2008; Avramov, Chordia, Jostova, and Philipov, 2009b). As Dichev (1998) argues, the puzzling relation cannot be fully explained by a risk-based explanation. My finding suggests a behavioral explanation: if market participants exhibit various cognitive biases more strongly for firms with greater credit risk, and collectively these cognitive biases affect stock returns, then I may observe a strong relation between credit risk and stock return. While the credit risk-return relationship is more readily observable than various cognitive biases, the latter may be the underlying mechanisms for the former. In other words, I conjecture that credit risk may affect stock returns through various cognitive biases among market participants such as anchoring bias, loss aversion, overconfidence, and mental accounting (e.g. Cen et al., 2013; Barberis and Huang, 2001; Grinblatt and Han, 2005; Cooper et al., 2004). However, individually the effect of a single cognitive bias on stock return may disappear once I control for credit risk.[5] I propose that a fruitful area of future research is to explore the interrelationships between credit risk, cognitive biases, and stock returns.

The study by Grinblatt, Jostova, and Philipov (2014) is also relevant to my study. They argue that the negative credit risk-return relation is driven by analyst optimism. I differ from their study mainly in two ways. First, as Grinblatt et al. (2014) acknowledge, they do not know the reason why analysts have the greatest optimism for stocks with the greatest credit risk; my findings suggest an explanation. As I show, stocks with the greatest credit risk have their FEPS the furthest away below the industry norm. According to anchoring bias, analysts make the most optimistic forecasts for these stocks. Second, the focus of my study is anchoring bias in analysts' earnings forecasts, while the focus of Grinblatt et al. (2014) is analyst optimism. Anchoring bias refers to the finding that "analysts make optimistic (pessimistic) forecasts when a firm's FEPS is lower (higher) than the industry norm" (CHW). The concept of anchoring bias involves an anchor and insufficient adjustments, which is more than just analyst optimism.

The rest of the paper is organized as follows. Section 2 reviews literature and develops hypotheses. Section 3 describes the data. Section 4 presents the results, and Section 5 concludes.

[5] For example, I find that the effect of anchoring disappears after I control for credit risk. Avramov, Chordia, Jostova, and Philipov (2007, 2009b, 2013) find that credit risk can explain a number of asset pricing anomalies, such as price momentum and the negative cross-sectional relation between the dispersion in analysts' earnings forecasts and future stock returns.

2.2. Hypothesis Development

As investment professionals, analysts have important influence in the stock market. Therefore, it is not surprising that analyst forecast errors have been extensively studied (e.g., Carleton, Chen, and Steiner, 1998; Cowen, Groysberg, and Healy, 2006; Trueman, 1994; Welch, 2000; Hong, Kubik, and Solomon, 2000; Clement and Tse, 2005). CHW are the first to apply the concept of anchoring bias to analysts' earnings forecasts, which increases my understanding about why and how analysts have biases in earnings forecasts.[6] They have two main findings. For firms with lower (higher) forecast earnings per share (FEPS) relative to their industry median FEPS, (1) analyst forecasts are more (less) optimistic, and (2) future risk-adjusted returns are lower (higher). The first finding suggests that analysts anchor their forecasts on the industry norm. Assuming that investors are affected by analysts' biased earnings forecasts and the market price reflects the bias, the second finding documents a return reversal following analyst forecasts, which confirms the existence of anchoring bias in analysts' earnings forecasts.

In this study, I examine the relation between credit risk and anchoring bias in analysts' earnings forecasts. Credit risk plays an important role in the capital market (e.g., Dichev, 1998; Vassalou and Xing, 2004; Campbell, Hilscher, and Szilagyi, 2008; Avramov, Chordia, Jostova, and Philipov, 2007, 2009b). In particular, several studies find that credit risk can explain some market anomalies. Avramov, Chordia, Jostova, and Philipov (2007) find that credit risk can explain momentum profitability. Avramov, Chordia, Jostova, and Philipov (2009a) find that the credit risk effect is concentrated in the worst-rated stocks around downgrades. Avramov, Chordia, Jostova, and Philipov (2009b) report that credit risk can explain the puzzling negative

[6] Anchoring bias is an important concept in the psychology literature (e.g., Tversky and Kahneman, 1974; Plous, 1989; Russo and Schoemaker, 1989; Wright and Anderson, 1989; Whyte and Sebenius, 1997; Brewer, Chapman, Schwartz, and Bergus, 2007; Qu, Zhou, and Luo, 2008). CHW provides a nice review of the literature on anchoring bias in Section II.

cross-sectional relation between dispersion in analysts' earnings forecasts and future stock returns. More broadly, Avramov, Chordia, Jostova, and Philipov (2013) find that several asset pricing anomalies can be explained by credit risk. The findings in these studies motivate us to examine whether credit risk can explain the effect of anchoring bias on analysts' forecast errors and future stock returns.

A key assumption underlying my study is that the probability of suffering from cognitive biases increases with the level of the uncertainty of the situation. As Avramov et al. (2009b) argue, firms with higher credit risk are associated with greater valuation uncertainty. I conjecture that analysts are more likely to suffer from anchoring bias when making earnings forecasts for firms with the worst credit ratings, as these firms' valuation is highly uncertain. Using idiosyncratic volatility, volume turnover, and firm age to proxy for valuation uncertainty, Kumar (2009) confirms that individual investors exhibit stronger behavioral biases when stocks are harder to value. I examine whether the anchoring bias effect is driven by firms with the greatest credit risk.

CHW construct a measure of the cross-sectional anchoring in analysts' earnings forecasts (CAF) as an individual firm's mean consensus forecasted earnings per share minus the industry median forecasted earnings per share, scaled by the absolute value of the latter. They find a positive relation between CAF and analysts' earnings forecast errors and future stock returns. Therefore, I state my Hypotheses 1 and 2 as follows:

Hypothesis 1: The positive relation between CAF and analysts' earnings forecast errors can be explained by the effect of credit risk.

Hypothesis 2: The positive relation between CAF and future stock returns can be explained by the effect of credit risk.

CHW also test the implication of anchoring bias in the context of stock splits. They find a positive relation between CAF and the probability of a stock split. If I can find empirical evidence to support my Hypotheses 1 and 2, then I can conclude that credit risk is able to explain the anchoring bias effect. Consequently, I would also expect credit risk to explain the positive relation between CAF and the likelihood of a stock split. I state my Hypothesis 3 as follows:

Hypothesis 3: The positive relation between CAF and the probability of a stock split can be explained by the effect of credit risk.

My first three hypotheses regard the effect of the credit rating *level* on the CAF effect. Next, I examine the effect of credit rating *change*, especially credit rating downgrade, on the CAF effect. When a firm's credit rating is downgraded, the firm's valuation uncertainty increases significantly. It is difficult to fully assess the magnitude of the effect of rating downgrade on a firm's future earnings, as rating downgrade makes the firm's suppliers, customers, creditors, and employees more likely to terminate their business/employment relationship with the firm. Assuming that rating downgrades are associated with a sharp increase in a firm's valuation uncertainty, I expect the effects of CAF on forecast errors and stock returns to be particularly strong around rating downgrades.

Hypothesis 4: The positive effects of CAF on analysts' earnings forecast errors and future stock returns are stronger around rating downgrades.

2.3. Data and Methodology

2.3.1 Data sources

I obtain stock returns from the Center for Research in Securities Prices (CRSP), accounting data from COMPUSTAT, and analysts' earnings estimates from the Institutional Brokers Estimate System (I/B/E/S). I use the unadjusted Detail History and Summary History datasets in I/B/E/S to avoid the potential problem pointed out by Payne and Thomas (2003). I use the earnings definition (i.e., primary or diluted EPS) as provided by I/B/E/S (Livnat and Mendenhall, 2006). I obtain the credit ratings from S&P Long-Term Domestic Issuer Credit Rating, which is available from COMPUSTAT on quarterly basis starting from the second quarter of 1985.[7] To have a whole year's data for each year during my sample period, my sample period starts in January 1986.

2.3.2 Sample filtering

My sample consists of all NYSE, AMEX, and NASDAQ listed common stocks in the intersection of the CRSP, COMPUSTAT, and the unadjusted summary historical file of I/B/E/S for the period from January 1986 to December 2014. To make my study more comparable with CHW, I use the following five sample selection filters. First, the consensus forecasts of the 1-year-ahead (FY1) EPS in the previous month should be available from the IBES unadjusted summary historical file. Second, the returns of the stock should be available in the current month and the previous 7 months. Third, the information required to compute Fama and French (1992) book-to-market ratio should be available from CRSP and COMPUSTAT, and stocks with negative book value of stockholder's equity in the previous month are excluded. Fourth, I exclude stocks below $5 at the beginning of each month to ensure that the results are not driven by highly illiquid, small stocks or bid-ask bounce (Jegadeesh and Titman, 1993; Jegadeesh and Titman, 2001; Diether et al., 2002; Avramov et al., 2009b). Fifth, I exclude any industry (based on SIC 2 digit codes) that has fewer than 5 firms, to stress the importance of having economically meaningful cross-sectional anchoring bias. In addition, I also require each stock to

[7] Before 1998, the credit ratings for different firms are based on the recent senior publicly traded debt. However, after 1998, the S&P assigns these ratings to the firm's most senior publicly traded debt.

have at least 24 months of non-missing return data in order to calculate the risk-adjusted returns. After the screening process, my sample has 13,767 firms.

2.3.3. Main variables

2. 3.3.1. Cross-sectional anchoring in analysts' earnings forecasts (CAF)

Following CHW, I measure the cross-sectional anchoring in analysts' earnings forecasts (CAF) as the difference between an individual firm's mean consensus forecasted earnings per share minus the industry median forecasted earnings per share, scaled by the absolute value of the latter. Industries are defined by standard industrial classification (SIC) 2-digit codes.[8]

$$CAF_{i,t} = \frac{F\_FEPS_{i,t} - I\_FEPS_{i,t}}{|I\_FEPS_{i,t}|} \quad , \tag{1}$$

where $CAF_{i,t}$ is the cross-sectional anchoring in analysts' earnings forecasts for firm *i* in month *t*; $F\_FEPS_{i,t}$ is the mean of the analyst forecasts (consensus forecasts) of the 1-year-ahead (FY1) EPS in month *t*; $I\_FEPS_{i,t}$ is the industry median of the analyst consensus forecast of the 1-year-ahead (FY1) EPS in month *t*.

2. 3.3.2. Credit risk (CR)

Following Avramov et al. (2009b), I measure credit risk by credit ratings; I transform the S&P ratings into numerical scores as follows: AAA=1, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19, CC=20, C=21, D=22.

2. 3.3.3. Forecast error (FE)

To make my results comparable with CHW, I measure analysts' forecast error ($FE_{i,t}$) for firm *i* in month *t* as in Equation (2).

[8] I also define industries using the Fama and French (1997) 48 industry classifications. In untabulated results, I find that my conclusions are robust to the alternative industry classification.

$$FE_{i,t} = \frac{Actual\_FEPS_{\,i} - F\_FEPS_{i,t}}{Price_{i,t}} \times 100 \quad , \tag{2}$$

where $Actual\_FEPS_{\,i}$ is the actual EPS for firm *i* that is announced at the end of the fiscal year, $F\_FEPS_{i,t}$ is the consensus EPS forecast for firm *i* in month *t*, and $Price_{i,t}$ is the stock price for firm *i* in month *t*.

2. 3.3.4. Risk-adjusted return (α)

I use both raw returns and risk-adjusted returns. I compute the risk-adjusted return (α_i) based on the Carhart (1997) 4-factor model in Equation (3).

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\,(MKT_t - R_{f,t}) + s_i\,SMB_t + h_i HML_t + u_i UMD_t + \varepsilon_{i,t}, \tag{3}$$

where $R_{i,t}$ is the monthly return for portfolio *i* in month *t*, and $R_{f,t}$ is the risk-free rate in month *t*. *MKT* is the monthly return on the market portfolio and *SMB*, *HML*, and *UMD* are monthly returns on the size, book-to-market, and momentum factors; the corresponding factor loadings are β_i, s_i, h_i, and u_i, which are estimated from a time-series regression over the entire sample period. $\varepsilon_{i,t}$ is the error term. Factor returns are obtained from Kenneth French's website.

2.3.4. Methodology

2. 3.4.1. Portfolio sorts

Each month, I divide stocks rated by S&P into quintiles (CR1-CR5) according to their credit rating. Within each credit rating quintile, I further divide stocks into quintiles according to their CAF. I will use these 25 CR-CAF portfolios as the main framework in all of my portfolio analysis. To test Hypothesis 1, I examine the average forecast errors (FE) for the 25 portfolios. To test Hypothesis 2, I consider raw return, risk-adjusted return, and ECAR, which is the 3-day cumulative abnormal return around earnings announcement. I compute the difference in the main variable between the highest and the lowest CAF groups and test the statistical significance of the difference.

2. 3.4.2. Regression analysis

To clearly identify the incremental explanatory power of credit risk, I add a credit rating variable to the main regression model in Equation (1) of CHW as follows:

$$DEP\_VAR_{i,t} = \alpha + \beta\ CAF_{i,t-1} + \lambda\ CR_{i,t-1} + \gamma^K X^K_{i,t-1} + \varepsilon_{i,t}\ , \qquad (4)$$

where $DEP\_VAR_{i,t}$ is FE when testing Hypothesis 1, and raw return, risk-adjusted return, and ECAR when testing Hypothesis 2. I also use a logit regression to test whether the positive relation between CAF and the probability of a stock split is subsumed by credit risk. In such a logit regression, $DEP\_VAR_{i,t}$ is a dummy variable that equals one if firm *i* conducts a significant stock split (i.e., 1 share is split into at least 1.5 shares) in month *t*, and zero otherwise. $CR_{i,t-1}$ (credit rating) is my main variable, as explained in Section 3.3.2. Alternatively, I also replace the numerical credit rating scores with a dummy variable that equals one if a stock has a NIG (non-investment grade) rating and zero otherwise. $X^K_{i,t-1}$ represents the control variables.

2.4. Empirical Results About Credit Rating and Anchoring Bias

I begin with comparing the rated and unrated samples. Panel A of Table 1 reports the monthly return from the CAF-based trading strategy, which is calculated as the return differential between the highest and lowest CAF quintiles (CAF_5 - CAF_1). I find that the CAF profitability exists only in non-January months or expansions.[9] Panel B of Table 1 presents the average size, book-to-market ratio, price, CAF, and forecast error for the five CAF portfolios within the rated and unrated firms, respectively. Rated firms are on average larger and have smaller book-to-market ratios and higher share prices. Unrated firms have a wider range of values of CAF than rated firms. While analysts' forecast errors are consistently negative for each of the five CAF

[9] My finding is consistent with Avramov et al. (2009b).

quintiles within rated and unrated firms, unrated firms have more negative forecast errors than rated firms.

[Insert Table 1 Here]

The last row in Panel B of Table 1 shows that rated and unrated firms have similar CAF strategy returns. Specifically, the CAF-based trading strategy return for a one-month holding period is 55 basis points per month for the 3,735 rated firms and 53 basis points per month for the 10,032 unrated firms. Moreover, the CAF strategy return is 28 basis points per month (t=1.39) for investment grade (IG) stocks and 110 basis points per month (t=4.86) for non-investment grade (NIG) stocks. The fact that CAF profitability exists only among NIG firms is my first important finding.

The last two columns in Panel B show the average credit rating scores and the corresponding S&P ratings for the five CAF portfolios. A striking pattern emerges: a higher CAF portfolio contains better-rated stocks. For example, the average credit rating for the highest CAF portfolio (CAF_5) is 7.52, corresponding to an A- rating; the average credit rating for the lowest CAF portfolio (CAF_1) is 13.43, corresponding to a BB- rating (non-investment grade). In untabulated results, I find that the Spearman correlation coefficient between CAF and credit rating is -0.51, which is statistically significant at the 0.01% level. The strong correlation between credit rating and CAF is another important finding.

2.4.1. Forecast error

In this section, I test Hypothesis 1 by using both portfolio sorts and regression analysis. Regardless of which approach I use, I find that the relation between CAF and forecast errors is stronger among firms with greater credit risk. The results confirm Hypothesis 1.

In Table 2, I report the average forecast error and CAF for each of the 25 CR-CAF portfolios in Panels A and B, respectively. Panel A shows that the average forecast error is negative for all the 25 portfolios.[10] Within each CAF quintile, the magnitude of the forecast error increases with the level of the credit risk, suggesting that analysts make more optimistic forecasts for stocks with higher credit risk. The positive relation between credit risk and analysts' forecast optimism turns out to be highly significant in my regression analysis in Panel C of Table 2.

[Insert Table 2 Here]

The last column of Panel A reports the difference in forecast errors between the highest and lowest CAF quintiles (CAF_5-CAF_1) within each credit rating quintile. The differences in the last column are all positive indicating that firms with higher CAF have higher forecast error. Moreover, the difference increases with the level of the credit risk, suggesting that anchoring bias is more pronounced for stocks with higher credit risk. Most importantly, the positive difference is statistically significant only for the two quintiles with the highest credit risk. In other words, the effect of CAF on forecast errors is substantially reduced once I control for credit risk. This is my portfolio-based evidence that is consistent with Hypothesis 1.

Panel B of Table 2 shows that the average CAF is positive for all the portfolios within the two highest-rated quintiles and negative for all the portfolios within the two lowest-rated quintiles.[11] According to CHW, if analysts suffer from anchoring bias, they should make pessimistic (optimistic) forecasts for a firm whose FEPS is above (below) the industry median,

[10] The overall negative forecast error is consistent with the findings in CHW and other studies that forecast errors are on average negative. In other words, analyst forecasts are on average optimistic.

[11] The last column in Panel B of Table 2 shows that CAF decreases monotonically with credit rating, which offers an explanation to an important unresolved issue in Grinblatt, Jostova, and Philipov (2014). While they argue that the negative credit risk-return relation is driven by analyst optimism, they acknowledge that they cannot explain why analysts have the greatest optimism for stocks with the greatest credit risk. As the last column in Panel B of my Table 2 shows, stocks with the greatest credit risk have their FEPS the furthest away below the industry norm (i.e., stocks with the greatest credit risk have the most negative CAF). As a result of anchoring bias, analysts make the most optimistic forecasts for these stocks.

which implies positive (negative) forecast errors. Therefore, as the highest- (lowest-) rated firms have positive (negative) CAF, they are expected to have positive (negative) forecast errors. However, it is not immediately clear why the forecast errors are negative for the highest-rated firms. This puzzling result may be related to my finding that the profit from the CAF-based trading strategy is not statistically significant for the highest-rated firms. A possible explanation is that some other factors may be driving the negative forecast errors, which offsets the positive effect of anchoring bias on forecast errors, especially for the best-rated firms. To address this issue, I use regression analysis to control for the effect of other factors on forecast errors.

I estimate Fama and MacBeth (1973) regression of forecast errors on lagged CAF, credit rating, and control variables. Panel C of Table 2 reports the time series average and *t*-statistic of the estimated coefficients. All the *t*-statistics are corrected using the Newey and West (1987) approach. In Models 1, 4, and 7, I find that without controlling for credit risk, CAF is statistically significant. On top of these three models, I add either credit rating (CR) or the non-investment grade (NIG) dummy and report my results in Models 2-3, 5-6, and 8-9, respectively. Once I include either CR or the NIG dummy, the coefficient of CAF is no longer statistically significant.[12]

In Column (10), I add an interaction term between the NIG dummy and CAF. The positive coefficient of CAF is still insignificant, suggesting that the effect of CAF on forecast errors is not statistically significant for investment grade stocks. In contrast, the interaction term has a significantly positive coefficient (t=4.43), suggesting that the effect of CAF on forecast errors is significantly more positive for non-investment grade stocks than for investment grade stocks. This represents my regression-based evidence that is consistent with Hypothesis 1.

2.4.2. Future stock return

In this section, I test Hypothesis 2 by both portfolio sorts and regression analysis. I find that once credit risk is controlled for, CAF cannot predict returns. The results confirm Hypothesis 2.

2.4.2.1. Portfolio results

Panels A1 and A2 of Table 3 show the average raw returns for each of the 25 CR-CAF portfolios over holding periods K=1 and 3 months, respectively. The last column reports the return differential between the highest and the lowest CAF quintiles (CAF_5-CAF_1) within each credit rating group. While the differences are all positive, they are statistically significant only for the two groups with the lowest credit ratings (CR5 and CR4).

[Insert Table 3 Here]

Panels B1 and B2 of Table 3 are similar to Panels A1 and A2 of Table 3, except that risk-adjusted returns are used instead of raw returns. The main results are similar. Only for the two groups with the lowest credit ratings (CR5 and CR4), the positive return differences in the last column are statistically significant. I find similar results for holding periods of 6 and 12 months (untabulated). To summarize, the trading strategy of buying stocks with the highest CAF and selling stocks with the lowest CAF generates significant payoff only for stocks with the highest credit risk.

2.4.2.2. Anchoring bias based trading strategy payoffs over diminishing subsamples

To find out the exact subsample of low quality stocks that can generate statistically significant profit for the CAF strategy, I calculate the CAF-based trading strategy return as I sequentially exclude firms with the worst credit rating from the sample. Table 4 reports the CAF

[12] I also split the last six-month return in the regression model into the last month return and the rest five-month return. The results remain similar. In all the other regressions throughout my study, the main results are robust to the

trading strategy payoffs over the diminishing subsamples. As the worst credit stocks are gradually excluded from the sample, the payoffs exhibit a declining trend. Once firms with S&P ratings of BB-D are excluded from the sample, the payoff is no longer statistically significant. In other words, the payoff becomes insignificant for the subsample of stocks rated AAA-BB+, which actually accounts for 93.62% of the market capitalization of rated firms and 56.80% of the total number of rated firms. To put it differently, the CAF profitability is derived from a sample of rated firms that accounts for less than 7% of the total market capitalization of all rated firms or less than 44% of all rated firms.

[Insert Table 4 Here]

Panel B of Table 4 shows that the credit risk effect on the CAF-return relation is not merely a size effect. Specifically, I gradually remove the smallest firms from the sample until only the biggest 20% of the stocks are kept in the sample; the CAF profitability is still economically and statistically significant. While smaller stocks tend to have worse credit ratings, I conclude that the credit risk effect is different than the size effect.

2.4.2.3. Regression results

In this section, I run monthly cross-sectional Fama and MacBeth (1973) regressions of future raw returns or risk-adjusted returns (i.e., Carhart four-factor alphas) on CAF, credit rating (CR), and control variables. Carhart four-factor alphas are estimated using the previous 24 months of returns. All independent variables are lagged one month. Panels A and B of Table 5 report the results from the regressions of raw returns and Carhart four-factor alphas, respectively. The main results are similar for both raw returns and Carhart alphas.

I start with the three benchmark models in columns 1, 4, and 7 of Table 5. The coefficient of CAF is positive and significant across the three models. I then add either CR or the NIG

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above variation in the past return regressors.

dummy variable to the three models and report the results in columns 2-3, 5-6, and 8-9 in Table 5. Once CR is added to the models, the coefficient of CAF is no longer statistically significant. In other words, the CAF-return relation becomes insignificant once credit rating is controlled for. The results confirm Hypothesis 2. The negative and significant coefficient of CR suggests that a higher credit rating (lower numerical value of CR) is associated with a higher future return. This finding is consistent with the negative credit risk-return relation documented in the literature (e.g., Dichev, 1998; Griffin and Lemmon, 2002; Campbell, Hilscher, and Szilagyi, 2008).

[Insert Table 5 Here]

In Column (10), I add an interaction term between the NIG dummy and CAF. The positive coefficient of CAF is still insignificant, suggesting that the effect of CAF on future returns is not statistically significant for investment grade stocks. In contrast, the interaction term has a significantly positive coefficient, suggesting that the effect of CAF on future returns is significantly more positive for non-investment grade stocks than for investment grade stocks.

To control for the effect of analyst forecast dispersion on future stock returns, I add analyst forecast dispersion in the last four regression models. The main results are similar with or without controlling for analyst forecast dispersion. Interestingly, analyst forecast dispersion is not significant in any of the models, which suggests that the well-documented negative analyst forecast dispersion-stock return relation can be subsumed by either the anchoring effect or the credit risk effect.

In untabulated results, I replace $R_{t-7:t-1}$ and $R_{t-1:t}$ with the buy-and-hold return in the past six months ($R_{t-6:t}$). My main results are robust to the alternative control variable. I have also added some other control variables, such as a firm's leverage and Amihud's illiquidity of stock, into the regression model. Again, my main results are the same: the coefficient of CR is consistently negative and significant; the coefficient of CAF is no longer statistically significant, as long as CR is controlled for. In summary, once credit risk is controlled for, anchoring bias plays no role in predicting stock returns.

2.4.2.4. Robustness tests

In this section, I conduct several robustness tests. The results strongly support Hypothesis 2. In particular, in the first two subsections, my robustness checks are based on a new measure of CAF or stock return that adjusts for credit risk. I argue that this approach can be generalized as a robustness check for studies on market participants' cognitive biases as well as stock market anomalies. Given that credit risk is a strong predictor of future stock returns, a credit-rating adjusted cognitive bias measure such as the credit-rating adjusted CAF measure, or more generally, a credit-rating adjusted anomaly measure, can be used in robustness checks. Alternatively, a credit-rating adjusted stock return can also be used in a robustness test.

2.4.2.4.1. Credit-rating adjusted CAF

First, I compute a credit-rating adjusted CAF measure. Specifically, I regress the CAF for stock *i* in month *t* (CAF_{it}) on the credit rating for stock *i* in month *t* (CR_{it}) as in Equation (5).

$$CAF_{it} = a_t + b_t CR_{it} + e_{it} . \tag{5}$$

I then define the credit-rating adjusted CAF as the sum of the intercept and residual from the regression in Equation (5).

$$CAF*_{it} = a_t + e_{it} , \tag{6}$$

where $CAF*_{it}$ refers to the credit-rating adjusted CAF for stock *i* in month *t*. The purpose of creating $CAF*_{it}$ is to test if this variable still has any predictive power of future stock returns. If credit rating can subsume CAF in explaining the cross-section of future stock returns, then the credit-rating adjusted CAF will have no predictive power of future stock returns. Further, a trading strategy based on the credit-rating adjusted CAF should provide insignificant payoffs.

Table 6 shows the cross-sectional mean return in month t+1 for each of the 25 portfolios that are formed through sequentially sorting stocks into five credit rating and then five CAF* groups in month t. The return differentials between the highest and lowest CAF* quintiles are reported in the last column. None of the return differentials is significantly different from zero. The result further confirms that once the credit risk is controlled for, the CAF-based trading strategy no longer generates significantly positive payoffs.

[Insert Table 6 Here]

2.4.2.4.2. Credit-rating adjusted return

Next, I adjust returns by subtracting from each stock monthly return the monthly return of the credit-rating decile to which the stock belongs. Panel A of Table 7 reports CAF strategy payoffs based on credit rating adjusted returns. I assume a one-month holding period. In contrast to the results in Panels A1 and B1 of Table 3, the return differentials, which are reported in the last column, are no longer significant. Once again, the result confirms that the profitability of the CAF based trading strategy is no longer significant, once the credit risk is controlled for.

[Insert Table 7 Here]

Similarly, Panel B of Table 7 reports CAF strategy payoffs based on size adjusted returns. Specifically, returns are adjusted by subtracting from each stock monthly return the monthly return of the size decile to which the stock belongs. Again, I assume a one-month holding period. In contrast to Panel A of Table 7, the return differentials in the last column are still statistically significant for the two worst-rated quintiles. The results are similar to those in Panels A1 and B1 of Table 3, suggesting that size is not driving the credit rating–return relation.

2.4.2.4.3. An alternative anchoring measure

I repeat my main analysis using an alternative anchoring measure, CAP, which is defined as the difference between the stock price per share of a firm and the industry median stock price, scaled by the value of the latter. In untabulated results, I find that my main conclusion is not sensitive to the alternative measure of anchoring. For example, the one-month raw return differential between the highest and lowest CAP quintiles is statistically significant for the two worst-rated quintiles (*t*-statistics= 1.76 and 1.99, respectively) but insignificant for the other three better-rated quintiles.

2.4.3. Earnings announcement return (ECAR)

To address the concern that the CAF-based trading strategies generate abnormal returns because inappropriate asset pricing models are used to measure abnormal returns, CHW examine whether CAF is positively related to the abnormal stock return around the next earnings announcement (ECAR). The rationale is that if the abnormal returns from the CAF strategy are generated because of benchmarking errors, then the abnormal returns would not cluster around earnings announcements (Chopra, Lakonishok, and Ritter, 1992). CHW not only confirm the positive relation between CAF and earnings announcement returns, but they also find that a significant portion of the CAF effect is concentrated around the earnings announcement dates. In this section, I re-examine the relation between CAF and ECAR after controlling for credit ratings. Table 8 reports my results.

[Insert Table 8 Here]

Panel A of Table 8 shows the average ECAR for the 25 CR-CAF portfolios. The last column reports the difference in ECAR between the highest and lowest CAF quintiles (CAF_5-CAF_1). I find that the difference is statistically significant only for the two lowest rated quintiles, consistent with my results in Table 3. Panel B of Table 8 reports the results from the Fama-MacBeth (1973) regressions of ECAR on CAF, CR (or NIG dummy), and control variables. Once CR or NIG dummy is controlled for, the coefficient on CAF is no longer statistically significant. In contrast, the coefficients on CR or the NIG dummy are consistently negative and highly significant. The results are consistent with the one-month return regression results in my Table 5 and further confirm that the credit risk effect subsumes the CAF effect.

2.4.4. Stock split

To test my third Hypothesis, I start with the portfolio analysis. Panel A of Table 9 shows the average stock split ratio (SSR) of the 5 by 5 portfolios sorted by credit rating and CAF. I define SSR as the change in the cumulative stock split driven factor used to adjust shares outstanding in the following 12 months. The last column reports the SSR difference between the highest and the lowest CAF quintiles within each credit rating quintile. While the differences are positive for all the credit rating quintiles, they are statistically significant only for the two lowest rated quintiles, suggesting that the positive relation between CAF and the stock split ratio exists mainly among the worst-rated firms.

[Insert Table 9 Here]

Next, I estimate a logit regression, in which the dependent variable equals one if a firm conducts a significant stock split in a month and zero otherwise. Panel B of Table 9 shows the regression results. In models 1 and 2, I include only CAF and a credit risk variable, which is either credit rating or the NIG dummy. The negative coefficient on credit rating is statistically significant, but the coefficient on CAF is not significant. I then add either credit rating or the NIG dummy to the regression models. The results for models 3-11 show that once credit risk is controlled for, the coefficient of CAF is no longer statistically significant. In other words, the positive effect of CAF on the probability of a stock split is subsumed by the effect of credit risk. The results are consistent with my third Hypothesis.

Note that both the coefficient of credit rating (CR) and the coefficient of the NIG dummy are consistently negative and highly significant across the models, suggesting that greater credit risk significantly reduces the probability of a stock split. I are not aware of any other study that reports the negative effect of credit risk on the probability of a stock split. Intuitively speaking, credit risk is more likely than anchoring bias to affect the managerial decision for a stock split.

2.5. Empirical Results About Credit Rating Downgrade and Anchoring Bias

In this section, I examine Hypothesis 4 in both portfolio sorts and regression analysis. Specifically, in portfolio sorts, I examine the CAF effect after credit rating downgrade periods are excluded from the sample. In regression analysis, I include a downgrade dummy into the regression models.

2.5.1. Forecast error

Since Compustat provides rating data on a quarterly basis, I assume that a rating change occurs at the beginning of the quarter (Avramov et al., 2009b). I exclude downgrade periods, which are defined as three months before and three months after the downgrade month. Then I re-form the 25 CR-CAF portfolios as in Panel A of Table 2. Panel A of Table 10 shows the average forecast errors for the 25 portfolios after excluding the downgrade periods. The average forecast errors are still negative for all the 25 portfolios, suggesting the pervasive nature of analyst optimism. The last column shows the forecast error difference between the highest and lowest CAF quintiles within each credit rating quintile. The forecast error differences for the two lowest rated quintiles drop from 2.51 % (CR4) and 4.30% (CR5) in Panel A of Table 2 to 0.41%

(CR4) and 0.59% (CR5) in Panel A of Table 10. Both are no longer statistically significant. The evidence is consistent with Hypothesis 4.

[Insert Table 10 Here]

Next, I run monthly regressions of forecast errors on the lagged CAF, a downgrade dummy, lagged CR, and lagged control variables. The downgrade dummy is equal to one if a month falls within the downgrade period and zero otherwise. The control variables include log(SIZE), log(BM), $RET_{t-6:t}$, ACCRUAL, ES_{RECENT}, EP, and Dispersion, which are defined in the appendix. Panel B of Table 10 shows the regression results. Once the downgrade dummy is included in the regression model, the coefficient of CAF is no longer significant, consistent with my expectation.

2.5.2. Future stock return

In this section, I repeat the portfolio analysis in Panel A of Table 3 after removing the firm-month observations during the downgrade periods from the sample. The results are reported in Panel A of Table 11. In contrast to the results in Panel A of Table 3, the return differences in the last column in Panel A of Table 11, including the two lowest rated quintiles (CR4 and CR5), are no longer statistically significant. The results suggest that beyond the periods when firm credit ratings are downgraded, the relation between CAF and future stock returns does not exist.

[Insert Table 11 Here]

Next, I run monthly cross-sectional regressions of returns on a constant, the lagged CAF, a downgrade dummy, lagged CR, and lagged control variables. The control variables include log(SIZE), log(BM), $RET_{t-6:t}$, ACCRUAL, ES_{RECENT}, EP, and Dispersion. Table 11, Panel B reports slope coefficients and *t*-statistics. In the first model, CAF has a statistically significant coefficient 0.17 (*t*=2.68). However, once the regression model includes the downgrade dummy, which has a statistically significant coefficient −1.06 (t=−3.89), CAF loses its statistical significance (t=0.81). The coefficient on CAF remains statistically insignificant after credit rating and control variables are further added into the regression model. The results suggest that the relation between CAF and future stock returns can be explained by credit rating level and credit rating downgrades, consistent with my expectation.

Based on the 25 CR-CAF portfolios that I have formed for portfolio analysis, I calculate the payoff from the CAF based trading strategy. Each month, I hold \$1 long in the highest CAF quintile (CAF_5) and \$1 short in the lowest CAF quintile (CAF_1); the two positions are held for one month. Graph A of Figure 1 shows the wealth process of the CAF based trading strategy for the highest rated quintile (CR1) and the lowest rated quintile (CR5) from January 1986 to December 2014. The payoff profile of the lowest rated quintile (CR5) is not only greater than the highest rated quintile (CR1) but also more volatile than CR1. The most recent peak of the payoff for the lowest rated quintile (CR5) is around the financial crisis in 2008. Presumably, this is the period when the overall credit risk and market uncertainty is the greatest. This peak is consistent with my conjecture earlier that people are more likely to suffer from cognitive bias, such as anchoring bias, when facing higher uncertainty.

[Insert Figure 1 Here]

Next, I exclude the downgrade periods (t-3, t+3) from the sample and plot the same wealth process of the CAF-based trading strategy in Graph B of Figure 1. The lowest-rated quintile CR5 in Graph B has a much less volatile wealth profile than in Graph A, which suggests that the profitability of the CAF-based trading strategy exists mainly during the downgrade periods.

In Figure 2, I take a closer look at how the key variables change around credit rating downgrades. Graphs A, B, and C of Figure 2 plot the average monthly CAF, forecast error, and stock return for the best- and worst- rated quintiles around downgrades, respectively. Month 0 is the month of downgrade. All the three graphs exhibit the same pattern: the best-rated (CR1) portfolio profile (dashed line) is relatively flat during the [-36, +36] months around rating downgrades, but the worst-rated (CR5) portfolio profile (solid line) drops significantly around rating downgrades. In other words, the CAF, forecast error, and stock return of the worst-rated stocks, but not the best-rated stocks, decrease significantly during periods of worsening credit conditions. My finding suggests that the positive relation between CAF and stock return emerges as the worst-rated firms experience significant price drop along with substantial drop in CAF and forecast errors.

[Insert Figure 2 Here]

2.6 Conclusion

In light of the recent finding that analysts suffer from the anchoring bias when making earnings forecasts, I find that credit risk is an important condition under which market participants exhibit strong cognitive biases. Using a sample of rated firms, I discover that the profitability of anchoring bias based trading strategies concentrates in the worst-rated firms, which account for less than 7% of the total market capitalization of all rated firms. My findings have important implications for future research. For example, future research can test whether credit risk affects stock returns through market participants' other cognitive biases such as loss aversion, overconfidence, and mental accounting (e.g. Barberis and Huang, 2001; Grinblatt and Han, 2005; Cooper et al., 2004). While individually the effect of a cognitive bias may seem to be explained by the effect of credit risk, collectively the various cognitive biases may be the exact mechanisms through which credit risk can predict stock returns.

Appendix: Variable definitions

Variable	Data Source	Explanation
Analyst Variables:		
CAF	I/B/E/S and COMPUSTAT	The cross-sectional anchoring measure of forecast earnings per share, which equals the difference between individual's firm mean consensus forecasted earnings per share minus the industry median forecasted earnings per share, divided by the absolute value of the latter. Industries are defined by SIC 2-digit codes.
FEPS	I/B/E/S	Mean of an individual firm's forecast 1-year-ahead earnings per share in the previous month from the unadjusted summary history file of the IBES. It is also called the consensus EPS forecast.
FE	I/B/E/S	Analysts' earnings forecast error = $\frac{\text{actual EPS} - \text{FEPS}}{\text{stock price}} \times 100$
Breadth	I/B/E/S	The natural logarithm of one plus the average number of stocks followed by the current analysts.
Experience	I/B/E/S	The natural logarithm of one plus the average number of months that the current analysts have been following the firm.
Horizon	COMPUSTAT	The natural logarithm of one plus the number of months before the next earnings announcement.
Dispersion	I/B/E/S	The standard deviation in analyst's EPS forecasts divided by the absolute value of the mean/consensus EPS forecast.
Credit Rating Variables:		
CR	COMPUSTAT	I obtain the credit ratings from S&P Long-Term Domestic Issuer Credit Rating, which is available from COMPUSTAT on a quarterly basis starting from the second quarter of 1985. Following Avramov et al. (2009b), I transform the S&P ratings into numerical scores as follows: AAA=1, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19, CC=20, C=21, D=22.
NIG dummy	COMPUSTAT	The NIG dummy equals one if a stock has a non-investment grade rating, and zero otherwise.
Downgrade dummy	COMPUSTAT	The downgrade dummy takes the value of one three months-around rating downgrades (i.e., from t-3 to t+3), and zero otherwise.
Stock Return Variables:		
$R_{t-6:t}$	CRSP	The past six-month return.
$R_{t-7:t-1}$	CRSP	Buy-and–hold return from month -7 to month -1.
$R_{t-1:t}$	CRSP	The past one month return.
Carhart α	CRSP and Kenneth library	Risk adjusted return according to the Carhart (1997) 4-factor model.
ECAR	CRSP	The cumulative 3-day abnormal return relative to the CRSP value-weighted index surrounding the next earnings announcement date during the 12 months following the portfolio formation.

ES_{RECENT}	CRSP and IBES	The 3-day market-adjusted abnormal return around the most recent earnings announcement date up to the beginning of month t, where the market return is proxied by the CRSP value-weighted index return.
Firm Characteristics Variables:		
BM	CRSP and COMPUSTAT	The Fama and French (1992) book to market ratio, where the value for July of year Y to year Y+1 is computed using the book value of equity for the fiscal year end in calendar year Y-1 from COMPUSTAT and the market value of equity at the end on December of year Y-1 from CRSP.
Size	CRSP	The market value of a firm's equity at the end of the previous month.
Leverage	COMPUSTAT	The most recent book value of debt divided by the sum of the book value of debt and the market value of equity.
Accrual	COMPUSTAT	Following Sloan (1996) and CHW, total accrual scaled by average total assets= (ΔCA- ΔCash) – (ΔCL- ΔSTD- ΔTP)-DEP)/TA, where ΔCA: change in the current assets, ΔCash: change in cash and cash equivalents (COMPUSTAT item1), ΔCL: change in current liabilities (COMPUSTAT item5), ΔSTD: change in debt included in current liabilities (COMPUSTAT item34), ΔTP: change in income taxes payable (COMPUSTAT item 71), DEP: Depreciation and amortization expense COMPUSTAT item 14), TA: is the average of the beginning of year and end of year book values of total assets (COMPUSTAT item 6).
EP	COMPUSTAT CRSP, and I/B/E/S	The historical earnings-to-price ratio. To calculate the historical earnings per share, I divide net income before extraordinary items for the most recently announced fiscal year-end by the number of shares outstanding. Then I divide the historical earnings per share by the stock price on the same day.

Table 1
Summary statistics for rated and unrated firms

Each month, stocks are sorted into five quintiles based on the cross-sectional anchoring bias in earnings per share forecast (CAF). CAF strategy return is generated by buying the highest and selling the lowest CAF quintiles (CAF_5-CAF_1), and holding the positions for 1 or 3 months. Portfolio returns are equally weighted across all stocks in a portfolio. For the three month holding period strategy, I measure the monthly return in month t+1 by calculating the equal weighted average return of the portfolios sorted in months t,t-1, and t-2. Panel A reports the time-series average of the monthly CAF profits (% per month) during different periods. Panel B reports the times series average of the cross-sectional mean characteristics for each CAF quintile. In Panel C, the first three columns report the percentage of firms that are unrated ("UR"), investment grade ("IG"; S&P rating BBB- or better), and non-investment grade ("NIG"; S&P rating BB+ or worse), respectively, within each CAF quintile. The next four columns present the equally weighted average returns. The last column reports the average numerical S&P rating for the rated firms. A better S&P rating is associated with a smaller number: AAA=1, AA+=2, AA=3, AA-=4, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19, CC=20, C=21, D=22. All variables are defined in the appendix. *t*-statistics are presented in parentheses. The sample period is from January 1986 to December 2014. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: CAF strategy return (% per month)

Sample	All firms		Unrated firms		Rated firms	
Number of firms	13,767		10,032		3,735	
Holding period (months)	1	3	1	3	1	3
Overall	0.54***	0.50***	0.53***	0.53***	0.55***	0.49***
	(3.26)	(3.13)	(3.24)	(3.24)	(3.28)	(2.82)
Non-January	0.60***	0.62***	0.68***	0.67***	0.61***	0.51***
	(3.24)	(3.20)	(3.42)	(3.37)	(3.13)	(2.51)
January	0.14	0.12	0.15	0.14	0.19	0.15
	(1.10)	(1.05)	(1.18)	(1.10)	(1.16)	(1.18)
Expansion	0.60***	0.55***	0.68***	0.62***	0.55***	0.56***
	(3.45)	(3.28)	(3.61)	(3.49)	(3.29)	(3.41)
Recession	0.35	0.35	0.28	0.24	0.44	0.47
	(1.38)	(1.51)	(1.63)	(1.60)	(0.37)	(0.66)

Panel B. Firm characteristics by CAF quintiles in rated and unrated firms

Sample	Unrated firms					Rated firms				
Number of firms	10,032					3,735				
CAF groups:	CAF_1	CAF_2	CAF_3	CAF_4	CAF_5	CAF_1	CAF_2	CAF_3	CAF_4	CAF_5
Size ($ billions)	0.41	0.69	0.75	0.83	1.54	2.47	4.150	6.65	9.99	14.86
BM (%)	87.36	77.77	63.01	58.38	59.73	81.99	60.22	51.8	48.98	50.63
Price	8.12	9.72	16.21	23.93	38.63	14.68	22.65	31.40	41.66	72.07
Dispersion	0.55	0.20	0.17	0.14	0.08	0.35	0.10	0.06	0.04	0.03
CAF	-1.90	-0.53	0.06	0.80	3.07	-1.04	-0.37	-0.02	0.48	2.01
FE	-8.47	-5.42	-4.23	-2.89	-1.78	-3.47	-1.62	-1.23	-0.89	-0.78

Panel C. Composition, returns (% per month), and credit rating by CAF quintiles

	Percentage of firms			Returns (% per month)					Credit rating score for rated firms	S&P letter rating for rated firms
CAF quintiles	UR	IG	NIG	UR	IG	NIG	Rated	All		
CAF_1 (lowest)	72.69	9.50	17.81	0.66	0.88	0.06	0.68	0.60	13.43	BB-
CAF_2	70.50	14.95	14.55	0.70	1.01	0.77	1.01	0.99	11.66	BB+
CAF_3	67.95	20.52	11.53	1.05	1.08	1.03	1.08	1.13	9.98	BBB-
CAF_4	57.59	33.19	9.22	1.19	1.09	1.03	1.09	1.13	8.77	BBB+
CAF_5 (highest)	55.12	37.42	7.46	1.19	1.16	1.06	1.24	1.14	7.52	A-
CAF_5- CAF_1				0.53***	0.28	1.10***	0.55***	0.54***		
				(3.24)	(1.39)	(4.86)	(3.28)	(3.26)		

Table 2
Analysts' forecast errors for portfolios sorted on credit rating and CAF

I first sort all stocks rated by S&P into five quintiles based on credit ratings, CR1-CR5. I then sort the stocks in each credit rating quintile into five quintiles based on CAF, CAF_1-CAF_5. The above double sorting is repeated every month based on the credit rating and CAF in the previous month. Panel A (B) reports time-series averages of FE (CAF) for the 5×5 portfolios. *t* –statistics are presented in parentheses. In Panel C, I run Fama and Macbeth (1973) cross-sectional regressions of FE at time *t* on CAF and other firm's characteristics at time *t*-1. I present the time-series average and *t*-statistic of the estimated coefficients. *t*-statistics are presented in parentheses and are corrected using the Newey and West (1987) approach. All variables are defined in the appendix. My sample period is from January 1986 to December 2014. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Forecast Errors (%)

	CAF Quintiles					
Credit Rating Quintiles	CAF_1 (lowest)	CAF_2	CAF_3	CAF_4	CAF_5 (highest)	CAF_5-CAF_1
CR1 (highest rated)	-1.05**	-0.56	-0.52	-0.53	-0.67	0.38
	(-2.10)	(-1.21)	(-1.10)	(-1.11)	(-1.45)	(0.85)
CR2	-1.12**	-0.68	-0.5890	-0.56	-0.64	0.42
	(-2.33)	(-1.54)	(-1.44)	(-1.34)	(-1.42)	(1.21)
CR3	-1.28***	-0.66	-0.60	-0.61	-0.51	0.77
	(-2.55)	(-1.46)	(-1.34)	(-1.48)	(-1.13)	(1.63)
CR4	-3.37***	-1.70***	-1.09***	-0.87*	-0.87*	2.51***
	(-4.33)	(-2.77)	(-2.54)	(-1.77)	(-1.77)	(4.35)
CR5 (lowest rated)	-5.53***	-4.53***	-3.37***	-1.88***	-1.23**	4.30***
	(-4.77)	(-4.54)	(-4.35)	(-2.77)	(-2.24)	(5.23)
CR1-CR5	4.48***	3.97***	2.85***	1.35***	0.56	
	(4.33)	(4.53)	(4.56)	(2.99)	(1.44)	
All rated firms	-3.47***	-1.62***	-1.23**	-0.89*	-0.78	
	(-4.33)	(-2.34)	(-2.10)	(-1.87)	(-1.64)	

Panel B. CAF

	CAF Quintiles					
Credit Rating Quintiles	CAF_1 (lowest)	CAF_2	CAF_3	CAF_4	CAF_5 (highest)	All rated firms
CR1 (highest rated)	0.65	0.80	0.95	1.12	1.38	1.05
CR2	0.30	0.35	0.39	0.87	1.22	0.58
CR3	-0.47	-0.40	-0.02	0.10	0.86	-0.05
CR4	-1.17	-0.62	-0.14	-0.13	-0.30	-0.51
CR5 (lowest rated)	-1.74	-0.65	-0.50	-0.45	-0.15	-0.72
All rated firms	-0.51	-0.17	0.10	0.42	0.66	

Panel C: Fama and Macbeth (1973) regressions of forecast errors on CAF, credit rating, and other lagged characteristics

	1	2	3	4	5	6	7	8	9	10
CAF_{t-1}	0.28***	0.04	0.05	0.29***	0.05	0.06	0.17***	0.05	0.06	0.04
	(5.68)	(1.59)	(1.64)	(5.42)	(1.11)	(1.62)	(3.98)	(1.40)	(1.50)	(0.87)
CR_{t-1}		-0.45***			-0.40***			-0.42***		
		(-8.23)			(-7.32)			(-9.01)		
NIG $dummy_{t-1}$			-0.23***			-0.20***			-0.19***	-0.11*
			(-5.83)			(-5.42)			(-5.01)	(-1.85)
CAF_{t-1} $\times$NIG $dummy_{t-1}$										1.36***
										(4.43)
Log($Size_{t-1}$)	0.40***	0.28***	0.28***	0.41***	0.47***	0.47***	0.38***	0.29***	0.26***	0.24***
	(8.77)	(5.94)	(6.42)	(8.24)	(9.11)	(9.10)	(9.63)	(9.01)	(8.15)	(8.10)
Log(BM_{t-1})	-0.28***	-0.15***	-0.19***	-0.25***	-0.21***	-0.22***	-0.32***	-0.21***	-0.19***	-0.18***
	(-7.54)	(-4.53)	(-5.24)	(-4.52)	(-3.98)	(-4.01)	(-3.54)	(-4.02)	(-3.98)	(-3.55)
$R_{t-6:t}$	0.04***	0.05***	0.05***	0.04***	0.04***	0.05***	0.03***	0.048***	0.05***	0.05***
	(4.56)	(5.13)	(5.52)	(5.76)	(6.20)	(5.99)	(6.31)	(7.32)	(6.83)	(6.73)
$Accrual_{t-1}$				-0.68***	-0.68***	-0.68***	-1.01***	-1.11***	-1.12***	-1.00***
				(-4.76)	(-4.82)	(-5.11)	(-5.93)	(-6.22)	(-5.93)	(-5.50)
ES_{RECENT}				0.05***	0.05***	0.05***	0.04***		0.04***	0.04***
				(6.42)	(5.98)	(6.22)	(6.72)		(5.83)	(5.56)
EP_{t-1}							6.01***	5.94***	5.99***	5.91***
							(7.32)	(6.93)	(7.02)	(6.78)
$Experience_{t-1}$							-0.16***	-0.01**	-0.02**	-0.02**
							(-3.12)	(-1.92)	(-2.22)	(-2.00)
$Breadth_{t-1}$							0.14***	0.16**	0.17**	0.15**
							(3.55)	(2.01)	(2.22)	(2.00)
Horizon							-0.82	-0.86***	-0.91***	-0.87***
							(-9.54)	(-8.79)	(-7.42)	(-7.99)
Average Adjusted R^2	15.32%	23.79%	21.01%	17.42%	24.71%	21.74%	22.12%	24.99%	23.01%	24.00%

Table 3

Returns by sequentially sorted on credit rating and CAF groups

For each month t, all stocks rated by S&P are divided into five quintiles based on credit ratings first, and then stocks within each credit rating quintile are further divided into five quintiles based on CAF. The 25 portfolios are held for one and three months. For the one month holding period strategy, for each rating/anchoring bias portfolio, I compute the cross sectional mean return for month t+1. For the three month holding strategy, the monthly return for each month t+1 are computed as the equally weighted average of the returns of portfolio sorted in month t, t-1, t-2. Raw returns are presented in Panels A1 and A2, and Carhart (1997) alphas, which are estimated using the entire sample period, are presented in Panels B1 and B2. All returns are in percentages per month. *t* statistics are presented in parentheses. All variables are defined in the appendix. The sample consists of 3,735 companies over the period of January 1986 to December 2014. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

	CAF Quintiles					
Credit Rating Quintiles	CAF_1 (lowest)	CAF_2	CAF_3	CAF_4	CAF_5 (highest)	CAF_5-CAF_1
Panel A1: Raw return, 1 month holding period						
CR1 (highest rated)	0.93***	0.98***	1.05***	1.07***	1.10***	0.17
	(4.30)	(4.59)	(4.76)	(4.89)	(4.95)	(0.59)
CR2	0.92***	1.06***	1.09***	1.16***	1.17***	0.25
	(4.21)	(4.61)	(4.89)	(4.95)	(4.96)	(0.80)
CR3	0.86***	1.15***	1.00***	1.11***	1.16***	0.30
	(4.76)	(4.75)	(3.98)	(4.54)	(4.98)	(1.26)
CR4	0.31	0.90***	0.97***	1.14***	0.98***	0.67**
	(1.25)	(3.56)	(3.78)	(3.98)	(4.98)	(3.36)
CR5 (lowest rated)	0.03	0.46**	0.51***	0.68***	0.74***	0.71***
	(0.78)	(2.48)	(2.60)	(3.35)	(3.56)	(3.79)
CR1-CR5	0.90***	0.52***	0.54**	0.39*	0.36*	
	(4.19)	(2.62)	(2.64)	(1.86)	(1.83)	
Panel A2: Raw return, 3 month holding period						
CR1 (highest rated)	0.94***	0.99***	1.07***	1.09***	1.22***	0.28
	(3.98)	(4.01)	(4.12)	(4.13)	(4.38)	(1.06)
CR2	0.93***	1.07***	1.11***	1.19***	1.20***	0.27
	(3.93)	(4.30)	(4.14)	(4.25)	(4.31)	(1.41)
CR3	1.08***	1.16***	1.02***	1.13***	1.20***	0.12
	(3.72)	(3.84)	(4.05)	(4.19)	(4.74)	(0.56)
CR4	0.65***	1.00***	0.99***	1.17***	1.28***	0.63**
	(3.69)	(4.09)	(4.03)	(4.25)	(4.51)	(3.18)
CR5 (lowest rated)	0.19	0.43**	0.56**	0.64***	0.88***	0.69***
	(0.78)	(2.45)	(2.68)	(2.78)	(3.95)	(3.62)
CR1-CR5	0.75***	0.56***	0.51***	0.54***	0.33*	
	(3.84)	(2.66)	(2.59)	(2.62)	(1.65)	

Credit Rating Quintiles	CAF Quintiles CAF_1 (lowest)	CAF_2	CAF_3	CAF_4	CAF_5 (highest)	CAF_5-CAF_1
Panel B1: Carhart 4-factor alpha, 1 month holding period						
CR1 (highest rated)	0.15	0.17	0.19	0.24	0.36	0.21
	(0.65)	(0.98)	(1.10)	(1.48)	(1.56)	(1.02)
CR2	0.05	0.09	0.11	0.14	0.34	0.29
	(0.15)	(0.21)	(0.48)	(0.56)	(1.05)	(1.09)
CR3	0.04	0.06	0.07	0.09	0.36	0.32
	(0.11)	(0.16)	(0.19)	(0.35)	(1.52)	(1.22)
CR4	-0.45***	-0.36***	-0.22	-0.20	-0.003	0.45***
	(-1.99)	(-1.29)	(-1.16)	(-1.49)	(-0.01)	(2.77)
CR5 (lowest rated)	-0.80***	-0.51**	-0.41**	-0.34*	-0.03	0.77***
	(-4.38)	(-3.1)	(-1.96)	(-1.65)	(-0.35)	(4.16)
CR1-CR5	0.95***	0.68***	0.60***	0.58***	0.39*	
	(4.81)	(3.76)	(3.56)	(2.86)	(1.70)	
Panel B2: Carhart 4-factor alpha, 3 month holding period						
CR1 (highest rated)	0.13	0.15	0.17	0.22	0.24	0.11
	(1.02)	(1.03)	(1.09)	(1.48)	(1.62)	(0.52)
CR2	0.04	0.07	0.10	0.12	0.31	0.27
	(0.15)	(0.32)	(0.46)	(0.52)	(1.52)	(1.09)
CR3	0.01	0.04	0.06	0.09	0.25	0.24
	(0.11)	(0.33)	(0.43)	(0.57)	(1.39)	(1.00)
CR4	-0.69***	-0.47***	-0.32	-0.30	-0.13	0.56**
	(-3.59)	(-2.95)	(-1.58)	(-1.44)	(1.29)	(1.96)
CR5 (lowest rated)	-0.80***	-0.61***	-0.51**	-0.44*	-0.13	0.67***
	(-4.04)	(-3.42)	(-2.06)	(-1.72)	(-0.65)	(2.58)
CR1-CR5	0.94***	0.76***	0.68***	0.66***	0.37*	
	(4.17)	(3.95)	(3.75)	(3.69)	(1.89)	

Table 4
CAF strategy payoffs over diminishing subsamples

Cross-sectional anchoring bias portfolios are constructed as explained in table 1. Each subsequent row in panel A (panel B) represents a monotonically decreasing sample of stocks obtained by sequentially excluding firms with the worst credit rating (smallest market capitalization), the first column characterizes each subsample. The second column presents the raw monthly profits from the anchoring bias based trading strategy for each subsample of firms. *t*-statistics are in parentheses. The third column shows the market capitalization of the given subsample as a percentage of the overall market capitalization of S&P rated firms. The fourth (fifth) column provides the average number (percentage) of firms per month in each subsample. All variables are defined in the appendix. The sample contains 3,735 companies over the period of January 1986 to December 2014. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Cross sectional anchoring bias profits by sequentially removing worst-rated stocks						Panel B: Cross-sectional anchoring bias profits by sequentially removing smallest stocks				
Stock sample	Excluded firms	CAF profits	Percent of total market cap	Number of firms	Percentage of firms	Stock sample	CAF profits	Percent of total market cap	Number of firms	Percentage of firms
All firms	None	0.55***(3.28)	100.00	1321.00	100.00	All firms	0.55***(3.28)	100.00	1321.00	100
AAA-C	D	0.55***(3.28)	99.99	1319.15	99.86	Biggest 96%	0.53*** (3.24)	99.88	1268.16	96
AAA-CC	C-D	0.55***(3.28)	99.99	1319.15	99.86	Biggest 92%	0.50*** (3.11)	99.85	1215.32	92
AAA-CCC-	CC-D	0.55***(3.28)	99.99	1318.75	99.83	Biggest 88%	0.49*** (2.77)	99.82	1162.48	88
AAA-CCC	CCC- -D	0.56***(3.38)	99.98	1317.96	99.77	Biggest 84%	0.47*** (2.64)	99.78	1109.64	84
AAA-CCC+	CCC - D	0.56*** (3.39)	99.98	1316.64	99.67	Biggest 80%	0.46*** (2.60)	99.74	1056.80	80
AAA-B-	CCC+ -D	0.55*** (3.28)	99.66	1316.64	99.67	Biggest 76%	0.44***(2.56)	99.69	1003.90	76
AAA-B	B- -D	0.52*** (3.10)	99.57	1284.80	97.26	Biggest 72%	0.42** (2.27)	99.63	951.12	72
AAA-B+	B-D	0.48*** (2.59)	99.14	1204.88	91.21	Biggest 68%	0.40* (1.723)	99.57	898.28	68
AAA-BB-	B+ -D	0.39** (1.89)	97.87	1050.19	79.50	Biggest 64%	0.42** (2.16)	99.50	845.44	64
AAA-BB	BB- -D	0.36* (1.69)	96.17	892.07	67.53	Biggest 60%	0.41** (2.15)	99.41	792.60	60
AAA-BB+	BB-D	0.29 (1.50)	93.62	750.32	56.80	Biggest 56%	0.41** (2.14)	99.31	739.76	56
AAA-BBB-	BB+ -D	0.28 (1.39)	91.48	665.12	50.35	Biggest 52%	0.44*** (2.21)	99.17	686.92	52
AAA-BBB	BBB- - D	0.28 (1.10)	86.38	561.56	42.51	Biggest 48%	0.39* (2.06)	99.00	634.08	48
AAA-BBB+	BBB-D	0.27 (1.05)	76.89	473.84	33.87	Biggest 44%	0.33* (1.89)	98.75	581.24	44
						Biggest 40%	0.30* (1.81)	98.39	528.40	40
						Biggest 36%	0.36** (1.96)	97.86	475.60	36
						Biggest 32%	0.46** (2.19)	97.00	422.72	32
						Biggest 28%	0.65** (3.62)	95.56	369.98	28
						Biggest 24%	0.87*** (3.65)	91.83	317.04	24
						Biggest 20%	0.82*** (3.98)	87.51	264.20	20

Table 5

Fama and Macbeth (1973) cross-sectional regressions of returns on anchoring bias and credit ratings

I run Fama and Macbeth (1973) cross-sectional regressions of raw returns or Carhart four-factor alphas at time *t* on CAF, CR, NIG dummy, and other firm characteristics at time *t*-1. Carhart four-factor alphas are estimated using the previous 24 months of returns. Panels A and B present the time series average and *t*-statistic of the estimated coefficients from the regressions of raw returns and Carhart alphas, respectively. All returns are in percentages per month. *t*-statistics are presented in parentheses and are corrected using the Newey and West (1987) approach. All variables are defined in the appendix. The sample consists of 3,735 firms over the period of January 1986 - December 2014. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A : Fama and Macbeth (1973) regressions of raw return on lagged characteristics

	1	2	3	4	5	6	7	8	9	10
CAF_{t-1}	0.11***	0.05	0.07*	0.10**	0.03	0.05	0.09**	0.02	0.05	0.04
	(2.93)	(1.41)	(1.90)	(2.20)	(0.70)	(1.14)	(2.10)	(0.49)	(0.98)	(0.63)
CR_{t-1}		-0.25***			-0.25***			-0.26***		
		(-3.61)			(-3.54)			(-3.58)		
NIG $dummy_{t-1}$			-0.01***			-0.01***			-0.01***	-0.01***
			(-3.59)			(-3.57)			(-3.64)	(-3.59)
CAF_{t-1} ×NIG $dummy_{t-1}$										0.16**
										(1.95)
$Log(Size_{t-1})$	-0.07	-0.08*	-0.02	-0.07	-0.06	-0.01	-0.08	-0.07	-0.05	-0.04
	(-1.36)	(-1.80)	(-0.44)	(-1.45)	(-1.48)	(-0.17)	(-1.45)	(-1.48)	(-1.12)	(-1.08)
$Log(BM_{t-1})$	0.39**	0.28*	0.14	0.15	0.18	0.13	0.10	0.47*	0.25	0.24
	(2.23)	(1.78)	(0.96)	(0.81)	(1.16)	(0.48)	(0.39)	(1.71)	(0.98)	(0.96)
$R_{t-7:t-1}$	0.34	0.47*	0.43*	0.26	0.39*	0.34	0.25	0.37	0.33	0.32
	(1.44)	(1.94)	(1.81)	(1.12)	(1.66)	(1.46)	(1.04)	(1.57)	(1.42)	(1.36)
$R_{t-1:t}$	-0.09**	-0.13***	-0.14***	-0.08**	-0.12*	-0.11*	-0.08	-0.12	-0.11*	-0.11*
	(-2.41)	(-2.57)	(-2.92)	(-1.96)	(-1.94)	(-1.74)	(-1.21)	(-1.81)	(-1.69)	(-1.68)
$Accrual_{t-1}$				-0.604***	-0.55***	-0.56***	-0.59***	-0.54***	-0.55***	-0.54***
				(-3.62)	(-3.47)	(-3.49)	(-3.84)	(-3.35)	(-3.37)	(-3.31)
ES_{RECENT}				0.06***	0.04***	0.05***	0.06***	0.05***	0.06***	0.05***
				(3.52)	(2.80)	(3.20)	(3.04)	(2.99)	(3.02)	(3.00)
EP_{t-1}							1.60***	1.54***	1.57***	1.51***
							(3.20)	(3.11)	(3.23)	(3.10)
$Disperion_{t-1}$							-0.08	-0.07	-0.19	-0.10
							(-0.82)	(-0.80)	(-0.92)	(-0.70)
Average Adjusted R^2	6.32%	7.54%	7.26%	7.28%	8.42%	8.12%	7.94%	9.20%	8.77%	9.16%

Panel B: Fama and Macbeth (1973) regressions of Carhart four-factor alpha on lagged characteristics										
	1	2	3	4	5	6	7	8	9	10
CAF_{t-1}	0.09***	0.02	0.03*	0.05***	0.01	0.02	0.04**	0.01	0.02	0.01
	(2.93)	(1.40)	(1.90)	(2.70)	(0.70)	(1.14)	(1.96)	(0.49)	(0.98)	(0.63)
CR_{t-1}		-0.11***			-0.10***			-0.10***		
		(-3.61)			(-3.54)			(-3.58)		
NIG $dummy_{t-1}$			-0.02***			-0.02***			-0.02***	-0.02***
			(-3.95)			(-3.57)			(-3.64)	(-3.59)
CAF_{t-1}										0.17*
×NIG $dummy_{t-1}$										(1.87)
$Log(Size_{t-1})$	-0.02	-0.03*	-0.01	-0.03	-0.03	-0.003	-0.03	-0.03	-0.002	-0.03
	(-1.36)	(-1.81)	(-0.44)	(-1.45)	(-1.48)	(-0.17)	(-1.45)	(-1.48)	(-0.12)	(-0.20)
$Log(BM_{t-1})$	0.02	0.10*	0.06	0.06	0.08	0.01	0.04	0.18*	0.09	0.09
	(0.25)	(1.78)	(0.96)	(0.81)	(1.16)	(0.18)	(0.39)	(1.71)	(0.98)	(0.97)
$R_{t-7:t-1}$	0.138	0.19**	0.17*	0.11	0.15	0.14	0.10	0.15	0.14	0.13
	(1.44)	(1.96)	(1.81)	(1.10)	(1.61)	(1.46)	(1.04)	(1.57)	(1.42)	(1.36)
$R_{t-1:t}$	-0.04	-0.05***	-0.05*	-0.03***	-0.05*	-0.04*	-0.03	-0.05*	-0.04*	-0.04*
	(-1.40)	(-2.07)	(-1.92)	(-1.31)	(-1.94)	(-1.74)	(01.21)	(-1.81)	(-1.64)	(-1.68)
$Accrual_{t-1}$				-0.24	-0.22***	-0.22***	-0.23***	-0.22***	-0.22***	-0.21***
				(-3.62)	(-3.47)	(-3.49)	(-3.48)	(-3.35)	(-3.37)	(-3.31)
ES_{RECENT}				0.04***	0.03***	0.04***	0.02***	0.03***	0.02***	0.02***
				(2.70)	(2.69)	(2.69)	(2.64)	(2.19)	(2.52)	(2.41)
EP_{t-1}							1.06***	1.54***	1.07***	1.05***
							(2.80)	(3.11)	(2.63)	(2.60)
$Disperion_{t-1}$							-0.02	-0.002	-0.01	-0.01
							(-0.74)	(-0.09)	(-0.32)	(-0.30)
Average Adjusted R^2	6.32%	7.54%	7.26%	7.28%	8.42%	8.12%	7.94%	9.20%	8.77%	9.16%

Table 6
Returns by sequentially sorted rating and CAF* groups

In this table, I adjust CAF by credit risk by regressing CAF on the stock's S&P credit rating as follows: $CAF_{it}=a_t+b_t\ CR_{it}+e_{it}$. I define $CAF_{it}^{*}=a_t+e_{it}$ as the credit-risk adjusted CAF. Then each month t, stocks are sorted into 25 portfolios based on a double sorting by five credit rating and five CAF* groups. For each CAF*-rating portfolio, I compute the cross sectional mean return for month t+1. I exclude stocks priced below $5 at the beginning of the month. All variables are defined in the appendix. The sample consists of 3,735 firms over the period of January 1986 - December 2014. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Returns by sequentially sorted credit rating and CAF* groups						
	CAF* Quintiles					
Credit Rating Quintiles	CAF^*_1 (lowest)	CAF^*_2	CAF^*_3	CAF^*_4	CAF^*_5 (highest)	CAF^*_5-CAF^*_1
CR1 (highest rated)	0.92***	0.97***	1.06***	1.26***	1.19***	0.27
	(4.70)	(5.39)	(5.83)	(5.62)	(5.63)	(0.78)
CR2	0.95***	1.06***	1.08***	1.17***	1.14***	0.19
	(4.18)	(5.08)	(5.51)	(5.92)	(5.42)	(0.62)
CR3	1.05***	1.13***	1.03***	1.09***	1.18***	0.139
	(4.08)	(4.76)	(4.78)	(4.72)	(4.83)	(0.39)
CR4	0.82***	0.91***	1.00***	1.08***	1.14***	0.31
	(3.98)	(4.32)	(4.81)	(5.06)	(5.43)	(1.42)
CR5 (lowest rated)	0.15	0.36**	0.46***	0.58**	0.53***	0.38
	(1.14)	(1.75)	(23.50)	(2.30)	(3.75)	(1.55)
CR1-CR5	0.76***	0.60***	0.59***	0.68**	0.66***	
	(3.87)	(3.51)	(2.62)	(2.98)	(2.75)	

Table 7

Anchoring bias strategy payoffs based on characteristic-adjusted returns

The table presents profits based on credit rating-adjusted returns (Panel A) or size-adjusted returns (Panel B). Returns are adjusted by subtracting from each stock monthly return the monthly return of the credit rating (size) decile to which the stock belongs. I assume a one–month holding period. All returns are percentages per month. t-statistics are presented in parentheses. All variables are defined in the appendix. The sample contains 3,735 companies over the period of January 1986 to December 2014. Superscripts ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

	CAF Quintiles					
Credit Rating Quintiles	CAF_1 (lowest)	CAF_2	CAF_3	CAF_4	CAF_5 (highest)	CAF_5-CAF_1
Panel A: Credit rating-adjusted returns						
CR1 (highest rated)	-0.09	-0.05	0.03	0.04	0.07	0.17
	(-0.64)	(-0.63)	(-0.22)	(0.55)	(0.63)	(1.29)
CR2	-0.16	-0.02	0.01	0.08	0.09	0.25
	(-1.49)	(-0.54)	(-0.01)	(0.62)	(0.63)	(1.50)
CR3	-0.03	0.05	-0.10	0.02	0.06	0.09
	(-0.36)	(0.62)	(-0.76)	(0.39)	(0.51)	(0.73)
CR4	-0.10	-0.02	-0.03	0.05	0.10	0.21
	(-1.11)	(-0.11)	(0.34)	(0.78)	(1.31)	(1.34)
CR5 (lowest rated)	-0.10	-0.22**	0.02	0.06	0.14	0.24
	(-1.33)	(-2.10)	(0.22)	(0.89)	(1.43)	(1.59)
All rated firms	0.15*	0.16**	0.18**	0.05	0.13*	
	(1.72)	(2.32)	(2.43)	(0.76)	(1.64)	
Panel B: Size-adjusted returns						
CR1 (highest rated)	0.29**	0.24*	0.20	0.36**	0.42***	0.14
	(1.99)	(1.65)	(1.54)	(2.24)	(2.56)	(1.10)
CR2	0.12	0.28*	0.17	0.06	0.16	0.04
	(1.15)	(1.78)	(1.33)	(0.24)	(1.11)	(0.05)
CR3	-0.10	-0.09	-0.13	-0.13	0.16	0.26
	(-0.78)	(-0.64)	(-1.12)	(-1.10)	(1.45)	(1.62)
CR4	-0.46***	-0.25	-0.16	0.17	0.28*	0.75***
	(-2.76)	(1.58)	(-1.51)	(1.54)	(1.78)	(2.76)
CR5 (lowest rated)	-0.87***	-0.67***	-0.10	-0.28*	-0.21	0.65***
	(-3.25)	(2.66)	(-1.10)	(1.76)	(1.62)	(2.61)
All rated firms	-0.42**	-0.06	0.13	0.23	0.25*	
	(-1.98)	(-0.31)	(1.10)	(1.55)	(1.65)	

Table 8
Ex post earnings announcement returns

Panel A reports the time-series averages of the means of ECAR for the 5×5 credit rating- and CAF-sorted portfolios. At the beginning of each month, all stocks are sorted into 5 groups (CR1-CR5) based on their credit rating scores at the end of the previous month. Stocks in each credit rating group are further sorted into 5 quintiles (CAF_1–CAF_5) based on their CAF in the previous month. The portfolios are held for 12 months after formation. Stocks priced below $5 are excluded from the sample. The t -statistics reported in parentheses are adjusted for serial correlation and heteroscedasticity using the Newey and West (1987) procedure. Panel B reports the results from the Fama-MacBeth (1973) regressions of earnings announcement returns. The dependent variable is the earnings announcement return (ECAR), which is defined as the cumulative 3-day abnormal return relative to the CRSP value-weighted index surrounding the next earnings announcement date during the 12 months following portfolio formation. The explanatory variables include a constant (not reported), CAF, credit rating, log(SIZE), log(BM), $RET_{-6:-0}$, ACCRUAL, ES_{RECENT}, EP_{t-1}, and Dispersion. All variables are defined in the appendix. For all dependent and explanatory variables (except for stock returns), values greater than the 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and 0.005 fractile values, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: ECAR (%) for CR and CAF Sorted Portfolios

	CAF Quintiles					
Credit Rating Quintiles	CAF_1 (lowest)	CAF_2	CAF_3	CAF_4	CAF_5 (highest)	CAF_5-CAF_1
CR1 (highest rated)	0.214	0.351***	0.405***	0.500***	0.465**	0.251
	(1.37)	(2.77)	(3.24)	(3.76)	(3.12)	(1.56)
CR2	0.217	0.212	0.216	0.324***	0.367***	0.107
	(1.40)	(1.38)	(1.41)	(2.76)	(2.98)	(0.98)
CR3	-0.111	0.164	0.155	0.223	0.123	0.231
	(-0.99)	(1.30)	(1.11)	(1.33)	(1.22)	(1.55)
CR4	-0.320***	0.259*	0.130	0.159	0.178	0.498***
	(-2.77)	(1.51)	(1.11)	(1.33)	(1.42)	(3.22)
CR5 (lowest rated)	-0.412***	-0.134	0.245*	0.202	0.154	0.566***
	(-3.01)	(-1.17)	(1.66)	(1.23)	(1.29)	(3.97)
CR1-CR5	0.534***	0.4851***	0.526***	0.308***	0.311***	
	(3.87)	(3.22)	(3.95)	(2.99)	(2.70)	

Panel B: Fama-MacBeth Regressions of ECAR

	1	2	3	4	5	6	7	8	9
CAF_{t-1}	0.045***	0.008	0.005	0.038**	0.004	0.005	0.042***	0.005	0.005
	(2.76)	(1.09)	(1.29)	(1.96)	(1.08)	(1.11)	(2.25)	(1.08)	(1.09)
CR_{t-1}		-0.038***			-0.045**			-0.045*	
		(-2.69)			(-1.99)			(-1.83)	
NIG Dummy			-0.003***			-0.003***			-0.003***
			(-4.29)			(-4.79)			(-4.29)
$Log(Size_{t-1})$	-0.038**	-0.015	-0.003	-0.028	-0.001	0.014	-0.026	0.001	0.014
	(-2.07)	(-0.70)	(-0.14)	(-1.56)	(-0.04)	(0.68)	(-1.50)	(0.02)	(0.74)
$Log(BM_{t-1})$	0.356***	0.285***	0.274**	0.275***	0.175	0.164	0.461***	0.326**	0.312*
	(3.31)	(2.56)	(2.52)	(2.23)	(1.38)	(1.28)	(2.66)	(2.01)	(1.86)
$R_{t-6:t}$	1.331***	1.342***	1.337***	1.351***	1.367***	1.351***	1.375***	1.386***	1.373***
	(10.04)	(10.22)	(10.05)	(8.99)	(9.15)	(8.99)	(9.15)	(9.31)	(9.12)
$Accrual_{t-1}$				-0.432***	-0.443***	-0.458***	-0.453***	-0.469***	-0.482***
				(-4.60)	(-4.70)	(-4.58)	(-4.80)	(-4.92)	(-5.03)
ES_{RECENT}				0.020***	0.017***	0.015***	0.014***	0.015***	0.014***
				(4.01)	(3.54)	(3.10)	(3.03)	(3.11)	(3.05)
EP_{t-1}							-0.051	-0.045	-0.052
							(-0.50)	(-0.46)	(-0.56)
$Disperion_{t-1}$							-0.082**	-0.043	-0.050
							(-1.95)	(-0.98)	(-1.16)
Average Adjusted R^2	1.40%	1.59%	1.62%	1.87%	2.07%	2.09%	2.23%	2.46%	2.48%

Table 9
Credit rating, anchoring, and stock split

Panel A reports the time-series averages of stock split ratios (SSR) for the 25 CR-CAF sorted portfolios. At the beginning of each month, all stocks are sorted into five groups based on the credit ratings. The portfolios are held for 12 months. Stocks priced below $5 are excluded from the sample. The t-statistics reported in parentheses are adjusted for serial correlation and heteroscedasticity using the Newey and West (1987) procedure. Panel B reports the panel logit regression results for the likelihood of a stock split. The dependent variable is a dummy variable that equals 1 if a firm completes a significant stock split (i.e., 1 share is split into 1.5 or more shares) in month t, and 0 otherwise. The explanatory variables include a constant (not reported), CAF, log(SIZE), log(BM), RET, Accrual, ES_{RECENT}, and EP. All variables are defined in the appendix. The z statistics reported in parentheses have been adjusted for clustered errors at both firm level and the year level. ***, **,* indicate the significance at the 1%, 5% and 10% levels, respectively.

Panel A: SSR

	CAF quintiles					
Credit Rating Quintiles	CAF_1 (lowest)	CAF_2	CAF_3	CAF_4	CAF_5 (highest)	CAF_5-CAF_1
CR1 (highest rated)	1.416***	1.488***	1.537***	1.488***	1.505***	0.022
	(6.56)	(6.99)	(7.31)	(6.97)	(7.01)	(1.21)
CR2	1.397***	1.470***	1.444***	1.413***	1.447***	0.051
	(6.41)	(6.89)	(6.42)	(6.11)	(6.33)	(1.54)
CR3	1.268***	1.300***	1.419***	1.401***	1.306***	0.043
	(6.11)	(6.23)	(6.46)	(6.39)	(6.21)	(1.24)
CR4	1.030***	1.221***	1.342***	1.346***	1.242***	0.212***
	(5.79)	(6.11)	(6.34)	(6.35)	(6.02)	(3.65)
CR5 (lowest rated)	1.001***	1.020***	1.084***	1.002***	1.112***	0.101***
	(5.86)	(5.98)	(5.99)	(5.84)	(5.98)	(2.66)
CR1-CR5	0.415***	0.460***	0.451***	0.401***	0.503***	
	(4.55)	(4.59)	(4.57)	(4.30)	(4.87)	

Panel B: Results from the likelihood Logit Regressions of Stock Split

	1	2	3	4	5	6	7	8	9	10	11
CAF_{t-1}	0.002	0.004	0.006***	-0.002	0.003	0.005**	0.002***	-0.001	0.006***	0.002	0.001
	(0.39)	(0.13)	(2.54)	(0.40)	(1.09)	(2.39)	(0.42)	(-0.20)	(2.99)	0.014	(0.22)
CR_{t-1}	-0.164***			-0.130***			-0.135***			-0.136***	
	(-11.18)			(-7.43)			(-7.39)			(-7.39)	
NIG $dummy_{t-1}$		-0.882***			-0.624***			-0.663***			-0.66***
		(-9.82)			(-6.36)			(-6.18)			(-6.19)
$Log(Size_{t-1})$			0.032***	0.021***	0.025***	0.032***	0.025***	0.034	0.032***	0.022***	0.03***
			(6.01)	(5.55)	(5.23)	(6.27)	(5.59)	(-5.96)	(5.99)	(4.93)	(6.90)
$Log(BM_{t-1})$			-0.183***	-0.140*	-0.121*	-0.163***	-0.146*	-0.105*	-0.093	-0.171*	-0.11*
			(-2.60)	(-1.90)	(-1.83)	(-2.40)	(-1.89)	(01.67)	(-1.42)	(-1.90)	(-1.69)
$R_{t-6:t}$			0.012**	0.054**	0.043*	0.022	0.019	0.003	0.022	0.023	0.003
			(1.02)	(2.96)	(1.73)	(1.12)	(0.89)	(0.15)	(0.89)	(0.97)	(0.13)
ES_{RECENT}						0.220***	0.200***	0.210***	0.201***	0.017***	0.015***
						(6.01)	(6.01)	(6.31)	(5.69)	(5.45)	(5.32)
$Accrual_{t-1}$						1.743***	1.644***	1.743***	1.901***	1.223***	1.221***
						(2.62)	(2.62)	(2.82)	(5.51)	(4.56)	(4.52)
EP_{t-1}									1.401***	1.254***	1.324***
									(5.69)	(5.54)	(5.21)
$Disperion_{t-1}$									-0.173***	-0.044	-0.035
									(-2.84)	(-1.35)	(-1.22)
Pseudo R^2	5.15%	3.49%	5.80%	9.50%	6.98%	7.22%	9.51%	8.55%	6.54%	10.32%	8.54%

Table 10
The effect of downgrades on the relation between CAF and analysts forecast errors

For Panel A, I first remove firms three months-around rating downgrades (i.e., from t-3 to t+3). Then, for each month t, all stocks rated by S&P are divided into 25 groups based on sequential sort by five credit rating and five CAF groups. For each rating/CAF group, I compute the time series forecast error. For Panel B, I run monthly cross-sectional regressions of forecast error, FE_{it}, on a constant, the lagged CAF, a downgrade dummy, lagged credit rating, and lagged control variables. The control variables include log(SIZE), log(BM), $RET_{t-6:t}$, ACCRUAL, ES_{RECENT}, EP, and Dispersion. All variables are defined in the appendix. Panel B presents the average slope coefficients, in cross-sectional regressions, averaged across all months in the sample, and multiplied by 100. The *t*-statistics, which are presented in parentheses, are the sample *t*-statistics of the estimated coefficients. All forecast errors are in percentages per month. The sample consists of 3,735 companies over the period January 1986 to December 2014. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Forecast error by sequentially sorted rating and CAF groups

	CAF Quintiles					
Credit Rating Quintiles	CAF_1 (lowest)	CAF_2	CAF_3	CAF_4	CAF_5 (highest)	CAF_5-CAF_1
CR1 (highest rated)	-0.89**	-0.55	-0.49	-0.40	-0.55	0.34
	(-1.97)	(-1.10)	(-1.41)	(1.52)	(0.58)	(0.98)
CR2	-1.08**	-0.66	-0.58	-0.56	-0.44	0.24
	(-2.23)	(-1.45)	(-1.12)	(-1.02)	(-1.54)	(0.76)
CR3	-1.16**	-0.86**	-0.69	-0.64	-0.40	0.36
	(-2.33)	(-1.77)	(-1.57)	(-1.43)	(-1.32)	(1.01)
CR4	-1.56**	-1.50***	-1.01***	-0.82*	-0.75**	0.41
	(-2.45)	(-2.43)	(-2.14)	(-1.88)	(-2.00)	(1.35)
CR5 (lowest rated)	-2.07***	-1.63***	-1.49***	-1.42***	-1.18***	0.59
	(-3.54)	(-2.76)	(-2.55)	(-2.52)	(-2.45)	(1.45)
CR1-CR5	1.18***	1.08***	1.00***	1.02***	0.63**	
	(-2.64)	(-2.59)	(-2.54)	(-2.54)	(-2.03)	

Panel B: Cross- sectional regression of forecast error on CAF and a downgrade dummy

	CAF_{t-1}	Downgrade Dummy $_{t-3:t+3}$	CR_{t-1}	Control $Variables_{t-1}$
1	0.32***			
	(4.68)			
2	0.10	-1.23***		
	(1.41)	(-4.89)		
3	0.04	-0.71***	-0.29***	
	(0.58)	(-3.42)	(-3.15)	
4	0.02	-0.65***	-0.25***	Included
	(0.35)	(-3.10)	(-3.00)	

Table 11
The effect of downgrades on the relation between CAF and future stock returns

For Panel A, I first remove firms three months-around rating downgrades (i.e., from t-3 to t+3). Then, for each month *t*, all stocks rated by S&P are divided into 25 groups based on the following sequential sort: stocks are sorted into five credit rating quintiles and then five CAF quintiles. For each rating/CAF group, I compute the time series average of stock returns. For Panel B, I run monthly cross-sectional regressions of stock return on a constant, the lagged CAF, a downgrade dummy, lagged credit rating, and lagged control variables. The control variables include log(SIZE), log(BM), $RET_{t-6:t}$, ACCRUAL, ES_{RECENT}, EP, and Dispersion. All variables are defined in the appendix. Panel B presents the average slope coefficients for CAF, downgrade dummy, and CR, averaged across all months in the sample, and multiplied by 100. The *t*-statistics, which are presented in parentheses, are the sample *t*-statistics of the estimated coefficients. All returns are in percentages per month. The sample consists of 3,735 companies over the period January 1986 to December 2014. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Returns (% per month) by sequentially sorted rating and CAF groups, excluding three months around downgrades (months t-3: t+3)

	CAF Quintiles					
Credit Rating Quintiles	CAF_1 (lowest)	CAF_2	CAF_3	CAF_4	CAF_5 (highest)	CAF_5-CAF_1
CR1 (highest rated)	0.95***	0.98***	1.05***	1.06***	1.10***	0.16
	(2.64)	(2.76)	(2.99)	(3.00)	(3.10)	(0.55)
CR2	0.93***	1.05***	1.08***	1.17***	1.17***	0.25
	(2.60)	(3.11)	(3.09)	(3.15)	(3.15)	(0.80)
CR3	1.07***	1.15***	1.02***	1.12***	1.15***	0.09
	(3.01)	(3.10)	(2.98)	(3.13)	(3.12)	(0.25)
CR4	0.78***	0.95***	0.96***	1.11***	1.21***	0.43
	(2.31)	(2.65)	(2.71)	(3.11)	(3.27)	(1.03)
CR5 (lowest rated)	0.46*	0.57*	0.73**	0.78**	0.91***	0.45
	(1.66)	(1.78)	(2.24)	(2.34)	(2.57)	(1.53)
All rated firms	0.75**	0.88***	0.98***	0.95***	1.00***	
	(2.42)	(2.62)	(2.85)	(2.64)	(2.98)	

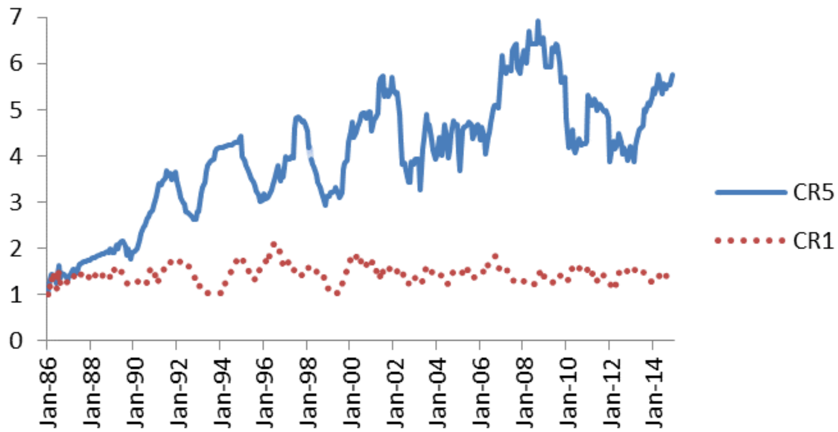
Panel B: Cross-sectional regression of returns on cross-sectional anchoring bias and a downgrade dummy

	CAF_{t-1}	Downgrade Dummy $_{t-3:t+3}$	CR_{t-1}	Control $Variables_{t-1}$
1	0.17***			
	(2.68)			
2	0.04	-1.06***		
	(0.81)	(-3.89)		
3	0.06	-0.75***	-0.14***	
	(1.48)	(-3.42)	(-2.95)	
4	0.04	-0.60***	-0.12***	Included
	(1.08)	(-2.44)	(-2.64)	

Figure 1
Wealth process of the anchoring bias based trading strategy for the highest and lowest credit rating quintiles

In Graph A, I sort all stocks that are rated by S&P into credit rating quintiles each month. I further sort the stocks in each credit rating quintile into cross-sectional anchoring bias quintiles each month. I assume the following trading strategy from January 1986 to December 2014: $1 long in the highest anchoring bias quintile (CAF_5) and $1 short in the lowest anchoring bias quintile (CAF_1). Assuming both the long and short positions are held for one month, I plot the wealth process for the highest rated quintile CR1 and the lowest rated quintile CR5. In Graph B, I repeat the same procedure in Graph A after excluding the return observations during the three months before and three months after a credit rating downgrade for the stocks that are downgraded.

Graph A. Entire sample period



Graph B. Non-downgrade periods

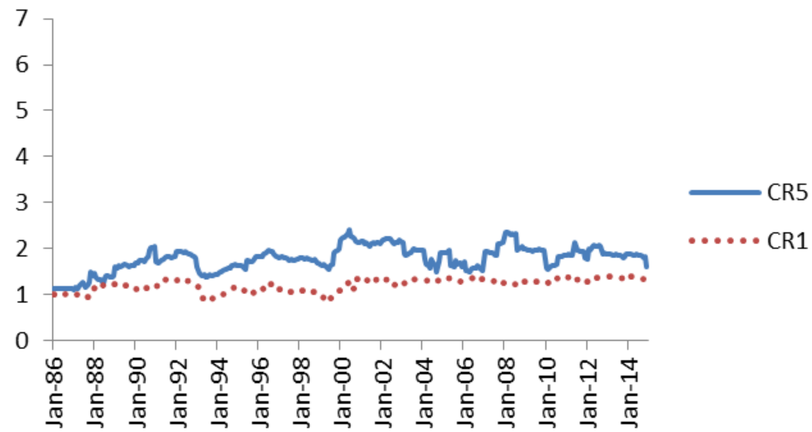
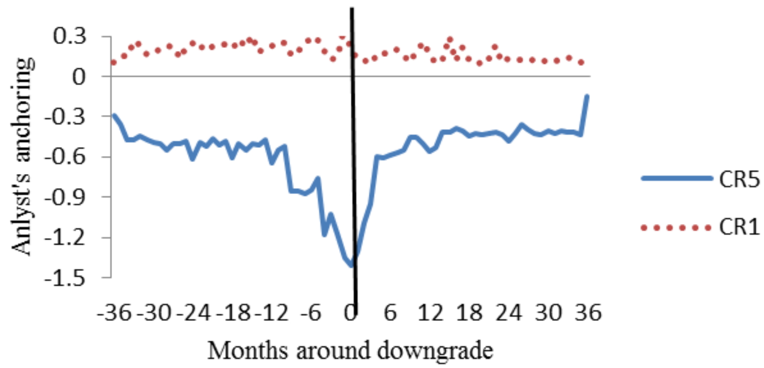


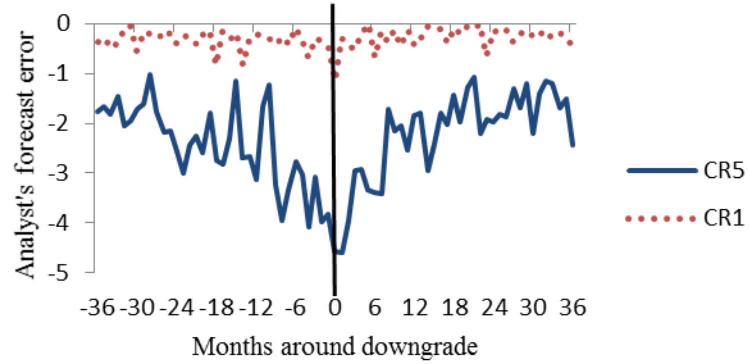
Figure 2
Monthly returns, anchoring, and forecast errors around credit rating downgrades

I divide the stocks with available S&P ratings into credit rating quintiles each month. CR1 represents the best rated quintile and CR5 represents the worst rated quintile. I then compute the equally weighted average anchoring (CAF), forecast error, and stock return for the stocks that have been downgraded in each month for each credit rating quintile. I plot the average monthly portfolio anchoring (CAF), forecast error, and return for CR1 and CR5 from month -36 to month +36 around the credit rating downgrade month (i.e., month 0) in Graphs A, B, and C, respectively. I assume that a downgrade happens in the first month of a quarter, as Compustat reports S&P ratings on a quarterly basis. The sample period is from January 1986 to December 2014.

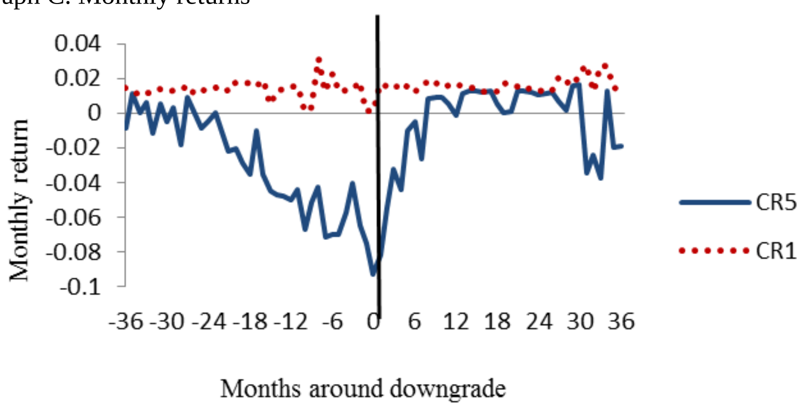
Graph A. Monthly anchoring (CAF)



Graph B. Monthly forecast errors



Graph C. Monthly returns



CHAPTER 3

INVESTOR SENTIMENT AND STYLE INVESTING

ABSTRACT

I examine the implications of investor sentiment for style investing. I hypothesize that when investor sentiment is high, there are more style "switchers" who allocate funds based on a style's relative past performance, leading to a stronger impact of style investing on asset prices. Consistent with my hypothesis, this study has two main findings. First, style returns have predictive power for future stock returns following high levels of sentiment but not low levels of sentiment. By focusing on the high-sentiment periods, style investing significantly affects the predictability of stock returns even during the early period of 1965-1987, and the significance of style investing increases during the later period of 1988-2014. Second, the correlation between past style returns and future stock returns can explain variation in momentum profits following high levels of sentiment but not low levels of sentiment. The profitability from the comovement-momentum based strategy under high sentiment is mainly driven by overpricing of losers socks due to short selling constraints. My results are robust to various sentiment indices, holding periods, different portfolio sorting and different regression specifications. My findings highlight the important role of investor sentiment in pricing financial assets.

Keywords: Investor sentiment; Style investing; Comovement; Momentum; Return predictability; Behavioral finance

Chapter 3

Investor Sentiment and Style Investing

3.1. Introduction

The effect of investor sentiment on asset prices is one of the most contentious issues in financial economics. While numerous studies have provided evidence to the debate (e.g., Lee, Shleifer, and Thaler, 1991; Ritter, 1991; Brown and Cliff, 2005; Baker and Wurgler, 2006, 2007; Lemmon and Portniaguina, 2006; Kaplanski and Levy, 2010; Yu and Yuan, 2011; Baker, Wurgler, and Yuan, 2012; Stambaugh et al., 2012; Yu, 2013; Huang, Jiang, Tu, and Zhou, 2016; Chou, Hsieh, and Shen, 2016), this study seeks to better understand the specific mechanisms through which investor sentiment affects asset prices. For example, Stambaugh et al. (2012) find that investor sentiment plays an important role in 8 out of 11 asset-pricing anomalies. However, they do not discuss the exact mechanism through which investor sentiment affects each anomaly. They expect future research to "develop a richer understanding of how sentiment plays a role in pricing financial assets." I take a step in this direction by showing that sentiment affects the extent to which style investing affects asset prices. A richer understanding of how sentiment drives asset prices away from their fundamental values is important for both market participants and policy makers.

This study provides more insight into the mechanism through which investor sentiment affects the predictability of stock returns. Specifically, I examine the relation between investor sentiment and style investing. An important assumption underlying my study is that investor sentiment drives investors' behaviors. In the style investing model of Barberis and Shleifer (2003), some investors can be irrational as they make investment decisions solely based on past style performance. I expect investor sentiment to affect the aggregate irrational investing behaviors among investors. Consequently, I expect investor sentiment to make a difference to the impact of style investing on asset prices. This study provides strong evidence that the style investing is a behavioral phenomenon that is partially derived from investor sentiment. The results help to answer the open question raised by Wahal and Yavus (2013) in their conclusion whether the rational or stock- specific behavioral biases are responsible for the predictability in stock returns

In the style investing model of Barberis and Shleifer (2003), there are two kinds of investors: “switchers” and “fundamental traders.” Switchers allocate funds based on different investment styles’ relative past performance: the styles that have performed well in the past attract more funds from the styles that have performed poorly; these fund inflows (outflows) positively (negatively) affect stock prices.[13] Due to several reasons discussed in Barberis and Shleifer (2003), fundamental traders are unable to push prices back to fundamental values quickly. An empirical prediction of Barberis and Shleifer’s (2003) model is that a style’s past return can predict the future return of a stock that belongs to the style. To provide empirical evidence for the style investing argument, Wahal and Yavus (2013) estimate Fama-Macbeth regressions of individual stock returns on the past returns of the style to which the stock belongs. They find a significant and positive coefficient on the style’s past return. The evidence that past style return can predict future stock return is consistent with the prediction of Barberis and Shleifer (2003).

I test two hypotheses. The first hypothesis is the stock return predictability hypothesis. I hypothesize that when investor sentiment is high, investors are more likely to suffer from a cognitive bias that leads to extrapolative expectations, which induces the irrational behaviors of switchers who allocate funds based on a style's relative past performance. Therefore, the positive relation between the past style return and future stock return would be stronger following high levels of sentiment. M first hypothesis (sentiment hypothesis) is that the predictive power of past style returns for future stock return is greater following high sentiment. I test my empirical prediction using the stock return regression framework examined in Wahal and Yavuz (2013). I expect the positive coefficient on past style return to be larger following high levels of sentiment.

My second hypothesis is the momentum profit predictability hypothesis. The second hypothesis also has important implications for the drivers of momentum. Specifically, I expect a greater impact of comovement on momentum profits following high levels of sentiment. My second hypothesis based on both the theoretical predictions of Barberis and Shlleifer (2003) and the empirical evidences provided by Wahal and Yavus (2013). There are many rational and behavioral hypotheses for momentum.[14] Style investing generates momentum through the mechanism of comovement of a stock with its style (Barberis and Shleifer, 2003). Empirically, Wahal and Yavuz (2013) use the contemporaneous correlation between a stock's return and its style's return to explain the variation in momentum profits.[15] Specifically, after sorting all stocks into comovement terciles, they find that a momentum portfolio that buys winners and sells losers in the high comovement tercile have higher returns than a momentum portfolio that buys winners and sells losers in the low comovement tercile. Their findings suggest that style investing drives momentum through comovement of a stock with its style, confirming the prediction by Barberis and Shleifer (2003). As modelled in Barberis and Shleifer (2003), switchers' style investing

[13] Intuitively, "if an asset performed well last period, there is a good chance that the outperformance was due to the asset's being a member of a 'hot' style. If so, the style is likely to keep attracting inflows from switchers next period, making it likely that the asset itself also does well next period" (Barberis and Shleifer, 2003).
[14] For example, see Conrad and Kaul (1998), Berk, Green, and Naik (1999), Johnson (2002), and Sagi and Seasholes (2007) for rational explanations and Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), Daniel, Hirshleifer, and Subrahmanyam (2001), and Barberis and Shleifer (2003) for behavioral explanations.

behaviors are irrational. According to my central assumption that investor sentiment drives investors' irrational behaviors, I expect investor sentiment to affect the degree to which style investing contributes to momentum. My second hypothesis states that the comovement of a stock with its style, which is generated by style investing, can explain the variation in momentum profits following high levels of sentiment.

To measure investor sentiment, I use three sentiment indices: the investor sentiment index constructed by Baker and Wurgler (2006, 2007), the University of Michigan's Consumer Sentiment Index, and the Consumer Confidence Index provided by the Organization of Economic Co-operation and Development (OECD). Following the literature, I orthogonalize the last two indices with respect to the same set of macroeconomic variables used by Baker and Wurgler (2006, 2007). I define high (low) sentiment as above (below) the median of the sample period. The results are robust to defining high (low) sentiment as the top (bottom) 30% of the distribution.[16]

Using all the NYSE, AMEX, and NASDAQ listed stocks from 1965 to 2014; I find evidence that is consistent with my two hypotheses. First, consistent with the first hypothesis, I find that the predictive power of past style returns for future stock returns concentrates among the periods following high levels of sentiment. Following low levels of sentiment, past style returns have no predictive power for future stock returns. The results are robust to using NYSE size breakpoints to compute style returns. Further, Wahal and Yavuz (2013) show that past style returns can predict future stock returns during the later period of 1988-2009, but not the early

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[15] For convenience, I use the term "comovement" to refer to the comovement of a stock with its style throughout our study.

[16] Following Antonio et al. (2013), I categorize the portfolio returns formed at the end of month t, as high sentiment or low sentiment using the weighted average of the residual sentiment from the previous three months as follows: 3/6 × residual (t) + 2/6 ×residual (t-1) + 1/6 × residual (t-2). Then a formation period is classified as high (low) sentiment if the 3-month rolling average ending in month t belongs in the top (bottom) 30% of the three month rolling average sentiment time series.

period of 1965-1987. However, after dividing the early period of 1965-1987 into high and low sentiment periods, I find that past style returns are able to predict future stock returns even during this early period, but only following high levels of sentiment.

Second, consistent with the momentum profit predictability hypothesis, I find that the comovement of a stock with its style can explain the variation in momentum profits following high levels of sentiment but not low levels of sentiment. The results are robust to various portfolio and regression methods, equal weighted and value weighted returns, different sentiment indices, and different holding periods. I also find that the winner-minus-loser momentum profits come mainly from shorting losers, consistent with the finding in Stambaugh et al. (2012). Following high sentiment, switchers (noise traders) are more likely to overprice the losers and this overpricing is not fully exploited by the fundamentals (informed traders) in the short run. This is because short sale constraints make it harder to short losers, which delays the price discovery process and thus contributes to the greater profitability of shorting losers than buying winners so that the profitability of the comovement- momentum based trading strategy mainly derived from the short leg (losers).

This study has four contributions. First, the findings not only add to the growing evidence on the impact of investor sentiment on asset prices, but also demonstrate an important channel through which investor sentiment affects asset prices. Stambaugh et al. (2012) find that investor sentiment plays an important role in 11 asset-pricing anomalies. However, they do not discuss the exact mechanism through which investor sentiment affects each anomaly. They expect future research to "develop a richer understanding of how sentiment plays a role in pricing financial assets." I take a step in this direction by showing that sentiment affects the extent to which style investing affects asset prices.

Second, this study provides strong evidence that the style investing is a behavioral phenomenon that is partially derived from investor sentiment. The results help to answer the open question raised by Wahal and Yavus (2013) in their conclusion whether the rational or stock- specific behavioral biases are responsible for the predictability in stock returns. I conclude that the investor sentiment is responsible for the style investing power in predicting asset returns.

Third, this study enhances our understanding of style investing. Style investing has become more important over time. Examples of recent studies that have examined style investing include Barberis and Shleifer (2003), Teo and Woo (2004), Chen and Bondt (2004), Froot and Teo (2008), and Wahal and Yavuz (2013). I identify an important condition under which style investing contributes to the predictability of stock returns. Further, as style investing causes comovement of a stock with its style, the finding that sentiment is related to the style investing-generated comovement also has implications for the growing literature on comovement (e.g., Forbes and Rigobon, 2002; Barberis, Shleifer, and Wurgler, 2005; Greenwood, 2008).

Fourth, the results help us better understand an important driver of momentum. In particular, I provide evidence for the style investing mechanism through which sentiment affects momentum. Two studies are most relevant to my study in this regard. Stambaugh et al. (2012) show that sentiment affects a number of anomalies, including momentum. However, they do not explain the exact mechanism through which sentiment affects each anomaly. Antoniou et al. (2013) take a closer look at how sentiment affects the profitability of momentum strategies. Based on the news diffusion model of Hong and Stein (1999), in which there are “newswatchers” and “momentum traders,” Antoniou et al. (2013) argue that investors’ cognitive dissonance is an important mechanism through which sentiment affects momentum. My study complements these two studies by showing that sentiment can also affect momentum through its impact on style investing.

My study differs from Antoniou et al. (2013) mainly in two ways. First, style investing is the mechanism of interest in my study through which sentiment affects asset prices. I find that the impact of style investing on asset prices is sensitive to investor sentiment. In contrast, style investing is not examined in Antoniou et al. (2013). Second, the style investing model of Barberis and Shleifer (2003) is the theoretical setting in which I examine how sentiment affects momentum profits, while Antoniou et al. (2013) examine how sentiment affects momentum profits according to the news diffusion model of Hong and Stein (1999).

The remainder of the paper is organized as follows. In Section 2, I describe the data sources, sample selection and main variables. In Section 3, I present the empirical results. In Section 4, I conclude.

3.2 Data and Methodology

3.2.1. Data sources

The main data sources are the Center for Research in Securities Prices (CRSP) and COMPUSTAT. I use the linking tables provided by the CRSP/COMPUSTAT Merged Database to merge CRSP with COMPUSTAT. To calculate firm size, I multiply the number of shares outstanding with the stock price at the end of June each year. Following Fama and French (1992), I calculate the book-to-market ratio by dividing the fiscal year-end book value of equity by the market value of equity at the end of December each year.

The unique feature of this study is establishing a link between style investing and sentiment. I use three sentiment indexes in this study: the investor sentiment index constructed by Baker and Wurgler (2006, 2007), which is available at Jeffrey Wurgler's website[17], the University of Michigan's Consumer Sentiment Index, which is available at the FRED (Federal Reserve Economic Data), and the consumer confidence index (CCI) published by the Organization of Economic Co-operation and Development (OECD), which is freely available at the OECD's website.

3.2.2. Sample filtering

My sample consists of all NYSE, AMEX, and NASDAQ listed common stocks in the intersection of the CRSP and COMPUSTAT with shares codes of 10 and 11 for the period from January 1965 to December 2014. I apply the following five sample selection filters. First, the returns of the stock should be available in the current month, future 12 months, and the previous 12 months. Second, the information required to compute the book-to-market ratio as in Fama and French (1992) should be available from CRSP and COMPUSTAT, and stocks with negative book value of stockholder's equity in the previous month are excluded. Third, I exclude stocks below $5 at the time of portfolio formation and those in the lowest size decile (based on NYSE size breakpoints) to ensure that the results are not driven by highly illiquid, small stocks or bid-ask bounce (Jegadeesh and Titman, 1993; Jegadeesh and Titman, 2001; Wahal and Yavus, 2013). After the screening process, my sample has 15,100 unique firms.

3.2.3. Main variables

3.2.3.1. Investor sentiment

To ensure the results are robust, I use three different sentiment indexes that have been used in the literature. The first sentiment index is the monthly market-based sentiment series formed by Baker and Wurgler (2006, 2007; BW hereafter). Baker and Wurgler construct their

[17] http://people.stern.nyu.edu/jwurgler/

composite index by taking the first principal component of six measures of investor sentiment. The principal component analysis filters out idiosyncratic noise in the six measures and captures their common component. The six measures are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium. To purge the effects of valid macroeconomic-related drivers of performance, Baker and Wurgler regress each of the six raw measures on the following six macroeconomic variables: growth in industrial production, real growth in durable consumption, nondurable consumption, services consumption, growth in employment, and the National Bureau of Economic Research (NBER) recession indicator. They use the regression residuals to proxy for sentiment. The BW sentiment index has been widely used in many studies such as Baker and Wurgler (2006, 2007, 2012), Yu and Yuan (2011), Baker, Wurgler, and Yuan (2012), Stambaugh, Yu, and Yuan (2012), Yu (2013), and Antonio et al. (2013).

The second sentiment index I use is the University of Michigan’s sentiment index, which is based on a monthly survey that is mailed to 500 randomly-selected households. The survey asks the participants their views about the economy. This index has been used to proxy for investor sentiment in studies such as Lemmon and Portniaguina (2006), Bergman and Roychowdhury (2008), and Stambaugh et al. (2012).

The third sentiment index I use in this study is the consumer confidence index provided by the OECD. As explained by the OECD, the index is “based on households' plans for major purchases and their economic situation, both currently and their expectations for the immediate future. Opinions compared to a ‘normal’ state are collected and the difference between positive and negative answers provides a qualitative index on economic conditions.” Based on the description, the CCI by the OECD is similar to the Consumer Confidence Index by the

Conference Board (CB), which has also been used in the literature.[18] However, an advantage of the CCI by OECD is that the data are provided for free at OECD's website, while historical data on the CCI by CB have to be purchased.[19]

Following the literature (e.g., Baker and Wurgler, 2006, Mclean and Zhao, 2009; Stambaugh et al., 2012; Antonio et al., 2013), I remove the effect of macroeconomic-related variables by orthogonalizing the last two indexes with respect to the same set of macroeconomic variables used by Baker and Wurgler (2007). Specifically, I regress each of the two indexes on six macroeconomic variables: growth in industrial production, real growth in durable consumption, nondurable consumption, services consumption, growth in employment, and NBER recession indicator. I use the regression residuals to proxy for sentiment. To separate high sentiment periods from low sentiment periods, I follow the methodology in Stambaugh et al. (2012) to define a month as following high (low) sentiment if the level of the sentiment index in the previous month is above (below) the median for the sample period.

Figure 1 shows the time series of the three sentiment indexes from 1965 to 2014 graphically. The horizontal line in each graph represents the median level for the sample period.

[**Insert Figure 1 Here**]

3.2.3.2. Style level past returns

Following Wahal and Yavuz (2003), I use market capitalization and the book-to-market ratio to identify styles as the value/ growth categorization is widely used by retail and institutional investors (e.g. Froot and Teo, 2008; Cooper, Gluten, Rau, 2005; Boyer, 2011; Kumar, 2009; Wahal and Yavus, 2013). At the end of each June, I identify 25 different styles as

[18] I have compared the time series of CCI by the OECD with CCI by the CB as plotted in Figure 1 of Antoniou et al. (2013); they look remarkably similar.
[19] Information about how to purchase historical data on the CCI by CB can be found at https://www.conference-board.org/data/datadetail.cfm?dataid=consumerconf.

the intersection between five size quintiles and five book-to-market quintiles. For the main analysis, I use the full set of securities' size breakpoints to determine size quintiles. As a robustness check, I also use the NYSE size breakpoints, which are obtained from Kenneth French's website. Using the market capitalization of each stock at the beginning of each month as the weight, I calculate monthly value-weighted style returns.

3.2.3.3. Comovement

As Barberis and Shleifer (2003) argue, style investing can generate comovement of a stock with its style. Wahal and Yavus (2013) measure comovement by style beta. I follow their method to measure comovement. Specifically, I calculate style beta (β_{is}) from the following regression of daily stock returns on the daily style returns.

$$R_{i,st} \;=\; a_i + \beta_{is} R_{st} + \varepsilon_{ist}. \tag{1}$$

$R_{i,st}$ is the return on stock *i* on day *t*, where stock *i* belongs to style *s*. R_{st} is the value-weighted return of style *s* on day *t*. The return of the style portfolio, R_{st}, is constructed after removing stock *i* from the portfolio. The regression is estimated using the past three months of daily returns, and requires each stock to have at least 20 return observations. I roll forward the regression, one month each time to generate time series of comovement measures (i.e., estimates of style betas, β_{is}).

3.3. Empirical Results

3.3.1. Sentiment, past style return, and future stock return

In this section, I test whether the predictive power of past style returns for future stock returns is stronger following high levels of sentiment (Hypothesis 1). I find robust evidence for the first hypothesis. To test the hypothesis, I incorporate the sentiment measure into the Fama and MacBeth (1973) regression framework examined in Wahal and Yavuz (2013). Specifically, following the method in Stambaugh et al. (2012), I divide all the months during the sample period into two groups based on the sentiment measure in the previous month. Each month, I estimate Fama and MacBeth regressions of future stock returns on size, book-to-market ratios, past stock returns, and past style returns for the high and low sentiment periods, respectively.

Wahal and Yavuz (2013) show that style returns measured over the prior six or 12 months can predict stocks' three-month, six-month, and 12-month future returns. I estimate the same regressions for periods following high and low levels of sentiment, respectively. I report the regression results for the three sentiment indexes (i.e., the BW index, the Michigan index, and the CCI) in Panels A, B, and C of Table 1, respectively. The results are similar across the three sentiment indexes. Past style returns consistently predict future stock returns following high levels of sentiment as the coefficients on the past style return are highly significant for all the regressions under the heading "high sentiment" in Table 1, A coefficient of 11 (for the 12 month dependent variable regressed against past 6 month style return) means that for every 1 percent difference in style returns over the past 6 months implies a 0.11% change in the future 12-month return. In other words, 0.10 difference in two styles over past six months leads to 1.10% difference in stock returns on average for two stocks in the two styles. In contrast, the corresponding coefficients are not significantly different from zero in most of the regressions under the heading "low sentiment," suggesting that past style returns have little predictive power for future stock returns following low levels of sentiment. The results are consistent with the first hypothesis. For example, in Panel A1, for the six-month future stock return regressed on six-month prior style and stock returns, the coefficient on the past style return under "High Sentiment" is more than twice as large as that under "Low Sentiment". As a robustness check, I also use NYSE size breakpoints to compute style returns. Again, I find evidence that supports the first hypothesis. For brevity, I do not tabulate the results.

[Insert Table 1 Here]

Next, I estimate the same regressions for two sub-periods: 1965-1987 and 1988-2014 and report the results in Table 2. Wahal and Yavuz (2013) report that past style returns can hardly predict future stock returns for the early period of 1965-1987. However, after I divide the period of 1965-1987 into two sub-periods according to the investor sentiment indexes, I find that following high levels of sentiment, past style returns can significantly predict future stock returns even during this early sample period. The results strongly support the hypothesis that the impact of style investing on asset pricing is stronger for high sentiment periods.

[Insert Table 2 Here]

3.3.2. Sentiment, comovement, and momentum

3.3.2.1. Main results

In this section, I examine the ability of investor sentiment in explaining the comovement-momentum relationship. I construct the stock level momentum strategies each month by taking a long position in winners (the top decile portfolio of the best performing stocks) and a short position in losers (the bottom decile portfolio of the worst performing stocks).

To test the second hypothesis, I first construct momentum portfolios using the methodology of Jegadeesh and Titman (1993). In each month, I sort all the stocks into deciles according to their past six-month returns. I compute equal-weighted returns for the decile portfolios. The top decile is called the “winner portfolio” and the bottom decile is called the “loser portfolio.” Next, I independently sort all the stocks into terciles based on their comovement (or style beta).

After independently sorting all stocks into comovement terciles and momentum deciles, Wahal and Yavuz (2013) find that a momentum portfolio that buys winners and sells losers in the highest comovement tercile (C3) have higher returns over the next 3-, 6-, and 12- month horizons than a momentum portfolio that buys winners and sells losers in the lowest comovement tercile (C1). The differences in the winner-minus-loser momentum profits between the highest and lowest comovement terciles are reported as the top two numbers (raw returns and three-factor alphas) in the columns under "C3-C1". They find that the momentum profits, which are measured as both raw returns and three-factor alphas, under "C3-C1" are significantly positive, suggesting that comovement has significant predictive power for momentum profits.

In Table 3, I report the results for the high sentiment periods in the first four columns, the low sentiment periods in the next four columns, and "high sentiment minus low sentiment" in the last four columns. I find that the top two numbers in the columns under "C3-C1," which represent the winner-minus-loser momentum profits (raw returns and three-factor alphas), are significantly positive for the high sentiment periods, but insignificant for the low sentiment periods. The difference in difference test results for high sentiment "C3-C1" minus low sentiment "C3-C1," as shown in the rightmost column of each panel, suggest that the explanatory power of comovement for momentum profits is significantly higher for high sentiment periods than low sentiment periods.

[Insert Table 3 Here]

Table 3 also shows that the winner-minus-loser returns, regardless of raw returns or alphas, come mainly from shorting losers, consistent with the finding in Stambaugh et al. (2012). The asymmetric profits from shorting losers and buying winners are because of short sale constraints, as discussed in Stambaugh et al. (2012). Short sale constraints make it harder to short losers than buying winners, which delays the price discovery process for loser stocks and thus contributes to the greater profitability of shorting losers than buying winners. While Table 3 reports equal weighted returns, I confirm in untabulated results that the main findings are robust to value weighted returns. Consistent with the second hypothesis, I find that the comovement of a stock with its style, which is generated by style investing, can explain the variation in momentum profits following high levels of sentiment, but not low levels of sentiment. The results are robust across the three sentiment indexes.

3.3.2.2. Robustness tests

While Table 3 reports portfolio results, I also report regression results in Table 4 as a robustness check. The average benchmark-adjusted returns for high and low sentiment periods are estimates a_H and a_L in the following regression (Stambaugh et al., 2012).

$$R_{i,t} = a_H \, d_{H,t} + a_L \, d_{L,t} + bMKT_t + sSMB_t + hHML_t + \varepsilon_{i,t}, \tag{2}$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high and low sentiment periods, and $R_{i,t}$ is the excess return in month *t* on either the comovement terciles (C1, C2, and C3) or the difference in the top and bottom comovement terciles (C3-C1). $MKT_t, SMB_t, and\ HML_t$ are returns on the Fama and French three factors in month *t*. Table 4 reports the coefficient estimates a_H under "High Sentiment," a_L under "Low Sentiment," and a_H - a_L under "High Sentiment - Low Sentiment." Consistent with my hypothesis, the winner-minus-loser benchmark-adjusted returns in the first row of the columns under "C3-C1" are significantly positive following high sentiment periods, but not following low sentiment periods. The difference in difference test results, as reported in the rightmost column of each panel in Table 4, suggest that the explanatory power of comovement for momentum profits is consistently higher following high sentiment periods than low sentiment periods.

[Insert Table 4 Here]

To get some perspective about the dynamics of momentum profitability across different comovement terciles, I plot figure 2 which represents the wealth accumulated by taking long (short) positions in winners (losers) stocks starting from January 1965. The highest comovement stocks significantly outperform the lowest comovement stocks. Moreover, it is evident that the payoff differential between C3 and C1 firms is greater around the high sentiment periods such as the dot com bubble. Investing $1 in momentum strategy among the lowest comovement stocks (C1) realizes a payoff of $1.12. The corresponding payoff is much larger at $6.09 when the investment universe compromised of highest comovement stocks (C3). Figure 2 provides visual evidence that the comovement-momentum profitability is much larger under high sentiment periods.

[Insert Figure 2 Here]

In Table 5, I report the results for further robustness checks, following the method in Stambaugh et al. (2012). I estimate the following three regressions.

$$R_{i,t} \;=\; a + s1\, S_{t-1} + u_t, \tag{3}$$

$$R_{i,t} \;=\; a + s2\, S_{t-1} + +bMKT_t + sSMB_t + hHML_t + u_t\,, \tag{4}$$

$$R_{i,t} \;=\; a + s3\, S_{t-1} + +bMKT_t + sSMB_t + hHML_t + \sum_{j=1}^{5} m_j X_{j,t} + u_t\,, \tag{5}$$

where $\mathrm{R}_{i,t}$ is the excess return in month *t* for the winner, loser, or winner-minus-loser portfolios. S_{t-1} is the lagged level of the sentiment index. In Equation (3), excess returns are regressed on just the lagged sentiment index. In Equation (4), excess returns are regressed on the lagged sentiment index as well as the returns on Fama and French three factors. Equation (5) further controls for $X_{j,t}$ (*j*=1-5), which are five additional macrovariables not used by Baker and Wurgler

(2006) when removing macro-related fluctuations in sentiment: the default premium, the term premium, the real interest rate, inflation, and consumption-wealth ratio (cay).

In Table 5, I report estimates of S1, S2, and S3 for the three comovement terciles (C1 through C3) as well as C3 -C1 under “winners,” “losers,” and “winners –losers.” All the three estimates, S1, S2, and S3, for C3-C1 under “winners –losers” in the rightmost column of Table 5 are significantly positive, suggesting that comovement has consistently higher explanatory power for momentum profits following high sentiment periods than low sentiment periods, regardless of whether momentum profits are measured as excess returns or benchmark-adjusted returns, and the results are robust to including macrovariables in addition to those already controlled for by Baker and Wurgler. In summary, I find highly robust evidence for my second hypothesis.

[Insert Table 5 Here]

3.3.3. Sentiment and market states

Next, I further explore whether the predictive power of comovement for momentum profits depends on the prior market return. Cooper et al. (2004) find that momentum profits are significant only after the prior market return is positive. They argue that the finding is consistent with two behavioral theories. First, according to Daniel et al. (1998), market gains contribute to greater overconfidence among investors, which leads to stronger overreaction and greater momentum. Second, increased wealth can reduce risk aversion, which leads to greater delayed overreaction according to the theory in Hong and Stein (1999). However, both behavioral theories predict greater momentum after positive prior market returns than negative prior market returns; they do not necessarily predict zero momentum after negative prior market returns.

Conceptually, investor sentiment and prior market returns can have independent effects on asset prices. Next, I examine whether the findings are sensitive to prior market returns.

Following Cooper et al. (2004), I define UP (DOWN) markets as positive (negative) returns on the CRSP value-weighted index (including dividends) over the prior 12, 24, or 36 months. I skip one month between the end of the formation period and the holding period. The main results are similar across the different horizons over which prior market returns are measured. For brevity, I report only the six-month holding period returns following positive or negative market returns that are measured over the prior 12 months in Table 6.

[Insert Table 6 Here]

Table 6 shows that investor sentiment can explain comovement's predictive power for momentum profits, regardless of whether the prior market is UP or DOWN. However, the winner-minus-loser momentum profits are higher following UP markets than DOWN markets. While the magnitude of the momentum profits varies with prior market returns, the findings confirm that investor sentiment has an independent effect on how the style investing generated comovement can explain momentum profits.

For robustness check , I Follow by estimating estimate the following regression model Cooper et al. (2004), augmented with investor sentiment as follows.

$$Profits = b_0 + b_1 SENT + b_2 MKT + b_3 MKT^2 + u, \tag{6}$$

where *MKT* is the lagged return of the value-weighted market index (including dividends) over the 12-, 24-, and 36-month periods prior to the beginning of the holding period, and MKT^2 is the square term of *MKT*. *SENT* is the 3-month weighted rolling average of the sentiment index ending in month *t*-1, divided by 1,000. The dependent variable *Profits* is the difference in the winner-minus-loser momentum profits between the top and bottom comovement terciles (C3-C1) in month *t*, which reflects the explanatory power of comovement for momentum profits. The *t*-statistics are calculated using Newey-West (1987) standard errors.

Table 7, Panel A reports the regression results for Equation (6). I also report the results for two variations of the regression. In Panel B, I omit MKT^2 from the regression model. In Panel C, I measure sentiment as the residual from the regression of the raw sentiment on the macroeconomic variables and market returns (over the same period as *MKT* is measured). Regardless of which regression model is used, how sentiment is measured, and which horizon is used to measure market returns, the coefficient on investor sentiment is consistently significant and positive, suggesting that sentiment is a robust determinant for the explanatory power of comovement for momentum profits.

[Insert Table 7 Here]

3.3.4. Short sale constraints

Table 3 shows that the winner-minus-loser momentum profit differences between the highest and lowest comovement terciles (under "C3-C1") come mainly from loser stocks. I argue that this is because short sale constraints delay the price discovery process, which contributes to greater momentum profits for loser stocks. To confirm this argument, I conduct further tests using three proxies for short sale constraints: institutional ownership, option listing status, and analyst forecast dispersion. Specifically, I first divide the sample into two groups based on each of the short sale constraints (SSC). High short sale constraints are indicated by low institutional ownership, no options listing, or high analyst forecast dispersion. Then I conduct the same test as in Table 3 within the high and low SSC stocks, respectively. Table 8 reports the results. I find that the main results in Table 3 are more pronounced for the high SSC stocks.

[Insert Table 8 Here]

Figure 3 illustrates the wealth process from investing $1 at the end of the first month of the sample period, growing at the rate of the long (winners), short (losers), or long-short (winners- losers) based on comovement-momentum strategy C3-C1. The strategy involves buying the stocks in the highest comovement tercile and shortening the stocks in the lowest comovement tercile. Panel A represents the winner's profile which is relatively flat over the entre sample period; while panel B depicts the losers profile which is fluctuates over the entire sample period. Specifically, losers underperform more around the high sentiment periods and they are more flat under low sentiment periods. In panel C, I plot the profitability of winners minus losers for the C3-C1 which is peaked under high sentiment especially around financial crises such as dot com bubble and the recent global financial crisis. While table 8 provides an evidence that the profits of the comovement- momentum based strategy is higher for the stocks that have more binding constraints (low institutional ownership, no listed options, high dispersion), figure 3 provides a visual evidence that the switchers overprice losers under high sentiment period because the high sentiment trigger their irrational behaviors and this overpricing of losers is not fully exploited by fundamentals due to short selling constraint. This argument supports Miller (1977) argument that short selling play an important role in restricting the ability of rational traders to exploit overpricing.

[Insert Figure 3 Here]

3.4. Conclusion

Style investing has become increasingly important for both institutional and retail investors. I am the first to report that the impact of style investing on asset prices is conditional on investor sentiment. Past style returns can significantly predict future stock returns only when investor sentiment is high. By examining the impact of style investing on asset prices following both high and low sentiment periods, I find that once I focus on the periods with high levels of sentiment, past style returns can significantly predict future stock returns even during the early period of 1965-1987. The finding is in sharp contrast to the finding in Wahal and Yavuz (2013) that style returns cannot predict future stock returns during the period of 1965-1987. The results highlight the important role of investor sentiment in asset pricing.

Style investing is also found to be a driver of momentum (Barberis and Shleifer, 2003; Wahal and Yavuz, 2013). I find that style investing drives momentum only when investor sentiment is high, but not when investor sentiment is low. The findings are robust to all the three sentiment indexes that have been widely used in the literature, as well as to various portfolio and regression methods. Moreover, I find that investor sentiment has an independent effect on how style investing contributes to momentum profits, regardless of whether the prior market return is positive or negative. By showing that sentiment can affect momentum profits through style investing, this study contributes to the discussion about how sentiment affects the predictability of stock returns. Future research can explore other mechanisms through which sentiment affects momentum and other asset pricing anomalies.

Appendix: Definitions of variables

Variable	Data Source	Explanation
Sentiment Variables		
Baker and Wurgler (2006) Index of sentiment	http://people.stern.nyu.edu/jwurgler/	Baker and Wurgler construct their composite index by taking the first principal component of six measures of investor sentiment: the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium, each with the effect of macroeconomic conditions removed. To remove the effect of macroeconomic-related variables, Baker and Wurgler regress each of the six raw measures on six macroeconomic variables (i.e., growth in industrial production, real growth in durable consumption, nondurable consumption, services consumption, growth in employment, and NBER recession indicator) and use the regression residual as sentiment proxies.
Michigan Index of consumer sentiment	Provided by the University of Michigan sentiment index the St. Louis Federal Reserve	Michigan sentiment index is based on a monthly survey that is mailed to a random set of five hundred households and asks their views about the economy. To remove the effect of macroeconomic-related variables, I regress the index on the six macroeconomic variables used by Baker and Wurgler (i.e., growth in industrial production, real growth in durable consumption, nondurable consumption, services consumption, growth in employment and NBER recession indicator). I use the residuals to proxy for sentiment.
The Consumer Confidence Index	provided by Organization for Economic Co-operation and Development (OECD) https://data.oecd.org/leadind/consumer-confidence-index-cci.htm	The Consumer Confidence Index is based on households' plans for major purchases and their economic situation, both currently and their expectations for the immediate future. Opinions compared to a "normal" state are collected and the difference between positive and negative answers provides a qualitative index on economic conditions. To remove the effect of macroeconomic-related variables, I regress the index on the six macroeconomic variables used by Baker and Wurgler (i.e., growth in industrial production, real growth in durable consumption, nondurable consumption, services consumption, growth in employment and NBER recession indicator). I use the residuals to proxy for sentiment.
High/ Low Sentiment		A high sentiment month is one in which the value of the sentiment proxy in the previous month is above the median value for the sample period and the low sentiment months are those with below-median values.
Style investing variables		
Investment Styles	CRSP/COMPUSTAT	At the end of each June, all the stocks with shares codes 10 and 11 traded on NYSE, AMEX, NASDAQ in the merged CRSP/Compustat database are independently sorted in to 5 size quintiles and 5 book-to-market quintiles. The intersection delivers 5×5=25 size and book-to-market style portfolios.
Prior style returns	CRSP/COMPUSTAT	Monthly value-weighted style returns measured over the prior six months and 12 months, respectively, where the weight is the beginning of the month market capitalization of each security in that month.

Comovement (style beta) Portfolios	CRSP/COMPUSTAT	I estimate the comovement (β_{is}) of each security *i* with respect to its style portfolio *s* (determined by size and book-to-market) by regressing daily stock returns on the daily style returns as in Equation (1): $R_{i,st} = a_i + \beta_{is} R_{st} + \varepsilon_{ist}$. $R_{i,st}$ is the return on stock *i* on day *t*, where stock *i* belongs to style *s*. R_{st} is the value-weighted return of style *s* on day *t*. The return of the style portfolio, R_{st}, is constructed after removing stock *i* from the portfolio. The regression is estimated using the past three months of daily returns, requiring each stock to have at least 20 return observations. I roll forward the regression one month each time to generate time series of comovement measures (i.e., estimates of style betas, β_{is}). Each month, all stocks are sorted into terciles (C1, C2, and C3) based on their β_{is}. The top comovement tercile is C3, and the bottom comovement tercile is C1.
Firm Characteristics Variables		
Book-to-Market ratio	CRSP/COMPUSTAT	The Fama and French (1992) book to market ratio, where the value for July of year Y to year Y+1 is computed using the book value of equity for the fiscal year end in calendar year Y-1 from COMPUSTAT and the market value of equity at the end on December of year Y-1 from CRSP
Size	CRSP	The market capitalization at the time of portfolio formation (updated monthly)
Additional Macroeconomic Variables not used by Baker and Wurgler (2006)		
Default premium	St. Louis Federal Reserve	The default premium is defined as the yield spread between BAA and AAA bonds
Term premium	CRSP	The term premium is defined as the yield spread between 20-years and 1-year treasuries.
Real interest rate	CRSP	The real interest rate is defined as the most recent monthly difference between the 30-day T-bill return and the consumer price index inflation rate.
Inflation rate	St. Louis Federal Reserve	Measured based on the consumer price index (CPI)
Consumption wealth ratio (cay)	Sydney Ludvigson's website , http://www.econ.nyu.edu/user/ludvigsons/.	The consumption wealth variables defined in Lettau and Ludvigson (2001)
Short Selling Constraints Variables		
Institutional ownership	Thomson Reuters	Institutional ownership is measured at the end of formation period and the break points is obtained from NYSE stocks
Options listing status	OptionMetrics	To obtain option listing status, I use the first and last date that the company has data on traded options in the OptionMetrics database
dispersion	IBES	Standard deviation of the fiscal year 1earninggs forecasts divided by the absolute mean value, as reported in the IBES summary file

Table 1

Fama-Macbeth regressions of future stock returns on prior style returns for different sentiment periods

This table reports results from Fama-Macbeth regressions of future stock returns on prior style returns. Regressions include controls for prior stock returns, the log of firm size and the log of book-to-market ratio. The regressions are estimated for high and low sentiment periods separately. I report results based on three sentiment indices: Baker and Wurgler's Sentiment Index (Panels A1 and A2), University of Michigan's Consumer Sentiment Index (Panels B1 and B2), and Consumer Confidence Index by OECD (Panels C1 and C2). The three sentiment indexes are explained in the appendix. I classify the returns each month as following either a high-sentiment month or a low-sentiment month. A high sentiment month is one in which the value of the sentiment proxy in the previous month is above the median value for the sample period and the low sentiment months are those with below-median values. In Panels A1, B1, and C1, future three, six, and 12 month returns are regressed on past six-month returns. In Panels A2, B2, and C2, future three, six, and 12 month returns are regressed on past 12-month returns. I allow one month between the end of the portfolio formation period and the subsequent holding period. The size, book-to-market, and past stock return regressors are winsorized at the 1st and 99th percentile each month. The sample consists of NYSE, AMEX, and NASDAQ stocks between 1965 and 2014. Stocks with missing or negative book values are excluded from the regressions. The style portfolios are defined as the intersection of 5 size quintiles and 5 book-to-market quintiles from all the stocks at the end of June each year. Monthly style returns are value-weighted returns of all the stocks in the style using the beginning of month market capitalization. The intercept is included in the regressions but is not reported. The *t*-statistics are in parentheses (bold indicating 5% significance) and are calculated using Newey-West approach with lags equal to 4 for three-month future returns, 9 for six-month future returns, and 18 for 12-month future returns. R^2 is the average adjusted R^2.

Baker and Wurgler Sentiment Index

Panel A1: Style and stock return regressors measured over prior 6 months

Dependent variable	Three-Month Future Stock Return						Six-Month Future Stock Return						Twelve -Month Future Stock Return					
	Low Sentiment			High Sentiment			Low Sentiment			High Sentiment			Low Sentiment			High Sentiment		
Model	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Style Return		1.31 (1.60)	0.80 (0.44)		3.16 (**2.59**)	2.70 (**2.27**)		4.32 (1.23)	2.99 (0.88)		8.75 (**4.19**)	6.60 (**3.20**)		8.46 (1.52)	7.83 (1.61)		14.16 (**3.83**)	11.45 (**3.16**)
Stock Return	1.32 (1.55)		1.36 (1.60)	2.50 (**3.34**)		2.45 (**3.28**)	3.32 (1.53)		3.38 (1.53)	5.14 (**2.86**)		5.07 (**2.81**)	4.03 (1.60)		4.05 (1.63)	6.65 (**3.27**)		6.47 (**3.22**)
Log Size	-0.58 (**-2.66**)	-0.62 (**-2.73**)	-0.61 (**-2.77**)	-0.16 (-1.09)	-0.16 (-1.10)	-0.23 (-1.62)	-1.11 (**-2.49**)	-1.16 (**-2.59**)	-1.19 (**-2.72**)	-0.31 (-1.01)	-0.28 (0.92)	-0.40 (-1.32)	-1.89 (**-2.24**)	-1.94 (**-2.39**)	-2.00 (**-2.51**)	-0.77 (-1.42)	-0.80 (-1.44)	-0.92 (-1.71)
Log BM	1.05 (**3.24**)	1.12 (**3.27**)	1.18 (**3.48**)	0.88 (**2.77**)	0.85 (**2.76**)	0.76 (**2.49**)	1.85 (**2.31**)	1.94 (**2.27**)	2.07 (**2.47**)	1.90 (**3.01**)	1.90 (**3.15**)	1.72 (**2.86**)	3.39 (**2.30**)	3.49 (**2.26**)	3.01 (**2.45**)	3.91 (**3.76**)	3.92 (**3.82**)	3.60 (**3.69**)
R^2	4.1%	3.3%	4.2%	4.2%	3.5%	4.4%	4.0%	3.3%	4.2%	4.7%	4.0%	4.8%	4.1%	3.5%	4.3%	4.6%	4.2%	4.8%

Panel A2: Style and stock return regressors measured over prior 12 months

Dependent variable	Three-Month Future Stock Return						Six-Month Future Stock Return						Twelve -Month Future Stock Return					
	Low Sentiment			High Sentiment			Low Sentiment			High Sentiment			Low Sentiment			High Sentiment		
Model	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Style Return		0.57 (0.50)	0.36 (0.31)		2.78 (**3.17**)	2.16 (**2.45**)		2.92 (1.52)	2.55 (1.51)		5.98 (**3.65**)	5.65 (**2.77**)		4.87 (1.38)	4.93 (1.59)		8.16 (**2.91**)	7.28 (**2.69**)
Stock Return	0.87 (1.03)		0.87 (1.03)	1.20 (**1.96**)		1.17 (**2.18**)	1.12 (0.83)		1.08 (0.79)	1.63 (1.74)		1.56 (1.63)	0.41 (0.26)		0.36 (0.22)	1.75 (1.82)		1.57 (1.78)
Log Size	-0.63 (**-2.88**)	-0.71 (**-3.06**)	-0.72 (**-3.25**)	-0.15 (-1.02)	-0.17 (-1.19)	-0.23 (-1.67)	-1.12 (**-1.49**)	-1.24 (**-2.75**)	-1.23 (**-2.80**)	-0.27 (-0.88)	-0.31 (-0.98)	-0.39 (-1.24)	-1.87 (**-2.17**)	-2.03 (**-2.41**)	-2.02 (**-2.42**)	-0.73 (-1.32)	-0.87 (-1.50)	-0.95 (-1.69)
Log BM	1.10 (**3.68**)	0.97 (**3.07**)	1.11 (**3.73**)	0.96 (**3.31**)	0.82 (**2.71**)	0.87 (**3.13**)	1.99 (**2.66**)	1.70 (**2.08**)	2.02 (**2.65**)	2.02 (**3.42**)	1.83 (**3.04**)	1.79 (**3.19**)	3.45 (**2.44**)	3.33 (**2.23**)	3.67 (**2.55**)	3.73 (**3.94**)	3.83 (**3.65**)	3.31 (**3.23**)
R^2	3.9%	3.2%	4.0%	4.6%	3.6%	4.7%	3.9%	3.3%	4.1%	4.8%	4.0%	5.0%	3.9%	3.5%	4.0%	4.7%	4.2%	4.8%

The University of Michigan's Consumer Sentiment Index

Panel B1: Style and stock return regressors measured over prior 6 months

Dependent variable	Three-Month Future Stock Return						Six-Month Future Stock Return						Twelve -Month Future Stock Return					
	Low Sentiment			High Sentiment			Low Sentiment			High Sentiment			Low Sentiment			High Sentiment		
Model	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Style Return		-1.20	-1.40		6.34	5.61		2.64	1.63		12.08	9.34		7.62	6.75		17.19	13.88
		(0.88)	(-1.02)		(**4.83**)	(**4.31**)		(1.07)	(0.63)		(**4.38**)	(**3.33**)		(1.59)	(1.63)		(**3.90**)	(**3.09**)
Stock Return	0.70		0.75	3.57		3.48	2.17		2.21	6.99		6.88	0.28		0.28	8.93		8.79
	(0.69)		(0.73)	(**6.81**)		(**6.68**)	(0.89)		(0.90)	(**8.16**)		(**8.13**)	(0.07)		(0.07)	(**6.28**)		(**6.23**)
Log Size	-0.47	-0.49	-0.51	-0.10	-0.10	-0.18	-0.88	-0.89	-0.94	-0.22	-0.20	-0.34	-1.69	-1.77	-1.78	-0.53	-0.53	-0.72
	(**-3.18**)	(**-3.15**)	(**-3.38**)	(-0.53)	(-0.57)	(-0.99)	(**-2.90**)	(**-2.81**)	(**-3.04**)	(-0.57)	(-0.53)	(-0.91)	(**-3.06**)	(**-3.12**)	(**-3.22**)	(-0.76)	(-0.76)	(-1.08)
Log BM	0.63	0.74	0.67	1.22	1.12	1.10	1.49	1.75	1.60	2.27	2.07	2.05	3.40	3.63	3.47	4.11	3.96	3.77
	(**2.14**)	(**2.37**)	(**2.23**)	(**3.36**)	(**3.27**)	(**3.18**)	(**2.38**)	(**2.52**)	(**2.43**)	(**3.01**)	(**2.93**)	(**2.86**)	(**2.80**)	(**2.80**)	(**2.78**)	(**3.11**)	(**3.36**)	(**3.32**)
R^2	3.6%	2.9%	3.8%	4.3%	3.6%	4.4%	3.8%	3.1%	4.0%	4.6%	3.9%	4.7%	3.8%	3.2%	3.9%	4.7%	4.1%	4.8%

Panel B2: Style and stock return regressors measured over prior 12 months

Dependent variable	Three-Month Future Stock Return						Six-Month Future Stock Return						Twelve -Month Future Stock Return					
	Low Sentiment			High Sentiment			Low Sentiment			High Sentiment			Low Sentiment			High Sentiment		
Model	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Style Return		-0.24	-0.63		4.44	3.83		2.51	2.14		7.42	6.00		5.32	5.21		10.03	8.32
		(-0.24)	(-0.59)		(**4.98**)	(**4.31**)		(1.47)	(1.10)		(**3.77**)	(**2.99**)		(1.63)	(1.66)		(**3.11**)	(**2.38**)
Stock Return	0.08		0.08	2.11		2.06	-0.43		-0.49	3.36		3.29	-2.69		-2.81	3.46		3.38
	(0.08)		(0.08)	(**5.36**)		(**5.26**)	(-0.18)		(-0.20)	(**4.55**)		(**4.44**)	(-0.74)		(-0.76)	(**3.13**)		(**3.01**)
Log Size	-0.51	-0.54	-0.58	-0.08	-0.13	-0.17	-0.89	-0.95	-0.97	-0.17	-0.24	-0.31	-1.66	-1.84	-1.79	-0.49	-0.60	-0.76
	(**-3.45**)	(**-3.39**)	(**-4.40**)	(-0.42)	(-0.68)	(-0.90)	(**-2.99**)	(**-2.90**)	(**-3.17**)	(-0.43)	(-0.59)	(-0.79)	(**-3.04**)	(**-3.15**)	(**-3.24**)	(-0.66)	(-0.83)	(-1.06)
Log BM	0.63	0.62	0.58	1.37	1.11	1.29	1.59	1.56	1.52	2.42	2.03	2.18	3.33	3.55	3.36	3.96	3.81	3.48
	(**2.34**)	(**2.06**)	(**2.15**)	(**4.15**)	(**3.30**)	(**4.20**)	(**2.64**)	(**2.35**)	(**2.51**)	(**3.53**)	(**2.82**)	(**3.28**)	(**2.82**)	(**2.81**)	(**2.84**)	(**3.16**)	(**3.11**)	(**2.83**)
R^2	3.9%	3.0%	4.1%	4.3%	3.6%	4.4%	4.0%	3.2%	4.1%	4.4%	3.9%	4.6%	3.7%	3.2%	3.9%	4.5%	4.1%	4.6%

Consumer Confidence Index by OECD

Panel C1: Style and stock return regressors measured over prior 12 months

Dependent variable	Three-Month Future Stock Return						Six-Month Future Stock Return						Twelve -Month Future Stock Return					
	Low Sentiment			High Sentiment			Low Sentiment			High Sentiment			Low Sentiment			High Sentiment		
Model	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Style Return		-0.87 (-0.63)	-1.26 (-0.98)		6.23 (**4.72**)	5.75 (**4.52**)		2.72 (1.07)	1.38 (0.52)		12.03 (**4.34**)	9.61 (**3.40**)		7.90 (1.54)	6.27 (1.52)		16.70 (**3.89**)	14.34 (**3.58**)
Stock Return	0.96 (0.93)		1.00 (0.96)	3.33 (**6.31**)		3.24 (**6.19**)	2.29 (0.92)		2.32 (0.93)	6.88 (**7.72**)		6.78 (**7.72**)	0.29 (0.07)		0.17 (0.04)	8.61 (**5.76**)		8.47 (**5.73**)
Log Size	-0.45 **(-2.95)**	-0.46 **(-2.92**)	-0.49 (**-3.20**)	-0.12 (-0.65)	-0.13 (-0.73)	-0.20 (-1.08)	-0.85 **(-2.79)**	-0.85 (-**2.73**)	-0.90 **(-2.97)**	-0.26 (-0.64)	-0.24 (-0.62)	-0.37 (-0.98)	-2.10 **(-3.48)**	-2.29 (**-3.67**)	-2.32 (**-3.83**)	-0.82 (-1.09)	-1.02 (-1.35)	-1.15 (-1.55)
Log BM	0.70 (**2.36**)	0.81 (**2.52**)	0.75 (**2.51**)	1.17 (**3.27**)	1.06 (**3.15**)	1.05 (**3.09**)	1.59 (**2.51**)	1.84 (**2.63**)	1.68 (**2.55**)	2.18 (**2.90**)	1.99 (**2.82**)	1.97 (**2.76**)	3.50 (**2.85**)	3.60 (**2.71**)	3.33 (**2.75**)	4.21 (**3.34**)	4.04 (**3.37**)	3.86 (**3.35**)
R^2	3.8%	3.1%	3.9%	4.1%	3.5%	4.3%	3.9%	3.2%	4.0%	4.5%	3.9%	4.7%	3.9%	3.2%	4.0%	4.6%	4.1%	4.7%

Panel C2: Style and stock return regressors measured over prior 12 months

Dependent variable	Three-Month Future Stock Return						Six-Month Future Stock Return						Twelve -Month Future Stock Return					
	Low Sentiment			High Sentiment			Low Sentiment			High Sentiment			Low Sentiment			High Sentiment		
Model	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Style Return		-0.10 (-0.14)	-0.61 (-0.58)		4.32 (**5.00**)	3.83 (**4.42**)		2.65 (1.55)	2.15 (1.18)		7.29 (**3.72**)	6.00 (**3.03**)		5.79 (1.51)	4.40 (1.35)		10.01 (**3.16**)	8.62 (**2.47**)
Stock Return	0.26 (0.26)		0.26 (0.26)	1.94 (**5.06**)		1.89 (**4.97**)	-0.43 (-0.18)		-0.45 (-0.19)	3.29 (**4.58**)		3.23 (**4.39**)	-2.43 (-0.64)		-2.52 (-0.66)	3.22 (**2.88**)		3.15 (**2.77**)
Log Size	-0.63 (**-3.15**)	-0.67 **(-3.24)**	-0.72 **(-3.68)**	-0.26 (-1.31)	-0.32 (-1.54)	-0.36 (-1.66)	-1.15 (**-2.62**)	-1.21 (-**2.58**)	-1.27 (**-3.15**)	-0.43 (-1.02)	-0.53 (-1.26)	-0.61 (-1.44)	-1.61 (**-3.12**)	-1.86 (**-3.27**)	-1.88 (**-3.35**)	-0.77 (-1.00)	-0.98 (-1.25)	-1.10 (-1.43)
Log BM	0.66 (**2.40**)	0.72 (**2.35**)	0.64 (**2.40**)	1.26 (**4.49**)	0.88 (**3.51**)	1.12 (**3.39**)	1.52 (**2.54**)	1.69 (**2.40**)	1.52 (**2.56**)	2.39 (**3.70**)	1.68 (**3.15**)	2.03 (**2.81**)	3.38 (**2.83**)	3.58 (**2.74**)	3.19 (**2.79**)	4.16 (**3.18**)	3.87 (**3.14**)	3.53 (**2.89**)
R^2	4.0%	3.1%	4.2%	4.1%	3.5%	4.3%	4.0%	3.2%	4.2%	4.4%	3.9%	4.5%	3.8%	3.2%	3.9%	4.4%	4.1%	4.6%

Table 2

Fama-Macbeth regressions of future stock returns on prior style returns for different sentiment periods in sub-periods

This table reports the average coefficients on prior style returns from Fama-Macbeth regressions of future stock returns. Regressions include controls for prior stock returns, the log of firm size and the log of book-to-market ratio. The average style return coefficients and *t*-statistics are reported for the early subperiod (1965-1987) in Panels A1, B1, and C1, and the later subperiod (1988-2014) in Panels A2, B2, and C2. In each panel, style returns are computed using all stocks as well as NYSE stocks to determine the size quintile breakpoints. Future stock returns are measured over three, six, and 12 months. Prior stock and style returns are measured over six and 12 months. I allow one month between the end of the portfolio formation period and the subsequent holding period. The regressions are estimated for high and low sentiment periods separately. I report results based on three sentiment indices: Baker and Wurgler's Sentiment Index (Panels A1 and A2), University of Michigan's Consumer Sentiment Index (Panels B1 and B2), and Consumer Confidence Index by OECD (Panels C1 and C2). The three sentiment indexes are explained in the appendix. I classify the returns each month as following either a high-sentiment month or a low-sentiment month. A high sentiment month is one in which the value of the sentiment proxy in the previous month is above the median value for the sample period and the low sentiment months are those with below-median values. The size, book-to-market, and past stock return regressors are winsorized at the 1st and 99th percentile each month. The sample consists of NYSE, AMEX, and NASDAQ stocks between 1965 and 2014. Stocks with missing or negative book values are excluded from the regressions. The style portfolios are defined as the intersection of 5 size quintiles and 5 book-to-market quintiles from all the stocks at the end of June each year. Monthly style returns are value-weighted returns of all the stocks in the style using the beginning of month market capitalization. The intercept is included in the regressions but is not reported. The *t*-statistics are in parentheses (bold indicating 5% significance) and are calculated using Newey-West approach with lags equal to 4 for three-month future returns, 9 for six-month future returns, and 18 for 12-month future returns. R^2 is the average adjusted R^2.

	Baker and Wurgler Sentiment Index											
	Low Sentiment						High Sentiment					
Future stock return horizon	Three Months		Six Months		Twelve Months		Three Months		Six Months		Twelve Months	
	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
Panel A1: 1965-1987												
Size breakpoints using all stocks:												
Prior 6-month style and stock returns	-1.16	(-0.49)	1.30	(0.29)	4.67	(0.85)	3.47	(**2.21**)	5.38	(**2.49**)	13.64	(**2.71**)
Prior 12-month style and stock returns	-0.44	(-0.28)	1.76	(0.59)	2.68	(0.55)	2.61	(**2.00**)	4.79	(**2.17**)	12.96	(**3.90**)
Size breakpoints using NYSE stocks:												
Prior 6-month style and stock returns	-0.94	(-0.34)	1.00	(0.19)	3.98	(0.49)	5.26	(**2.93**)	9.40	(**2.84**)	17.70	(**2.84**)
Prior 12-month style and stock returns	-0.83	(-0.42)	1.30	(0.40)	1.44	(0.29)	5.57	(**3.50**)	9.54	(**3.48**)	15.88	(**3.33**)
Panel A2: 1988-2014												
Size breakpoints using all stocks:												
Prior 6-month style and stock returns	3.60	(1.17)	5.52	(1.07)	9.86	(1.48)	3.69	(**2.47**)	7.32	(**2.52**)	10.10	(**2.99**)
Prior 12-month style and stock returns	1.50	(0.77)	4.86	(1.60)	8.85	(1.99)	1.89	(**1.99**)	4.38	(**1.96**)	9.49	(**2.98**)
Size breakpoints using NYSE stocks:												
Prior 6-month style and stock returns	5.63	(0.98)	13.68	(1.17)	17.60	(1.32)	4.99	(**2.43**)	14.35	(**3.58**)	21.46	(**3.32**)
Prior 12-month style and stock returns	4.49	(1.54)	9.63	(1.77)	14.03	(1.56)	4.63	(**2.69**)	10.88	(**3.30**)	15.77	(**4.00**)

Future stock return horizon	The University of Michigan's Consumer Sentiment Index											
	Low Sentiment						High Sentiment					
	Three Months		Six Months		Twelve Months		Three Months		Six Months		Twelve Months	
	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
Panel B1: 1965-1987												
Size breakpoints using all stocks:												
Prior 6-month style and stock returns	-2.08	(-0.95)	-1.07	(-0.27)	3.94	(0.60)	5.38	(**4.51**)	8.59	(**3.66**)	17.68	(**3.54**)
Prior 12-month style and stock returns	-1.33	(-0.90)	-0.26	(-0.10)	1.76	(0.45)	4.16	(**3.88**)	7.49	(**3.40**)	10.95	(**2.45**)
Size breakpoints using NYSE stocks:												
Prior 6-month style and stock returns	1.14	(0.46)	4.97	(0.89)	6.09	(1.26)	4.43	(**2.38**)	7.09	(**2.33**)	11.87	(**2.04**)
Prior 12-month style and stock returns	1.14	(0.68)	4.39	(1.47)	8.47	(1.60)	4.89	(**2.61**)	8.11	(**2.44**)	10.86	(**1.96**)
Panel B2: 1988-2014												
Size breakpoints using all stocks:												
Prior 6-month style and stock returns	-0.87	(-0.49)	3.80	(1.14)	9.01	(1.70)	5.78	(**2.63**)	9.90	(**2.12**)	11.53	(**3.03**)
Prior 12-month style and stock returns	-0.06	(-0.04)	4.06	(1.46)	7.98	(1.62)	3.57	(**2.54**)	6.88	(**2.08**)	9.34	(**2.75**)
Size breakpoints using NYSE stocks:												
Prior 6-month style and stock returns	1.84	(0.67)	4.80	(1.56)	10.24	(1.39)	8.26	(**2.90**)	20.07	(**3.34**)	30.49	(**3.94**)
Prior 12-month style and stock returns	1.48	(0.91)	5.96	(1.73)	7.48	(1.60)	7.57	(**3.33**)	13.65	(**3.06**)	21.01	(**3.65**)

	Consumer Confidence Index by OECD											
	Low Sentiment						High Sentiment					
Future stock return horizon	Three Months		Six Months		Twelve Months		Three Months		Six Months		Twelve Months	
	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
Panel C1: 1965-1987												
Size breakpoints using all stocks:												
Prior 6-month style and stock returns	-2.05	(-0.95)	-1.61	(-0.42)	2.93	(0.46)	5.60	(**4.60**)	9.50	(**4.11**)	19.25	(**3.86**)
Prior 12-month style and stock returns	-1.31	(-0.97)	-0.07	(-0.05)	1.42	(0.37)	3.46	(**2.93**)	7.54	(**3.36**)	11.70	(**2.59**)
Size breakpoints using NYSE stocks:												
Prior 6-month style and stock returns	1.02	(0.43)	4.63	(0.84)	11.52	(1.60)	4.26	(**2.37**)	7.54	(**2.09**)	12.90	(**2.04**)
Prior 12-month style and stock returns	1.10	(0.69)	4.53	(1.48)	8.06	(1.59)	5.06	(**2.61**)	8.08	(**2.32**)	10.55	(**2.76**)
Panel C2: 1988-2014												
Size breakpoints using all stocks:												
Prior 6-month style and stock returns	-0.59	(-0.32)	3.90	(1.12)	9.16	(1.76)	5.41	(**2.59**)	9.69	(**2.14**)	10.86	(**2.23**)
Prior 12-month style and stock returns	-0.07	(-0.05)	4.02	(1.44)	7.86	(1.66)	3.52	(**2.65**)	4.90	(**2.57**)	11.13	(**2.65**)
Size breakpoints using NYSE stocks:												
Prior 6-month style and stock returns	1.67	(0.58)	7.62	(1.41)	8.95	(1.19)	8.30	(**3.02**)	20.24	(**3.50**)	31.31	(**3.64**)
Prior 12-month style and stock returns	1.10	(0.70)	5.76	(1.59)	7.18	(1.54)	7.80	(**3.53**)	13.70	(**3.17**)	21.05	(**3.44**)

Table 3

Monthly returns and three-factor alphas for momentum and comovement based portfolios, conditional on investor sentiment

The table shows monthly returns and Fama and French three-factor alphas for winner minus loser, winner (top decile), and loser (bottom decile) portfolios in each comovement tercile (C1, C2 and C3) as well as the return difference between the top comovement tercile and the bottom comovement tercile (C3-C1), conditional on investor sentiment. Stock returns are measured over three, six, and 12 month holding periods (K) after portfolio formation. The columns of interest are “C3-C1” under “High Sentiment Periods”, “Low Sentiment Periods”, and “High Sentiment – Low Sentiment”. Each month, all NYSE, AMEX, NASDAQ stocks that exist in the intersection of CRSP and Compustat from 1965 to 2014 are ranked independently into ten deciles based on the return in the past six months and into three comovement terciles (C1, C2, and C3) based on their comovement (style beta). The top comovement tercile is C3, and the bottom comovement tercile is C1. The appendix explains how I measure comovement. I exclude stocks in the smallest NYSE size decile and the stocks under $5 at the time of portfolio formation. The stocks with negative BE/ME are exclude from the analysis. I report results based on three sentiment indices: Baker and Wurgler’s Sentiment Index (Panel A), University of Michigan’s Consumer Sentiment Index (Panel B), and Consumer Confidence Index by OECD (Panel C). The three sentiment indexes are explained in the appendix. I classify the returns each month as following either a high-sentiment month or a low-sentiment month. A high sentiment month is one in which the value of the sentiment proxy in the previous month is above the median value for the sample period and the low sentiment months are those with below-median values. The *t*-statistics are in parentheses (bold indicating 5% significance)

	Panel A. Baker and Wurgler's Sentiment Index											
	High Sentiment Periods				Low Sentiment Periods				High Sentiment –Low Sentiment			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Three-month future stock return												
Winner-loser returns	1.05	1.22	1.50	0.45	0.68	0.70	0.80	0.12	0.37	0.52	0.70	0.33
	(5.85)	**(6.72)**	**(6.97)**	**(2.52)**	**(3.37)**	**(3.59)**	**(4.26)**	(0.98)	(1.37)	**(1.95)**	**(2.07)**	**(1.98)**
Winner-loser alphas	1.21	1.34	1.66	0.45	0.99	0.94	1.12	0.13	0.22	0.40	0.54	0.32
	(5.01)	**(5.02)**	**(4.60)**	**(2.64)**	**(3.60)**	**(3.54)**	**(4.13)**	(1.13)	(0.94)	(1.06)	(0.98)	**(2.35)**
Winner returns	1.54	1.62	1.51	-0.03	1.73	1.74	1.78	0.04	-0.20	-0.13	-0.27	-0.07
	(7.00)	**(6.80)**	**(4.78)**	(-0.14)	**(7.01)**	**(6.88)**	**(5.96)**	(0.24)	(-0.59)	(-0.36)	(-0.62)	(-0.27)
Winner alphas	1.01	1.04	0.97	-0.04	0.87	0.84	0.79	-0.08	0.14	0.20	0.18	0.04
	(5.52)	**(5.38)**	**(3.70)**	(-0.15)	**(5.06)**	**(4.44)**	**(2.76)**	(-0.29)	(0.55)	(0.74)	(0.78)	(0.07)
Loser returns	0.48	0.40	0.01	-0.47	1.05	1.05	0.98	-0.07	-0.57	-0.65	-0.98	-0.40
	(2.18)	(1.66)	(0.04)	**(-3.43)**	**(4.03)**	**(3.69)**	**(2.67)**	(-1.01)	(-1.65)	(-1.74)	**(-2.00)**	**(-1.98)**
Loser alphas	-0.20	-0.29	-0.69	-0.49	-0.12	-0.10	-0.43	-0.21	0.08	-0.20	-0.26	-0.34
	(-1.17)	**(-2.13)**	**(-4.25)**	**(-3.09)**	(-0.11)	(-0.51)	**(-1.98)**	(-1.59)	(0.14)	(-0.83)	(-1.75)	**(-2.06)**
Six-month future stock return												
Winner-loser returns	1.01	1.12	1.42	0.41	0.83	0.77	0.87	0.04	0.18	0.35	0.55	0.37
	(8.10)	**(8.64)**	**(9.66)**	**(3.37)**	**(5.69)**	**(5.34)**	**(6.23)**	(0.31)	(0.93)	(1.79)	**(2.70)**	**(1.99)**
Winner-loser alphas	1.08	1.17	1.54	0.46	0.95	1.14	1.08	0.13	0.13	0.03	0.46	0.32
	(5.03)	**(4.67)**	**(5.07)**	**(1.99)**	**(5.01)**	**(5.21)**	**(5.19)**	(1.19)	(1.16)	(0.08)	(0.94)	**(1.95)**
Winner returns	1.41	1.46	1.39	-0.02	1.73	1.64	1.67	-0.06	-0.33	-0.18	-0.28	0.05
	(9.12)	**(8.79)**	**(6.22)**	(-0.09)	**(9.62)**	**(8.88)**	**(7.85)**	(-0.45)	(-1.38)	(-0.72)	(-0.90)	(0.24)
Winner alphas	0.90	0.92	0.90	0.00	0.82	0.85	0.81	-0.01	-0.09	0.07	0.19	0.28
	(4.63)	**(5.06)**	**(3.72)**	(-0.01)	**(5.82)**	**(4.25)**	**(2.67)**	(-1.27)	(-0.12)	(0.26)	(0.86)	(1.56)
Loser returns	0.40	0.35	-0.03	-0.43	0.90	0.87	0.80	-0.10	-0.51	-0.52	-0.83	-0.32
	(2.68)	**(2.12)**	(-0.15)	**(-4.38)**	**(5.07)**	**(4.24)**	**(3.43)**	(-0.95)	**(-2.18)**	**(-2.00)**	**(-2.75)**	**(-2.24)**
Loser alphas	-0.19	-0.25	-0.54	-0.34	-0.13	-0.19	-0.28	-0.14	-0.06	0.06	-0.26	-0.20
	(-1.99)	**(-2.27)**	**(-5.79)**	**(-3.47)**	(-0.85)	**(-2.12)**	**(-3.13)**	(-1.24)	(-0.01)	(0.25)	(-0.33)	**(-1.94)**
12-month future stock return												
Winner-loser returns	0.61	0.73	0.94	0.33	0.73	0.73	0.65	-0.07	-0.12	0.00	0.28	0.40
	(6.04)	**(6.72)**	**(8.19)**	**(3.67)**	**(6.54)**	**(6.33)**	**(6.73)**	(-0.72)	(-0.77)	(-0.02)	(1.89)	**(2.92)**
Winner-loser alphas	0.82	0.94	1.24	0.41	0.95	1.33	1.03	0.08	-0.12	-0.39	0.21	0.33
	(4.34)	**(4.14)**	**(5.07)**	**(2.20)**	**(4.60)**	**(6.80)**	**(6.12)**	(0.20)	(-0.44)	(-1.30)	(0.03)	**(1.93)**
Winner returns	1.12	1.16	1.11	-0.01	1.62	1.67	1.53	-0.09	-0.50	-0.51	-0.42	0.08
	(9.85)	**(9.15)**	**(6.97)**	(-0.12)	**(11.75)**	**(11.40)**	**(10.16)**	(-0.44)	**(-2.78)**	**(-2.64)**	(-1.89)	(0.60)
Winner alphas	0.66	0.76	0.72	0.05	0.83	1.18	0.84	0.01	-0.16	-0.42	-0.12	0.04
	(3.86)	**(4.24)**	**(3.36)**	(0.31)	**(4.57)**	**(6.61)**	**(4.00)**	(0.06)	(-0.66)	(-1.66)	(-0.41)	(0.19)
Loser returns	0.51	0.43	0.18	-0.34	0.89	0.94	0.88	-0.02	-0.38	-0.51	-0.70	-0.32
	(4.69)	**(3.76)**	(1.37)	**(-4.61)**	**(7.79)**	**(7.20)**	**(6.12)**	(-0.26)	**(-2.41)**	**(-2.92)**	**(-3.62)**	**(-3.13)**
Loser alphas	-0.16	-0.18	-0.52	-0.36	-0.12	-0.15	-0.19	-0.07	-0.04	-0.03	-0.33	-0.29
	(-1.99)	**(-2.19)**	**(-4.76)**	**(-3.31)**	(-1.17)	(-1.17)	**(-2.39)**	(-1.62)	(-0.32)	(-0.22)	(-0.86)	**(-1.93)**

	High Sentiment Periods				Low Sentiment Periods				High Sentiment –Low Sentiment			
Panel B. University of Michigan's Sentiment Index												
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Three-month future stock return												
Winner-loser returns	1.24	1.65	**2.01**	0.77	0.56	0.47	0.58	0.02	0.68	1.18	1.43	0.75
	(4.67)	**(6.51)**	**(5.98)**	**(2.85)**	**(2.39)**	(1.85)	**(2.15)**	(0.11)	(1.92)	**(3.28)**	**(3.32)**	**(2.23)**
Winner-loser alphas	1.57	1.88	2.46	0.89	0.87	0.69	0.74	-0.13	0.70	1.20	1.72	1.02
	(4.80)	**(5.62)**	**(4.75)**	**(2.21)**	**(2.61)**	(1.72)	(1.72)	(-0.10)	(1.82)	**(2.29)**	**(2.55)**	**(2.57)**
Winner returns	1.58	1.92	1.84	0.26	1.70	1.76	1.77	0.07	-0.12	0.16	0.07	0.19
	(5.23)	**(6.06)**	**(3.97)**	(0.84)	**(5.39)**	**(5.23)**	**(4.62)**	(0.36)	(-0.27)	(0.34)	(0.12)	(0.52)
Winner alphas	1.02	1.32	1.41	0.39	0.72	0.63	0.44	-0.28	0.30	0.69	0.97	0.67
	(5.01)	**(7.94)**	**(4.42)**	(1.09)	**(2.63)**	**(1.98)**	(1.31)	(-1.13)	(0.89)	(1.92)	**(2.09)**	(1.54)
Loser returns	0.35	0.26	-0.17	-0.51	1.14	1.28	1.19	0.05	-0.80	-1.02	-1.36	-0.56
	(1.10)	(0.79)	(-0.40)	**(-2.54)**	**(3.55)**	**(3.55)**	**(3.03)**	(0.27)	(-1.78)	**(-2.09)**	**(-2.37)**	**(-2.09)**
Loser alphas	-0.55	-0.57	-1.05	-0.50	-0.15	-0.06	-0.30	-0.15	-0.40	-0.51	-0.75	-0.35
	(-2.27)	**(-2.49)**	**(-4.00)**	**(-2.77)**	(-0.31)	(-0.36)	(-1.49)	(-1.11)	(-1.69)	(-1.79)	**(-2.26)**	**(-1.99)**
Six-month future stock return												
Winner-loser returns	1.36	1.61	**2.01**	0.65	0.70	0.62	0.83	0.13	0.66	0.99	1.19	0.53
	(7.87)	**(10.23)**	**(9.97)**	**(3.41)**	**(3.65)**	**(2.73)**	**(3.53)**	(0.94)	**(2.57)**	**(3.57)**	**(3.84)**	**(2.22)**
Winner-loser alphas	1.68	1.76	2.24	0.56	0.87	0.91	0.97	0.10	0.81	0.85	1.27	0.46
	(6.31)	**(6.58)**	**(5.86)**	**(2.56)**	**(2.73)**	**(2.14)**	**(2.94)**	(1.28)	**(1.96)**	(1.70)	**(1.97)**	**(1.96)**
Winner returns	1.72	**1.95**	1.93	0.21	1.61	1.66	1.72	0.10	0.11	0.30	0.21	0.11
	(8.87)	**(9.76)**	**(6.36)**	(0.97)	**(7.07)**	**(6.85)**	**(6.36)**	(0.84)	(0.36)	(0.95)	(0.53)	(0.43)
Winner alphas	1.19	1.34	1.33	0.14	0.64	0.63	0.54	-0.10	0.55	0.71	0.79	0.24
	(5.85)	**(7.77)**	**(4.37)**	(0.43)	**(2.32)**	**(2.08)**	(1.88)	(-0.59)	(1.60)	**(2.04)**	(1.90)	(0.66)
Loser returns	0.36	0.34	-0.08	-0.44	0.92	1.03	0.89	-0.03	-0.55	-0.69	-0.97	-0.41
	(2.07)	(1.72)	(-0.34)	**(-2.94)**	**(4.12)**	**(4.01)**	**(3.18)**	(-0.22)	**(-1.96)**	**(-2.13)**	**(-2.62)**	**(-2.16)**
Loser alphas	-0.49	-0.42	-0.92	-0.43	-0.23	-0.28	-0.43	-0.20	-0.26	-0.14	-0.49	-0.23
	(-3.18)	**(-2.62)**	**(-5.64)**	**(-2.71)**	**(-1.99)**	(-1.73)	**(-3.45)**	(-1.44)	(-1.38)	(-0.62)	(-1.20)	**(-1.92)**
12-month future stock return												
Winner-loser returns	1.01	1.33	1.38	0.37	0.53	0.46	0.56	0.03	0.48	0.87	0.82	0.34
	(6.59)	**(8.60)**	**(9.00)**	**(2.66)**	**(3.47)**	**(2.69)**	**(3.40)**	(0.29)	**(2.23)**	**(3.77)**	**(3.62)**	**(1.97)**
Winner-loser alphas	1.26	1.63	1.77	0.51	0.90	1.05	1.04	0.14	0.36	0.58	0.73	0.37
	(5.09)	**(7.16)**	**(8.20)**	**(2.04)**	**(2.97)**	**(2.76)**	**(3.09)**	(0.88)	(0.92)	(1.30)	(1.83)	**(1.94)**
Winner returns	1.47	1.65	1.50	0.03	1.43	1.46	1.40	-0.03	0.04	0.19	0.10	0.06
	(8.79)	**(9.04)**	**(6.59)**	(0.19)	**(8.81)**	**(8.26)**	**(7.59)**	(-0.33)	(0.16)	(0.75)	(0.33)	(0.33)
Winner alphas	1.09	1.37	1.26	0.17	0.51	0.68	0.49	-0.02	0.59	0.69	0.77	0.19
	(5.34)	**(7.07)**	**(4.82)**	(0.66)	**(1.99)**	**(2.24)**	(1.33)	(-0.76)	(1.80)	(1.90)	**(2.23)**	(0.96)
Loser returns	0.45	0.32	0.11	-0.34	0.90	1.00	0.84	-0.06	-0.45	-0.68	-0.72	-0.28
	(3.68)	**(2.46)**	(0.68)	**(-2.93)**	**(5.41)**	**(5.49)**	**(4.40)**	(-0.75)	**(-2.16)**	**(-3.03)**	**(-2.86)**	**(-1.98)**
Loser alphas	-0.17	-0.26	-0.51	-0.34	-0.39	-0.37	-0.55	-0.16	0.23	0.11	0.04	-0.19
	(-1.43)	**(-2.97)**	**(-3.58)**	**(-2.91)**	**(-3.57)**	**(-2.44)**	**(-4.39)**	(-1.54)	(1.42)	(0.61)	(0.70)	(-1.88)

Panel C. Consumer Confidence Index by OECD

	High Sentiment Periods				Low Sentiment Periods				High Sentiment –Low Sentiment			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Three-month future stock return												
Winner-loser returns	1.25	1.74	**2.07**	0.81	0.37	0.29	0.33	-0.04	0.89	1.45	1.74	0.85
	(4.70)	**(6.82)**	**(6.05)**	**(2.97)**	(1.52)	(1.08)	(1.18)	(-0.18)	**(2.47)**	**(3.93)**	**(3.94)**	**(2.50)**
Winner-loser alphas	1.60	**1.96**	**2.54**	0.94	0.63	0.58	0.57	-0.06	0.97	1.38	**1.97**	1.01
	(4.84)	**(5.87)**	**(4.99)**	**(2.45)**	**(2.13)**	(1.43)	(1.34)	(-0.23)	**(2.17)**	**(2.64)**	**(2.98)**	**(2.12)**
Winner returns	1.66	**2.01**	1.92	0.26	1.62	1.68	1.66	0.04	0.04	0.33	0.26	0.22
	(5.43)	**(6.32)**	**(4.08)**	(0.84)	**(5.13)**	**(4.96)**	**(4.30)**	(0.21)	(0.08)	(0.71)	(0.42)	(0.60)
Winner alphas	1.05	1.36	1.45	0.40	0.66	0.56	0.33	-0.33	0.39	0.80	1.12	0.74
	(5.17)	**(8.31)**	**(4.41)**	(1.11)	**(2.47)**	(1.77)	(0.97)	(-1.30)	(1.15)	**(2.23)**	**(2.37)**	(1.66)
Loser returns	0.40	0.27	-0.15	-0.55	1.26	1.39	1.34	0.08	-0.85	-1.13	-1.48	-0.63
	(1.29)	(0.80)	(-0.35)	**(-2.68)**	**(3.82)**	**(3.71)**	**(3.27)**	(0.43)	(-1.88)	**(-2.25)**	**(-2.53)**	**(-2.29)**
Loser alphas	-0.55	-0.60	-1.09	-0.54	0.03	-0.01	-0.24	-0.27	-0.58	-0.58	-0.85	-0.28
	(-2.26)	**(-2.64)**	**(-4.22)**	**(-2.90)**	(0.16)	(-0.08)	(-1.21)	(-1.19)	(-1.91)	**(-2.03)**	**(-2.61)**	**(-1.92)**
Six-month future stock return												
Winner-loser returns	1.31	1.64	2.04	0.73	0.54	0.51	0.67	0.14	0.77	1.14	1.37	0.60
	(7.53)	**(10.30)**	**(9.92)**	**(3.81)**	**(2.75)**	**(2.15)**	**(2.83)**	(1.02)	**(2.95)**	**(3.99)**	**(4.34)**	**(2.55)**
Winner-loser alphas	1.58	1.75	2.26	0.68	0.80	0.89	0.91	0.12	0.78	0.86	1.35	0.54
	(6.11)	**(6.48)**	**(6.09)**	**(2.02)**	**(2.32)**	(1.87)	**(2.54)**	(1.75)	(1.82)	(1.58)	**(2.40)**	**(1.95)**
Winner returns	1.75	1.99	1.99	0.24	1.48	1.57	1.61	0.13	0.27	0.42	0.38	0.11
	(9.03)	**(9.89)**	**(6.57)**	(1.10)	**(6.51)**	**(6.46)**	**(5.84)**	(1.04)	(0.91)	(1.33)	(0.93)	(0.43)
Winner alphas	1.15	1.29	1.32	0.17	0.61	0.64	0.52	-0.09	0.54	0.65	0.80	0.26
	(5.79)	**(7.35)**	**(4.69)**	(0.60)	**(2.12)**	(1.93)	(1.61)	(-0.28)	(1.54)	(1.72)	(1.86)	(0.76)
Loser returns	0.44	0.35	-0.05	-0.49	0.94	1.07	0.94	-0.01	-0.50	-0.71	-0.99	-0.49
	(2.60)	(1.78)	(-0.20)	**(-3.22)**	**(4.02)**	**(3.87)**	**(3.10)**	(-0.04)	(-1.71)	**(-2.11)**	**(-2.55)**	**(-2.45)**
Loser alphas	-0.43	-0.46	-0.94	-0.51	-0.18	-0.24	-0.39	-0.21	-0.24	-0.22	-0.55	-0.31
	(-2.83)	**(-2.83)**	**(-5.63)**	**(-3.32)**	(-1.37)	(-1.31)	**(-3.21)**	(-1.52)	(-1.20)	(-0.88)	(-1.40)	**(-1.97)**
12-month future stock return												
Winner-loser returns	1.04	1.35	1.41	0.38	0.46	0.40	0.50	0.04	0.58	0.96	0.91	0.33
	(6.71)	**(8.71)**	**(9.10)**	**(2.70)**	**(2.96)**	**(2.29)**	**(3.02)**	(0.40)	**(2.63)**	**(4.09)**	**(3.99)**	**(1.95)**
Winner-loser alphas	1.20	1.54	1.70	0.49	0.87	1.04	1.06	0.19	0.33	0.49	0.64	0.31
	(5.62)	**(7.39)**	**(8.45)**	**(2.10)**	**(2.79)**	**(2.59)**	**(2.96)**	(1.16)	(0.87)	(1.09)	(1.56)	**(1.98)**
Winner returns	1.53	1.67	1.52	0.00	1.30	1.35	1.29	-0.01	0.23	0.32	0.24	0.01
	(9.04)	**(8.95)**	**(6.62)**	(-0.02)	**(8.48)**	**(7.95)**	**(7.23)**	(-0.12)	(1.01)	(1.27)	(0.82)	(0.04)
Winner alphas	1.12	1.27	1.17	0.05	0.49	0.66	0.46	-0.03	0.63	0.61	0.71	0.08
	(6.02)	**(7.16)**	**(4.94)**	(0.20)	**(1.97)**	**(2.16)**	(1.21)	(-0.15)	**(2.01)**	(1.75)	**(2.11)**	(0.21)
Loser returns	0.49	0.32	0.11	-0.38	0.84	0.95	0.78	-0.05	-0.35	-0.63	-0.67	-0.32
	(4.04)	**(2.42)**	(0.66)	**(-3.22)**	**(5.10)**	**(5.20)**	**(4.08)**	(-0.69)	(-1.70)	**(-2.81)**	**(-2.64)**	**(-2.29)**
Loser alphas	-0.08	-0.27	-0.53	-0.45	-0.38	-0.39	-0.60	-0.22	0.30	0.12	0.07	-0.23
	(-0.75)	**(-3.12)**	**(-3.89)**	**(-4.10)**	**(-3.22)**	**(-2.53)**	**(-4.70)**	(-1.59)	(1.84)	(0.68)	(0.34)	**(-1.93)**

Table 4

Monthly benchmark-adjusted returns for momentum and comovement based portfolios, conditional on investor sentiment

The table shows benchmark-adjusted returns for winner minus loser, winner, and loser portfolios in each comovement tercile (C1, C2, and C3) over a six-month post portfolio formation holding period. The average adjusted returns in high and low sentiment periods are estimates of a_H and a_L in the following regression, respectively.

$$R_{i,t} = a_H\, d_{H,t} + a_L\, d_{L,t} + bMKT_t + sSMB_t + hHML_t + \varepsilon_{i,t}, \tag{2}$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high and low sentiment periods, and $R_{i,t}$ is the excess return in month *t* for each comovement tercile (C1, C2, and C3) or the return difference between the top comovement tercile and the bottom comovement tercile (C3-C1). $MKT_t, SMB_t, and\ HML_t$ are returns on the Fama and French three factors in month *t*. The columns of interest are "C3-C1" under "High Sentiment (coefficient of a_H)", "Low Sentiment (coefficient of a_L)", and "High Sentiment – Low Sentiment". Each month, all NYSE, AMEX, NASDAQ stocks that exist in the intersection of CRSP and Compustat from 1965 to 2014 are ranked independently into ten deciles based on the return in the past six months and into three comovement terciles (C1, C2, and C3) based on their comovement (style beta). The top comovement tercile is C3, and the bottom comovement tercile is C1. The appendix explains how I measure comovement. I exclude stocks in the smallest NYSE size decile and the stocks under $5 at the time of portfolio formation. The stocks with negative BE/ME are exclude from the analysis. I report results based on three sentiment indices: Baker and Wurgler's Sentiment Index (Panel A), University of Michigan's Consumer Sentiment Index (Panel B), and Consumer Confidence Index by OECD (Panel C). I classify the returns each month as following either a high-sentiment month or a low-sentiment month. A high sentiment month is one in which the value of the sentiment index in the previous month is above the median value for the sample period and the low sentiment months are those with below-median values. Then I compute all the returns mentioned above separately for the high and low sentiment months. The *t*-statistics are in parentheses (bold indicating 5% significance) and they are based on the heteroscedasticity-consistent standard errors of White (1980).

Panel A. Baker and Wurgler's Sentiment Index												
	High Sentiment (coefficient a_H)				Low Sentiment (coefficient a_L)				High Sentiment – Low Sentiment (a_{H-} a_L)			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser benchmark adjusted return	0.87	1.05	1.24	0.38	1.08	1.16	0.95	-0.12	-0.21	-0.10	0.29	0.50
	(9.00)	**(10.44)**	**(12.68)**	**(4.42)**	**(7.08)**	**(7.26)**	**(6.17)**	(-0.90)	(-1.17)	(-0.55)	(1.56)	**(3.13)**
Winner benchmark adjusted return	0.72	0.89	0.81	0.10	0.77	0.90	0.60	-0.17	-0.05	0.00	0.21	0.27
	(10.23)	**(13.70)**	**(10.76)**	(1.22)	**(6.96)**	**(8.71)**	**(5.01)**	(-1.40)	(-0.42)	(-0.03)	(1.52)	(1.84)
Loser benchmark adjusted return	-0.15	-0.16	-0.43	-0.28	-0.31	-0.26	-0.36	-0.05	0.16	0.10	-0.07	-0.23
	(-2.82)	**(-2.74)**	**(-7.49)**	**(-4.75)**	**(-3.64)**	**(-2.82)**	**(-3.95)**	(-0.56)	(1.57)	(0.92)	(-0.67)	**(-2.06)**

Panel B. University of Michigan's Sentiment Index												
	High Sentiment (coefficient a_H)				Low Sentiment (coefficient a_L)				High Sentiment – Low Sentiment (a_{H-} a_L)			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser benchmark adjusted return	1.33	1.77	2.20	0.87	0.74	0.69	0.94	0.19	0.58	1.07	1.27	0.68
	(7.26)	**(9.63)**	**(10.62)**	**(4.67)**	**(3.99)**	**(3.71)**	**(4.43)**	(1.00)	**(2.23)**	**(4.10)**	**(4.28)**	**(2.56)**
Winner benchmark adjusted return	1.11	1.28	1.21	0.10	0.77	0.73	0.59	-0.18	0.34	0.55	0.62	0.28
	(8.28)	**(11.50)**	**(8.92)**	(0.60)	**(5.63)**	**(6.41)**	**(4.26)**	(-1.08)	(1.78)	**(3.48)**	**(3.21)**	(1.19)
Loser benchmark adjusted return	-0.22	-0.49	-0.99	-0.77	0.02	0.03	-0.35	-0.37	-0.24	-0.52	-0.65	-0.40
	(-1.97)	**(-4.32)**	**(-7.78)**	**(-6.05)**	(0.20)	(0.29)	**(-2.67)**	(-1.75)	(-1.53)	**(-3.23)**	**(-3.54)**	**(-2.20)**

Panel C. Consumer Confidence Index by OECD												
	High Sentiment (coefficient a_H)				Low Sentiment (coefficient a_L)				High Sentiment – Low Sentiment (a_{H-} a_L)			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser benchmark adjusted return	1.36	1.71	2.17	0.81	0.72	0.76	0.97	0.25	0.64	0.95	1.20	0.56
	(7.41)	**(9.28)**	**(10.47)**	**(4.37)**	**(3.85)**	**(4.04)**	**(4.58)**	(1.31)	**(2.44)**	**(3.62)**	**(4.06)**	**(2.12)**
Winner benchmark adjusted return	1.13	1.25	1.20	0.08	0.75	0.75	0.59	-0.16	0.37	0.50	0.61	0.23
	(8.42)	**(11.27)**	**(8.89)**	(0.47)	**(5.52)**	**(6.63)**	**(4.32)**	(-0.94)	**(1.96)**	**(3.16)**	**(3.15)**	(1.00)
Loser benchmark adjusted return	-0.23	-0.45	-0.97	-0.74	0.03	0.00	-0.37	-0.41	-0.26	-0.45	-0.60	-0.33
	(-2.06)	**(-4.00)**	**(-7.59)**	**(-5.78)**	(0.29)	(-0.04)	**(-2.87)**	(-1.82)	(-1.65)	**(-2.78)**	**(-3.27)**	**(-1.95)**

Table 5

Investor sentiment and style investing: predictive regressions of excess returns and benchmark-adjusted returns for momentum and comovement based portfolios

This table reports the results from the predictive regressions of the excess returns on winner, loser, and winner-minus-loser portfolios over a six-month holding period. The table reports estimates of S_1, S_2, and S_3 in the following three regressions.

$$R_{i,t} \ = a + S_1\, S_{t-1} + mkt \ + \varepsilon_{i,t} \tag{3}$$

$$R_{i,t} \ = a + S_2\, S_{t-1} + +bMKT_t + sSMB_t + hHML_t + +\varepsilon_{i,t} \tag{4}$$

$$R_{i,t} \ = a + S_3\, S_{t-1} + +bMKT_t + sSMB_t + hHML_t + \textstyle\sum_{j=1}^{5} m_j\, X_{jt} + u_{i,t} \tag{5}$$

where $R_{i,t}$ is the excess return in month *t* on the winner, loser, or winner-minus-loser portfolios for each of the comovement terciles (C1 through C3) and C3-C1. S_{t-1} is the level of the sentiment index in month *t*-1. $MKT_t, SMB_t, and\ HML_t$ are returns on the Fama and French three factors in month *t*. In Equation (5), X_{jt} (j=1-5) are five additional macroeconomic variables not used by Baker and Wurgler (2006) when removing the macro-related fluctuations in sentiment: the default premium, the term premium, the real interest rate, inflation, and consumption-wealth ratio (CAY). The column of interest is C3-C1. Each month, all NYSE, AMEX, NASDAQ stocks that exist in the intersection of CRSP and Compustat from 1965 to 2014 are ranked independently into ten deciles based on the return in the past six months and into three comovement terciles (C1, C2, and C3) based on their comovement (style beta). The top comovement tercile is C3, and the bottom comovement tercile is C1. The appendix explains how I measure comovement. I exclude stocks in the smallest NYSE size decile and the stocks under $5 at the time of portfolio formation. The stocks with negative BE/ME are exclude from the analysis. I report results based on three sentiment indices: Baker and Wurgler's Sentiment Index (Panel A), University of Michigan's Consumer Sentiment Index (Panel B), and Consumer Confidence Index by OECD (Panel C). The sentiment indices are defined in the appendix. The *t*-statistics are in parentheses (bold indicating 5% significance) and they are based on the heteroscedasticity-consistent standard errors of White (1980).

Panel A. Baker and Wurgler's Sentiment Index

Sample	Winners				Losers				Winners – Losers			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
S1	-0.15	-0.17	-0.18	-0.03	-0.32	-0.37	-0.59	-0.27	0.17	0.20	0.41	0.24
	(-0.99)	(-1.59)	(-1.90)	(-0.15)	(-1.84)	**(-2.11)**	**(-2.65)**	**(-2.01)**	(-1.11)	**(2.26)**	**(3.15)**	**(1.97)**
S2	0.10	0.07	0.02	-0.08	0.01	0.01	-0.25	-0.26	0.09	0.06	0.20	0.17
	(1.92)	(1.70)	(-0.21)	(-0.19)	(0.09)	(0.12)	(-0.75)	**(-1.99)**	(1.23)	(0.98)	(0.35)	**(1.96)**
S3	0.07	-0.03	-0.11	-0.18	-0.02	0.04	-0.22	-0.24	0.09	-0.07	0.02	-0.08
	(0.59)	(-0.24)	(-1.17)	(-1.42)	(-0.16)	(0.34)	(-1.48)	**(-2.10)**	(0.52)	(-0.37)	(0.08)	(-0.35)

Panel B. University of Michigan's Sentiment Index

Sample	Winners				Losers				Winners – Losers			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
S1	-0.06	0.23	0.11	0.17	-0.37	-0.57	-0.69	-0.33	0.31	0.80	0.81	0.49
	(-0.33)	(0.97)	(0.48)	(0.95)	**(-2.35)**	**(-3.16)**	**(-3.33)**	**(-2.48)**	(1.84)	**(3.45)**	**(4.15)**	**(2.91)**
S2	0.18	0.58	0.52	0.34	-0.15	-0.34	-0.39	-0.24	0.33	0.93	0.92	0.58
	(1.53)	**(3.10)**	**(3.67)**	**(2.04)**	(-1.61)	**(-3.02)**	**(-3.80)**	**(-2.18)**	**(2.13)**	**(3.77)**	**(4.58)**	**(3.19)**
S3	0.22	0.64	0.41	0.18	-0.15	-0.14	-0.26	-0.11	0.38	0.78	0.67	0.29
	(1.41)	**(2.49)**	**(2.13)**	(0.86)	(-1.17)	(-0.95)	(-1.86)	(-0.70)	(1.70)	**(2.39)**	**(2.51)**	**(1.97)**

Panel C. Consumer Confidence Index by OECD

Sample	Winners				Losers				Winners – Losers			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
S1	-0.01	0.24	0.16	0.17	-0.31	-0.47	-0.59	-0.28	0.30	0.72	0.75	0.45
	(-0.06)	(1.17)	(0.78)	(1.09)	**(-2.29)**	**(-2.99)**	**(-3.29)**	**(-2.47)**	**(2.02)**	**(3.49)**	**(4.49)**	**(3.05)**
S2	0.18	0.52	0.48	0.30	-0.15	-0.30	-0.37	-0.22	0.32	0.82	0.85	0.53
	(1.67)	**(3.16)**	**(3.94)**	**(2.10)**	(-1.78)	**(-3.02)**	**(-4.13)**	**(-2.31)**	**(2.33)**	**(3.83)**	**(4.97)**	**(3.32)**
S3	0.26	0.64	0.44	0.18	-0.18	-0.12	-0.28	-0.11	0.44	0.77	0.72	0.28
	(1.84)	**(2.71)**	**(2.60)**	(0.92)	(-1.52)	(-1.01)	**(-2.23)**	(-0.77)	**(2.22)**	**(2.62)**	**(3.06)**	**(1.96)**

Table 6

Monthly returns and three-factor alphas for momentum and comovement based portfolios, conditional on different market states and investor sentiment

The table shows monthly returns and Fama and French three-factor alphas for winner, loser, and winner-minus-loser momentum portfolios in each comovement terciles (C1, C2, and C3) as well as C3-C1 over a six-month holding period, conditional on investor sentiment and market state. The column of interest is C3-C1 across different sentiment periods. The state of the market is defined as UP (DOWN) if the return of the value-weighted market index (including dividends) over the 12- month period prior to the beginning of the holding period, as measured by Cooper et al. (2004), is positive (negative). I allow 1 month between the end of the formation period and the holding period. Each month, all NYSE, AMEX, NASDAQ stocks that exist in the intersection of CRSP and Compustat from 1965 to 2014 are ranked independently into ten deciles based on the return in the past six months and into three comovement terciles (C1, C2, and C3) based on their comovement (style beta). The top comovement tercile is C3, and the bottom comovement tercile is C1. The appendix explains how I measure comovement. I exclude stocks in the smallest NYSE size decile and the stocks under $5 at the time of portfolio formation. The stocks with negative BE/ME are exclude from the analysis. I report results based on three sentiment indices: Baker and Wurgler’s Sentiment Index (Panel A), University of Michigan’s Consumer Sentiment Index (Panel B), and Consumer Confidence Index by OECD (Panel C). The sentiment indices are defined in the appendix. The *t*-statistics are in parentheses (bold indicating 5% significance) and they are based on the heteroscedasticity-consistent standard errors of White (1980).

Panel A. Baker and Wurgler’s Sentiment Index

	UP Markets								DOWN Markets							
	Low Sentiment Periods				High Sentiment Periods				Low Sentiment Periods				High Sentiment Periods			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser returns	-0.52	-1.16	-1.03	-0.51	1.20	1.56	1.91	0.71	0.22	0.07	-0.22	-0.44	0.83	0.89	1.28	0.45
	(-1.02)	(-1.77)	(-1.40)	(-0.91)	**(7.24)**	**(10.00)**	**(10.30)**	**(4.29)**	(0.38)	(0.14)	(-0.43)	(-0.84)	**(4.13)**	**(4.58)**	**(5.92)**	**(1.98)**
Winner-loser alphas	-0.47	-1.08	-0.76	-0.28	1.33	1.72	2.14	0.81	0.28	0.40	0.22	-0.07	1.05	1.04	1.46	0.42
	(-1.18)	(-1.61)	(-1.06)	(-0.46)	**(7.56)**	**(10.26)**	**(10.03)**	**(4.49)**	(0.53)	(0.93)	(0.62)	(-0.14)	**(4.42)**	**(4.74)**	**(5.76)**	**(1.97)**
Winner returns	1.60	1.38	0.90	-0.70	1.46	1.66	1.61	0.14	1.95	1.89	2.07	0.11	1.61	1.70	1.68	0.07
	(2.96)	**(2.04)**	(0.99)	(-1.34)	**(6.59)**	**(7.07)**	**(5.22)**	(0.76)	**(2.73)**	**(2.67)**	**(2.60)**	(0.30)	**(6.48)**	**(6.51)**	**(5.38)**	(0.32)
Winner alphas	0.29	-0.19	-1.14	-1.42	1.07	1.30	1.38	0.32	0.70	0.82	0.86	0.16	0.88	0.83	0.63	-0.25
	(0.90)	(-0.78)	**(-3.42)**	**(-4.09)**	**(7.64)**	**(11.64)**	**(9.91)**	(1.82)	**(2.05)**	**(2.30)**	**(2.30)**	(0.43)	**(4.94)**	**(5.51)**	**(3.28)**	(-1.08)
Loser returns	2.12	2.55	1.93	-0.19	0.27	0.10	-0.30	-0.57	1.74	1.81	2.29	0.55	0.78	0.81	0.40	-0.38
	(2.97)	**(2.68)**	(1.62)	(-0.29)	(1.29)	(0.46)	(-1.19)	**(-4.93)**	**(2.11)**	**(2.10)**	(1.80)	(1.11)	**(3.29)**	**(3.14)**	**(1.26)**	**(-2.40)**
Loser alphas	0.76	0.89	-0.38	-1.14	-0.26	-0.42	-0.76	-0.49	0.42	0.41	0.65	0.23	-0.17	-0.21	-0.84	-0.67
	(2.21)	(1.81)	(-0.77)	(-1.82)	**(-2.47)**	**(-3.98)**	**(-6.54)**	**(-4.48)**	(1.23)	(1.26)	(1.73)	(0.59)	(-1.47)	**(-2.00)**	**(-5.78)**	**(-4.55)**

Panel B. University of Michigan’s Sentiment Index

	UP Markets								DOWN Markets							
	Low Sentiment Periods				High Sentiment Periods				Low Sentiment Periods				High Sentiment Periods			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser	0.30	-0.01	0.00	-0.30	1.27	1.75	2.14	0.87	-0.49	-0.99	-1.07	-0.58	0.90	0.95	1.28	0.38
returns	(0.46)	(-0.02)	(0.00)	(-0.41)	**(6.59)**	**(9.63)**	**(9.55)**	**(4.24)**	(-1.05)	(-1.62)	(-1.67)	(-1.28)	**(5.07)**	**(5.66)**	**(7.07)**	**(2.22)**
Winner-loser	-0.27	-0.52	-0.47	-0.21	1.48	2.02	2.54	1.06	-0.29	-0.46	-0.59	-0.29	1.05	1.09	1.41	0.36
alphas	(-0.39)	(-0.78)	(-0.69)	(-0.29)	**(6.56)**	**(9.75)**	**(9.13)**	**(4.62)**	(-0.68)	(-0.87)	(-1.16)	(-0.71)	**(6.08)**	**(6.36)**	**(7.50)**	**(2.00)**
Winners	1.24	0.70	-0.37	-1.61	1.33	1.58	1.50	0.18	2.03	2.09	2.37	0.33	1.71	1.78	1.77	0.06
returns	(1.51)	(0.82)	(-0.34)	**(-2.63)**	**(5.53)**	**(6.37)**	**(4.28)**	(0.76)	**(4.09)**	**(3.51)**	**(3.18)**	(0.87)	**(6.69)**	**(6.43)**	**(5.57)**	(0.35)
Winners alphas	0.82	0.65	-0.10	-0.92	1.08	1.39	1.55	0.47	0.16	0.10	-0.15	-0.32	0.96	0.95	0.81	-0.14
	(2.28)	**(2.06)**	(-0.22)	**(-1.96)**	**(6.66)**	**(11.98)**	**(8.44)**	(1.91)	(0.58)	(0.36)	(-0.42)	(-1.02)	**(6.65)**	**(6.95)**	**(5.82)**	(-0.90)
Losers returns	0.94	0.71	-0.37	-1.31	0.06	-0.17	-0.63	-0.69	2.52	3.08	3.43	0.91	0.81	0.83	0.48	-0.32
	(0.94)	(0.65)	(-0.25)	(-1.52)	(0.26)	(-0.73)	(-2.20)	**(-5.09)**	**(4.08)**	**(3.83)**	**(3.70)**	(1.90)	**(3.37)**	**(3.25)**	(1.67)	**(-2.50)**
Losers alphas	1.08	1.17	0.37	-0.71	-0.39	-0.63	-0.99	-0.60	0.46	0.56	0.43	-0.02	-0.10	-0.14	-0.60	-0.50
	(2.06)	**(1.99)**	(0.61)	(-0.93)	**(-3.02)**	**(-4.63)**	**(-7.00)**	**(-5.23)**	(1.73)	(1.60)	(1.27)	(-0.07)	(-0.95)	(-1.60)	**(-5.47)**	**(-3.94)**

Panel C. Consumer Confidence Index by OECD

	UP Markets								DOWN Markets							
	Low Sentiment Periods				High Sentiment Periods				Low Sentiment Periods				High Sentiment Periods			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser	0.49	-0.22	-0.10	-0.59	1.27	1.69	2.10	0.83	-0.54	-0.84	-0.97	-0.43	0.90	1.01	1.32	0.42
returns	(0.64)	(-0.34)	(-0.13)	(-0.72)	**(6.61)**	**(9.38)**	**(9.41)**	**(4.08)**	(-1.26)	(-1.46)	(-1.63)	(-1.00)	**(5.04)**	**(5.93)**	**(7.23)**	**(2.43)**
Winner-loser	-0.32	-0.81	-0.90	-0.59	1.47	1.94	2.49	1.02	-0.51	-0.38	-0.52	-0.01	1.08	1.19	1.47	0.39
alphas	(-0.43)	(-1.01)	(-1.02)	(-0.70)	**(6.66)**	**(9.49)**	**(9.35)**	**(4.57)**	(-1.30)	(-0.80)	(-1.17)	(-0.02)	**(6.10)**	**(6.79)**	**(7.67)**	**(2.14)**
Winner returns	1.31	0.51	-0.58	-1.89	1.46	1.70	1.67	0.21	1.96	2.11	2.33	0.37	1.56	1.64	1.58	0.02
	(1.51)	(0.56)	(-0.50)	**(-3.05)**	**(6.08)**	**(6.89)**	**(4.79)**	(0.92)	**(4.00)**	**(3.67)**	**(3.26)**	(0.98)	**(6.09)**	**(5.89)**	**(4.92)**	(0.10)
Winner alphas	0.93	0.28	-0.87	-1.79	1.07	1.36	1.53	0.46	0.06	0.15	-0.16	-0.22	0.99	1.01	0.83	-0.16
	(2.28)	(0.84)	(-1.77)	**(-4.13)**	**(6.76)**	**(11.98)**	(8.93)	(1.80)	(0.22)	(0.55)	(-0.48)	(-0.69)	**(6.78)**	**(7.30)**	**(5.86)**	(-0.94)
Loser returns	0.82	0.72	-0.48	-1.30	0.19	0.01	-0.43	-0.62	2.50	2.96	3.30	0.80	0.66	0.63	0.25	-0.41
	(0.71)	(0.58)	(-0.29)	(-1.39)	(0.88)	(0.04)	(-1.49)	**(-4.75)**	**(4.42)**	**(3.90)**	**(3.77)**	(1.76)	**(2.70)**	**(2.40)**	(0.86)	**(-3.08)**
Loser alphas	1.24	1.09	0.04	-1.20	-0.40	-0.59	-0.96	-0.56	0.57	0.53	0.36	-0.21	-0.09	-0.18	-0.63	-0.55
	(2.13)	(1.69)	(0.06)	(-1.54)	**(-3.14)**	**(-4.28)**	**(-6.74)**	**(-5.06)**	**(2.19)**	(1.56)	(1.17)	(-0.63)	(-0.83)	**(-2.01)**	**(-5.82)**	**(-4.28)**

Table 7

Regression of momentum comovement profits on market returns and investor sentiment

Panels A1, B1, and C1 present the regression results based on the model in Table V of Cooper et al. (2004), augmented with investor sentiment as follows.

$$Profits = b_0 + b_1 SENT + b_2 MKT + b_3 MKT^2 + u, \tag{6}$$

where *MKT* is the lagged return of the value-weighted market index (including dividends) over the 12, 24, and 36 month periods prior to the beginning of the holding period, and MKT^2 is the square term of *MKT*. *SENT* is the 3-month weighted rolling average of the sentiment residual ending in month *t*-1, divided by 1,000. The dependent variable *Profits* is the difference in the winner-minus-loser momentum profits between the top and bottom comovement terciles (C3-C1) in month *t*, which reflects the explanatory power of comovement for momentum profits. I also report the results for two variations of the regression. In Panels A2, B2, and C2, I omit MKT^2 from the regression model. In Panels A3, B3, and C3, I measure sentiment as the residual from the regression of the raw sentiment on the macroeconomic variables and market returns (over the same period as *MKT* is measured). The *t*-statistcis, which are in parentheses (bold indicating 5% significance), are calculated using Newey-West (1987) standard errors, where the lag is set as K-1. The results are based on J, K=6.

Baker and Wurgler's Sentiment Index

Panel A1: Cooper et al. regression with sentiment: $Profits = B_0 + B_1 SENT + B_2 MKT + B_3 MKT^2 + u$ (K, J=6)

Sample		12 month market return			24 month market return			36 month market return		
	Parameter	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2
Constant	B_0	0.01	**3.67**	2.35%	0.00	**2.47**	2.72%	0.00	1.62	2.36%
SENT	B_1	0.33	**2.33**		0.34	**2.27**		0.49	**2.69**	
MKT	B_2	0.01	1.79		0.00	-0.48		0.02	2.47	
MKT^2	B_3	-0.09	**-2.60**		-0.02	-1.18		-0.01	-1.26	

Panel A2: Regression with market returns and sentiment: $Profits = B_0 + B_1 SENT + B_2 MKT + u$ (K, J=6)

Sample		12 month market return			24 month market return			36 month market return		
	Parameter	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2
Constant	B_0	0.00	**2.07**	1.22%	0.00	**1.80**	1.34%	0.00	1.82	1.96%
SENT	B_1	0.34	**2.32**		0.36	**2.32**		0.48	**2.65**	
MKT	B_2	0.00	-0.45		-0.01	-0.75		0.00	-0.37	

Panel A3: Cooper et al. regression with sentiment orthogonal to market returns: $Profits = B_0 + B_1 SENT + B_2 MKT + B_3 MKT^2 + u$ (K, J=6)

Sample		12 month market return			24 month market return			36 month market return		
	Parameter	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2
Constant	B_0	0.01	**3.69**	3.10%	0.00	**2.51**	2.25%	0.00	1.74	2.64%
SENT	B_1	0.42	**2.47**		0.47	**2.61**		0.62	**2.99**	
MKT	B_2	-0.01	-0.76		0.00	-0.45		0.02	1.36	
MKT^2	B_3	-0.09	**-2.65**		-0.02	-1.20		-0.01	-1.37	

University of Michigan's Sentiment Index

Panel B1: Cooper et al. regression with sentiment: $Profits = B_0 + B_1 SENT + B_2 MKT + B_3 MKT^2 + u$ (K, J=6)

Sample	12 month market return				24 month market return			36 month market return		
	Parameter	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2
Constant	B_0	0.01	2.55	3.5%	0.01	1.91	4.2%	0.00	0.67	3.0%
SENT	B_1	0.40	**2.90**		0.45	**3.12**		0.40	**2.87**	
MKT	B_2	0.02	0.94		0.02	1.00		0.01	0.48	
MKT^2	B_3	-0.09	**-2.75**		-0.03	**-2.71**		-0.01	-1.43	

Panel B2: Regression with market returns and sentiment: $Profits = B_0 + B_1 SENT + B_2 MKT + u$ (K, J=6)

Sample	12 month market return				24 month market return			36 month market return		
	Parameter	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2
Constant	B_0	0.00	1.38	1.92%	0.00	1.87	2.07%	0.00	0.90	2.58%
SENT	B_1	0.41	**2.41**		0.42	**2.45**		0.39	**2.76**	
MKT	B_2	0.01	0.24		0.01	1.13		0.01	1.54	

Panel B3: Cooper et al. regression with sentiment orthogonal to market returns: $Profits = B_0 + B_1 SENT + B_2 MKT + B_3 MKT^2 + u$ (K, J=6)

Sample	12 month market return				24 month market return			36 month market return		
	Parameter	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2
Constant	B_0	0.01	**2.52**	2.59%	0.01	**2.96**	2.71%	0.00	1.83	1.92%
SENT	B_1	0.25	**2.94**		0.53	**2.81**		0.46	**2.58**	
MKT	B_2	0.00	-0.25		0.00	0.10		0.01	1.75	
MKT^2	B_3	-0.11	-1.69		-0.04	**-2.08**		-0.01	-1.76	

Consumer Confidence Index by OECD

Panel C1: Cooper et al. regression with sentiment: $Profits = B_0+B_1SENT+B_2MKT+B_3MKT^2+u$ (K, J=6)

Sample		12 month market return			24 month market return			36 month market return		
	Parameter	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2
Constant	B_0	0.01	**3.89**	3.85%	0.01	**3.05**	4.15%	0.00	0.82	3.09%
SENT	B_1	0.34	**2.88**		0.40	**3.08**		0.34	**2.76**	
MKT	B_2	0.01	1.69		0.01	0.99		0.01	1.80	
MKT^2	B_3	-0.09	**-2.71**		-0.03	**-2.71**		-0.01	-1.44	

Panel C2: Regression with market returns and sentiment: $Profits = B_0+B_1SENT+B_2MKT+ u$ (K, J=6)

Sample		12 month market return			24 month market return			36 month market return		
	Parameter	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2
Constant	B_0	0.00	**2.80**	1.89%	0.00	1.86	2.09%	0.00	0.90	2.63%
SENT	B_1	0.34	**2.96**		0.35	**2.81**		0.33	**2.64**	
MKT	B_2	-0.01	-0.82		-0.01	-1.31		0.01	1.61	

Panel C3: Cooper et al. regression with sentiment orthogonal to market returns: $Profits = B_0+B_1SENT+B_2MKT+B_3MKT^2+u$ (K, J=6)

Sample		12 month market return			24 month market return			36 month market return		
	Parameter	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2	Estimate	*t*-stat.	Adj. R^2
Constant	B_0	0.01	**3.96**	2.40%	0.01	**2.47**	2.81%	0.00	0.32	2.06%
SENT	B_1	0.50	**2.91**		0.49	**2.82**		0.42	**2.59**	
MKT	B_2	0.00	-0.28		0.02	**2.10**		0.01	1.80	
MKT^2	B_3	-0.11	**-3.14**		-0.04	**-2.11**		-0.01	-1.33	

Table 8
Momentum-comovement profits and short-selling constraints

After the sample is divided into two groups based on proxies of short-selling constraints (i.e., institutional ownership, options listing status, and analyst forecast dispersion), the table shows monthly returns for winner-minus-loser, winner (top decile), and loser (bottom decile) portfolios in each comovement tercile (C1, C2 and C3) as well as the return difference between the top comovement tercile and the bottom comovement tercile (C3-C1), conditional on investor sentiment. Stock returns are measured over a six-month holding period (K=6) after portfolio formation. Each month, all NYSE, AMEX, NASDAQ stocks that exist in the intersection of CRSP and Compustat from 1965 to 2014 are ranked independently into ten deciles based on the return in the past six months and into three comovement terciles (C1, C2, and C3) based on their comovement (style beta). The top comovement tercile is C3, and the bottom comovement tercile is C1. The appendix explains how I measure comovement. I exclude stocks in the smallest NYSE size decile and the stocks under $5 at the time of portfolio formation. The stocks with negative BE/ME are exclude from the analysis. I report results based on three sentiment indices: Baker and Wurgler's Sentiment Index (Panels A1-A3), University of Michigan's Consumer Sentiment Index (Panels B1-B3), and Consumer Confidence Index by OECD (Panels C1-C3). The three sentiment indexes are explained in the appendix. I classify the returns each month as following either a high-sentiment month or a low-sentiment month. A high sentiment month is one in which the value of the sentiment proxy in the previous month is above the median value for the sample period and the low sentiment months are those with below-median values. The *t*-statistics are in parentheses (bold indicating 5% significance)

Baker and Wurgler's Sentiment Index (J, K=6)																
Panel A1: By Institutional Ownership																
	Low Institutional Ownership								High Institutional Ownership							
Sample	Low Sentiment				High Sentiment				Low Sentiment				High Sentiment			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser returns	0.25	0.88	0.84	0.60	-1.01	-0.37	0.18	1.18	-0.36	-0.34	-0.37	0.00	0.35	0.47	0.65	0.31
	(0.84)	**(3.47)**	**(3.56)**	(1.60)	(-2.40)	(-0.56)	(0.49)	**(3.19)**	(-1.07)	(-0.97)	(-1.12)	(-0.02)	**(1.99)**	**(2.85)**	**(4.25)**	**(2.11)**
Winner returns	1.68	1.62	1.20	-0.47	2.77	2.82	2.80	0.03	1.92	2.01	2.18	0.27	1.12	0.97	1.02	-0.08
	(6.15)	**(5.29)**	**(3.43)**	(-1.62)	**(7.91)**	**(8.03)**	**(6.65)**	(0.12)	**(12.63)**	**(13.61)**	**(10.69)**	(1.68)	**(7.59)**	**(6.33)**	**(5.37)**	(-0.70)
Loser returns	1.43	0.73	0.35	-1.07	3.78	3.19	2.63	-1.15	2.28	2.34	2.55	0.27	0.77	0.51	0.37	-0.40
	(3.74)	**(1.99)**	(0.98)	**(-3.92)**	**(6.77)**	**(4.28)**	**(5.18)**	**(-3.39)**	**(6.37)**	**(6.40)**	**(6.88)**	(1.72)	**(4.16)**	**(2.99)**	**(2.26)**	(-1.77)
Panel A2: By Options Listing Status																
	No Listed Options								With Listed Options							
Sample	Low Sentiment				High Sentiment				Low Sentiment				High Sentiment			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser returns	0.08	1.10	0.78	0.70	-0.24	0.42	0.69	0.93	0.58	0.48	0.83	0.25	-2.21	-1.37	-1.15	1.06
	(0.30)	**(5.08)**	**(3.53)**	(1.69)	(-0.93)	(1.85)	**(2.40)**	**(4.15)**	(1.24)	(1.27)	(1.79)	(0.58)	(-2.29)	(-1.52)	(-1.33)	(1.74)
Winner returns	1.33	1.52	1.20	-0.13	2.30	2.43	2.59	0.29	0.74	0.47	0.42	-0.32	1.48	2.40	2.15	0.67
	(5.04)	**(5.34)**	**(3.50)**	(-0.69)	(9.04)	**(8.99)**	**(8.25)**	(1.64)	(1.88)	(1.04)	(0.72)	(-0.76)	**(3.50)**	**(5.15)**	**(3.35)**	(1.38)
Loser returns	1.26	0.42	0.43	-0.83	2.54	2.01	1.90	-0.64	0.17	-0.02	-0.41	-0.58	3.69	3.77	3.30	-0.38
	(3.56)	(1.26)	(1.18)	**(-2.07)**	**(6.94)**	**(5.87)**	**(4.51)**	**(-3.31)**	(0.30)	(-0.03)	(-0.64)	(-1.81)	**(3.55)**	**(3.77)**	**(3.42)**	(-0.72)
Panel A3: By Analyst Forecast Dispersion																
	High Forecast Dispersion								Low Forecast Dispersion							
Sample	Low Sentiment				High Sentiment				Low Sentiment				High Sentiment			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser returns	0.18	0.52	0.91	0.66	-0.19	0.59	0.92	1.20	0.70	0.86	1.10	0.18	1.08	1.38	1.83	0.80
	(0.44)	(1.19)	(2.39)	(1.50)	(-0.38)	(1.27)	(1.94)	**(2.14)**	(1.53)	**(2.26)**	**(3.33)**	(0.37)	**(3.22)**	**(4.39)**	**(6.17)**	**(1.96)**
Winner returns	2.06	2.47	2.63	0.49	1.69	2.43	2.48	0.26	1.45	1.23	1.39	-0.10	1.11	1.54	1.27	0.12
	(6.05)	**(7.63)**	**(6.77)**	(1.52)	**(5.88)**	**(7.37)**	**(7.15)**	(0.58)	**(5.06)**	**(4.15)**	**(4.03)**	(-0.40)	**(3.68)**	**(4.10)**	**(3.13)**	(0.41)
Loser returns	1.88	1.97	1.85	-0.07	1.77	1.88	1.58	-0.86	0.85	0.26	-0.21	-0.16	0.09	0.16	-0.61	-0.68
	(4.56)	**(4.13)**	**(3.95)**	(-0.27)	(3.81)	(4.26)	(3.04)	**(-2.58)**	(1.73)	(0.66)	(-0.76)	(-0.31)	(0.24)	(0.44)	(-0.26)	(-1.93)

University of Michigan's Sentiment Index (J, K=6)

Panel B1: By Institutional Ownership

Sample	Low Institutional Ownership								High Institutional Ownership							
	Low Sentiment				High Sentiment				Low Sentiment				High Sentiment			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser returns	-0.82	-0.69	-0.33	0.49	0.19	1.28	1.35	1.17	-0.60	-0.51	-0.53	0.07	0.61	0.69	0.88	0.27
	(-2.09)	(-1.15)	(-0.89)	(1.28)	(0.61)	(5.01)	(6.89)	(**3.49**)	(-1.86)	(-1.61)	(-1.76)	(0.38)	(3.93)	(4.10)	(5.81)	(1.87)
Winner returns	2.75	2.49	2.41	-0.34	1.61	1.81	1.41	-0.18	1.60	1.41	1.68	0.08	1.33	1.41	1.37	0.03
	(8.79)	(7.40)	(6.25)	(-1.37)	(5.37)	(5.65)	(3.72)	(-0.70)	(8.95)	(8.27)	(7.89)	(0.68)	(10.35)	(9.69)	(7.15)	(0.24)
Loser returns	3.57	3.18	2.74	-0.83	1.41	0.53	0.06	-1.35	2.18	1.92	2.21	0.02	0.72	0.72	0.49	-0.23
	(6.82)	(4.67)	(5.88)	(**-2.48**)	(3.55)	(1.38)	(0.16)	(**-4.99**)	(6.12)	(5.52)	(6.19)	(0.13)	(4.81)	(4.26)	(3.16)	(**-2.06**)

Panel B2: By Options Listing Status

Sample	No Listed Options								With Listed Options							
	Low Sentiment				High Sentiment				Low Sentiment				High Sentiment			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser returns	-0.66	-0.25	-0.41	0.25	0.11	1.49	1.30	1.19	-3.03	-2.51	-2.58	0.45	1.07	1.30	1.84	0.77
	(-1.80)	(-0.72)	(-0.84)	(0.70)	(0.32)	(**5.27**)	(**5.02**)	(**3.86**)	(**-2.68**)	(**-2.28**)	(**-2.72**)	(1.46)	(1.74)	(**2.25**)	(**2.84**)	(**1.98**)
Winner returns	2.18	2.23	2.20	0.01	1.75	2.21	1.94	0.19	0.53	1.30	0.73	0.20	1.53	1.63	1.83	0.30
	(**5.72**)	(**5.67**)	(**5.07**)	(0.05)	(**5.11**)	(**5.97**)	(**4.31**)	(0.75)	(0.92)	(**1.98**)	(1.08)	(0.58)	(**3.38**)	(**2.85**)	(**2.36**)	(0.75)
Loser returns	2.85	2.48	2.60	-0.24	1.64	0.72	0.63	-1.00	3.56	3.81	3.31	-0.25	0.46	0.33	-0.01	-0.47
	(**5.43**)	(**4.91**)	(**4.14**)	(-0.73)	(**3.59**)	(1.65)	(1.35)	(**-4.00**)	(**2.95**)	(**2.87**)	(**2.81**)	(-1.01)	(0.63)	(0.45)	(-0.01)	(-1.72)

Panel B3: By Analyst Forecast Dispersion

Sample	High Forecast Dispersion								Low Forecast Dispersion							
	Low Sentiment				High Sentiment				Low Sentiment				High Sentiment			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser returns	-0.55	-0.44	-0.35	0.20	1.03	1.80	1.83	0.87	-0.40	-0.48	-0.49	-0.24	1.33	1.51	1.63	0.30
	(-1.22)	(-0.70)	(0.24)	(1.60)	(**3.94**)	(**6.30**)	(6.06)	(**2.53**)	(-0.79)	(-0.85)	(-0.84)	(-0.46)	(**3.28**)	(**3.92**)	(**4.00**)	(**1.95**)
Winner returns	1.98	2.14	2.01	0.03	1.66	2.09	1.98	0.35	1.73	1.97	1.75	0.03	2.07	1.76	2.10	0.03
	(**5.14**)	(**6.48**)	(**6.17**)	(0.30)	(**6.57**)	(**7.32**)	(**5.51**)	(1.15)	(**5.58**)	(**5.50**)	(**5.69**)	(0.15)	(**7.71**)	(**6.97**)	(**7.30**)	(0.09)
Loser returns	2.53	2.58	2.36	-0.17	0.64	0.29	0.15	-0.49	1.98	2.40	2.24	0.32	0.74	0.24	0.47	-0.27
	(**3.61**)	(**4.08**)	(**3.82**)	(-0.45)	(**2.19**)	(**1.03**)	(0.47)	(**-2.08**)	(**3.96**)	(**4.24**)	(**3.67**)	(0.69)	(**2.09**)	(0.70)	(0.51)	(-1.69)

Consumer Confidence Index by OECD (J, K=6)

Panel C1: By Institutional Ownership

Sample	Low Institutional Ownership								High Institutional Ownership							
	Low Sentiment				High Sentiment				Low Sentiment				High Sentiment			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser returns	-0.81	-0.67	-0.24	0.56	0.17	1.23	1.26	1.10	-0.66	-0.63	-0.52	0.13	0.65	0.78	0.86	0.21
	(-2.06)	(-1.09)	(-0.66)	(1.46)	(0.54)	**(4.85)**	**(6.41)**	**(3.29)**	**(-2.00)**	**(-1.91)**	(-1.72)	(0.68)	**(4.32)**	**(5.25)**	**(5.73)**	(1.64)
Winner returns	2.62	2.51	2.41	-0.21	1.73	1.80	1.42	-0.30	1.60	1.42	1.70	0.14	1.34	1.40	1.35	0.01
	(8.20)	**(7.29)**	**(6.14)**	(-0.86)	**(5.85)**	**(5.74)**	**(3.80)**	(-1.21)	**(8.90)**	**(8.28)**	**(7.86)**	(1.07)	**(10.36)**	**(9.67)**	**(7.19)**	(0.08)
Loser returns	3.43	3.17	2.65	-0.77	1.55	0.56	0.16	-1.40	2.23	2.05	2.22	-0.01	0.69	0.62	0.49	-0.20
	(6.50)	**(4.59)**	**(5.58)**	**(-2.26)**	**(3.90)**	(1.49)	(0.43)	**(-5.29)**	**(6.20)**	**(5.73)**	**(6.19)**	(-0.08)	**(4.69)**	**(4.04)**	**(3.17)**	(-1.94)

Panel C2: By Options Listing Status

Sample	No Listed Options								With Listed Options							
	Low Sentiment				High Sentiment				Low Sentiment				High Sentiment			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser returns	-0.66	-0.25	-0.41	0.25	0.11	1.49	1.30	1.19	-3.35	-2.39	-2.84	0.51	1.08	1.41	2.05	0.98
	(-1.80)	(-0.72)	(-0.84)	(0.70)	(0.32)	**(5.27)**	**(5.02)**	**(3.86)**	**(-2.74)**	**(-2.20)**	**(-2.71)**	(1.24)	(1.76)	**(2.47)**	**(2.89)**	(1.92)
Winner returns	2.18	2.23	2.20	0.01	1.75	2.21	1.94	0.19	0.27	1.08	0.49	0.22	1.39	1.55	1.87	0.48
	(5.72)	**(5.67)**	**(5.07)**	(0.05)	**(5.11)**	**(5.97)**	**(4.31)**	(0.75)	(0.68)	(1.66)	(0.73)	(0.30)	**(3.06)**	**(2.74)**	**(2.18)**	(0.72)
Loser returns	2.85	2.48	2.60	-0.24	1.64	0.72	0.63	-1.00	3.62	3.47	3.33	-0.29	0.31	0.14	-0.18	-0.50
	(5.43)	**(4.91)**	**(4.14)**	(-0.73)	**(3.59)**	(1.65)	(1.35)	**(-4.00)**	**(2.74)**	**(2.63)**	**(2.59)**	(-0.97)	(0.43)	(0.20)	(-0.21)	(-1.82)

Panel C3: By Analyst Forecast Dispersion

Sample	High Forecast Dispersion								Low Forecast Dispersion							
	Low Sentiment				High Sentiment				Low Sentiment				High Sentiment			
	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1	C1	C2	C3	C3-C1
Winner-loser returns	-0.47	-0.84	-0.67	-0.38	1.20	1.52	2.17	0.95	-0.73	-0.47	0.01	0.57	1.17	1.87	1.86	0.76
	(-093)	(-1.53)	(-1.13)	(-0.71)	**(3.60)**	**(4.00)**	**(6.83)**	**(3.12)**	(-1.17)	(-0.74)	(0.01)	(1.35)	**(4.52)**	**(6.62)**	**(6.22)**	**(2.29)**
Winner returns	1.57	1.62	1.61	0.02	1.95	1.77	2.24	0.31	1.46	2.01	1.78	0.23	1.69	2.05	2.01	0.33
	(5.20)	**(5.35)**	**(5.29)**	(0.10)	**(7.27)**	**(7.08)**	**(7.30)**	(1.14)	**(4.81)**	**(6.11)**	**(5.68)**	(0.98)	**(6.78)**	**(7.12)**	**(5.55)**	(1.10)
Loser returns	1.96	2.37	2.28	0.33	0.72	0.24	0.11	-0.58	2.19	2.48	2.04	-0.15	0.54	0.18	0.14	-0.40
	(3.92)	**(4.14)**	**(3.68)**	(0.69)	**(2.07)**	(0.70)	(0.35)	**(-1.96)**	**(3.38)**	**(3.89)**	**(3.59)**	(-0.41)	(1.85)	(0.67)	(0.45)	(-1.72)

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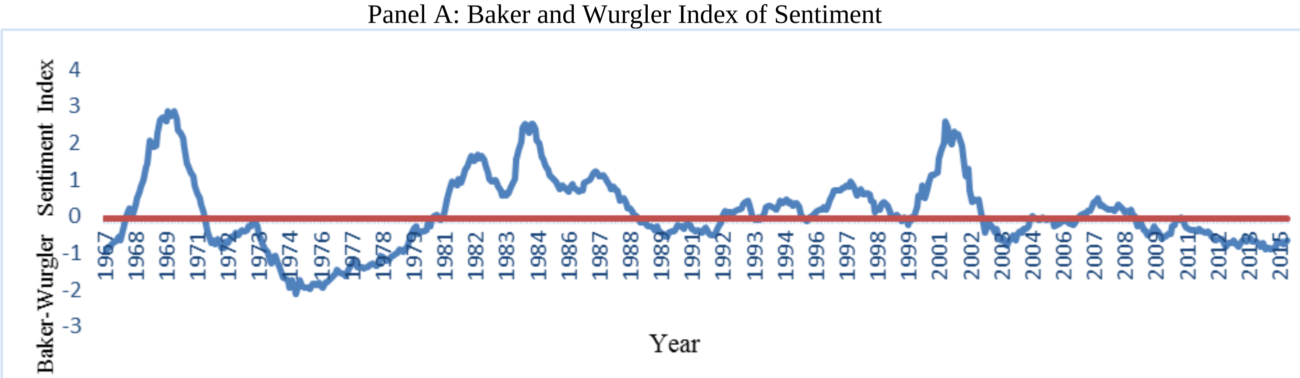
Figure 1

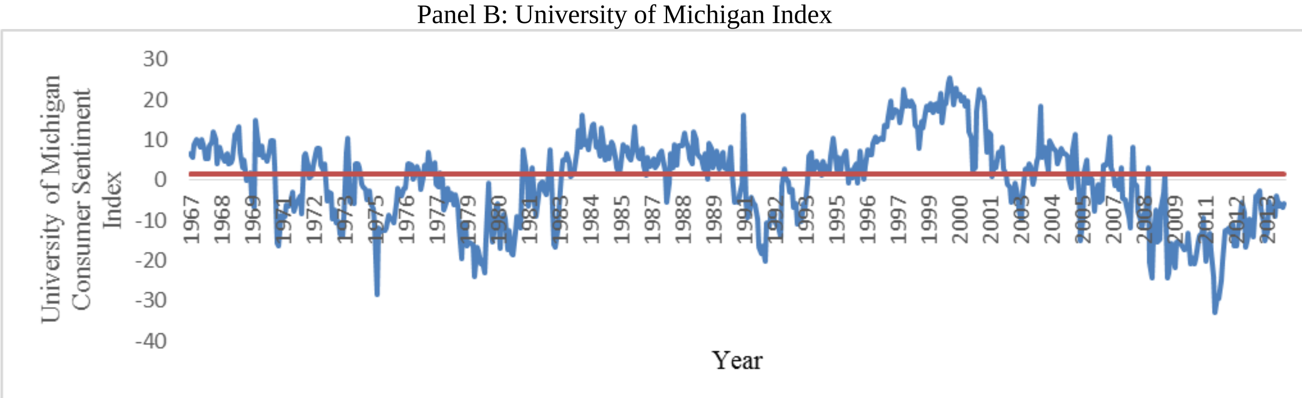
Three investor sentiment indexes from 1965 to 2014

Figure 1 shows three investor sentiment indexes from 1965 to 2014: the Baker and Wurgler Index of Sentiment in Panel A, the University of Michigan Consumer Sentiment index in Panel B, and the Consumer Confidence Index by OECD in Panel C. The three sentiment indexes are explained in the appendix. In each panel, the horizontal line represents the median value of the sample period. A high sentiment month is one in which the value of the sentiment is above the median value for the sample period and the low sentiment months are those with below-median values.

Panel A: Baker and Wurgler Index of Sentiment



Panel B: University of Michigan Index



Panel C: Consumer Confidence Index by OECD

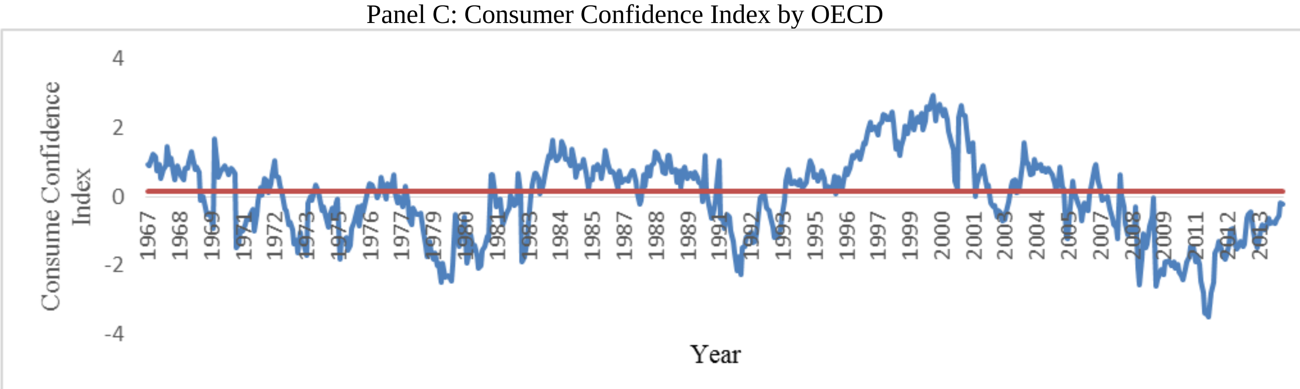


Figure2

Wealth process of the momentum based trading strategy and the comovement-momentum based trading strategy

I sort all NYSE, AMEX, NASDAQ stocks into ten momentum deciles and in an independent sort, I sort all stocks into three comovement terciles. I assume the following trading strategy from January 1965 to December 2014: $1 long in the winner portfolio (D10) and $1 short in the loser's portfolio (D1). Assuming both the long and short positions are held for three months, I plot the wealth process for the highest comovement C3, the lowest comovement C1, and the middle comovement. Graph B illustrates the wealth process from the momentum – comovement based trading strategy which represents the momentum profits results from taking a long position in the highest comovement portfolio C3 and taking a short position in the lowest comovement portfolios C1.

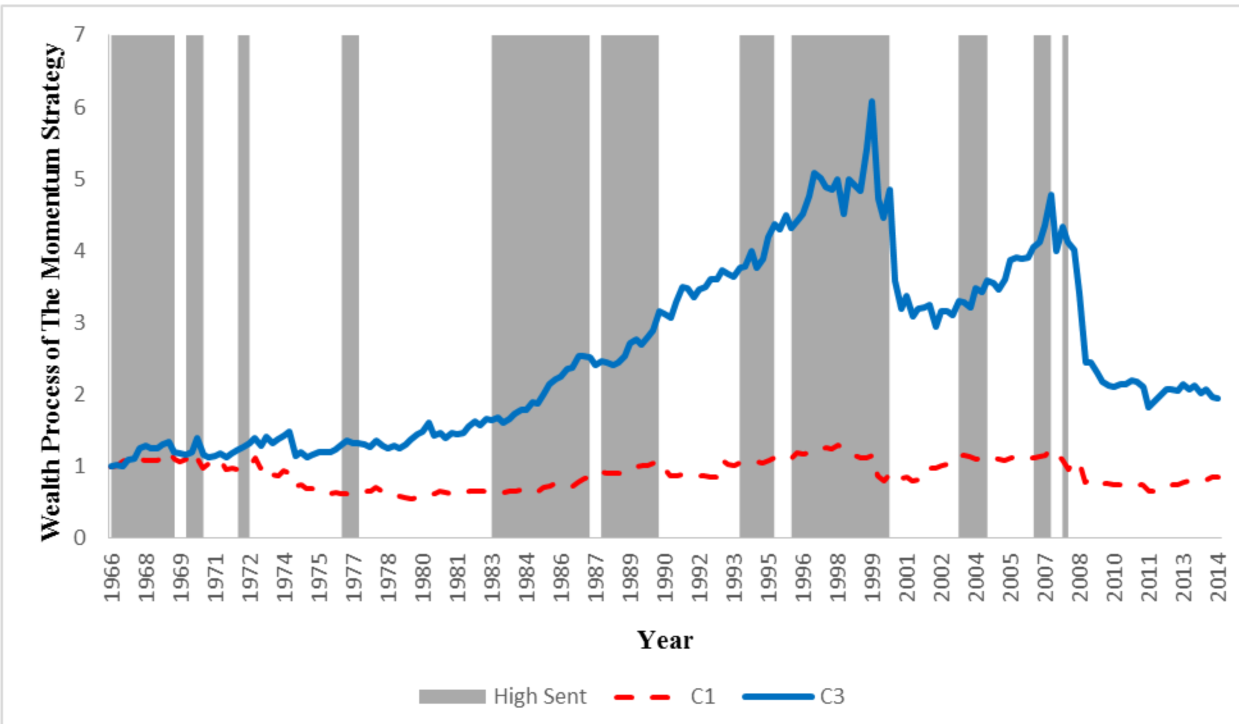
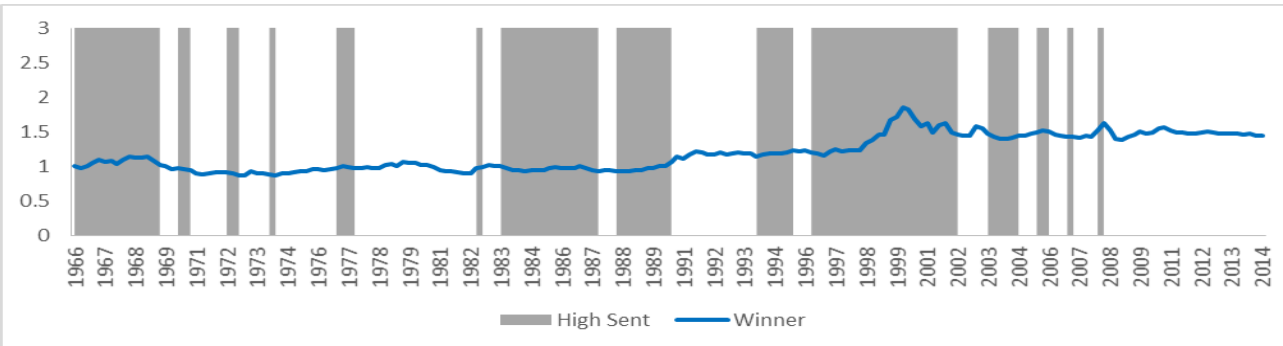


Figure 3

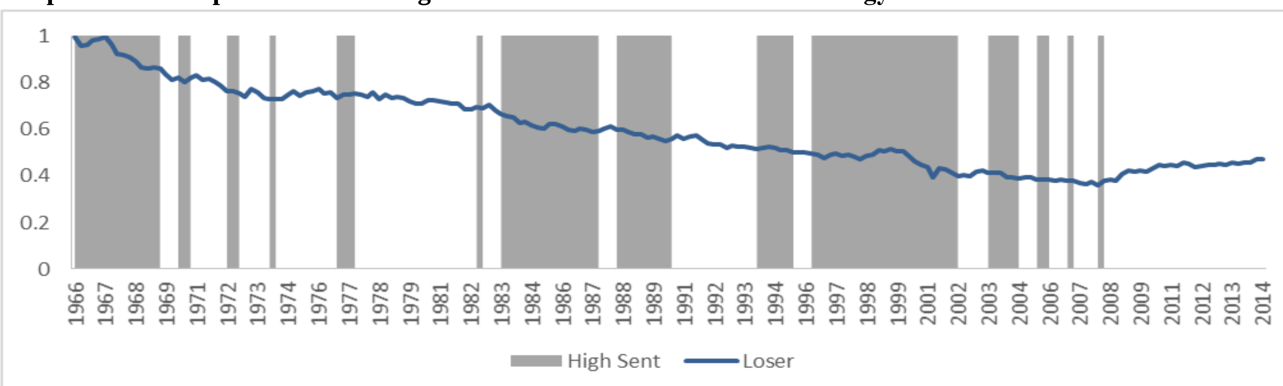
Wealth process of long minus short the comovement trading strategy (C3-C1)

In Graph A, I plot the wealth process of the strategy whereby I invest $1 in the strategy that takes a long position in the intersection of high comovement stocks and winner stocks and a short position in the intersection of low comovement stocks and winner stocks. Graph B repeats the strategy using loser stocks. Graph C repeats the strategy using winner minus loser returns

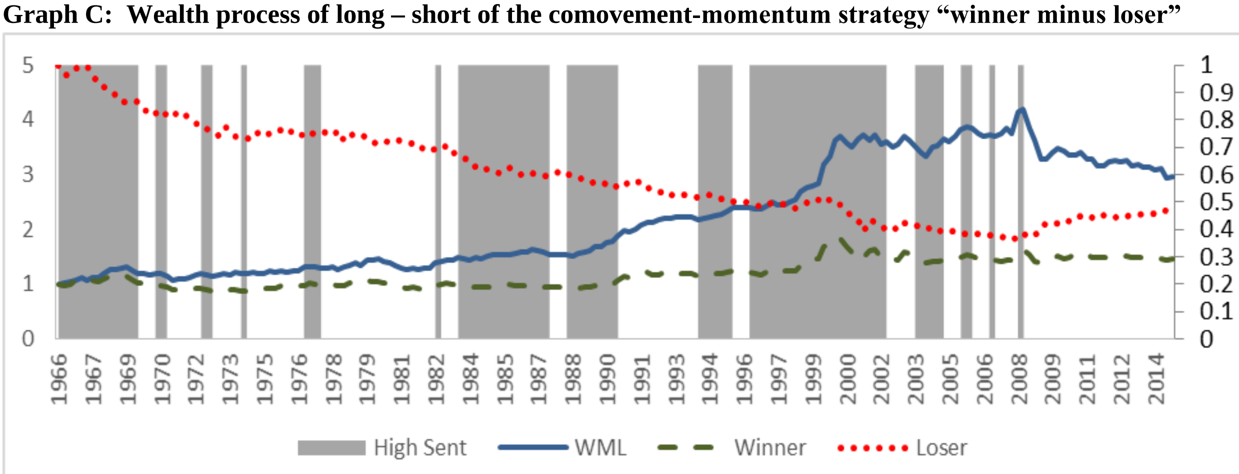
Graph A: Wealth process of long leg of the comovement-momentum strategy "winner"



Graph B: Wealth process of short leg of the comovement-momentum strategy "loser"



Graph C: Wealth process of long – short of the comovement-momentum strategy "winner minus loser"



CHAPTER 4

STYLE INVESTING AND RETURN PREDICTABILITY

ABSTRACT

Using a sample of 7,524 IPOs during 1975-2013, I find strong evidence that the pre-IPO return of the style which the IPO stock belongs to , which I refer to as the pre-IPO style return, can predict both the IPO stock's underpricing and the post-IPO returns. I determine the style of each IPO stock based on its size and book-to-market ratio immediately after IPO. I find that the pre-IPO style return is positively related to IPO underpricing and negatively related to the post-IPO returns over the three-, six-, and 12-month horizons. Moreover, the style return in the IPO month is negatively related to the post-IPO returns up to three years. Our findings suggest that style investing plays an important role in the formation of the market price of a stock as soon as the stock enters the public capital market.

Keywords: Initial public offerings; IPOs; Style investing; Underpricing; Return predictability

Chapter 4

Style Investing and IPO return predictability

4.1. Introduction

The importance of style investing has been gaining more attention over time. Examples of recent studies that have examined style investing include Barberis and Shleifer (2003), Teo and Woo (2004), Chen and Bondt (2004), Froot and Teo (2008), and Wahal and Yavuz (2013). The influence of style investing on asset prices is intuitively expressed by Barberis and Shleifer (2003) as follows, "if an asset performed well last period, there is a good chance that the outperformance was due to the asset's being a member of a 'hot' style…If so, the style is likely to keep attracting inflows from switchers next period, making it likely that the asset itself also does well next period." Barberis and Shleifer (2003) argue that style investing can generate momentum and reversals in both style and individual stock returns.

However, we are not aware of any study that examines whether style investing affects the returns of a stock as soon as the stock enters the public capital market. For companies that have just gone public, their stocks are new to the investing public. Without prior trading record, are the initial public offering (IPO) stocks' returns predictable by the pre-IPO return of an investment style which an IPO stock belongs to? For convenience, I will refer to the pre-IPO return of an investment style which an IPO stock belongs to as the pre-IPO style return or the IPO stock's past style return, or simply the past style return. There is no empirical evidence on whether and how the pre-IPO style return affects the IPO stock's underpricing, intermediate aftermarket returns, and long-run returns. The objective of this study is to fill this gap in the literature.

Conceptually, if investors have extrapolative expectations and trade an IPO stock as soon as it becomes a new member of an existing investment style, I expect the IPO stock's returns to be affected by the past style return, just as any other stock's returns are affected by the past style return in the model of Barberis and Shleifer (2003). Barberis and Shleifer (2003) build a model of style investing in which there are two kinds of investors: "switchers" and "fundamental traders". Switchers allocate funds based on different investment styles' relative past performance: the styles that have performed well in the past attract more funds from the styles that have performed poorly; the fund inflows positively affect the market price of the past winner style and the fund outflows negatively affect the market price of the past loser style. Due to the reasons discussed in Barberis and Shleifer (2003), fundamental traders are unable to push prices back to fundamental values. An empirical prediction of Barberis and Shleifer' (2003) model is that a style's past return can predict the future return of a stock that belongs to the same style. Using all the common stocks trading on the NYSE, Amex, and NASDAQ between 1965 and 2009, Wahal and Yavuz (2013) find empirical evidence that supports this prediction. Specifically, they find that style returns measured over the prior 12-months are significant predictors of future stock returns over one, three, six, and 12-month horizons.

Motivated by the above studies, I hypothesize that the past style returns can predict an IPO stock's returns. However, it is an empirical question when and how an IPO stock's market prices are affected by style investing. Therefore, I examine not only the IPO stock's first-day return (i.e., underpricing) but the post-IPO returns over various time horizons. If some investors' decision to buy an IPO stock in the aftermarket is motivated by extrapolating the pre-IPO style return for a certain time period after the IPO stock starts to trade, then as the investors' aftermarket purchases contribute to a higher market price, I would expect the past style return to be positively correlated with the IPO stock's return within a certain time horizon. If I find a negative correlation between the pre-IPO style return and the post-IPO stock return with a certain time horizon, then it suggests that the style return momentum has ended and the reversal has taken place within this time horizon.

Specifically, I first examine the correlation between the pre-IPO style return and the IPO stock's first day return. The IPO stock's first day return is also referred to as IPO underpricing, which is measured by the market closing price on the first trading day minus IPO offer price, scaled by the IPO offer price. I then examine the correlation between the past style return and the post-IPO stock returns over various time horizons such as three months, six months, 12 months, 24 months, and 36 months following the IPO. On the one hand, if investors extrapolate the past style return for the IPO stock and continue to buy the IPO stocks beyond the first trading day in the aftermarket, then I would expect a positive correlation between the past style return and the IPO stock's aftermarket returns over a certain horizon. On the other hand, if investors' buying trend reverses sometime after the IPO stock starts to trade, then I would expect a negative correlation between the past style return and the post-IPO stock return over a certain time horizon. In other words, it is an empirical question when the price trend reverses after the IPO stock starts to trade.

Using both portfolio sorts and regression analysis, I have two main findings. First, I find that higher past style returns are associated with higher underpricing. Second, I find that higher past style returns are associated with lower post-IPO returns over the three-, six-, and 12-month horizons. The results suggest that style investing plays an important role in the market price of IPO stocks.

Specifically, I first sort IPO stocks into five quintiles based on their style returns over the past 12 months. I find that the quintile of IPO stocks with the highest past style returns is significantly more underpriced than the quintile with the lowest past style returns. The difference in underpricing between the two extreme quintiles is 5.77% (*t*-statistic=3.74), which is about 32% of the average underpricing in our sample. Moreover, the 3-month, 6-month, and 12-month post-IPO raw returns are significantly lower for the quintile of the IPO stocks with the highest past style returns than the quintile with the lowest past style returns. The differences in the 3-month, 6-month, and 12-month post-IPO raw returns between the two extreme quintiles are 7.65% (*t*-statistic=4.41), 21.65% (*t*-statistic=9.54), and 37.72% (*t*-statistic=11.78), respectively. Furthermore, I calculate the IPO stock's adjusted returns by subtracting the IPO stock's style return from the IPO stock's raw returns. I find that the difference in the 3-month, 6-month, and 12-month post-IPO adjusted returns between the two quintiles with the highest and lowest past style returns are reduced to 2.89% (*t*-statistic=1.78), 10.60% (*t*-statistic=4.99), and 13.54% (*t*-statistic=4.67), respectively, which are still statistically and economically significant.

Our regression analysis yields similar results. First, I regress IPO underpricing on the pre-IPO 12-month style return, along with a number of control variables, including industry dummies and year dummies. I find that the pre-IPO 12-month style return is positively correlated with IPO underpricing. A one standard deviation increase in the pre-IPO 12-month style return (25.8%) is associated with about 2% increase in underpricing. Second, I regress the 3-month, 6-month, and 12-month post-IPO raw returns and style-adjusted returns on the pre-IPO 12-month style return and control variables, including industry dummies and year dummies. I find that the coefficient on the pre-IPO 12-month style return is consistently negative across all the regressions, suggesting that the pre-IPO style return is negatively correlated with the post-IPO stock returns over the three-, six-, and 12-month horizons. For example, a one standard deviation increase in the pre-IPO 12-month style return is associated with about 14% and 5% decreases in the 12-month post-IPO raw return and style-adjusted return, respectively.

I also discover that the style return in the calendar month of the IPO (the IPO month hereafter) is negatively correlated with the three-, six-, and 12-month post-IPO stock returns, regardless of whether the post-IPO stocks returns are adjusted by the style returns. For example, a one standard deviation increase in the style return in the IPO month (6.32%) is associated with about 8% and 4% decreases in the 12-month post-IPO raw return and style-adjusted return, respectively. Note that our measure of the pre-IPO style return ends at the end of the month before the IPO month and our measure of the post-IPO return starts from the end of the IPO month. In other words, the style return in the IPO month does not overlap with either our pre-IPO style return or any of the post-IPO style returns. I interpret this finding as evidence consistent with the influence of style investing on IPO stock's market prices.

Are our results driven by small firms? I find no such evidence in our robustness checks. After excluding small firms, which are defined as firms with the pre-IPO last-twelve-month sales below $60 million (in 2014 purchasing power), our conclusions are not affected. Similarly, our results remain robust if I include a small firm dummy variable in the regression model.

Our findings help us better understand the determinants of IPO stocks' returns. While the IPO literature has identified numerous factors that affect IPO underpricing, no study shows such a strong impact of the past style return on IPO stock underpricing. Furthermore, post-IPO stock returns with the first year of the IPO are hard to predict. However, I find that the past style return is a strong predictor of the post-IPO stock returns within the first year of the IPO. Our evidence suggests that style investing plays an important role in the formation of the market price of a stock as soon as the stock enters the public capital market.

Our analysis proceeds as follows. In the next section, I discuss the style investing model of Barberis and Shleifer (2003) in more detail and develop our hypotheses in the context of IPO stocks. I describe both our sample of IPO stocks and the sample of stocks for the investment style formation in Section 3. I present the empirical results in Section 4. The conclusion is in the last section.

4.2. Hypothesis development

In the style investing model of Barberis and Shleifer (2003), there are two kinds of investors: "switchers" and "fundamental traders". Switchers allocate funds at the level of an investment style and their fund allocation to a style depends on that style's past performance relative to other styles. Specifically, the styles that have performed well in the past attract more funds from the styles that have performed poorly. The fund inflows positively affect the market price of the past winner style and the fund outflows negatively affect the market price of the past loser style. Given that fact that some institutions chase the best-performing style, this argument is consistent with the evidence that institutions' demand shifts influence stock prices (Gompers and Metrick, 2001). While the fundamental traders try to act as arbitrageurs, Barberis and Shleifer (2003) argue that their ability to push prices back to fundamental values is subject to limitations. In particular, concerns about shifts in switcher sentiment make fundamental traders less aggressive in correcting mispricing (De Long et al., 1990).

I develop our hypothesis based on the style investing model of Barberis and Shleifer (2003). Due to the extrapolative expectations of the switchers, they may trade an IPO stock immediately as the stock joins a particular investment style. Therefore, the switchers' influence on the IPO stock's market price can show up as early as the first trading day of the IPO stock. In particular, not only the IPO stock's opening price on the first trading day may be affected by switchers' trading, the same influence may continue until the market closes on the first trading day. Barberis and Shleifer (2003) argue that style investing generates momentum and reversals in style and individual stock returns. However, it is an empirical question when exactly the return reversal starts to take place. If the return reversal starts to occur sometime in the middle of the first trading day of the IPO stock, then I may not be able to observe any return momentum by examining the IPO stock's first day return (or underpricing), which is measured as the closing price on the first trading day of IPO minus the offer price, and then scaled by the offer price. However, if I are able to identify the style return momentum as early as the first trading day of the IPO stock, it would be strong evidence for the style investing hypothesis in the context of IPO stocks.

Specifically, I examine the correlation between the pre-IPO style return and the IPO underpricing. As argued above, a positive correlation would be strong evidence that switchers trade the IPO stock based on their extrapolative expectations. If there is a negative correlation between the pre-IPO style return and IPO underpricing, then it suggests that the style return reversal takes place as early as the first trading day of the IPO stock. If there is no correlation between the pre-IPO style return and IPO underpricing, then I are not able to conclude whether the style investing hypothesis applies to IPO stocks.

As I argue before, it is an empirical question when exactly the style return reversal starts. Therefore, I will also examine the correlation between the pre-IPO style return and the post-IPO returns over various time horizons. As an IPO can occur on any date within a calendar month, I follow the literature to measure the post-IPO stock returns from the end of the calendar month of the IPO. I measure the post-IPO stock returns over three-, six-, 12-, 24-, and 36-month periods to examine how far in the future past style returns can influence the post-IPO stock returns. If I are able to find a positive correlation between the past style return and the post-IPO stock return within a certain time horizon, for example, the post-IPO three-month period, then it would be strong evidence that the style return momentum can last for about three months following the IPO. If I find a negative correlation between the past style return and the post-IPO three-month period, then I can infer that the style return reversal takes place sometime during the three-month period following the IPO. If there is no correlation between the past style return and post-IPO stock returns, then I are not able to conclude whether the IPO stocks' market prices are affected by the style switchers.

4.3. Sample

I obtain the IPOs conducted during 1980 and 2013 from the SDC new issues database. I supplement the sample with the IPOs during 1975-1979, which are obtained from Professor Jay Ritter.[20] After excluding American depositary receipts (ADR) and American depositary shares (ADS), units, real estate investment trusts (REIT), closed-end funds, stocks with offer price under $5, and stocks with missing value for the filing prices, I are left with 7,524 IPOs in the sample.

Table 1 shows summary statistics of our IPO sample. On average, IPO stocks in our sample are underpriced by 18% and have raw returns of 5.20%, 5.75%, and 6.07% over the 3-, 6-, and 12-month periods following the IPO. The average style return is 20.6% over 12 months

[20] Available at https://site.warrington.ufl.edu/ritter/files/2016/01/Jay-Ritters-1975-1984-IPO-Database.pdf.

prior to the IPO, which is consistent with the idea that firms go public when market conditions are favorable. About 83% of the IPO stocks are listed on the Nasdaq, 62% of the IPOs are underwritten by a top-tier investment bank, and 37% of the firms are backed by venture capitals (VCs). All the variables are defined in the appendix.

[**Insert Table 1 Here**]

The sample that I use to form style portfolios consists of all NYSE, AMEX, and NASDAQ listed common stocks in the intersection of the CRSP and COMPUSTAT with shares codes of 10 and 11 for the period from January 1974 to December 2014. I apply the following sample selection filters: the information required to compute the book-to-market ratio as in Fama and French (1992) should be available from CRSP and COMPUSTAT; stocks with negative book value of stockholder's equity are excluded; I exclude stocks below $5 at the time of portfolio formation and those in the lowest size decile (based on NYSE size breakpoints) to ensure that the results are not driven by highly illiquid, small stocks or bid-ask bounce (Jegadeesh and Titman, 1993; Jegadeesh and Titman, 2001; Wahal and Yavus, 2013). I form 25 style portfolios based on size and book-to-market ratios.

To compute each IPO stock's size, I multiply the first available share price and shares outstanding from CRSP. I use the post-issue equity value from the IPO prospectus as the book value of equity. Based on its size and book-to-market ratio, I assign each IPO stock to one of the 25 styles at the end of the calendar month immediately prior to the IPO, assuming that the most recent calendar month-end prior to the IPO date represents the most relevant time when investors can identify the style that the IPO stock belongs to. For simplicity, I refer to this style as the "IPO stock style". I compute value-weighted returns for the IPO stock style over the 12 months prior to the calendar month of the IPO and the three, six, and 12 months after the calendar month of the IPO. I also compute the IPO stock style's return during the IPO month. Figure 1 shows the timeline. Note that the style return in the IPO month does not overlap with either the pre-IPO style return or any of the post-IPO returns.

[**Insert Figure 1 Here**]

I sort all the IPOs into five quintiles based their style returns over the 12 months prior to the calendar month of the IPO. Quintile 1 has the lowest pre-IPO style return and quintile 5 has the highest pre-IPO style return. In untabulated results, I notice that except for quintile 1, all the other four quintiles have positive pre-IPO style returns. Specifically, the average pre-IPO style return for quintiles 5, 4, 3, and 2 are about 60%, 28%, 17%, 8%, respectively. In contrast, the average pre-IPO style return for quintile 1 is about –10%. The variation in the pre-IPO style returns across the five quintiles is significant.

4.4. Empirical results

4.4.1. Portfolio sorts

Table 2 reports the mean underpricing and post-IPO returns for the five quintiles. I also test for equality in underpricing and post-IPO returns between quintiles 1 and 5 and report the results in the last column of Table 2. I have two findings consistent with our hypotheses. First, IPO stocks with the lowest past style returns have lower underpricing than IPO stocks with the highest past style return. Specifically, the mean underpricing is 16.54% for the quintile with the lowest past style return and 22.31% for the quintile with the highest past style return. The difference in underpricing is 5.77%, which is significant both statistically and economically.

Second, IPO stocks with the lowest past style returns have higher post-IPO returns than IPO stocks with the highest past style returns. Specifically, the differences in the post-IPO three-, six-, and 12-month raw returns are 7.65% (*t*-statistic=4.41), 21.65% (*t*-statistic =9.54), and

37.72% (*t*-statistic =11.78), respectively. All the differences are both statistically and economically significant. After subtracting the style returns from the IPO stock raw returns, the differences in the post-IPO three-, six-, and 12-month stock returns are reduced to 2.89% (*t*-statistic =1.78), 10.60% (*t*-statistic =4.99), and 13.54% (*t*-statistic =4.67), respectively. While the difference in the mean post-IPO three-month style-adjusted returns is only marginally significant, the differences in the mean post-IPO six- and 12-month style-adjusted returns are still highly significant.

[**Insert Table 2 Here**]

4.4.2 . Regression analysis

4.4.2.1 Regression of IPO underpricing

Table 3 reports the results of the regression of underpricing on past style return and control variables. I follow Loughran and Ritter (2004) to include VC-backed dummy, top-tier underwriter dummy, firm assets, firm age, book-to-market ratio, share overhang, offer price revision, Nasdaq dummy, pure primary offer dummy, and pre-IPO market return, which is measured as the Nasdaq index return over 15 trading days prior to the IPO. I also control for year and industry fixed effects by including year dummies and Fama and French 48 industry dummies. In untabulated results, I replace Fama and French 48 industry dummies with Fama and French 49 industry dummies.[21] Our main results remain robust. All the variables are defined in the appendix. The *t*-statistics are based on White's (1980) heteroscedasticity-consistent standard errors. Across the three regression models, the IPO stock's past style return is a significant predictor of IPO underpricing. In particular, based on the results in model (3), a one standard deviation increase in the pre-IPO 12-month style return (25.8%) is associated with about 1.7%

[21] For Fama-French (1997) industries, Ken French has an updated 49 (instead of 48) industries on his website. The main change is that the computer industry is split into software and hardware industries.

increase in IPO underpricing. The regression results are consistent with our results based on portfolio sorts in Table 2.

[**Insert Table 3 Here**]

Interestingly, the market return prior to the IPO is often found to be a significant predictor for IPO underpricing (e.g., Lowry and Shu, 2002; Zhu, 2009; Hao, 2011; Hanley and Hoberg, 2012). However, it is not a significant predictor once I control for past style return in the regression. It is possible that the explanatory power of the market return prior to the IPO is partly driven by the IPO stock's style return prior to the IPO.

4.4.2.2. Regression of post-IPO returns within a year

Next, I regress post-IPO returns on the pre-IPO 12-month style return and control variables. In Panels A and B of Table 4, I report the results for the regressions of post-IPO raw returns and style-adjusted returns, respectively. For completeness, I also include the style return in the IPO month as an independent variable. Note that our measure of the pre-IPO style return ends at the end of the month before the IPO month and our measure of the post-IPO return starts from the end of the IPO month. In other words, the style return in the IPO month does not overlap with either our pre-IPO style return or post-IPO style returns. While the style investing hypothesis does not provide any direct prediction about the coefficient on the IPO month style return, I are interested in the empirical effect of the style return in the IPO month on the post-IPO stock returns.

Table 4 shows that both the pre-IPO 12-month style return and the IPO month style return are negatively correlated with the post-IPO stock returns. The negative coefficients on the pre-IPO 12-month style return and the IPO month style return are consistently significant across all the regressions in Panels A and B. For example, a one standard deviation increase in the pre-

IPO 12-month style return (25.8%) is associated with about 14% and 5% decreases in the 12-month post-IPO raw return and style-adjusted return, respectively. A one standard deviation increase in the style return in the IPO month (6.32%) is associated with about 8% and 4% decreases in the 12-month post-IPO raw return and style-adjusted return, respectively.

[**Insert Table 4 Here**]

IPO stock returns, especially aftermarket returns, are hard to predict. While the adjusted R-squared values for the underpricing regression in Table 3 range from 0.22 to 0.43, the adjusted R-squared values for the regressions of post-IPO returns are much lower. In particular, Panel A of Table 4 shows that the adjusted R-squared values range from 0.08 to 0.11 for the regressions of post-IPO raw returns and from 0.02 to 0.04 for the regressions of post-IPO style-adjusted returns. Both of the two style return variables, i.e., the pre-IPO 12 month style return and the style return in the IPO month, contribute significantly to the explanatory power of the regression model. For example, in untabulated results, I find that the adjusted R-squared is reduced by about 35% if I exclude the style returns in the 12 months prior to the IPO and in the IPO month from the regression model in Panel B of Table 4.

Are our findings driven by small firms? To address this question, I exclude small firms, which are defined as firms with the pre-IPO last-twelve-month sales below $60 million (in 2014 purchasing power). I then re-run the regressions in Panels A and B of Table 4 and report the results in Panels A and B of Table 5. Both the past style return and IPO month style return are still negatively related to the post-IPO stock returns. In untabulated results, I also add a small firm dummy, which equals one if the pre-IPO last-twelve-month sales is below $60 million (in 2014 purchasing power), and zero otherwise. Our main result remains robust. The result is generally consistent with the finding in Wahal and Yavuz (2013). Table 3 of Wahal and Yavuz

(2013) shows that past style return can predict future stock return even after the smallest stocks (i.e., stocks below the 10th percentile in size) are removed from the sample.

[**Insert Table 5 Here**]

4.4.2.3 Regression of post-IPO returns beyond a year

As I find that the IPO stock's past style return is able to predict the post-IPO returns within a year following the IPO, I are interested in how far after the IPO the past style returns can still predict the post-IPO stock returns. Therefore, I examine whether past style returns can predict post-IPO returns beyond one year after the IPO. However, studies on post-IPO long-run returns are often subject to criticism about how the long-run abnormal returns are measured. In particular, a market-adjusted or style-adjusted return is not considered the most appropriate measure of long-run stock performance.

To minimize concerns about the post-IPO long-run stock performance measurement, I use the event-time factor-adjusted returns (e.g., Lyandres et al., 2008; Dong et al., 2011). Specifically, I regress each IPO's monthly excess returns on the Fama and French (1992) three factors for the post-IPO two-year (24 months) and three-year (36 months) periods, respectively. The two-year (or three-year) returns start from the end of the calendar month of the IPO and cover 24 months (or 36 months) afterwards or until the delisting date, whichever is earlier. The intercept from the regression is the three factor-adjusted monthly abnormal return.

I then use the two-year or three-year three factor-adjusted monthly return as the dependent variable. The independent variables are the same as in Table 4. Table 6 shows that the past style return is not able to significantly predict post-IPO two-year or three-year returns, suggesting that the effect of past style return on post-IPO stock returns does not exist significantly beyond one year following the IPO.

I continue to find that the IPO month style return can predict the post-IPO three-factor alphas over the 24-month horizon (t-statistic=−2.88) and the 36-month horizon (t-statistic=−1.71). Specifically, the coefficient on the IPO month style return in the regression of the post-IPO 24-month return is −0.03, which represents a decrease of 0.03% per month or 0.36% per year. To put differently, a one standard deviation increase in the style return in the IPO month (6.32%) is associated with about 0.19% decrease in the three factor-adjusted monthly return within two years after the IPO. The negative correlation between the IPO month style return and post-IPO stock returns further confirms that the style return plays an important role in determining the IPO stock's returns.

[**Insert Table 6 Here**]

While I find that style investing seems to reverse its influence on an IPO stock's market price within three months after the IPO, it is not clear why the extrapolation of past style return for the IPO stock return seems to stop after the IPO month. One possibility is that as the short sale constraints are relaxed after an IPO stock is traded, more short sellers may trade the IPO stock, facilitating the incorporation of negative opinions into the stock price. Alternatively, stock options may be introduced for an IPO stock sometime after the IPO stock starts to trade, further facilitating negative opinions to be incorporated into the stock price. Taken together, as investors with negative opinions find their ways into the stock market, the IPO stock's return reverses.

4.5 Conclusion

For companies that have just gone public, their stocks are new to the public capital market. Are IPO stock returns predictable by the past style return? In light of the argument of style investing, I identify a new predictor of IPO stock returns, the pre-IPO style return, i.e., the pre-IPO return of the style which the IPO stock belongs to. I find that not only can the pre-IPO style return predict the IPO underpricing; pre-IPO style return can also predict post-IPO 3-month, 6-month, and 12-month stock returns. While the pre-IPO style return cannot predict IPO stock returns beyond the first year after the IPO, the style return in the calendar month of the IPO has predictive ability for the IPO stock's one-, two-, and three-year returns. Our findings suggest that as soon as a new stock enters the public capital market, investors immediately extrapolate their style's past return and trade the IPO stock as if the pre-IPO style return will continue in the future. However, the influence of the style investing on the market price of the IPO stock seems to reverse its direction within three months after the IPO, giving rise to a negative correlation between the pre-IPO style return and the post-IPO stock returns measured over three months until one year after the IPO.

Appendix: Definitions of variables

Variable	Explanation
Underpricing	(Closing price on the first trading day of IPO−offer price) / offer price
VC-backed dummy	A dummy variable equals one if the firm is venture capitalist backed, and zero otherwise.
Top tier dummy	A dummy variable equals one if the underwriter's reputation rank is 9, and zero otherwise. Carter–Manaster (1990) rank is the integer part of the IPO lead underwriter reputation ranks that are downloadable from Jay Ritter's website at http://bear.cba.ufl.edu/ritter/Rank.htm. It assigns higher prestige to underwriters that are listed more prominently on tombstone advertisements. The reputation ranks range from 1 (lowest) to 9 (highest).
Pure primary dummy	A dummy variable equals one if the offering is 100% primary (i.e., no secondary shares sold), and zero otherwise.
Offer price revision	(offer price−midpoint of the original file price range) /midpoints of the original file price range.
Age	The number of years between the founding year and the IPO year. Founding years are downloadable from Jay Ritter's website.
Nasdaq dummy	An indicator variable that equals one if the IPO stock is listed on Nasdaq and zero otherwise.
Market Cap	The market capitalization in $million, measured using the market closing price on the first trading day.
Overhang	Share overhang, which is calculated as shares outstanding after the IPO/shares sold in IPO.
Nasdaq15 return	Nasdaq15 return is value-weighted Nasdaq Composite's compounded return (including distributions) over the 15 trading days prior to IPO, ending on the day before the IPO date.
Small firm dummy	A dummy variable equals one if the pre-IPO last twelve month sales is below $60 million (in 2014 purchasing power), and zero otherwise.
Pre-IPO 12-month style return	Value-weighted return of a style portfolio compounded over 12 months prior to the IPO, where style is defined based on size and book-to-market ratio at the beginning of each month during the 12 months.
Style return in IPO month	Value-weighted return of a style portfolio during the month the IPO, where style is defined based on size and book-to-market ratio at the beginning of the IPO month.

Table 1
Summary statistics

The sample consists of 7,524 IPOs during 1975-2013, excluding ADRs, units, REITs, closed-end funds, stocks with offer price under $5, and stocks with missing value for the following variables.

Variable	N	Mean	Median	Std Dev	Maximum	Minimum
Underpricing (%)	7524	18.00	6.53	39.20	697.50	-43.27
Pre-IPO 12-month style return (%)	7524	20.60	16.84	25.80	130.07	-51.05
VC-backed dummy	7524	0.37	0.00	0.48	1.00	0.00
Top tier dummy	7524	0.62	1.00	0.49	1.00	0.00
Ln(assets) (in 2014 purchasing power)	7524	4.11	3.94	1.81	12.89	-4.22
ASSETS	7524	560.51	30.90	6,682.40	295,711.00	0.01
Sales (in 2014 purchasing power)	7524	368.74	57.38	2,078.44	106,690.81	0.01
Small firm dummy (for sales under $60 million in 2014 purchasing power)	7524	0.51	1.00	0.50	1.00	0.00
Ln(1+AGE)	7524	2.29	2.20	0.99	4.39	0.00
AGE (years)	7524	15.39	8.00	18.98	80.00	0.00
Ln(book-to-market)	7524	0.25	0.24	0.14	1.48	0.00
book-to-market	7524	0.30	0.28	0.21	3.40	0.00
Market Cap ($million)	7524	502.52	121.36	2,388.77	81,738.99	2.14
Overhang	7524	4.01	3.51	2.20	69.03	1.00
Offer price revision (%)	7524	-0.42	0.00	22.55	299.67	-230.13
Nasdaq dummy	7524	0.83	1.00	0.38	1.00	0.00
Pure primary dummy	7524	0.57	1.00	0.49	1.00	0.00
NASDAQ15 return (%)	7524	1.07	1.22	4.51	25.11	-21.81
Style return in IPO month (%)	7524	0.68	0.90	6.32	31.51	-34.64
Post-IPO 3-month raw return (%)	7524	5.20	0.00	42.96	605.88	-89.29
Post-IPO 6-month raw return (%)	7524	5.75	-3.72	59.47	938.69	-96.30
Post-IPO 12-month raw return (%)	7524	6.07	-9.09	82.03	1,106.06	-99.53
Post-IPO 3-month style-adjusted return (%)	7524	4.52	-0.32	39.46	577.85	-133.62
Post-IPO 6-month style-adjusted return (%)	7524	3.73	-4.09	54.88	915.78	-148.77
Post-IPO 12-month style-adjusted return (%)	7524	2.33	-11.01	77.36	1,010.15	-205.07

Table 2
IPO underpricing and post-IPO stock returns sorted on pre-IPO 12-month style return

The sample consists of IPOs during 1975-2013, excluding ADRs, units, REITs, closed-end funds, and stocks with offer price under $5. I sort the sample into five quintiles based on the pre-IPO 12-month return of the style to which the IPO stock belongs to. Quintile 5 has the highest style return prior to the IPO. I report the mean underpricing and post-IPO stock returns over 3, 6, and 12 months after the IPO for each quintile. The last column shows the return differences between the bottom and the top quintiles.

	Pre-IPO 12-month style return quintiles					
	1 (Low return)	2	3	4	5 (High return)	1 minus 5 (t-stat)
Underpricing (%)	16.54	14.77	14.80	21.57	22.31	-5.77***
						(-3.74)
Post-IPO 3-month stock raw return (%)	8.78	8.35	5.10	2.64	1.13	7.65***
						(4.41)
Post-IPO 6-month stock raw return (%)	14.69	11.26	9.56	0.17	-6.96	21.65***
						(9.54)
Post-IPO 12-month stock raw return (%)	26.38	12.32	5.12	-2.15	-11.33	37.72***
						(11.78)
Post-IPO 3-month style-adjusted stock return (%)	6.46	5.55	3.70	3.34	3.57	2.89*
						(1.78)
Post-IPO 6-month style-adjusted stock return (%)	9.77	5.21	4.10	0.40	-0.83	10.60***
						(4.99)
Post-IPO 12-month style-adjusted stock return (%)	10.14	3.69	0.98	-0.40	-2.76	13.54%***
						(4.67)

Table 3
Regression of underpricing (%) on pre-IPO 12-month style return

The dependent variable is IPO underpricing (%). The independent variable of primary interest is the pre-IPO 12-month style return. The sample consists of IPOs during 1975-2013, excluding ADRs, units, REITs, closed-end funds, and stocks with offer price under $5. The *t*-statistics are based on White's (1980) heteroscedasticity-consistent standard errors. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

	(1)		(2)		(3)	
Parameter	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept	16.79***	5.07	18.30***	9.66	24.40***	6.72
Pre-IPO 12-month style return	**18.19*****	**5.01**	**4.57*****	**2.67**	**6.45****	**2.31**
VC-backed dummy			5.03***	6.23	2.46***	2.93
Top tier dummy			3.39***	4.28	0.88	1.12
Ln(assets)			-1.02***	-4.23	-1.17***	-4.59
Ln(1+AGE)			-1.49***	-4.38	-1.34***	-3.94
Ln(book-to-market)			-38.89***	-10.88	-32.98***	-10.03
Overhang			2.12***	7.28	1.66***	6.48
Offer price revision			0.80***	15.56	0.71***	14.38
Nasdaq dummy			-0.11	-0.07	-0.66	-0.41
Pure primary dummy			6.71***	9.50	2.70***	4.11
NASDAQ15 return			0.09	0.96	0.09	0.93
FF 48 Industry dummies	Yes		No		Yes	
Year dummies	Yes		No		Yes	
Adj. R^2	0.218		0.368		0.429	

Table 4
Regression of post-IPO stock returns on pre-IPO style returns

The dependent variable is the post-IPO **raw** returns over 3, 6, or 12 months in Panel A, and the post-IPO style-adjusted returns over 3, 6, or 12 months in Panel B. The independent variable of primary interest is the pre-IPO 12-month style return. The sample consists of IPOs during 1975-2013, excluding ADRs, units, REITs, closed-end funds, and stocks with offer price under $5. The *t*-statistics are based on White's (1980) heteroscedasticity-consistent standard errors. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Regressions of post-IPO **raw** returns over 3, 6, and 12 months

	3-month		6-month		12-month	
Parameter	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept	0.245***	4.60	0.196***	2.91	0.091	0.97
Pre-IPO 12-month style return	**-0.207*****	**-7.32**	**-0.361*****	**-9.04**	**-0.560*****	**-11.96**
Style return in IPO month	**-0.802*****	**-11.09**	**-1.068*****	**-9.66**	**-1.234*****	**-9.50**
Underpricing (%)	0.000	0.49	0.000	-0.31	0.000	0.61
VC-backed dummy	-0.008	-0.62	-0.048***	-2.89	-0.021	-0.85
Top tier dummy	0.032***	2.91	0.038**	2.55	0.078***	3.67
Ln(assets)	0.001	0.19	0.004	0.81	0.020***	3.09
Ln(1+AGE)	-0.007	-1.22	-0.009	-1.21	0.012	1.23
Ln(book-to-market)	-0.006	-0.18	-0.012	-0.27	0.009	0.18
Overhang	0.003	1.34	0.008**	1.97	0.008	1.59
Nasdaq dummy	-0.098***	-4.16	-0.147***	-4.58	-0.172***	-4.09
Pure primary dummy	0.014	1.47	-0.008	-0.56	-0.036*	-1.78
FF 48 Industry dummies	Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes	
Adj. R^2	0.075		0.109		0.097	

Panel B. Regressions of post-IPO **style-adjusted returns** over 3, 6, and 12 months

	3-month		6-month		12-month	
Parameter	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept	0.176***	3.56	0.097	1.50	-0.012	-0.13
Pre-IPO 12-month style return	**-0.110*****	**-4.13**	**-0.200*****	**-5.25**	**-0.204*****	**-4.46**
Style return in IPO month	**-0.613*****	**-8.63**	**-0.728*****	**-7.46**	**-0.560*****	**-4.72**
Underpricing (%)	0.000	-1.01	-0.001*	-1.73	0.000	-1.01
VC-backed dummy	-0.011	-0.96	-0.053***	-3.26	-0.024	-0.99
Top tier dummy	0.034***	3.25	0.045***	3.06	0.075***	3.57
Ln(assets)	-0.005	-1.49	-0.004	-0.86	0.004	0.65
Ln(1+AGE)	-0.007	-1.33	-0.007	-0.91	0.016	1.59
Ln(book-to-market)	-0.045	-1.49	-0.097**	-2.35	-0.122**	-2.34
Overhang	0.003	1.02	0.004	0.99	0.001	0.28
Nasdaq dummy	-0.105***	-4.64	-0.152***	-4.85	-0.194***	-4.65
Pure primary dummy	0.003	0.32	-0.016	-1.12	-0.034*	-1.69
FF 48 Industry dummies	Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes	
Adj. R^2	0.024		0.035		0.036	

Table 5
Regression of post-IPO stock returns on pre-IPO style returns after excluding small firms

The dependent variable is IPO underpricing (%). The independent variable of primary interest is the pre-IPO 12-month style return. The sample consists of IPOs during 1975-2013, excluding ADRs, units, REITs, closed-end funds, stocks with offer price under $5, and small firms (i.e., firms with the pre-IPO last-twelve-month sales below $60 million in 2014 purchasing power). The *t*-statistics are based on White's (1980) heteroscedasticity-consistent standard errors. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Panel A. Regressions of post-IPO **raw** returns (%) over 3, 6, and 12 months

	3-month		6-month		12-month	
Parameter	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept	19.42***	3.06	10.94	1.35	16.85	1.33
Pre-IPO 12-month style return (%)	**-0.24*****	**-8.10**	**-0.34*****	**-8.06**	**-0.48*****	**-7.96**
Style return in IPO month (%)	**-0.66*****	**-7.23**	**-1.09*****	**-7.49**	**-1.20*****	**-6.53**
Underpricing (%)	0.03	0.54	-0.03	-0.52	-0.11*	-1.65
VC-backed dummy	2.17	1.44	-1.73	-0.80	-0.01	0.00
Top tier dummy	-1.25	-0.91	1.07	0.52	5.17*	1.71
Ln(assets)	0.69	1.39	1.53**	2.35	1.39	1.36
Ln(1+AGE)	-0.97*	-1.81	-0.80	-1.06	1.88	1.60
Ln(book-to-market)	0.52	0.14	0.66	0.12	1.90	0.29
Overhang	0.14	0.60	0.06	0.18	0.36	0.76
Nasdaq dummy	1.48	1.17	4.58***	2.58	2.14	0.77
Pure primary dummy	-0.92	-0.89	-2.47	-1.61	-5.89**	-2.44
FF 48 Industry dummies	Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes	
N	3681					
Adj. R^2	0.074		0.101		0.080	

Panel B. Regressions of post-IPO **style-adjusted returns (%)** over 3, 6, and 12 months

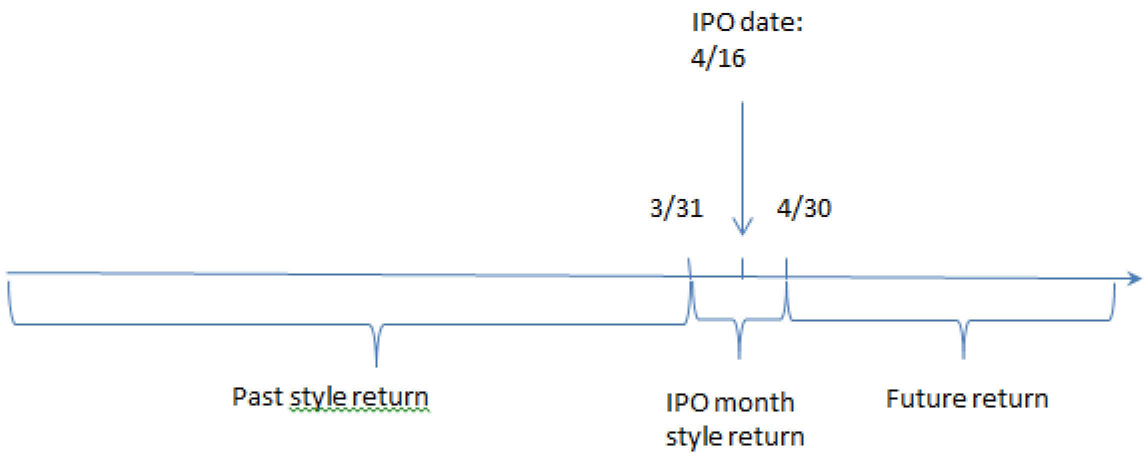
	3-month		6-month		12-month	
Parameter	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept	14.46***	2.63	4.02	0.53	8.62	0.68
Pre-IPO 12-month style return (%)	**-0.13*** **	**-4.82**	**-0.17*** **	**-4.06**	**-0.20*** **	**-3.34**
Style return in IPO month (%)	**-0.48*** **	**-5.53**	**-0.71*** **	**-5.77**	**-0.60*** **	**-3.48**
Underpricing (%)	-0.05	-0.94	-0.10**	-2.16	-0.15**	-2.35
VC-backed dummy	1.61	1.13	-3.14	-1.50	-0.76	-0.23
Top tier dummy	-0.65	-0.50	1.38	0.69	4.40	1.46
Ln(assets)	-0.15	-0.34	0.42	0.66	-0.30	-0.30
Ln(1+AGE)	-0.95**	-1.96	-0.66	-0.91	1.89	1.61
Ln(book-to-market)	-1.97	-0.54	-5.18	-0.95	-5.52	-0.86
Overhang	0.00	0.01	-0.33	-1.09	-0.10	-0.22
Nasdaq dummy	1.58	1.38	4.40**	2.56	3.58	1.32
Pure primary dummy	-1.73*	-1.79	-3.61**	-2.43	-5.85**	-2.46
FF 48 Industry dummies	Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes	
	3681					
Adj. R^2	0.039		0.038		0.029	

Table 6
Regression of long-run factor-adjusted returns (%) on pre-IPO 12-month style return

The dependent variable is the long-run monthly factor-adjusted return using the Fama and French (1993) three factors as control variables. Specifically, I regress each IPO's monthly excess returns on the Fama and French three factors for two-year (24 months) and three-year (36 months) periods, respectively. The independent variable of primary interest is the pre-IPO 12-month style return. The sample consists of IPOs during 1975-2013, excluding ADRs, units, REITs, closed-end funds, and stocks with offer price under $5. The t-statistics are based on White's (1980) heteroscedasticity-consistent standard errors. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

	24-month alpha (1975-2013)		36-month alpha (1975-2012)	
Parameter	Estimate	t-stat	Estimate	t-stat
Intercept	-2.30	-0.64	-0.19	-0.18
Pre-IPO 12-month style return (%)	0.00	-1.18	0.00	0.27
Style return in IPO month (%)	**-0.03*****	**-2.88**	**-0.01***	**-1.71**
Underpricing (%)	0.00	-0.69	0.00	0.21
VC-backed dummy	0.04	0.28	0.02	0.15
Top tier dummy	0.64***	4.45	0.76***	5.79
Ln(assets)	0.02	0.40	-0.06	-1.22
Ln(1+AGE)	0.22***	3.33	0.27***	4.45
Ln(book-to-market)	0.28	0.69	0.38	1.00
Overhang	0.03	0.82	0.03	1.03
Nasdaq dummy	-0.08	-0.50	-0.06	-0.39
Pure primary dummy	-0.15	-1.19	-0.24**	-2.16
Small firm dummy	-0.66***	-4.01	-0.52***	-3.56
FF 48 Industry dummies	Yes		Yes	
Year dummies	Yes		Yes	
N	7,275		7,268	
Adj. R^2	0.027		0.037	

Figure 1
Timeline of an example of IPO month style return and style past return



CHAPTER 5

CONCLUSION

The findings of the three essays of this dissertation have significant implications for behavioral finance and asset pricing theories. Specifically, the first essay highlights the importance of credit risk as a condition under which market participants exhibit strong cognitive biases. Using a sample of rated firms, I discover that the profitability of anchoring bias based trading strategies concentrates in the worst-rated firms, which account for less than 7% of the total market capitalization of all rated firms. My findings have important implications for future research. For example, future research can test whether credit risk affects stock returns through market participants' other cognitive biases such as loss aversion, overconfidence, and mental accounting (e.g. Barberis and Huang, 2001; Grinblatt and Han, 2005; Cooper et al., 2004).

Style investing has become increasingly important for both institutional and retail investors. The second essay is the first study to report that the impact of style investing on asset prices is conditional on investor sentiment. Past style returns can significantly predict future stock returns only when investor sentiment is high. By examining the impact of style investing on asset prices following both high and low sentiment periods, I find that once I focus on the periods with high levels of sentiment, past style returns can significantly predict future stock returns even during the early period of 1965-1987. The finding is in sharp contrast to the finding in Wahal and Yavuz (2013) that style returns cannot predict future stock returns during the period of 1965-1987. The results highlight the important role of investor sentiment in asset pricing.

Style investing is also found to be a driver of momentum (Barberis and Shleifer, 2003; Wahal and Yavuz, 2013). I find that style investing drives momentum only when investor sentiment is high, but not when investor sentiment is low. The findings are robust to all the three sentiment indexes that have been widely used in the literature, as well as to various portfolio and regression methods. Moreover, I find that investor sentiment has an independent effect on how style investing contributes to momentum profits, regardless of whether the prior market return is positive or negative. By showing that sentiment can affect momentum profits through style investing; this study contributes to the discussion about how sentiment affects the predictability of stock returns. Future research can explore other mechanisms through which sentiment affects momentum and other asset pricing anomalies.

Motivated by the findings of the second essay, I examine the relation between IPO stock returns and its past style return in my third essay. In light of the argument of style investing, I find a new predictor of IPO stock returns, the pre-IPO style return, i.e., the pre-IPO return of the style which the IPO stock belongs to. I find that the pre-IPO style return can predict not only the IPO underpricing but also the post-IPO 3-month, 6-month, and 12-month stock returns. While the pre-IPO style return cannot predict IPO stock returns beyond the first year after the IPO, the style return in the calendar month of the IPO has predictive ability for the IPO stock's one-, two-, and three-year returns. The findings of the third essay suggest that as soon as a new stock enters the public capital market, investors immediately extrapolate their style's past return and trade the IPO stock as if the pre-IPO style return will continue in the future. However, the influence of style investing on the market price of the IPO stock seems to reverse its direction within three months after the IPO, giving rise to a negative correlation between the pre-IPO style return and the post-IPO stock returns measured over three months until one year after the IPO.

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