Monetary policy, Investor Sentiment and Stock Returns

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Abstract

This doctoral thesis empirically investigates the response of the U.S. market-wide and cross-sectional stock returns to monetary policy shocks *after* the Federal Open Market Committee (FOMC) meetings, across different sentiment states between June-89 to October-14. It also examines the impact of investor sentiment states on the market-wide stock price drift *before* the scheduled FOMC announcements.

Chapter 1 demonstrates that the state of investor sentiment strongly affects the transmission of conventional and non-conventional monetary policy to the stock market. In particular, monetary policy shocks significantly affect market-wide stock returns only during sentiment-correction periods. In contrast, during periods of optimism build-up, the stock market response is statistically insignificant. The sentiment-based state dependence in the response of stock market returns to monetary policy shocks sheds important light on a sentiment channel in the monetary policy transmission mechanism.

We extend our empirical analysis to cross-sectional stock returns in Chapter 2. Our estimates show that monetary policy shocks significantly affect cross-sectional stock returns only during sentiment-correction periods. We construct a long-short strategy, according to which we define the stocks which are more exposed to investor sentiment as the short leg. Our results show that monetary policy shocks positively drive the long-short spread, with a larger impact on the short leg stocks. Specially, Federal Funds Rate (FFR) surprises have larger impacts on the stocks with high accruals, young stocks, stocks with high asset growth rate, stocks with low book-to-market ratio, stocks with high cash to asset ratio, stocks with low gross profitability, high investment stocks, past loser stocks, stocks with high net operating assets, stocks with low asset tangibility, less profitable stocks, stocks with high return volatility, and large stocks before the zero lower bound (ZLB) was reached. The long-short strategy is reconstructed after the ZLB was reached due to changes in stocks' sensitivity to investor sentiment. However, it is still the short leg stocks that are more affected by the path surprises. The stronger response of the short leg implies that the stocks which are more exposed to investor sentiment are also more sensitive to monetary policy shocks.

Finally in Chapter 3 we examine how investor sentiment states affect the stock price drift before the scheduled FOMC announcements. We find that the returns on the S&P500 index increase significantly over the pre-FOMC window only during periods of high sentiment. We also find that investors allocate assets from low risk short-term T-bills to stocks on the pre-FOMC window during periods of high sentiment. Our findings on the pre-FOMC announcement order imbalance show that there are more buyer-initiated trade than seller-initiated trade on the S&P500 constituents during periods of high sentiment. These findings provide a behavioural explanation to the pre-FOMC announcement puzzle.

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Declaration

I declare that except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

Signature   Date

Lists of abbreviations

BWI .... Baker and Wurgler's Sentiment Index

CCI .... Consumer Confidence Index

CSI .... Consumer Sentiment Index

FFR .... Federal Funds Rate

FOMC .... Federal Open Market Committee

LSAP .... Large Scale Asset Purchases

PLS .... Partial Least Square

ZLB .... Zero Lower Bound

Introduction

The ultimate goals of monetary policy are to promote maximum sustainable output and employment and to promote stable prices. However, the most immediate impact of monetary policy is on financial markets; by affecting asset prices and returns, policymakers are able to modify economic behavior to achieve their ultimate objectives (Bernanke and Kuttner (2005)). In general, the Fed employs two kinds of monetary tools. For the majority outside the financial crisis, the Fed employs conventional monetary policy, which mainly focuses on adjusting the target Federal Funds Rate (FFR). However, in order to combat the declining financial and economic conditions during the 2008 crisis, the FOMC kept cutting the target FFR, and finally pushed it towards the zero-lower bound (ZLB) in late 2008. After that, the ability of the Fed to boost financial markets and stimulate economic growth using the conventional monetary policy tools is restricted. Realizing the limits of the conventional monetary policy, the Fed started to employ unconventional monetary policy. In late 2007, the Fed began to provide non-sterilized liquidity facilities. More measures including more explicit forward guidance through FOMC statements and large-scale asset purchase (LSAP) programmes were employed at 2009, after the ZLB was reached.

The financial economics literature documents a significant stock price response to monetary policy shifts (Thorbecke (1997); Ehrmann and Fratzscher (2004); Bernanke and Kuttner (2005); Kontonikas and Kostakis (2013); Maio (2014)). Stock prices respond positively to monetary easing. These studies typically interpret their findings within the efficient markets framework in which stock prices adjust efficiently as rational agents incorporate monetary policy news. As suggested by a dividend discount model of stock valuation, shifts in monetary policy affect stock prices through changes in the rates that market participants use to discount future cash flows, and through changes in the expected cash flows (Patelis (1997)).[1] In these studies, investor sentiment has no role affecting the response of stock returns to monetary policy news.

On the other hand, behavioural financial economists question the assumptions underlying rational asset pricing, and establish that investor sentiment affects stock prices (Lee, Shleifer, and Thaler (1991); Kumar and Lee (2006); Baker and Wurgler (2006); Stambaugh, Yu, and Yuan (2012); Chung, Hung, and Yeh (2012); Shen, Yu, and Zhao (2017)). However, despite

[1] Using a returns variance decomposition framework, Bernanke and Kuttner (2005) find that revisions in expected returns, that is, discount rate news, explain the impact of monetary policy shocks on the stock market.

the importance of investor sentiment on asset prices, little has been done on the role that sentiment plays in the transmission of news to the stock market. An exception is the study of Mian and Sankaraguruswamy (2012), who investigate the impact of sentiment in the incorporation of accounting information into stock prices.

Motivated by these findings, this thesis investigates how investor sentiment affect the impact of monetary policy shocks on asset prices over the June-1989 to October-2014 sample period. We consider both market-wide stock returns (see Chapter 1) and the cross-section of stock returns (see Chapter 2). Moreover, we also examine how inventor sentiment affects the pre-FOMC stock price drift documented by Lucca and Moench (2015) (see Chapter 3).

Chapter 1 investigates the role that investor sentiment plays in the response of U.S. market-wide stock returns to monetary policy shocks over June-1989 to October-2014. We find that the state of investor sentiment strongly affects the transmission of monetary policy shocks to the stock market. For conventional monetary policy prior to the ZLB, our key findings are as follows. First, the impact of monetary policy shocks on the stock market concentrates on the sentiment-correction phase that follows overvaluation episodes, particularly when sentiment is high at the start of the year but then falls. In contrast, during periods when sentiment starts at low level but then increases and optimism grows, the stock market does not show a statistically significant price reaction to monetary policy shocks. Importantly, these effects of sentiment are not driven by economic recessions or the incorporation of the recent financial crisis in the pre-ZLB sample. Our findings that the market response to the monetary policy news is dependent on the state of sentiment is stronger during monetary policy easing cycles.

Second, the stock market impact of monetary policy shocks is characterized by sign asymmetry. The market response following periods of high sentiment is significant for expansionary FFR surprises, but not tightening surprises. Third, our evidence indicates that accounting for endogeneity does not alter our conclusions. Fourth, the effect of FFR surprises is predominantly contemporaneous and displays only very short-run persistence. Fifth, the positive returns associated with expansionary policy shocks are broad-based across U.S. industries and their pattern is consistent with the implications of the CAPM. The industry effects are also conditional on the state of investor sentiment.

Furthermore, we find that the impact of path surprises is statistically significant only during periods when sentiment decreases. In contrast to the findings from FFR shocks prior to the ZLB, the effect of path surprises is not only driven by expansionary news. We show that, amongst liquidity facilities' and LSAPs' announcements, only those related to the establishment of central bank liquidity swaps matter. Conditional on the state of investor sentiment, the stock market reacted positively to these announcements. Finally, we show that our results remain strong and consistent to a host of robustness checks.

Importantly, this chapter contributes to the nascent line of work that seeks to incorporate findings from behavioural finance to examine the stock market reaction to news, as well as the established literature that studies the effects of the Fed's conventional and non-conventional policy actions on financial markets. We develop a new measure of sentiment states, based upon changes in sentiment and show that it reveals important information about the trading behaviour of investors during periods of sentiment adjustment. Hence, we extend the previous literature on the asset pricing implications of sentiment, which overlooks the dynamic behaviour of sentiment. Our work is also related to the literature on state dependence in the relationship between stock market and monetary policy. Several studies consider business cycle effects and show that the stock market response is stronger during recessions (Basistha and Kurov (2008); Perez-Quiros and Timmermann (2000)). In contrast, our focus is on sentiment states, which have small or zero correlation with the business cycle. Furthermore, sentiment corrections are not solely associated with bear markets but also occur during bull markets. Hence, our analysis is distinct from previous studies that condition the stock market response to policy surprises on bull-bear regimes (Chen (2007); Jansen and Tsai (2010); Kurov (2010)).

This chapter also relates to a recent study by Mian and Sankaraguruswamy (2012), who examine whether stock price changes in response to firm-specific earnings surprises are affected by lagged sentiment. They conclude that behavioral biases affect how accounting information is impounded into stock prices. Our work has a different angle by focusing on market-wide news that stem from shifts in monetary policy, as opposed to firm-specific news. Two other related recent studies are those of Garcia (2013) and Cenesizoglu (2014), who also argue that investors' sensitivity to news is characterised by state dependence. In Garcia's (2013) analysis, however, this is related to the state of the business cycle, with the sensitivity to news being stronger during economic downturns; whereas we focus on sentiment downturns that, as we argue above, are distinct from recessions. Similarly, in Cenesizoglu (2014) it is the underlying state of the economy that matters. This chapter extends previous work by Bernanke and Kuttner (2005), Lucca and Moench (2015) and Savor and Wilson (2014), among others, who find that the CAPM performs well on days associated with monetary policy news. We show that the CAPM does a good job in explaining the observed cross-industry variation of FOMC announcement-day returns only during sentiment-correction phases. Different from our event study analysis, Antoniou et al. (2015) use monthly data for asset-pricing tests and show that the security market line is positively slopped only following low sentiment periods. Finally, a related strand of the literature tests for pre-announcement effects on returns and/or order imbalance and volatility, without, however, accounting for the possible impact of sentiment states (Lucca and Moench (2015); Bernile, Hu, and Tang (2016); Kurov et al. (2017); Neuhierl and Weber (2017); Cieslak et al. (2018)).

In Chapter 2 we analyzes the effect of investor sentiment states on the response of cross-sectional stock returns to monetary policy news using an event study approach over the Jun-89 to Oct-14 sample period. We consider 15 portfolio sorts which are commonly used by previous literature on stock market anomalies: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size).

We first construct a long-short strategy for each portfolio. Specifically, we consider the extreme deciles, 1 and 10 only. We classify the short leg as the decile which is more exposed to investor sentiment. For the pre-ZLB period, we define the deciles which are with lower returns following periods of high sentiment as with higher sentiment-sensitivity. For the ZLB period, because the level of investor sentiment is always low, we define the deciles with higher average returns as with higher sentiment-sensitivity. Our results show that, before the ZLB was reached, stocks with high accruals, young stocks, stocks with high asset growth rate, stocks with low book-to-market ratio, stocks with high cash to asset ratio, stocks with low gross profitability, high investment stocks, past loser stocks, stocks with high net operating assets, distressed stocks, stocks with low asset tangibility, less profitable stocks, stocks with high return volatility, and large stocks are defined as the short leg. However, sentiment-sensitivity for portfolios sorted by total accruals, asset growth, book-to-market ratio, investment to asset, net operating assets, and size have changed, after the ZLB was reached. The short leg of those portfolios at the pre-ZLB period become the long leg at the ZLB period.

Further, we find that, in line with our results on market-wide stock returns in Chapter 1, conventional monetary policy news affect the cross-sectional stock returns only following periods of high sentiment. Unconventional monetary policy affect cross-sectional stock returns only during periods of decreasing sentiment. Importantly, the effect of monetary policy shocks differs across the cross-section of stocks. For the conventional monetary policy shocks, we find a positive and significant impact on the long-short spread of most portfolios following periods of high sentiment, which results from the larger impact on the short-leg. For instance, consider the size-sorted portfolio, the impact of FFR shocks on the short-leg (large) stocks is about four times larger than the impact on the long-leg (small) stocks (-8.01 vs. -1.73). For the unconventional monetary policy shocks, although our results suggest changes in the long-short strategy for some portfolios, we still find that path surprises positively drive the long-short spread, only during periods of decreasing sentiment. It is also the short leg stocks that are more affected. For example, the stocks with high asset growth rate are more exposed to investor sentiment at the pre-ZLB period. During the ZLB period, however, the stocks with low asset growth rate are more sensitive to investor sentiment. Our results point out that, stocks with high asset growth rate are more affected by conventional monetary policy at the pre-ZLB period, and stocks with low asset growth rate are more affected by unconventional monetary policy at the ZLB period. These results indicate that stocks which are more sensitive to investor sentiment, are also more sensitive to monetary policy shocks.

This chapter enhances our argument in Chapter 1, that the state of investor sentiment strongly affects the transmission of conventional and non-convectional monetary policy to asset prices. By investigating the responses of 15 stock portfolios, this chapter contributes to previous studies that examine the differential impact of monetary policy shocks on the returns of portfolios constructed on the basis of fundamental characteristics (Thorbecke (1997); Ehrmann and Fratzscher (2004); Kontonikas and Kostakis (2013); Maio (2014)), which cover only the value, size, momentum and financial constrain anomalies. In addition, our evidence that the region of the cross-section of stocks that are more exposed to investor sentiment are also likely to be more sensitive to monetary policy news indicates the existence of a behavioural channel in the transmission of monetary policy shocks to stock returns.

In Chapter 3, we examine the impact of investor sentiment on the pre-FOMC announcement stock price drift over the period from February 1994 to October 2015. We show that, the state of investor sentiment strongly affects stock returns over the pre-FOMC window, which we define as one day before the scheduled FOMC announcement day, the last trading day before investors can observe signals about policy decisions. We find that the positive drift of the S&P500 index over the pre-FOMC window concentrates only on the sentiment-exuberance state. Specifically, in high sentiment months, the S&P500 index increases about 23 basis points on the pre-FOMC window. In contrast, in low sentiment months, FOMC meetings do not feature statistically significant pre-announcement returns.

Further, we find that the pre-FOMC drift does not contain information about the subsequent outcome of the FOMC announcement. The positive and significant pre-FOMC drift during high sentiment months occurs, regardless of whether the subsequent FOMC announcement delivers an unexpected cut or rise in the FFR. We also find a pre-FOMC effect in the short-term fixed income securities during periods of high sentiment.

Moreover, other macroeconomic releases do not feature statistically significant preannouncement returns, even after we consider the state of investor sentiment. Using the Google Search Volume Index (SVI) as a proxy for investor attention, we show that, compared with other macroeconomic announcements, FOMC announcement grabs more attention among investors. We also find that, the pre-FOMC drift is not related to the business cycle. It is also unrelated to the yet-to-be-realized policy decision, as measured by the unexpected change in the FFR, as defined in Kuttner (2001), or the market participants' expectation about the future path of monetary policy, as measured using the approach of Gürkaynak, Sack, and Swanson (2005). Finally, our evidence shows that there are more buying activities than selling activities, i.e., a positive order imbalance, over the pre-FOMC window during high sentiment months, which points out potential behavioural explanation for the pre-FOMC puzzle.

This chapter contributes to the developing standard of literature that how stock price changes in anticipation of macro-economy and/or monetary policy announcement (Lucca and Moench (2015); Bernile, Hu, and Tang (2016); Kurov et al. (2017)). We extend the literature by incorporating insides behavioural finance. This chapter is the first to show that the positive drift of the S&P500 index occurs only during periods of high sentiment. Our findings of the sentiment conditionality of pre-FOMC drift, together with the inability of the rational based stories to explain the drift, points to a behavioural explanation. Our findings also relates to the studies on pre-announcement drifts of individual stock returns before earnings announcements (see, for example Lamont and Frazzini (2007)). Most of these studies point to the behavioral “attention-grabbing" effect as a potential explanation. Our results offers a new angle by considering the state of investor sentiment.

This chapter also contributes to the literature on the effect of monetary policy shifts on stock prices (Thorbecke (1997); Bernanke and Kuttner (2005); Chen (2007); Wright (2012); Swanson (2015)). These studies mainly focus on the price effect on FOMC announcement days.

The remainder of this thesis is structured as follows. We first review the literature that has been cited in this thesis, and then present the chapters with empirical studies. In Chapter 1 we investigate the impact of investor sentiment states on the response of the U.S market-wide stock returns to monetary policy shocks over the June-1989 to October-2014 sample. In Chapter 2 we investigate the responses of U.S. portfolio returns to monetary policy shocks across different sentiment states over the June-1989 to October-2014 sample. In Chapter 3 we investigate how investor sentiment states affect the pre-FOMC drift in stock returns over February-1994 to October-2015. Chapter 4 concludes. The estimates presented in Chapters 3 has been submitted to a special issue of the European Journal of Finance. The working paper derived from Chapter 1 is available at SSRN (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3184974), and the working paper derived from Chapter 2 will be available online soon.

Literature review

The relationship between monetary policy and asset returns has been extensively researched in the past decades. Recent studies also document the important role that investor sentiment plays in asset pricing. Moreover, researchers also document that there is a stock price drift ahead of FOMC announcements. Given the sheer volume and scope of material, it is important to outline which studies are included in this thesis. In Chapter 1 of this thesis we examine the impact of Federal Funds rate (FFR) shocks on the U.S. market-wide stock returns across different sentiment states following the event study methodology in Bernanke and Kuttner (2005). In Chapter 2 we extend the analyses in Chapter 1, we investigate the impact of FFR shocks on the cross-sectional stock returns across different sentiment states. We consider 15 stock portfolios which have been widely used in previous studies (see e.g. Baker and Wurgler (2006); Stambaugh et al. (2012); Novy-Marx (2013)). In Chapter 3 we provide a behaviorial explanation to the pre-FOMC drift introduced by Lucca and Moench (2015). In this chapter, we review the papers which cited these studies. We start by reviewing the frameworks which examine the impact of monetary policy on stock returns. We subsequently review the studies on investor sentiment and stock returns. Finally, we evaluate the empirical studies which link monetary policy to investor sentiment.

On monetary policy and stock returns

The response of stock returns to monetary policy

There is a large number of studies on monetary policy and stock returns in the past decades. Most of the early studies use the VAR model to examine the response of stock returns to monetary policy. Since 1990s, more and more studies started to use the event study methodology to analyse the impact of monetary policy on stock returns. According to Rigobon and Sack (2004) the event study methodology avoids the pitfalls of endogeneity and lack of identification by developing and employing a truly exogenous measure of monetary policy shocks. In this thesis, we also employ an event study methodology to examine the impact of monetary policy on stock returns across different sentiment states. Thus, in this literature review section, we mainly focus on the papers which employ an event-study methodology or examine the state-dependence of monetary policy impact.

Thorbecke (1997) examine the impact of monetary policy on stock returns with both the VAR and the event study methodology. In their event study analysis, they measure monetary policy shocks as the changes in the federal funds rate. They find that changes in the federal funds rate are negatively related to stock returns, which is the same as the results they obtained from the VAR model. Their evidence on the size-sorted stock portfolio show that monetary shocks have larger effects on small firms than large firms.

Krueger and Kuttner (1996) argue that the Fed funds futures rate could be used as a predictor of federal reserve policy. The show that FFR futures provided efficient and unbiased forecasts of the target FFR. They find that there is a very small risk premium in FFR futures, and that they were good at forecasting potential future target FFR changes by the Fed. They concluded that "traders, investors, or economists interested in predicting near-term Fed actions would be hard pressed to improve on the Fed funds futures rate." In a subsequent study, Kuttner (2001) provide a measure of monetary policy surprises extracted from the FFR futures contract. The measure is defined as the difference between the actual realised target FFR and the expected FFR gauged from the one-month ahead 30-Day FFR futures contract which tracked the underlying instrument of the effective FFR. They employ an event study analysis, and the event-dates considered are the FOMC meeting days when the Fed changed the target FFR. On each event-day, they measure measured the unexpected component of FFR changes (Δi_t^u) as the change in the implied rate on the spot-month FFR futures contract ($f_{m,t}^0$), as traded on the CBOT, relative to the day before the change ($f_{m,t-1}^0$). In order to counteract the fact that the settlement price for the FFR future contract was based upon the average effective FFR over the month, they developed a scaling adjustment for the unexpected FFR changes related to the number of days in the month affected by the change. Equation 1 presents the definition of the unexpected FFR shocks.

$$\Delta i_t^u = \frac{D}{D-t}(f_{m,t}^0 - f_{m,t-1}^0) \tag{1}$$

Where $f_{m,t}^0$ is the current-month implied futures rate (100 minus the futures contract price), and D is the number of days in the month. Moreover, when the FOMC meeting falls on one of the last three days of the month, the unscaled change in the one-month futures rate ($f_{m,t}^1 - f_{m,t-1}^1$) is used to calculate the FFR surprise. Also, when the FOMC meeting occurs on the first day of the month, $f_{m-1,D}^1$, instead of $f_{m,t-1}^0$, is used to measure the surprise. They also consider the expect component of FFR change, which is calculated as the actual target FFR changes minus the computed unexpected FFR changes:

$$\Delta i_t^e = \Delta i_t - \Delta i_t^u \tag{2}$$

They then examine the impact of Δi_t^e and Δi_t^u on bill, note, and bond yields. They find that there is a strong relationship between the unexpected component of FFR changes and the market interest rates. However, the response to expected changes is small. This methodology of defining unexpected FFR changes subsequently became one of the most popular measures of defining monetary policy shocks in the empirical literature.

Following the event study analysis of Kuttner (2001), Bernanke and Kuttner (2005) examine the impact of monetary policy on daily stock returns on the FOMC meeting days. They consider both scheduled and unscheduled FOMC meetings over June 1989 to December 2002. They also investigate the impact of both expected and unexpected FFR changes.

$$R_t = \beta_0 + \beta_1 \Delta i_t + \varepsilon_t \tag{3}$$

$$R_t = \beta_0 + \beta_1 \Delta i_t^e + \beta_2 \Delta i_t^u + \varepsilon_t \tag{4}$$

Their evidence show that there is no significant impact of the actual target FFR changes on market-wide stock returns. However, they find that unexpected component of the FFR changes significantly affect stock returns on the FOMC meeting days. Specifically, an unanticipated 25-basis-point cut in the Federal funds rate target is associated with about a 1% increase in broad stock indexes. Moreover, consistent with the efficient markets hypothesis, according to which that the expected component of monetary policy has already been priced into the market, they find that the impact of the expected FFR changes on stock returns is statistically insignificant. They further a sub-sample analysis, which is from February 1994 to December 2002. In February 1994 the Fed started to announce its decisions and publish accompanying statements, a development that enhanced transparency in monetary policy. They find that the coefficient of unexpect FFR changes on market-wide stock returns become larger (-8.13%) and statistically significant for the post-1994 period. The coefficient decrease in magnitude, but remains significant after controlling for outliers. Bernanke and Kuttner (2005) also develop a measure of monthly FFR shocks.

$$\Delta i_t^u = \frac{1}{D} \sum_{d=1}^{D} i_{t,d} - f_{m-1,D}^1 \tag{5}$$

where $i_{t,d}$ is the funds rate target on day d of month t, and $f_{m-1,D}^1$ is the rate corresponding to the 1-month futures contract on the last (Dth) day of month t-1.

They examine the responses of Fama-French industry portfolio returns to expected and unexpected FFR changes, using monthly data. They find that the 10 stock portfolio returns are negatively related to FFR unexpected changes, however insignificant responses were observed for Energy and Utilities. The strongest significant negative responses were yielded for Telecoms (-16.10%), High Tech (-14.73%) and Durables (-12.45%). They also investigate whether monetary policy affects stock values through its effects on real interest rates,expected future dividends,or expected future stock returns. They use the VAR based decomposition method of Campbell and Ammer (1993), and they find that monetary policy's impact on equity prices comes predominantly through its effect on expected future excess equity returns.

Ehrmann and Fratzscher (2004) also analyses the effects of U.S. monetary policy on stock markets using an event study methodology. They also focus on the unexpected component of monetary policy. Similar to Kuttner (2001) and Bernanke and Kuttner (2005), monetary policy surprise is defined as the difference between the announcement of the FOMC decision and the market expectation. However, different to these studies, they did not extract the unexpected component of FFR from the FFR futures contract. Instead, the expectation data for monetary policy decisions originate from a Reuters poll among market participants, conducted on Fridays before each FOMC meeting. They use the mean of the survey as the expectations measure. They find that monetary policy affects individual stocks in a strongly heterogeneous fashion. Industrial sectors that are cyclical and capital-intensive react frequently two to three times stronger to U.S. monetary policy than non-cyclical industries. They also find that firms that are financially constrained respond significantly more to monetary policy than less constrained ones. Specifically, firms with low cash flows, small size, poor credit ratings, low debt to capital ratios, high price-earnings ratios, or a high Tobin's q are affected significantly more by monetary policy.

Chen (2007) provide evidence that the impact of monetary policy on stock returns is state dependent. They employ the Markov-switching model framework and consider various measures of monetary policy, including discount rate changes, FFR changes and orthogonalized innovations from VAR models. They find that monetary policy has larger effects on stock returns in bear markets. Because the aggregate measures considered were subject to critique concerning potential endogeneity and measurement error associated with aggregate monthly data, they also employ an event study methodology. Similar to Ehrmann and Fratzscher (2004), they measure FFR shocks by gauging expectations from survey data, and extending the linear specification of their model to a Markov-switching framework. Their event study results also show that the impact of monetary policy shocks on stock returns is larger in the bear market. Jansen and Tsai (2010) also find similar results, that monetary policy shocks have larger impact on stock returns in the bear market. Moreover, they show that controlling for the capacity for external finance, stock returns of firms in bear states respond more than firms in bull states. Capacity for external finance is more important in a bear market, as it partially mitigates the larger impact of monetary policy in a bear market.

Basistha and Kurov (2008) examines cyclical variation in the effect of Fed policy on the stock market. They utilise an equivalent dataset and employ the same event study methodology of Bernanke and Kuttner (2005). They find that the effect of unexpected changes in the fed funds target rate on stock returns depends on the state of the business cycle and on credit market conditions. Specifically, during the NBER recession periods, the coefficient of the monetary surprise in recession is about -6.83, which indicates that a hypothetical unexpected 100-basis point cut of the fed funds target during recessions lead to a stock prices jump of 6.83 percent. In contrast, during economic expansion, the coefficient is only -2.68. The impact of FFR shocks on stock returns during recessions is more than double the size of the impact in expansions. They also investigate the impact of FFR shocks on stock returns across different credit conditions. They consider two credit conditions indicators: the percentage of loan officers reporting tightening credit standards, and the spread between higher yielding bonds and AAA rated bond yields, both normalised by sample mean and standard deviation. The response of stock returns to FFR shocks doubled in magnitude when the credit conditions variable increased by one standard deviation. This implies that stocks are associated with larger magnitude responses to monetary policy shocks during periods of tightening credit market conditions. Moreover, in the cross-section, they show that financially constrained firms respond more than relatively unconstrained firms to monetary shocks in adverse macroeconomic conditions.

Kontonikas, MacDonald, and Saggu (2013) examine the response of US stock returns to FFR surprises between 1989 and 2012, with an emphasis on the impact of the recent financial crisis, using the same event study methodology of Bernanke and Kuttner (2005). They find that outside the crisis period, there is a significant negative relationship between FFR shocks and stock returns. However, an important structural shift occurs during the crisis, changing the response of stock returns to FFR shocks and the nature of state dependence. Throughout the crisis period, stocks did not react positively to unexpected FFR cuts, which were interpreted as signals of worsening future economic conditions. Their findings highlight the severity of the crisis and the ineffectiveness of conventional monetary policy close to the zero lower bound.

During the 2007-2009 financial crisis, due to the ineffectiveness of conventional monetary policy, the Fed applied unconventional monetary policy, which includes the forward guidance, the provision of non-sterilized liquidity facilities and the large scale purchases of longer-term assets from the private sector.

Forward guidance implies that the central bank attempts to influence the path of future short-term rates by communicating to the public and financial markets. Forward guidance has been intensively used since 2009, but it has long been a part of the Fed's toolkit, with elements of it traced to FOMC statements of the Greenspan era. Gürkaynak, Sack, and Swanson (2005) develop a methodology to identify two dimensions of the Fed's policy: changes in the current FFR target and changes in forward guidance. They show that both target surprises and path surprises are useful to describe monetary policy shocks. Path surprises should capture news conveyed to market participants by the FOMC's statement about the expected path of policy above and beyond what they learn for the FFR target level. They calculate path surprises using principal component analysis. Using an event study methodology, they find that path surprises have no significant impact on stock returns over the January 1990 to December 2004 sample period. However, they find that path surprises have a great impact on longer-term Treasury yields.

Ait-Sahalia et al. (2012) examines the impact of macroeconomic and financial sector policy announcements in the United States, the United Kingdom, the euro area, and Japan on interbank credit and liquidity risk premia during the crisis. Using an event study methodology, they find that market significantly moves surrounding announcements related to central bank liquidity swaps. Wright (2012) use a high-frequency event-study approach to examine the impact of the LSAP program. They find that stimulative monetary policy shocks lower Treasury and corporate bond yields, but the effects die off fairly fast, with an estimated half-life of about two months. In a subsequent paper, Rogers et al. (2014) examine the effects of unconventional monetary policy by the Federal Reserve, Bank of England, European Central Bank and Bank of Japan on bond yields, stock prices and exchange rates. They use intraday data to identify monetary policy surprises (MPS) through changes in bond yields. Specifically, they focus on the days with LSAP announcements. They findings show that the unconventional monetary policy are indeed effective in easing broad financial conditions.

Stock price drift before monetary policy announcements

In the past few decades, the majority of the studies on monetary policy focus on the post-FOMC announcement response of stock returns. However, there are also several studies which examine the pre-announcement drift in the stock market. Bomfim (2003) examine pre-announcement effects on the stock market in the context of public disclosure of monetary policy decisions. They focus on a pre-announcement window which is one day right before a scheduled FOMC announcement. They find that the conditional volatility is abnormally high on FOMC announcement days. However, on the pre-announcement window, they find a “calm-before-the-storm" effects in the stock market, according to which the conditional volatility is abnormally low. They also document that the effect is significant only after February 1994, when the FOMC started to adopt the practice of making its policy decisions during the days of regularly scheduled FOMC meetings.

In a recent paper, Lucca and Moench (2015) find large average excess returns on U.S.equities in anticipation of monetary policy decisions made at scheduled meetings of the FOMC in the past few decades. They refer this phenomenon as the pre-FOMC announcement drift. They use intraday data on the S&P500 index over February 1994 to March 2011, and they employ a pre-announcement window, which is from 2p.m on the day before a scheduled FOMC announcement to 2pm on the announcement days. Their findings show that since 1994, there is an increase of 49 basis points in the S&P500 index in the 24 hours before scheduled FOMC announcements. These returns do not revert in subsequent trading days and are orders of magnitude larger than those outside the 24-hour pre-FOMC window. As a result, about 80% of annual realized excess stock returns since 1994 are accounted for by the pre-FOMC announcement drift. They also find that the realized volatility and trading volume are lower in the pre-announcement window as compared to other days. Moreover, they show that the pre-FOMC drift happens in other major international equity indices. However, there is no such effect in U.S. Treasury securities and money market futures. Furthermore, they show that there is no significant stock price drift ahead of other major U.S. macroeconomic news announcements. They also show that the pre-FOMC drift is not affected by business or monetary cycles. They examine several explanations, however, none of them could fully explain the pre-FOMC drift. First, the pre-FOMC drift cannot be explained by the traditional asset pricing theory, according to which higher returns are earned as compensations for higher systematic risks. Their evidence shows that both the realized and implied volatility are actually lower on the pre-announcement window. They also consider the information leakage story. However, they find that the pre-FOMC drift is not related to the monetary policy shocks after the announcements. Moreover, motivated by the lower trading volume and volatility level on the pre-FOMC window, they consider another explanation based on the “volatility feed" back effect. According to Campbell and Hentschel (1992), because of its persistence, an unexpected decline in volatility leads to a downward revision in future expected volatility, and thus to lower risk and higher contemporaneous returns. They examine the pre-FOMC drift again after controlling for the liquidly and volatility. Their findings show that, although decreases by about 20% in magnitude, the pre-FOMC drift is still statistically significant. Thus the “volatility feed" back effect can only partially explain the pre-FOMC drift. They call the pre-FOMC drift as a “puzzle".

Following Lucca and Moench (2015), Bernile et al. (2016) also examine the pre-FOMC drift. Different to Lucca and Moench (2015), they employ a narrow (1-hour) window ahead of scheduled FOMC announcements, with an emphasis on the news embargo periods. They find that investors’ trading activity, as proxied by the E-mini S&P500 futures’ abnormal order imbalances (measured as the difference between buyer- and seller-initiated trading volumes divided by the total trading volume), is in the direction of subsequent policy surprises and contain information that predicts the market reaction to the policy announcements during the embargo periods. Specifically, the abnormal order imbalances are 7.75–8.73% higher for FOMC surprise announcements compared with non-surprise ones. They argue that information leakage is the main drive of the pre-FOMC drift during such periods. They find similar pre-FOMC drift in the order imbalances of some other futures contracts. However, there is no evidence of pre-announcement drift ahead of other macro-economic announcements. Kurov et al. (2017) also investigate the pre-announcement drift with an expanded set of 20 macroeconomic announcements. They also find evidence of informed trading on the pre-announcement window. With a detailed discussion of the pre-announcement information leakage, they show that pre-announcement informed trading is limited neither to the FOMC announcements nor to the last minute before the official release time. Specifically, their findings show that the pre-announcement information leakage is most likely to happen ahead of announcements released by organizations that are not subject to Principal Federal Economic Indicator (PFEI) guidelines. Moreover, they also find that the pre-announcement information leakage is related to the release procedures. The release procedures fall into one of three categories. The first category involves posting the announcement on the organization's website at the official release time, so that all market participants can access the information at the same time. The second category involves pre-releasing the information to selected journalists in "lock-up rooms". The third category involves the least secure pre-release procedure: Instead of being pre-released in lock-up rooms, these announcements are electronically transmitted to journalists who are asked not to share the information with others. They find that the announcements pre-released under the least secure procedure are associated with a stronger pre-announcement drift. In a most recent study, Boguth et al. (2018) show that a large risk premium is earned in the 24 hours preceding FOMC announcements. They argue that the large risk premium corresponds with high uncertainly and high investor attention level. Thus the pre-FOMC drift is a result of investors' massive attention on the FOMC meetings. Moreover, they show that, since 2011, the large risk premium and stock price drift ahead of a FOMC announcement occur only if the Chair of the Federal Reserve holds a press conference after the FOMC announcement. The risk premium is small ahead of the FOMC announcements which are not followed by a press conference and there is no pre-FOMC stock price drift either. One possible explanation is that if there is no scheduled press conference after a FOMC meeting, investors will not pay too much attention to that meeting. The lack of attention leads to the disappearing pre-FOMC drift on these days.

On investor sentiment and stock returns

"*Classical finance theory leaves no role for investor sentiment.*" (Baker and Wurgler (2006))

Investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by the facts at hand (Baker and Wurgler (2007)). Traditional finance model, according to which investors are fully rational, suggests that investors will diversify to optimize the statistical properties of their portfolios. This leads to the equilibrium that stock price equals the rational present value of expected future cash flows. However, in the real world, there are many events that defy the rational explanation: the Great Crash of 1929, the Tronics Boom of the early 1960s, the Go-Go Years of the late 1960s, the Nifty Fifty bubble of the early 1970s, the Black Monday crash of October 1987, and the Internet or Dot.com bubble of the 1990s. Therefore, researchers in behavioral finance challenge the view that investors are fully rational, and present evidence that psychological and behavioral elements impact stock prices.

De Long et al. (1990) examine the noise trader risk in the financial market. They develop a model according to which there are two types of investors in the stock market: rational and irrational traders. Rational traders (who are usually treated as arbitrageurs) are sentiment-free. Irrational (noise) traders, however, are subject to exogenous sentiment. They provide evidence that the unpredictable noise traders' beliefs create a risk in the price of the asset, as a result, noise trading could drive the market price away from its fundamental values, even in the absence of fundamental risk. They argue that the attractiveness of arbitrage are reduced due to the risk created by the opinions of irrational traders. In a market where noise traders are presented, rational arbitrageurs are limited in various ways. Because movements in investor sentiment are unpredictable, arbitrageurs need to run the risk to bet against mispricing. As a consequence of such 'noise trader risk,' arbitrage positions can lose money in the short run. Shleifer and Vishny (1997) expand the discussions on the limits of arbitrage. They develop a model in which both the noise traders and the arbitrageurs are considered. Their evidence also shows that betting against sentimental investors is costly and risky. The assumptions developed in these studies, that investors are subject to sentiment and there are limits to arbitrage, have been widely used by researchers in behaviorial finance.

Kahneman and Tversky (1979) develop the prospect theory, according to which investors evaluate outcomes according to their perception on gains and losses relative to a reference point, typically the purchase price. They do not concern final wealth levels; investors are more sensitive to losses than to gains of the same magnitude (loss aversion); and investors are risk-averse for gains and risk seeking for losses. Thus, investors' behaviorial biases can produce overreaction to some events and underreaction to others (Barberis et al. (1998)). The study of Hong and Stein (1999) shows that the medium-term momentum phenomena can be understood by appealing to investor underreaction due to the slowly diffusing news about future fundamentals. In principle, underraction can be linked with varies behavioral mechanisms. For example, Barberis et al. (1998) argue that it is the conservatism bias (see also Edwards (1968)) that leads to the underraction. Baker and Stein (2004) link underreaction with investor sentiment. According to the model they develop, when short-sales constraint is considered, as dumb (sentiment) investors become more optimistic, smart investors will be driven to the sidelines. Because overconfident dumb investors rely more on their own private information, and underreact to the information contained in trade, the market become more liquid. They argue that liquidity is a good proxy of investor sentiment. If a market is unusually liquid, then the prices are being dominated by irrational investors, who tend to underreact to the information embodied in either order flow or equity issues. Thus high liquidity is a sign that the sentiment of these irrational investors is positive, and that expected returns are therefore abnormally low.

These theoretical studies show that investor sentiment plays an important role in asset pricing. However, the sentiment sources are not straightforward to measure. In order to empirically examine the role of investor sentiment in the capital market, researchers employed several proxies of investor sentiment in the past few decades. Most of these studies focus on either (or both) (1) the relation between changes in a proxy for sentiment and contemporaneous returns or (2) the relation between a proxy for sentiment levels and subsequent returns. Moreover, the literature examines these issues for both the market (e.g., do high sentiment levels forecast lower future market returns?) and the cross-section of returns (e.g., do high sentiment levels forecast small stocks subsequently underperforming large stocks?).

Investor Surveys. A direct measure of investor sentiment could be obtained by asking investors how optimistic they are. There are several survey-based sentiment measures that have been widely used in previous studies. For example, the bull-bear spread extracted from the Investors Intelligence surveys. Investors Intelligence compiles a weekly bull-bear spread by categorizing approximately 150 market newsletters. Each week, the newsletters are read and marked as bullish, bearish, or neutral again based on the expectation of future market movements. Another commonly used sentiment measure is the Consumer Sentiment Index (CSI) compiled by the University of Michigan. The CSI is based on surveys conducted by the University of Michigan in which 500 U.S. participants are asked questions about their outlook on the economy. The Consumer Confidence Index (CCI) compiled by the Conference Board is also a survey-based sentiment index that has been widely used in previous studies. Compared with the CSI, it uses a larger pool of respondents (5,000) and somewhat different questions. Using these sentiment measures, researchers find empirical evidence that investor sentiment plays an important role in asset valuation. Brown and Cliff (2005) shows that the bull-bear spread extracted from the Investors Intelligence surveys could predict future stock returns. They find that market pricing errors implied by an independent valuation model are positively related to sentiment. Moreover, they find that high investor sentiment is followed by lower market returns over the next 1–3 years. Lemmon and Portniaguina (2006) explore the time-series relationship between investor sentiment and the small-stock premium using CCI as a measure of investor optimism. They find that investor sentiment forecasts the returns of small stocks and stocks with low institutional ownership in a manner consistent with the predictions of models based on noise-trader sentiment. Moreover, Stambaugh, Yu, and Yuan (2012) explore the role of investor sentiment in a broad set of anomalies in cross-sectional stock returns. They argue that, due to the short-sale impediments, overpricing should be more prevalent than underpricing. Then, anomalies should be stronger following periods of high sentiment, to the extent that the anomalies reflect mispricing. Using CSI as a measure of investor sentiment, they find evidence that support their view. Periods of high sentiment are followed by low returns in both the long and the short legs. Specifically, because the short legs of the strategies are more exposed to investor sentiment, the returns of the short legs go much lower, as compared to the long legs, which leads to the stronger anomalies following periods of high sentiment.

Investor Mood. There are also papers that measure fluctuations in investor sentiment as exogenous changes in human emotions. Using an event study methodology, previous studies have linked stock returns either to a single event or to a continuous variable that impacts investor mood. For example, Kamstra et al. (2003) find that the market-wide stock returns are on average lower through the fall and winter, during which the seasonal depression is more pronounced. They argue that declining hours of daylight in the winter affect human sentiment, risk tolerance, and in turn, stock returns. They report patterns from different latitudes and both hemispheres which also appear consistent with this interpretation. Hirshleifer and Shumway (2003) investigate the relationship between weather and stock returns. They find that morning sunshine in the city of a country's leading stock exchange is strongly significantly correlated with stock returns. They attribute this phenomena to the phycological argument that sunny weather is associated with upbeat mood, and optimism among investors leads to an increase in the stock returns. Edmans et al. (2007) also examine the stock market reaction to sudden changes in investor mood. They proxy investor mood by international soccer results. They find a significant market decline after soccer losses. For example, a loss in the World Cup elimination stage leads to a next day abnormal stock return of -49 basis points. This loss effect is stronger in small stocks and in more important games. They also find a loss effect after international cricket, rugby, and basketball games. However, there is no evidence of a corresponding reaction to wins in any of these sports. Moreover, Cao and Wei (2005) link temperature to market-wide stock returns. They find a significant negative relationship between temperature and stock returns in eight international markets. They attribute this to the notion that lower temperatures can cause aggression, which in turn, leads to high stock returns.

Retail Investor Trades. Because the inexperienced retail or individual investor is more likely than the professional to be subject to sentiment. It is reasonable to proxy investor sentiment by retail investor trades. Using the transaction data of 1.85 million retail investors over 1991–1996, Kumar and Lee (2006) show that retail investors buy and sell stocks in concert, which is consistent with systematic sentiment. Moreover, they find that the retail investor sentiment proxied by retail investor trades has incremental explanatory power (over the standard risk factors and innovations in macroeconomic variables) for small stocks, value stocks, stocks with low institutional ownership, and stocks with lower prices. When retail investors grow relatively bullish (bearish), the stocks in these portfolios enjoy higher (lower) contemporaneous excess returns. They also find that, stocks which are difficult to arbitrage are more sensitive to changes in retail sentiment. In a following study, Barber and Odean (2007) investigate the implications of retail investor trades for subsequent, rather than contemporaneous, cross-sectional returns over a longer sample period. They find that small trade order imbalance forecasts future returns; stocks heavily bought underperform stocks heavily sold by 4.4 percentage points the following year. They also document that small stocks are most likely to be influenced by trades of retail investors.

Mutual Fund Flows. According to Frazzini and Lamont (2008), individual retail investors actively reallocate their money across different mutual funds. One can measure individual sentiment by looking at which funds have inflows and which have outflows. Brown, Goetzmann, Hiraki, Shirishi, and Watanabe (2003) propose a market sentiment measure which is based on how fund investors are moving into and out of, for example, "safe" government bond funds and "risky" growth stock funds. They find evidence that is consistent with the hypothesis that daily mutual fund flows may be instruments for investor sentiment about the stock market. Moreover, Frazzini and Lamont (2008) examine the dumb money effect. They show that individual investors send their money to mutual funds which own stocks that do poorly over the subsequent few years (dumb money). They use mutual fund flows as a measure of individual investor sentiment for different stocks. They find that when funds holding a particular stock experience strong inflows, the subsequent return of that stock is lower. They also document that the dumb money effect is related to the value effect: high sentiment stocks tend to be growth stocks. Ben-Rephael, Kandel, and Wohl (2012) also measure investor sentiment as the net exchange between bond funds and equity funds. Different to Frazzini and Lamont (2008), which focus on individual stocks, their focus is on the effect of mutual fund investments on the market as a whole. Using the aggregate mutual fund flows data over January 1984 to December 2008, they find that one standard deviation of net exchanges is related to 1.95% of the contemporaneous market returns, while about 85% of the contemporaneous relation is reversed within four months, and the remainder is reversed within ten months. At the portfolio level, they also find that the sentiment effect is stronger in smaller stocks and in growth stocks.

Option Implied Volatility. The CBOE Volatility Index (VIX) is constructed on any trading day using the implied volatilities of options on equities in the S&P 100 index (Bandopadhyaya and Jones (2008)). It is commonly referred to as the fear index or the fear gauge. For example, Whaley (2000) discusses the spikes in the VIX series since its 1986 inception, which include the crash of October 1987 and the 1998 Long Term Capital Management crisis.

Trading Volume. Previous studies also use trading volume, or more generally liquidity, as an investor sentiment measure. According to the model developed by Scheinkman and Xiong (2003), over confidence and speculative bubbles are accompanied by large trading volume and high price volatility. Moreover, Baker and Stein (2004) show that irrational investors are more likely to trade, and thus add liquidity, when they are optimistic and betting on rising stocks rather than when they are pessimistic and betting on falling stocks. Baker and Wurgler (2007) argue that the ratio of trading volume to the number of shares listed on the New York Stock Exchange (NYSE), is a simple proxy for this concept.

Closed-End Fund Discount. Closed-end funds are investment companies who issue a fixed number of shares, which then trade on stock exchanges. The closed-end fund discount is the difference between the net asset value of a fund's actual security holdings and the fund's market price. If closed-end funds are disproportionately held by retail investors, the average discount on closed-end equity funds may be a sentiment index, with the discount increasing when retail investors are bearish (Baker and Wurgler (2007)). There is a series of papers which debate about closed-end fund discounts as a measure of sentiment. For example, Lee, Shleifer, and Thaler (1991) find that the discounts on closed-end funds narrow when small stocks do well. Neal and Wheatley (1998) also find that the closed-end fund discounts predict the difference between small and large firm returns using data from 1933 to 1993.

Sentiment Matrix. As presented above, a number of sentiment proxies have been used in previous studies. However, there are no definitive or uncontroversial measures. Baker and Wurgler (2006) form a composite sentiment index, which is based on the common variation in six underlying proxies of investor sentiment: the closed-end fund discount (CEFD), NYSE share turnover (TURN), the number and average first-day returns on IPOs (NIPO and RIPO), the equity share in new issues (S), and the dividend premium (P_{t-1}^{D-ND}). They measure investor sentiment as the first principal component of the correlation matrix of the six variables (or their lags). Moreover, in order to remove the impact of macro-economic factors on investor sentiment, they also provide an orthogonalized version of investor sentiment index. They regress the six variables on five macro-economic variables: the growth in the industrial production index (Federal Reserve Statistical Release G.17), growth in consumer durables, nondurables, and services (all from BEA National Income Accounts Table 2.10), and a dummy variable for NBER recessions. They take the first principal component of the six residuals series from these regressions as the “pure" sentiment measure, which is immune to macro-economic variations. Specifically, the orthogonalized sentiment index is obtained with the following equation:

$$\begin{aligned} Sentiment_t = &-0.198CEFD_t + 0.225TURN_{t-1} + 0.234NIPO_t \\ &+ 0.263RIPO_{t-1} + 0.211St - 0.243P_{t-1}^{D-ND} \end{aligned} \tag{6}$$

They investigate how investor sentiment affects the cross-section of stock returns. They find that when beginning-of-period proxies for sentiment are low, subsequent returns are relatively high for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. When sentiment is high, on the other hand, these categories of stock earn relatively low subsequent returns. The BW’s composite sentiment index has been widely used in the previous studies (see e.g Yu and Yuan (2011); Stambaugh, Yu, and Yuan (2012); McLean and Zhao (2014)). Moreover, Huang et al. (2015) use the partial least squares (PLS) method to develop a new sentiment index, based on an extension of the BW approach, aiming to align the investor sentiment measure with the purpose of predicting future stock returns. By eliminating a common noise component in sentiment proxies, they argue that their new index has much greater predictive power than the existing sentiment indices.

Searching Volume. Da et al. (2014) use daily Internet search volume as a proxy of market-level sentiment. They aggregate the Google searching volume of queries related to household concerns (e.g., “recession, “unemployment," and “bankruptcy"), they construct a Financial and Economic Attitudes Revealed by Search (FEARS) index as a new measure of investor sentiment. They find that the their FEARS index predicts aggregate market returns in a way that is consistent with theories of investor sentiment. In particular, the FEARS index is correlated with low returns today but predicts high returns tomorrow, and such effect is stronger among stocks that are favored by sentiment investors and are difficult to arbitrage.

Most of the studies on investor sentiment focus on the contemporaneous impact or the predict power of investor sentiment on asset pricing. There are also studies which consider investor sentiment as a state factor. Yu and Yuan (2011) investigate the market’s mean–variance tradeoff across different sentiment states. The sentiment proxy they use is the sentiment index developed by Baker and Wurgler (2006). They find that the there is a positive relationship between stock market's expected excess return and the market's conditional variance during periods of low sentiment. During periods of high sentiment, however, the relationship becomes insignificant. A plausible explanation is that there are more sentiment traders in the market during the high sentiment periods. Sentiment traders tend to be inexperienced and naive investors, who are likely to have a poor understanding of how to measure risk. Thus heavy presence of sentiment investors during high sentiment periods should undermine an otherwise positive mean–variance tradeoff in the stock market. They also document a negative correlation between returns and contemporaneous volatility innovations in the low-sentiment periods, which is consistent with the stronger positive ex ante relation during such periods. Mian and Sankaraguruswamy (2012) examine how market-wide investor sentiment (proxied by the sentiment index of Baker and Wurgler (2006)) affects the response of stock returns to firm-specific earnings news. Their findings show that the stocks prices are more sensitive to good earnings news during high sentiment periods. During periods of low sentiment, however, stock prices are more sensitive to bad earnings news. The impact of sentiment is especially pronounced for the earnings news of small stocks, young stocks, high volatility stocks, non-dividend-paying stocks, and stocks with extremely high and low market-to-book ratios. They argue that misreaction to earnings news is one possible channel through which sentiment causes mispricing of stocks. Antoniou et al. (2013) examine how investor sentiment states affect the profitability of momentum strategies. They sentiment measure they use is the Consumer Confidence Index. They argue that news which contradicts investors' sentiment are diffusing slowly. Thus, losers (winners) become underpriced under optimism (pessimism). They show that momentum profits arise under optimism. An analysis of net order flows from small and large trades indicates that small investors are slow to sell losers during optimistic periods. Momentum-based hedge portfolios formed during optimistic periods experience long-run reversals. Li and Luo (2016) provide a sentiment-based explanations of the positive cross-sectional relation between cash holdings and future stock returns using the sentiment index of Baker and Wurgler (2006). They find that the cash holding effect is significant when sentiment is low, especially among stocks with high transaction costs, high short selling costs, and large idiosyncratic volatility. When sentiment is high, however, the effect is insignificant. A plausible explanation is that, due to the limits-to-arbitrage, high costs and risk prevent rational investors from exploiting the cash holding effect during periods of high sentiment. Shen et al. (2017) provide a sentiment-based explanation to the fact that firms with high exposure to macro risk factors do not earn higher unconditional expected returns. Using the sentiment index developed by Baker and Wurgler (2006), they find that high-risk firms earn significantly higher returns than low-risk firms following low-sentiment periods whereas the exact opposite occurs following periods of high-sentiment. They argue that it is because sentiment-driven investors undermine the traditional risk-return tradeoff during high-sentiment periods.

On monetary policy and investor sentiment

Previous studies show that investor sentiment plays an important role in the financial market, however, only a limited number of studies have linked investor sentiment to monetary policy. Kurov (2010) investigate the impact of conventional monetary policy shocks on market-wide investor sentiment proxied by the sentiment index of Baker and Wurgler (2006) and the bull-bear spread extracted from the Investor Intelligence survey. Using an event study methodology, they show that conventional monetary policy affect investor sentiment in bear market periods, but not in bull market periods. Specifically, they find that a 100 basis point cut in the fed funds target rate in bear market leads to a seven standard deviations increase in investor sentiment, as proxied by the BWI. They argue that investors are likely to pay more attention to Fed policy decisions in bear markets because of intense media coverage and due to the fact that the Fed is often viewed as the provider of the market-wide "put." The increased level of investor attention is likely to contribute to the effect of monetary shocks on sentiment in bear markets. Moreover, they also examine the effect of sensitivity of stock returns to sentiment changes on the response of disaggregated stock returns to monetary news. They find that the stocks which have a larger sentiment β (more sensitive to changes in investor sentiment), are more exposed to target rate surprises in bear market periods. Lutz (2015) investigate the impact of conventional and unconventional monetary policy on several sentiment indices. The sentiment measures they used include the sentiment index of Baker and Wurgler (2006), the Consumer Sentiment Index compiled by the University of Michigan, the bull-bear spread extracted from the Investor Intelligence survey, the mutual funds flow, the closed-end fund discount and the Gallup U.S. Daily Economic Conditions Index. For conventional monetary policy, they employ a structural factor-augmented vector autoregression framework. Their results show that expansionary conventional monetary policy shocks increase investor sentiment. For unconventional monetary policy, they use an event study methodology. They also find that unconventional monetary policy shocks have an economically meaningful impact on investor sentiment.

Although few studies have empirically linked investor sentiment to monetary policy. Investor sentiment is one of the key concerns of central bankers, especially at the unscheduled meetings. For example, the former Fed chair Greenspan states in his book that "*The deflation of the tech-stock bubble had been the great financial drama of the preceding months. The NASDAQ lost a stunning 50 percent of its value between March [2001] and year-end...while the total losses were small in comparison with the paper wealth that the bull market had created, these were significant declines, and the Wall Street outlook remained gloomy, putting a damper on public confidence....**the downturn was at the top of the agenda...Sentiment...usually does not shift smoothly from optimism to neutrality to gloom; it's like the bursting of a dam, in which a flood backs up until cracks appear and the dam is breached. The resulting torrent carries with it whatever shreds of confidence there were, and what remains is fear.** We seemed to* *be confronting such a breach....On January 3, the first business day of the New Year, we convened again via conference call and cut the fed funds rate by half percentage point."*(Greenspan (2007)). Moreover, according to Bernanke and Kuttner (2005), the large effect of monetary shocks on expected excess returns may be related to the influence of monetary policy on the riskiness of stocks or on investor risk aversion. They note, however, that their results are also consistent with investor overreaction or excess sensitivity of stock prices to monetary shocks. In other words, investor psychology may play a significant role in the response of equity investors to monetary news.

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Chapter 1

Investor Sentiment Regimes and the Market-Wide Stock Price Reaction to Monetary Policy

1.1 Abstract

This chapter shows that the state of investor sentiment strongly affects the transmission of conventional and non-convectional monetary policy to the stock market. During sentiment-correction periods, the excess stock market return is 2% (1%) on the day of an unexpected 25 basis points cut in the FFR (interest rate path). Stock market also responds significantly to announcements of central bank liquidity swaps. Furthermore, the industry portfolios' response is consistent with the implications of the CAPM, which suggests that during such periods investors process information more systematically. In contrast, during periods of optimism build-up, the stock market response is statistically insignificant.

1.2 Introduction

"*Animal spirits, sentiment, psychology, whatever you want to call it, was central to the economic and financial story...*" (B. Bernanke, 2015)

In classical finance theory investor sentiment does not play a role in the transmission of news to the stock market. Behavioural finance literature, however, documents that investor sentiment affects stock prices (Lee, Shleifer, and Thaler (1991); Kumar and Lee (2006)). In the presence of limited arbitrage, the build-up of optimism when sentiment increases leads to an extended period of market overvaluation (De Long et al. (1990); Lee, Shleifer, and Thaler (1991)). The eventual correction of the mispricing is associated with lower future stock returns (Baker and Wurgler (2006); Stambaugh, Yu, and Yuan (2012); Huang et al. (2015)). Despite the importance impacts of investor sentiment on stock prices, little has been done to examine its role in the transmission of news to the stock market.

In this chapter, we focus on news related to the monetary policy stance, stemming from the Federal Reserve's actions. Market participants and the financial press commonly assign a large weight to the FOMC decisions to explain stock price changes. Policymakers also closely monitor the immediate stock market response to monetary policy news because the policy effect on the economy is indirect and delayed. A substantial literature documents a significant stock price response to monetary policy shifts (Thorbecke (1997); Ehrmann and Fratzscher (2004); Bernanke and Kuttner (2005); Maio (2014); Ozdagli (2017)). These studies, however, do not consider the role of sentiment on asset prices and interpret their findings within the efficient markets framework.[1] Given the evidence of sentiment-driven mispricing, a question that naturally arises is whether the stock market response to monetary policy news depends on the state of investor sentiment.

The phases of sentiment build-up and subsequent corrections may run over periods of time, which implies that mispricing evolves over time (Baker and Wurgler (2006); Yu and Yuan (2011); Chung, Hung, and Yeh (2012)). In order to capture these phases, we classify sentiment states using two approaches. The first approach follows the existing literature and uses a classification based on the *level* of sentiment (Baker and Wurgler (2006); Yu and Yuan (2011); Antoniou et al. (2015)). This intends to capture the effect of monetary policy news following periods of high versus low sentiment. The second approach is novel and focuses on *changes* in sentiment, in order to identify periods of optimism build-up vs. periods of waning sentiment. The effects of investors' trading behavior during these periods of sentiment adjustments has not been closely studied. The two approaches are inherently related given the mean-reverting property of sentiment (Baker and Wurgler (2006); Yu and Yuan (2011); Chung, Hung, and Yeh (2012)). The correction phase that is of particular interest for our analysis is associated with periods when sentiment starts at a high level but then decreases. We employ three alternative measures of sentiment: the University of Michigan Consumer Sentiment Index, the U.S. Consumer Confidence Index and the Sentiment Index constructed by Baker and Wurgler (2006). We orthogonalize each sentiment measure to a set of macroeconomic variables in order to remove the effects of business cycle variation. This is important in order to distinguish between behavioural and rational explanations, since the latter focus on the state of the economy linking time-varying expected returns to macroeconomic variables.[2]

We use an event study methodology to estimate the stock market reaction to monetary policy

[1] The dividend discount model of stock valuation suggests that shifts in monetary policy can affect stock prices through changes in the rates that market participants use to discount future cash flows, and through changes in the expected cash flows (Patelis (1997)). Using a returns variance decomposition framework, Bernanke and Kuttner (2005) demonstrate the importance of revisions in expected returns, that is, discount rate news, in explaining the impact of monetary policy shocks on the stock market.

[2] See, among others, Perez-Quiros and Timmermann (2000), Chordia and Shivakumar (2002), Liu and Zhang (2008), and Maio (2013).

news conditional on sentiment states. Our sample covers the period from June 1989 to October 2014, hence including the pre-crisis period, the financial crisis of 2007-2008 and its aftermath. We analyze both conventional and non-conventional monetary policy shocks. The former are measured through unexpected changes in the FFR using the methodology of Kuttner (2001). With the significant impact of the crisis, the Fed cut rates to reach the ZLB by the end of 2008 and turned to non-conventional monetary policy. Given the almost zero volatility of FFR shocks at the ZLB, our analysis of conventional monetary policy focuses on the pre-ZLB era. In terms of non-conventional policy, the Fed implements so-called "forward guidance", with which to influence the path of future short-term rates through various communication channels. Moreover, the Fed implemented major changes in the size and composition of its balance sheet through LSAP and the provision of liquidity facilities. As a proxy for news related to forward guidance, we calculate path surprises following the approach of Gürkaynak, Sack, and Swanson (2005). Our analysis also covers the impacts of the LSAP and the liquidity facilities announcements.

We find that the state of investor sentiment strongly affects the transmission of monetary policy shocks to the stock market. For conventional monetary policy prior to the ZLB, our key findings are as follows. First, the impact of monetary policy shocks on the stock market concentrates on the sentiment-correction phase that follows overvaluation episodes, particularly when sentiment is high at the start of the year but then falls. During these periods, the excess stock market return is about 2% on the day of an unexpected cut of 25 basis points in the FFR. In contrast, during periods when sentiment starts at low level but then increases and optimism grows, the stock market does not show a statistically significant price reaction to monetary policy shocks. Importantly, these effects of sentiment are not driven by economic recessions. In fact, it is only during the periods when sentiment starts high but outside of recessions the stock market shows a statistically significant response to FFR shocks. We also consider the link with the monetary policy cycle and find that the effect of sentiment on the transmission of monetary news is stronger during easing cycles.

Second, the stock market impact of monetary policy shocks is characterized by sign asymmetry. The market response following periods of high sentiment is significant for expansionary FFR surprises, but not tightening surprises. Third, we consider the possibility of endogeneity arising from reverse feedback, where the Fed is responding to market developments, and the possibility of joint-response by the market and the Fed to economic news. Our evidence indicates that accounting for endogeneity does not alter our key conclusions regarding the impact of sentiment. Fourth, the effect of FFR surprises is predominantly contemporaneous and displays only very short-run persistence. Fifth, the positive returns associated with expansionary policy shocks are broad-based across U.S. industries and their pattern is consistent with the implications of the CAPM. The industry effects are also conditional on the state of investor sentiment.

Furthermore, we find that the state of sentiment matters for non-conventional policy during the ZLB era. Compared with the pre-ZLB period, a key difference during the ZLB period is that sentiment is low, relative to its historical level. Thus, we can only consider states based on the change in sentiment. The impact of path surprises is statistically significant only during periods when sentiment decreases. Specifically, a daily excess stock market return is about 1% in response to an unexpected decline of 25 basis points in the interest rate path. In contrast to the findings from FFR shocks prior to the ZLB, the effect of path surprises is not only driven by expansionary news. We show that amongst liquidity facilities and LSAP announcements, only those related to the establishment of central bank liquidity swaps matter. Conditional on the state of investor sentiment, the stock market reacted positively to these announcements. Finally, we show that our results remain strong and consistent to a host of robustness checks.

A potential explanation for our results is related to changes in investor sentiment. The psychology literature suggests that when individuals are in a positive emotional state, they engage in more heuristic processing of information (Tiedens and Linton (2001); Mackie and Worth (1989); Bless et al. (1990); Batra and Stayman (1990)). During periods when investors start with a pessimistic state and then turn to become optimistic, their reliance on non-systematic processing of information is likely to increase. At the end point of this process, investors are in an exuberant sentiment state and are less rational overall, the stock market is overvalued (Shiller (1990); De Bondt (1998)). Essentially, investors assign excessively optimistic valuations, either by overestimating the size of future cash flows or by underestimating risk (Mian and Sankaraguruswamy (2012); Kaplanski et al. (2015)). This setup is consistent with the absence of a significant response to monetary policy news when sentiment is rising and stocks are overpriced. On the other hand, when fundamentals are revealed and sentiment starts to wane, investors come to their senses and noise traders' activity is lessened (Yuan (2015)).[3] During such phases, investors are more likely to process information systematically and become more sensitive to news (Garcia (2013)), including those arising from the actions of the Fed. Our finding that the CAPM fits well the announcement-day returns during these periods is in line with this interpretation.

An alternative explanation is centered around investor attention. Attention is a scarce cognitive resource (Kahneman (1973)) and investors have limited attention (Kahneman (1973); Da, Engelberg, and Gao (2011)). Previous studies show that investor attention to market-wide developments is likely to be stronger during economic downturns (Peng and Xiong (2006)); Peng, Xiong, and Bollerslev (2007)), which could imply a stronger response to monetary policy news. As we demonstrate, however, sentiment correction periods occur not only in recessions but also during expansions, a finding that reinforces our sentiment-based explanation.

Is the stock market reaction to monetary policy news consistent with rational asset pricing? At first glance, the answer is negative since the evidence strongly supports the notion of sentiment dependence. While our analysis supports a behavioral interpretation, we should point out

[3]Several studies have analysed the behavioural biases of noise traders and their impact on asset pricing (Abreu and Brunnermeier (2003); Shleifer (2000); Shiller (2015); De Long et al. (1990); Miller (1977); Jones and Lamont (2002), Lamont and Stein (2004), and Nagel (2005)).

that a rational explanation could be in line with the stock market reaction to FFR surprises during sentiment-correction phases. The positive response to expansionary news can be interpreted within the dividend discount model or more advanced macroeconomic-based models that highlight the importance of a risk factor related to the stance of monetary policy (Balvers and Huang (2009); Lioui and Maio (2014)). However, these models cannot explain why only expansionary news matter. Moreover, there is empirical evidence, which suggests that the Fed's interventions can also have a direct impact on sentiment (Lutz (2015)), especially during bear markets (Kurov (2010)). Thus, it is more appropriate to view our results primarily from a behavioural viewpoint.[4]

This chapter contributes to the nascent line of work that seeks to incorporate findings from behavioural finance to examine the stock market reaction to news, as well as the established literature that studies the effects of the Fed's conventional and non-conventional policy actions on financial markets. We develop a new measure of sentiment states, based upon changes in sentiment and show that it reveals important information about the trading behaviour of investors during periods of sentiment adjustment. Hence, we extend the previous literature on the asset pricing implications of sentiment, which overlooks the dynamic behaviour of sentiment. Our work is also related to the literature on state dependence in the relationship between stock market and monetary policy. Several studies consider business cycle effects and show that the stock market response is stronger during recessions ((Basistha and Kurov (2008); Perez-Quiros and Timmermann (2000)). In contrast, our focus is on sentiment states, which have small or zero correlation with the business cycle. Furthermore, sentiment corrections are not solely associated with bear markets but also occur during bull markets. Hence, our analysis is distinct from previous studies that condition the stock market response to policy surprises on bull-bear regimes (Chen (2007); Jansen and Tsai (2010); Kurov (2010)).

This chapter also relates to a recent study by Mian and Sankaraguruswamy (2012), who examine whether stock price changes in response to firm-specific earnings surprises are affected by lagged sentiment. They conclude that behavioral biases affect how information is impounded into stock prices. Our work has a different angle by focusing on market-wide news that stem from shifts in monetary policy, as opposed to firm-specific news. Another related recent study is that of Garcia (2013), who also argues that investors' sensitivity to news may be state dependent. In Garcia's (2013) analysis, however, this is related to the state of the business cycle, with the sensitivity to news being stronger during economic downturns; whereas we focus on sentiment downturns that, as we argue above, are distinct from recessions. Finally, this chapter extends previous work by Bernanke and Kuttner (2005), Lucca and Moench (2015) and Savor and Wilson (2014), among others, who find that the CAPM performs well on days associated with monetary policy news. We show that the CAPM does a good job in explaining the observed

[4]The asymmetric response during correction phases is consistent with the investors' belief that the Fed can reverse declining stock prices via monetary easing (Kurov (2010); Cieslak et al. (2018)).

cross-industry variation of FOMC announcement-day returns only during sentiment-correction phases. Different from our event study analysis, Antoniou et al. (2015) use monthly data for asset-pricing tests and show that the security market line is positively slopped only following low sentiment periods.

The rest of the chapter proceeds as follows. Section 1.3 describes the data and variables that we employ in the empirical analysis. Section 1.4 presents evidence related to the role of investor sentiment in the transmission of monetary policy news to the stock market. Section 1.5 presents the results from various robustness checks. Finally, Section 1.6 concludes.

1.3 Data and sample

1.3.1 Monetary policy news

Target rate surprises

Up to the recent financial crisis, the conduct of monetary policy in the U.S. was characterized by targeting the FFR, which is the interest rate on overnight loans of reserves between banks, and by increasing transparency (Bernanke and Blinder (1992); Bernanke and Mihov (1998); Romer and Romer (2004)). Our full sample (June 1989 - October 2014) includes 227 FOMC meetings, 23 of which were unscheduled.[5] In line with Bernanke and Kuttner (2005), we exclude the unscheduled FOMC meeting that occurred in the aftermath of the 11 September 2001 terrorist attack (17 September 2001) from the sample. Finally, we remove the most prominent outlier, as identified by the difference in the statistic of Welsch and Kuh (1977), that corresponds to the unscheduled FOMC meeting on 22 January 2008.[6]

Using the methodology proposed by Kuttner (2001), we isolate the unexpected component of changes in the target FFR (Δi_t^u) on day t in the month when the FOMC meeting takes place:

$$\Delta i_t^u = \frac{D}{D-t}(f_{m,t}^0 - f_{m,t-1}^0) \tag{1.1}$$

where $f_{m,t}^0$ is the current-month implied futures rate (100 minus the futures contract price), and D is the number of days in the month.[7]

[5] The dates provided by Kuttner (2003) are used to identify FOMC meetings prior to February 1994, when there were no press releases regarding FOMC decisions and market participants had to infer whether the FOMC had taken a policy action from the signals provided by daily open market operations (Thornton (2014)). In February 1994 the Fed started to announce its decisions and publish accompanying statements, a development that enhanced transparency in monetary policy. The corresponding dates are obtained from the Federal Reserve website at http://www.federalreserve.gov/monetarypolicy/fomccalendars.htm.

[6] On that day, the market declined by almost 1%, in spite of a massive FFR cut of 75 basis points, almost all of which was unexpected.

[7] Following Kuttner (2001), when the FOMC meeting falls on one of the last three days of the month, the unscaled change in the one-month futures rate ($f_{m,t}^1 - f_{m,t-1}^1$) is used to calculate the FFR surprise. Also, when the FOMC meeting occurs on the first day of the month, $f_{m-1,D}^1$, instead of $f_{m,t-1}^0$, is used to measure the surprise.

[Insert Figure 1.1 around here]

This market-based proxy for monetary policy shocks has been extensively used in previous studies that analyze the response of stock prices to monetary policy shifts (Bernanke and Kuttner (2005); Kurov (2010); Kontonikas, MacDonald, and Saggu (2013)). The source of the futures data is Bloomberg, while the FFR data is obtained from the Federal Reserve Economic Database (FRED) maintained by the Federal Reserve Bank of St. Louis. Figure 1.1 plots actual and unexpected changes in the target FFR on FOMC meeting dates. Typically, large expansionary monetary policy shocks, as reflected in unexpected declines in the FFR, materialize during, or near, periods of economic slowdown. Table 1.1 reports that the average FFR change is equal to -0.04%, ranging from a minimum of -0.75% to a maximum of 0.75%. There are 82 FOMC meetings that are associated with FFR changes, 51 of which are of expansionary nature ($\Delta i < 0$), while 31 are contractionary ($\Delta i > 0$). On average, target rate surprises are expansionary with a mean of -0.02%.

[Insert Table 1.1 around here]

During October 2008, in the aftermath of the Lehman Brother's collapse, the Fed reduced the target FFR from 2% to 1%. This was followed by another major cut in the FFR at the FOMC meeting on 16 December 2008, from 1% to the range of 0%–0.25%. Since then and until the end of the sample period, there are no further rate changes and the volatility of FFR shocks dies out. Motivated by these developments, when we estimate the impact of FFR shocks on the stock market, we focus on the period before the ZLB (June 1989 - December 2008).

Path surprises

In order to alleviate the constraint to monetary stimulus that the ZLB posed, the Fed provides frequent assurances about its intention to keep the policy rate at near zero in the future, the so-called forward guidance (Bernanke (2013); Doh and Connolly (2013)). Generally, forward guidance implies that the central bank attempts to influence the path of future short-term rates by communicating to the public and financial markets. Forward guidance has been intensively used since 2009, but it has long been a part of the Fed's toolkit, with elements of it traced to FOMC statements of the Greenspan era (Contessi and Li (2013)). It has been closely associated with a shift towards greater transparency in the conduct of monetary policy (Poole and Rasche (2003)).[8]

[8]The outcome of a meeting was announced by the FOMC for the first time in February 1994. The FOMC formally announced in February 1995 that all changes in the stance of monetary policy would be immediately communicated to the public. Since January 2000, the FOMC issues a statement that reports the settings of the target FFR and the balance of risks. At the beginning of forward guidance during the ZLB, the Fed adopted a qualitative tone in its communication with post-FOMC meeting statements including phrases such as the FFR will remain near zero for "an extended period" (FOMC statement of March 18, 2009). This then evolved to date-based guidance, specifying future dates such as "at least through mid-2015" (September 13, 2012). Finally, a threshold-based approach was adopted linking the first rate increase to developments in inflation and unemployment.

Gürkaynak, Sack, and Swanson (2005) develop a methodology to identify two dimensions of the Fed's policy: changes in the current FFR target and changes in forward guidance. They show that both target surprises and path surprises are useful to describe monetary policy shocks. Path surprises should capture news conveyed to market participants by the FOMC's statement about the expected path of policy above and beyond what they learn for the FFR target level (Wongswan (2009)).

Following Gürkaynak, Sack, and Swanson (2005), we calculate path surprises using principal component analysis. The starting point is the definition of a matrix that contains five columns and a number of rows equal to the number of relevant policy announcements. The first two columns of the matrix correspond to the changes in the price of current-month and three-month-ahead FFR futures contracts. The third to fifth columns are the changes in the prices of the second, third, and fourth eurodollar futures contracts with maturity of up to four quarters. We obtain two principal components, which are then transformed so that the first factor corresponds to current target rate surprises, while the second factor (path factor) corresponds to moves in interest rate expectations over the coming year that are not affected by changes in the current target rate.[9]

Our analysis of the impact of path surprises focuses on the ZLB era, in line with Wright (2012) and Swanson (2015), which necessarily narrows the sample to 47 observations for the period January 2009 to October 2014. The average path surprise in Table 1.1 is equal to -0.01%, with the variable ranging from -0.62% to 0.46%.

LSAPs and liquidity facilities announcements

Responding to the crisis and the ZLB constraint, in addition to using more explicit forward guidance, the Fed resolved to change the size and composition of its balance sheet by the provision of non-sterilized liquidity facilities and large scale purchases of longer-term assets from the private sector, mainly mortgage backed securities (MBS) and Treasury bonds. The Fed's interventions aimed to improve financial markets conditions and to put downward pressures on long-term borrowing costs. We consider several announcements of expansionary nature, capturing the initiation or continuation of LSAPs and liquidity facilities programmes. The liquidity facilities provided by the Fed include: dollar and foreign currency liquidity swaps between the Fed and other central banks, the primary dealer credit facility, the asset-backed commercial paper money market mutual fund liquidity facility, the primary and secondary credit, seasonal credit, commercial paper funding facility, and the term auction facility (TAF).

Table 1.2 reports that the first such event in our sample occurs on 12 December 2007, and is related to the initial announcement of the TAF and the authorization of swap lines with other central banks in order to provide liquidity in U.S. dollars to markets overseas. In total, there are 46 unique liquidity facility announcements spanning the period from December 2007 to October

[9]For more details on the estimation procedure, see Gürkaynak, Sack, and Swanson (2005).

2013, more than half of which are associated with TAF and central bank liquidity swaps. The Fed's liquidity facilities were heavily used in autumn of 2008 in the aftermath of the collapse of Lehman Brothers.[10] There are also 22 LSAPs related events, with the first of these occurring on 25 November 2008 and reflecting the initial announcement of the first round of quantitative easing (QE1).[11] This was followed by the first hint about purchases of Treasuries in a speech by chairman Bernanke on 1 December 2008. It is important to note that both aforementioned announcements, along with several other LSAPs and liquidity facility announcements, do not overlap with the FOMC meetings.

[Insert Table 1.2 around here]

Unlike FFR changes, for which we can use market-based expectations to isolate their surprise component, direct measures of expectations regarding the size of LSAPs and liquidity facilities programmes are not available. Hence, we do not attempt to measure "balance sheet shocks", in line with previous related studies (Gagnon et al. (2011); Ait-Sahalia et al. (2012); Fiordelisi, Galloppo, and Ricci (2014); Ricci (2015)).[12] Instead, we adopt an event study approach in which we evaluate the behaviour of stock returns in short windows surrounding the LSAPs and liquidity facility announcements.

1.3.2 Investor sentiment states

We employ three proxies for investor sentiment: Baker and Wurgler's (2006, 2007) Sentiment Index (BWI), the University of Michigan's Consumer Sentiment Index (CSI) and the U.S. Consumer Confidence Index (CCI).[13] The BWI is a commonly used measure of investor sentiment (Yu and Yuan (2011); Stambaugh, Yu, and Yuan (2012); Shen, Yu, and Zhao (2017)). By taking the first principal component of five financial variables that can reflect sentiment, the BWI filters out idiosyncratic noise in its constituents and captures common variation.[14] We also

[10] The record growth in the monetary base around that period captures the impact of these liquidity facilities (Kontonikas, Nolan, and Zekaite (2015)).

[11] On that day, the Fed announced its intention to purchase $100 billion in housing-related government sponsored enterprises debt and up to $500 billion in agency mortgage backed securities.

[12] Two notable exceptions include Rosa (2012) and Swanson (2015). The former study measures the surprise component of asset purchases by the Fed using a methodology based upon interpreting the wording of related articles in the Financial Times. Swanson (2015), on the other hand, attempts to disentangle LSAPs from forward guidance effects during the ZLB using an adaptation of the method of Gürkaynak, Sack, and Swanson (2005). He finds that stock prices respond respond positively to shifts in LSAPs measured as the component of FOMC announcements that is non-related to changes in forward guidance. Unlike our study, Swanson (2015) considers only events related with FOMC meetings excluding important announcements made outside FOMC meetings such as the first QE1 announcement (25 November 2008).

[13] We obtained CSI and CCI from the FRED and OECD databases, respectively. BWI data is available at Jeffrey Wurgler's website: http://people.stern.nyu.edu/jwurgler/.

[14] The BWI is formed as the first principal component of the closed-end fund discount, the number and the first-day returns of IPOs, the equity share in total new issues and the dividend premium. NYSE turnover, that featured in the set of variables used in the calculation of the sentiment index in Baker and Wurgler (2006), is dropped in the most recent update of their dataset. The updated BWI exhibits very similar behaviour over time with the earlier edition.

use two consumer confidence indexes, measured outside of the financial markets, as a proxy for investor optimism (see, Lemmon and Portniaguina (2006); Antoniou, Doukas, and Subrahmanyam (2013) and McLean and Zhao (2014)). The CSI is based on surveys conducted by the University of Michigan in which 500 U.S. participants are asked questions about their outlook on the economy. The CCI is another survey-based measure compiled by the Conference Board. Compared to the CSI, it uses a larger pool of respondents (5,000) and somewhat different questions.

A rational explanation for the sentiment-dependence in the relationship between stock returns and monetary policy shocks puts emphasis on the state of the economy. In order to distinguish between behavioural and rational explanations, the effects of business cycle variation should be removed from the sentiment indicators. Baker and Wurgler (2006) orthogonalize each of the constituent variables of their sentiment index with respect to a set of macroeconomic conditions before conducting the principal component analysis.[15] We obtain the orthogonalized BWI from their data set, and also orthogonalize the CSI and CCI by regressing them on the same set of macroeconomic variables that they used. The residuals from these regressions capture sentiment (optimism or pessimism) that is not justified by economic fundamentals (Lemmon and Portniaguina (2006)). The orthogonalized sentiment indexes are standardized so that they have zero mean and unit variance.

Figure 1.2 plots the orthogonalized sentiment indexes. They all rise during the 1990s but start to decline from around 2000, following the culmination of the dot-com boom. Sentiment declines during the recent global financial crisis, but somewhat recovers afterward. While the CCI and CSI are highly correlated, the BWI exhibits different dynamics. For example, the late 1990s dot-com boom episode features more prominently in the BWI, as compared to the survey-based indicators.

[Insert Figure 1.2 around here]

In order to examine whether the relationship between stock returns and monetary policy shifts is conditional on the state of investor sentiment, we construct a level-based dummy variable based on the orthogonalized sentiment indexes. The dummy variable, S_t^H, is equal to 1 (0) if the FOMC meeting occurs during those years that start with high (low) sentiment level. In line with Baker and Wurgler (2006), we define a year as starting with high (low) sentiment if the sentiment indicator at the December of the previous year is above (below) the full sample mean value. In our empirical analysis, this dummy reflects the effects of monetary policy news *following* periods of high sentiment. Note that we use the terms “following periods of high sentiment" and “high start of the year sentiment" interchangeably throughout the paper.

[15]This set of macroeconomic variables include the growth in industry production, the real growth in durable, nondurable and services consumption, the growth in employment, and a dummy variable that indicates recessions as classified by NBER business cycle dates. It is also used by other studies to remove business cycle information from sentiment proxies (Yu and Yuan (2011); McLean and Zhao (2014); Huang et al. (2015))

Importantly, investor sentiment exhibits a mean-reversion property. Following periods of high sentiment, a correction phase ensues, during which sentiment tends to decline (Baker and Wurgler (2006); Yu and Yuan (2011); Chung, Hung, and Yeh (2012)). On the other hand, having reached a low point, sentiment tends to build-up. This motivates the construction of a changes-based dummy variable, S_t^D, set to 1 (0) *during* periods of decreasing (increasing) sentiment, that is, years when the sentiment indicator at the December of that year is lower (higher) than at the December of the previous year. Given mean-reversion in sentiment, we expect to obtain qualitatively similar results across the two dummy variables. Note that, as Baker and Wurgler (2007) emphasize, changes in the level of their BWI should not be used to measure changes in sentiment (e.g. month-to-month, $BWI_t - BWI_{t-1}$) due to lag structures, among other considerations. Hence, we only use the CSI and CCI sentiment measures to generate dummies based on December-to-December changes.[16]

[Insert Figure 1.3 around here]

Figures 1.3 and 1.4 plot the sentiment dummies based on levels and changes of the sentiment indexes. The changes-based dummy identifies more states than the level based-dummy, while they are both more active than the NBER recession indicator. Specifically, using the CSI, there are 8 instances of the falling sentiment state and 3 instances of the high (start of the year) sentiment state. From 2009 onwards, there is no variation in the three level-based dummy variables. They are always equal to 0, indicating low (start of the year) sentiment in the aftermath of the recent financial crisis. The changes-based dummies display some variation during that period, reflecting the fact that the recovery of sentiment has not been strongly sustained.

[Insert Figure 1.4 around here]

Table 1.3 reports the correlation coefficients between the sentiment dummies. Three stylized facts emerge. First, correlations are stronger among the two survey-based measures of sentiment and smaller between them and the BWI proxy. For example, the CSI-CCI correlation for the level-based dummy variable is 0.81, while the CSI-BWI correlation is 0.59. Second, the correlation between level- and changes-based sentiment dummies is positive, in line with the idea that sentiment is mean-reverting, and stronger in the case of the CCI (0.41). Third, changes-based sentiment dummies and the NBER recession indicator are positively correlated. This finding reflects periods when decreasing sentiment overlaps with recessionary episodes. As presented in Figure 1.2 and 1.4, though, declines in sentiment occur not only during recessions but also during expansions.

[Insert Table 1.3 around here]

[16] Baker and Wurgler (2007) explain how to estimate monthly changes in investor sentiment using their methodology. In robustness checks, we calculate changes-based sentiment dummies using the average monthly sentiment changes during the year, as opposed to December-to-December changes. This enables us to incorporate the BWI in the analysis, in a way consistent with the recommendation of Baker and Wurgler (2007). The results that we obtain are in line with the baseline findings.

1.3.3 Stock returns

We measure daily returns on the stock market, using both CRSP value-weighted and equally-weighted returns. Returns are in excess of the 1-month Treasury bill rate and are calculated in the event space using data between the end of the FOMC announcement day and the end of the previous trading day. We also use data on 49 industry-classified portfolios, obtained from the database of K. French.

1.4 Econometric models and results

This section contains event study estimates of the stock market response to monetary policy actions. Section 1.4.1 analyzes the impact of FFR shocks over the sample period June 1989 - December 2008, i.e. before the ZLB. Section 1.4.2 examines the impact of path surprises at the ZLB (January 2009 - October 2014), while Section 1.4.3 considers announcements of LSAPs and liquidity facilities.

1.4.1 The impact of FFR shocks before the zero lower bound

We begin our empirical investigation by examining the response of stock market returns to target FFR surprises on FOMC announcement days conditional on the start-of-the-year level of sentiment. To this end, we introduce an interaction term of the FFR surprise with the previously defined level-based sentiment dummy, S_t^H, in the following regression model for excess stock returns:

$$R_t = \beta_0 + \beta_1 (1 - S_t^H) \Delta i_t^u + \beta_2 S_t^H \Delta i_t^u + \varepsilon_t \tag{1.2}$$

where R_t denotes the excess CRSP market return between the FOMC meeting day and the previous trading day.

[Insert Table 1.4 around here]

We use both value- and equally-weighted excess market returns for the estimation of Equation 1.2 with White (1980) standard errors. Table 1.4 Panel A reports estimates of Equation 1.2. Starting with value-weighted returns, the stock market reaction to unexpected FFR changes when sentiment is high at the beginning of the year ($S_t^H = 1$), as captured by β_2, is significant, both economically and statistically. The negative sign of β_2 indicates that following periods of high sentiment the stock market responds positively (negatively) to monetary easing (tightening) shocks. The results reveal an about 2% 1-day excess stock market return in response to an unexpected cut of 25 basis points in the FFR. On the other hand, when sentiment is low at the start of the year the market response to FFR surprises, as captured by β_1, is statistically insignificant. Hence, the impact of monetary policy news is stronger following periods of high sentiment.

Using equally-weighted market returns, the magnitude of the effect of FFR shocks following periods of high sentiment, declines by about a third as compared with the case of value-weighed returns. Nevertheless, the effect remains sizeable and statistically significant. Thus, the market response to target rate surprises is not exclusively driven by the reaction of large stocks. Finally, using the full sample (June 1989 - October 2014) and a pre-crisis sample (June 1989 - August 2007), we obtain similar insights for value- and equally-weighted returns.[17]

Table 1.3 shows a positive correlation between level- and changes-based sentiment states, in line with the idea that sentiment can exhibit mean-reversion. This prompts us to examine whether changes in investor sentiment affect the relationship between FFR shocks and stock market returns. Therefore, we replace the sentiment level-based dummy variable of Equation 1.2 with the changes-based dummy, S_t^D, and re-estimate Equation 1.3:

$$R_t = \beta_0 + \beta_1(1 - S_t^D)\Delta i_t^u + \beta_2 S_t^D \Delta i_t^u + \varepsilon_t \tag{1.3}$$

The results are presented in Table 1.4 Panel B. They reveal that the stock market responds significantly to FFR shocks during periods of decreasing investor sentiment ($S_t^D = 1$), as captured by β_2. In contrast, the impact of monetary policy news on the stock market is insignificant when sentiment is increasing.

The correlation between level- and changes-based sentiment states is modest, ranging from 0.17 to 0.41. This indicates that, on average, high levels of sentiment tend to be followed by a period of correction, whereby sentiment decreases. However, there are also occasions where sentiment is high at the start of the year and rises to an even higher level by its end. In order to examine whether the monetary policy effect that we identified concentrates during periods of correction, when optimism wanes, we use an alternative classification of sentiment states. Specifically, we re-estimate Equation 1.3 using a sentiment state indicator, S_t^{HD}, that accounts for the joint effect of the sentiment's level *and* changes on the reaction of stock market returns to FFR surprises. This is a dummy variable that is equal to 1 if the FOMC meeting occurs during a year when sentiment starts at a high level but then declines, and 0 otherwise.[18]

Table 1.4 Panel C reports the results, and provides further evidence on the important role of sentiment states in the transmission of monetary policy shocks to the stock market. In particular, we find that the effect of policy shifts is statistically significant only during years when sentiment starts at high level but then subsequently declines. Estimates of the coefficient of interest

[17] These results are available upon request. We date the start of the financial crisis to September 2007. By the end of the summer in 2007 major doubts about the stability of the financial system had emerged and the first major central bank interventions in response to increasing interbank market pressures took place. In September 2007, the Fed proceeded to the first major FFR cut (0.5%) since 2003, hence initiating a long cycle of monetary expansion. The 2007-2009 dating scheme is consistent with previous analyses of the recent financial crisis (Brunnermeier (2009); Kontonikas, MacDonald, and Saggu (2013)).

[18] A year is defined as of high sentiment at the start but then decreasing sentiment if the sentiment proxy at the December of the previous year exceeds the full sample mean value and the sentiment proxy at the December of that year is lower than at the December of the previous year.

(β_2) are close in magnitude to those reported in Table 1.4 Panel A, where the sentiment dummy is based on the level on sentiment solely. Finally, we also consider a 4-way decomposition in which we use dummies to classify periods of “high & increasing", “high & decreasing", “low & increasing", and “low & decreasing" sentiment. The findings (available upon request) are consistent with those in Table 1.4, and show that the response of stock market returns to FFR shocks is statistically significant only during periods of “high & decreasing" sentiment, that is, when sentiment is hight at the start of the year but then falls. On the other hand, during periods of “exuberance” (“depression”) when sentiment is already high (low) and keeps increasing (decreasing) the effect of monetary news is statistically insignificant. The same holds for periods of optimism build-up when sentiment is low at the start of the year but then rises. Note that all the subsequent analysis for the pre-ZLB period has been repeated using the “high & decreasing" definition of the sentiment dummy and the results (available upon request) are indicating that the monetary policy effects concentrate during the correction phase.

[Insert Figure 1.5 around here]

These findings are in line with the idea that the impact of monetary policy actions is mostly potent when sentiment-driven overvaluation is followed by a correction. Figure 1.5 plots S_t^{HD} along with a bear market indicator. While there is no commonly accepted definition for bull vs. bear market states, the bear indicator that we use are consistent with the standard notion of significant and sustained stock price declines. It is a dummy variable that is equal to 1 when the S&P 500 stock market index is lower than its full sample 2-year moving average, and 0 otherwise (Kontonikas, MacDonald, and Saggu (2013)). Figure 1.5 shows that sentiment correction phases ($S_t^{HD} = 1$) sometimes overlap with bear market episodes, for example the one associated with the recent global financial crisis. However, sentiment correction may also occur during bull markets. The correlation between sentiment correction phases and bear markets is small (0.2). Therefore, our analysis is distinct from previous studies that condition the stock market response to policy surprises on bear vs. bull states, and find a stronger response during bear states (Chen (2007); Jansen and Tsai (2010); Kurov (2010)).[19]

Controlling for the business cycle and the monetary cycle

Previous studies show that the impact of monetary policy on the stock market is stronger during recessions, thereby suggesting conditionality upon the state of business cycle (Basistha and Kurov (2008); Perez-Quiros and Timmermann (2000)). To examine this possibility within our framework, we interact our sentiment states with business cycle indicators. Specifically, we estimate Equation 1.4, which conducts a 4-way decomposition of the monetary policy impact:

[19] Unreported findings (available upon request) show that the stock market response to FFR surprises during sentiment correction phases is strongly significant during both bear and bull markets, and insignificant otherwise.

$$\begin{aligned} R_t = \beta_0 + \beta_1(1-S_t^H)(1-Rec_t)\Delta i_t^u + \beta_2(1-S_t^H)Rec_t\Delta i_t^u \\ + \beta_3 S_t^H(1-Rec_t)\Delta i_t^u + \beta_4 S_t^H Rec_t \Delta i_t^u + \varepsilon_t \end{aligned} \tag{1.4}$$

where Rec_t is a variable that captures the state of the economy, measured by the NBER business cycle chronology ($NBER_t$) and the real time probability of recession ($Recprob_t$). $NBER_t$ is a dummy variable that is equal to 1 if the FOMC meeting occurs during a month that a U.S. economy is in recession, as classified by the NBER business cycle dates. $Recprob_t$ is equal to the real time recession probability at the month when the FOMC meeting takes place, obtained from the dynamic-factor Markov-Switching model of Chauvet and Piger (2008). There is a close correspondence between the two business cycle indicators, with the correlation coefficient being equal to 0.9.

The estimation results in Table 1.5 Panel A are novel and intriguing. They highlight, again, the important role of sentiment for the transmission of monetary policy shocks to the stock market. At the same time, they reveal that this finding is not driven by recessionary periods. In fact, only outside recessions do stock market returns respond significantly to FFR shocks following high sentiment periods, as captured by β_3. The corresponding effect during recessions, as captured by β_4, has a fairly large magnitude but is statistically insignificant. Using the recession probability indicator in Panel B, we obtain similar results. It appears, then, that the results from previous studies regarding the impact of recessions on the relationship between monetary policy and the stock market are affected by the fact that they do not account for sentiment states.

[Insert Figure 1.6 around here]

Moreover, motivated by previous evidence which identifies comovement between the business cycle and the monetary cycle (Chen, Kontonikas, and Montagnoli (2012)), we proceed by interacting states defined by sentiment with those defined by the state of the monetary cycle. To do so, we re-estimate Equation 1.4 replacing the Rec_t indicator with Eas_t. The latter is a dummy variable that is equal to 1 if the FOMC meeting occurred during a monetary easing cycle and 0 otherwise. An easing cycle is defined as starting with a negative FFR target rate change and ending with a positive FFR target rate change. This definition is consistent with Lucca and Moench (2015). Figure 1.6 plots the dummy variable that reflects monetary cycles. We identify five easing cycles over the full sample period: the first three occurred in the 1990s, and the other two in the 2000s. While recessionary periods always overlap with expansionary monetary policy cycles, the latter have typically longer duration and precede, and/or continue after, recessions. For example, the early 2000s expansionary cycle commenced in January 2001 and ended in May 2004, thereby encompassing a shorter-lived recessionary episode, which lasted from March to November of 2001. The correlation between the monetary cycle and the business cycle indicators is positive but far from perfect (0.25).

[Insert Table 1.6 around here]

The findings in Table 1.6 show that the impact of sentiment on the transmission of monetary policy news to the stock market materialises during easing cycles, as captured by β_4. Considering the evidence in Tables 1.5 and 1.6 together, it appears that following high sentiment periods, FFR surprises affect the stock market when output is expanding and the monetary policy stance is expansive.

Sign asymmetry and the role of unscheduled meetings

Equation 1.2 above assumes a symmetric stock market reaction to monetary policy surprises, with no distinction between expansionary shocks and contractionary shocks. It is plausible, though, that the stock market response depends on the type of news, as classified by the sign of the monetary policy shock. Previous evidence by Bernanke and Kuttner (2005) provides only weak support for this type of asymmetry. Neuhierl and Weber (2017), on the other hand, provide evidence in line with a more important role for expansionary surprises. However, both studies do not account for sentiment states in their empirical framework. To do so, we estimate the following regression model that allows for both sentiment dependence and sign asymmetry:

$$R_t = \beta_0 + \beta_1(1 - S_t^H)\Delta i_t^{un} + \beta_2(1 - S_t^H)\Delta i_t^{up} + \beta_3 S_t^H \Delta i_t^{un} + \beta_4 S_t^H \Delta i_t^{up} + \varepsilon_t \tag{1.5}$$

where Δi_t^{un} and Δi_t^{up} denote negative and positive unexpected FFR target rate changes, respectively. The negative FFR surprises variable is defined as follows: $\Delta i_t^{un} = \Delta i_t^u D_t^n$, where D_t^n is a dummy variable that is equal to 1 if $\Delta i_t^u < 0$, and 0 otherwise. In a similar fashion, the positive FFR surprises variable is: $\Delta i_t^{up} = \Delta i_t^u D_t^p$, where D_t^p is a dummy variable that is equal to 1 if $\Delta i_t^u > 0$, and 0 otherwise.

[Insert Table 1.7 around here]

Table 1.7 reports estimates of Equation 1.5 and shows that the reaction of stock market returns to FFR shocks following periods of high sentiment solely materializes in response to expansionary surprises. This effect is captured by β_3, which is negative and significant at the 1% level across all alternative specifications. On the other hand, the effect of tightening surprises is always statistically insignificant, irrespectively of the state of investor sentiment. These effects are not driven by small number of observations since 33 (21) out of the 88 (53) FOMC meetings associated with unexpected FFR cuts (increases) occur following low sentiment periods (see Table A.1 in the Appendix A). These findings highlight that the stock market response to monetary policy news is highly asymmetric, driven by expansionary surprises, and at the same time, is conditional on investor sentiment.

According to the “Fed put” story, policy is eased in times of trouble but not tightened accordingly when financial conditions are good (Diamond and Rajan (2012); Cieslak et al. (2018)). Unscheduled meetings, in particular, may be reactive or endogenous, with the Fed providing monetary stimulus in response to adverse economic and/or financial developments, such as the Long-Term Capital Management (LTCM) crisis (Ozdagli (2017); Neuhierl and Weber (2017)). With the exception of two cases, unscheduled FOMC meetings are associated with expansionary policy surprises (see Table A.2 in the Appendix A). Bernanke (2015) also highlights that a rate move between regularly scheduled FOMC meetings is usually taken responding to an emergency. Summarising internal debates in the Fed regarding unscheduled meetings, he points out the issue of whether a surprise cut would "reassure or roil markets". Related to this, expansionary shocks in unscheduled meetings over the pre-ZLB period tend to boost the stock market, with the average stock return being about 1%.

[Insert Table 1.8 around here]

To examine whether our results regarding the importance of expansionary surprises are driven by the incorporation of unscheduled, and possibly endogenous, FOMC meetings in the sample, we proceed to re-estimate Equation 1.5 removing all unscheduled meetings. The results are reported in Table 1.8 and show that, overall, the effect of expansionary surprises is robust to the exclusion of unscheduled meetings. The magnitude of β_3 mildly declines but the effect remains statistically significant in all cases. Hence, alleviating the possibility of reverse-feedback type of endogeneity, does not alter our key conclusions regarding the impact of sentiment on the transmission of policy shocks to the stock market.

Accounting for joint-response bias

Apart from the possibility of reverse-feedback, discussed above, event-study endogeneity may also arise due to the simultaneous reaction of stocks and the market-based policy surprise proxy to new information. For instance, news indicating a weaker economic outlook would tend to reduce stock valuations and make an FFR cut more likely, implying a downward bias in the size of the estimated policy impact (Bernanke and Kuttner (2005)). Thornton (2014) proposes a procedure to address the joint-response bias which has some important advantages relative to alternative methods. It is simple to implement, provides an indication of the magnitude of the joint-response bias, and does not rely on either the use of intraday data or the identification through heteroskedasticity of Rigobon and Sack (2004). The latter method makes strong assumptions regarding the variance of shocks on FOMC meetings vs. other days.

Thornton's (2014) method involves using the market-based monetary policy surprises on all days as a latent variable. This variable accounts for the link between stock returns and market-based policy surprises on days when there are no news from the Fed. In order to account for the joint-response bias that arises due to the reaction of stock returns and the market-based proxy to "ambient news", rather than monetary policy actions, the following regression model can be estimated using daily data:

$$R_t = \beta_0 + \beta_1 FOMC_t + \beta_2 \Delta i_t^u + \beta_3 FOMC_t \Delta i_t^u + \varepsilon_t \tag{1.6}$$

where $FOMC_t$ is a dummy variable that is equal to 1 on FOMC announcement days and 0 otherwise.

In Equation 1.6, the β_2 coefficient reflects the joint-response bias, whereas β_3 denotes the marginal change in stock returns associated with unexpected policy events. Thornton (2014) uses a similar model to evaluate the results from an event study considering changes in Treasury yields around FOMC announcements. He shows that the joint-response bias in the Treasuries' event study is large, since in contrast to β_2 which is always significant, β_3 is insignificant in many cases. However, estimates of Equation 1.8 using stock market returns as the dependent variable, provide little evidence to support the joint response bias. Specifically, β_2 is significant only at the 10% level, while β_3 is significant at the 1% level and its magnitude is close to non-corrected event study estimates (results are available upon request). We modify Thornton's framework to account for sentiment states by considering Equation 1.7:

$$\begin{aligned} R_t = {} & \beta_0 + \beta_1 (1 - S_t^H) FOMC_t + \beta_2 (1 - S_t^H) \Delta i_t^u + \beta_3 (1 - S_t^H) FOMC_t \Delta i_t^u \\ & + \beta_4 S_t^H FOMC_t + \beta_5 S_t^H \Delta i_t^u + \beta_6 S_t^H FOMC_t \Delta i_t^u + \varepsilon_t \end{aligned} \tag{1.7}$$

where S_t^H is a dummy variable that is equal to 1 (0) during a year that starts with high (low) sentiment level.

[Insert Table 1.9 around here]

The results from Equation 1.7 are presented in Table 1.9. Following periods of high sentiment, estimates of the joint response bias and the marginal effect of unexpected policy actions, as respectively captured by β_5 and β_6, are both highly significant. Their sum is somewhat smaller relative to the baseline findings in Table 1.4 Panel A, which are not adjusted for the joint-response bias. However, the differences are not statistically significant. Overall, adjusting for joint-response bias makes little difference. For example, following high sentiment periods defined using the CSI, the bias-corrected effect of policy surprises in Table 1.9 is -7.68, close to the -7.15 non-corrected impact in Table 1.4 Panel A. On the other hand, following periods of low sentiment, all related estimates are statistically insignificant at the 5% level. Overall, these results imply that the joint-response bias is relatively small and the event study estimates are reliable.

Persistence of monetary policy effects

Our analysis has focused on the contemporaneous effect of FFR shocks on the stock market. It interesting, though, to examine whether the significant contemporaneous impact that we identified persists over time. To this end, we compute 2- and 3-day stock market returns and estimate their corresponding response coefficients to FFR shocks. In particular, we first utilise the following regression model:

$$R_{t,t+1} = \beta_0 + \beta_1(1 - S_t^H)\Delta i_t^u + \beta_2 S_t^H \Delta i_t^u + \varepsilon_t \tag{1.8}$$

where $R_{t,t+1}$ denotes the cumulative 2-day excess CRSP market return between the day following the FOMC announcement and the day preceding it. To examine a longer window, we also estimate the following model:

$$R_{t,t+2} = \beta_0 + \beta_1(1 - S_t^H)\Delta i_t^u + \beta_2 S_t^H \Delta i_t^u + \varepsilon_t \tag{1.9}$$

where $R_{t,t+2}$ denotes the cumulative 3-day excess CRSP market return between the second day following the FOMC announcement and the day preceding it.

[Insert Table 1.10 around here]

The results for 2- and 3-day cumulative returns are reported in Table 1.10 Panels A and B, respectively. Overall, these results point to the following conclusions. Firstly, the response of 2-day cumulative returns to monetary policy news is strongly significant, with a magnitude somewhat higher than that of the contemporaneous response in Table 1.4. Secondly, when we calculate returns over a 3-day window the magnitude and statistical significance of the returns response is diminished. Hence, the impact of policy surprises is predominantly contemporaneous and displays some persistence only in the very short-run (see also Florackis, Kontonikas, and Kostakis (2014)).

Evidence from industry portfolios

It is interesting to examine whether the impact of sentiment on the transmission of monetary policy shocks, that we identified for a broad market index, also materialises at the industry level. The reaction of industries to policy surprises may exhibit heterogeneity due to demand effects or different sensitivities to monetary policy (Neuhierl and Weber (2017)). We obtain data on 49 industry portfolios from the K. French database and re-estimate Equation 1.2 using industry excess returns as the dependent variable. Figure 1.7 plots the industry-related findings (individual regressions' results are available upon request). They can be summarised as follows. First, the reaction of industry-classified stock returns to monetary policy shocks is typically stronger when sentiment is high at the start of the year. The effect of FFR shocks is statistically significant at the 5% level in 25 industries using the BWI sentiment indicator, and in 24 industries using the CSI. On the other hand, following periods of low sentiment the impact of monetary news tends to be statistically insignificant. Second, there is heterogeneity in the response of different industries to FFR surprises. The most responsive industries include high-tech related (hardware, chips, software), financials, entertainment, retail and durables (cars), while utilities and the energy sector (oil, coal) are two of the least responsive industries. These findings are generally consistent with the evidence in previous studies (Bernanke and Kuttner (2005); Ehrmann and Fratzscher (2004)).

Bernanke and Kuttner (2005) show that the pattern of responses of industry portfolios to monetary policy shocks is consistent with the implications of the CAPM. Lucca and Moench (2015) also consider industry portfolios among their test assets over the period 1994-2010. They show that average portfolio excess returns on FOMC announcement days are in line with a comovement with the market portfolio, as implied by the CAPM (see also Savor and Wilson (2014)). The aforementioned studies, however, do not account for the role of sentiment states. To address this issue, we follow Lucca and Moench (2015) by adopting a two-step procedure. In the first step, we estimate portfolio betas from a regression of the industry-classified portfolio's excess return on the excess return of the market portfolio at a daily frequency using all days in the sample (including FOMC announcement days). We use two alternative samples: June 1989 - October 2014 (full sample) and June 1989 - December 2008 (pre-ZLB). We then estimate for each FOMC meeting (scheduled and unscheduled) a cross-sectional regression of industry-classified returns on the CAPM betas that we obtain from the first step, and calculate the average intercept and slope and the associated Shanken-adjusted standard errors.[20]

[Insert Figure 1.8 around here]

Figure 1.8 scatter plots the actual average excess return earned on FOMC announcement days (in percent) for the 49 industry-classified portfolios (horizontal axis) against the excess return implied by the CAPM (vertical axis). The pattern is very similar to that in Lucca and Moench (2015) who consider only scheduled meetings. In particular, it appears that the single market factor model provides a good description of the cross-section of industry-classified returns on FOMC announcement days. For the full sample, the average slope coefficient from the cross-sectional regressions is estimated to be 0.43 (vs. 0.47 in Lucca and Moench (2015)) and statistically significant at the 1% level, whereas at the pre-ZLB period it is mildly reduced to 0.38, but remains statistically significant. The intercept (alpha) is not statistically different from zero in both samples.

[Insert Figure 1.9 around here]

To account for sentiment states we modify the second step of the estimation procedure. Specifically, we consider FOMC meetings following periods of high and low sentiment separately, by splitting the full set of meetings in two related sub-sets and conducting the cross-sectional analysis for each sub-set. The results, plotted in Figure 1.9, are striking. Following

[20] In line with our previous analysis, we exclude the unscheduled meetings of 17 September 2001 and 22 January 2008.

high sentiment periods, the slope coefficient rises to about 0.6, while the intercept remains insignificant, thereby indicating that exposure to aggregate market risk plays a key role in explaining the cross-sectional variation of returns. On the other hand, following low sentiment periods, the relationship between actual returns and returns implied by the CAPM is rather flat, not following the 45 degree line. These findings indicate that the CAPM does well in explaining the observed cross-sectional variation of FOMC announcement-day returns only following periods of high sentiment.

1.4.2 The impact of path surprises at the zero lower bound

In this section, we examine the impact of path surprises on stock returns during the ZLB era between January 2009 and October 2014. The level-based sentiment dummy variable cannot be used to identify sentiment states since, as shown in Figure 1.3, it is equal to zero throughout the ZLB period. On the other hand, the changes-based sentiment dummy exhibits some variation, as displayed in Figure 1.4. Since 2005, the CSI and CCI changes-based dummies overlap. Therefore, we only use the CSI changes-based dummy to identify the impact of the state of sentiment on the response of stock market returns to path surprises at the ZLB:

$$R_t = \beta_0 + \beta_1(1 - S_t^D)path_t + \beta_2 S_t^D path_t + \varepsilon_t \tag{1.10}$$

The findings in Table 1.11 Panel A indicate that, consistent with the evidence from FFR shocks that we document earlier, the stock market response to path surprises is conditional on the state of investor sentiment. The effect is statistically significant during periods of decreasing sentiment, with the negative sign of β_2 indicating a positive (negative) response to expansionary (tightening) path surprises. The 1-day excess return in response to an unexpected decline of 25 basis points in the interest rate path during periods of decreasing sentiment is about 1.13%. On the other hand, the impact of path surprises is not significant during periods of increasing sentiment. Our results are in agreement with Wright (2012) and Swanson (2015), who find that expansionary monetary policy shocks boosted the stock market during the ZLB period. Importantly, however, we show that this effect materialises only when sentiment is declining.

[Insert Table 1.11 around here]

Motivated by the evidence in Section 1.4.1. regarding sign asymmetry in the effect of FFR shocks, we proceed by estimating Equation 1.11. This regression model allows for sentiment dependence and sign asymmetry related to the impact of path surprises:

$$R_t = \beta_0 + \beta_1(1 - S_t^D)path_t^n + \beta_2(1 - S_t^D)path_t^p + \beta_3 S_t^D path_t^n + \beta_4 S_t^D path_t^p + \varepsilon_t \tag{1.11}$$

where $path_t^n$ and $path_t^p$ denote negative and positive path surprises, respectively. Negative path surprises are calculated as $path_t^n = path_t D_t^n$, where D_t^n is a dummy variable that is equal to 1 if $path_t < 0$, and 0 otherwise. Positive path surprises are calculated as $path_t^p = path_t D_t^p$, where D_t^p is a dummy variable that is equal to 1 if $path_t > 0$, and 0 otherwise.

Table 1.11 Panel B reports estimates of Equation 1.9 and shows that the reaction of stock market returns to path surprises during periods of decreasing sentiment is not only driven by expansionary shocks. In fact, the effect of tightening path surprises, as depicted by β_4, is almost twice in magnitude compared to that of expansionary surprises, as captured by β_3. On the other hand, irrespectively of their sign, the effect of path surprises is always statistically insignificant during increasing sentiment periods. These findings highlight an important difference between the response of stock market returns to FFR shocks before the ZLB and the reaction to path surprises at the ZLB.

1.4.3 The impact of LSAPs and liquidity facilities announcements

We examine the effects of the Fed's interventions, through LSAPs and the provision of liquidity facilities, between December 2007 and October 2013. We adopt an event study approach in which we calculate and evaluate abnormal returns (ARs) in short windows surrounding non-conventional policy announcements of expansionary nature; that is, announcements related to the initiation or continuation of LSAPs and liquidity facilities programmes. We focus on the following event windows: 5-days (-1,+3), i.e. one day before and three days following an announcement; 3-days (-1,+1); and one-day (0,0). By keeping the event window narrow, we are able to better identify the announcement effect because this avoids contaminating the impact of one particular announcement with that of previous and subsequent announcements (see also, Ait-Sahalia et al. (2012)).

We further classify these events according to the state of investor sentiment at the time when they occur, and then conduct event study analyses across each of the sentiment states. Since there is little variation in the level-based sentiment dummy over the period of the non-conventional policy announcements, we only use the CSI changes-based dummy to define sentiment states.[21] For example, there are 13 events related to the announcements of central bank liquidity swaps, 9 of which occur during periods of decreasing sentiment, and the remaining 4 occur during periods of increasing sentiment.[22]

We obtain ARs using the constant mean model (MacKinlay (1997)) and a 20-day estimation period that ends prior to the event window. We calculate the Cumulative Average Abnormal Returns (CAARs) and test whether a market reaction is significantly different from zero using the Boehmer, Masumeci, and Poulsen (1991) test statistic that addresses the event-induced in-

[21] As we have already pointed out, the values taken by the CSI and CCI changes-based dummies are the same since 2005.

[22] The announcements related to TAF and liquidity facilities other than central bank liquidity swaps occurred only during periods of decreasing sentiment.

crease in return volatility (Ricci (2015)). To do so, we first obtain the cumulative standardized abnormal returns (CSARs):

$$CSAR_i(t_1,t_2) = \sum_{t=t_1}^{t_2} \frac{AR_{i,t}}{S(AR_i)} \tag{1.12}$$

where (t_1,t_2) is the event window and $S(AR_i)$ denotes the standard deviation of abnormal returns. The standardized t test statistic is then calculated as follows:

$$t = \frac{\frac{1}{N}\sum_{i=1}^{N} CSAR_i(t_1,t_2)}{\sqrt{\frac{1}{N(N-1)}[CSAR_i(t_1,t_2) - \frac{1}{N}\sum_{i=1}^{N} CSAR_i(t_1,t_2)]^2}} \tag{1.13}$$

where N is the number of observations in the sample.

Table 1.12 reports that the stock market benefits from the Fed's establishment of the US dollar and foreign-currency liquidity lines. This effect is conditional, though, on the state of investor sentiment, manifesting itself only during periods of decreasing sentiment. The CAARs are positive and significant in two out of three event windows that we analyze. There is a tendency for the CAARs to increase as the window expands.[23] For example, the (0,0) CAAR associated with the announcement of central bank liquidity swaps during periods of decreasing sentiment is 1.51%, increasing to 3.11% when the window expands to (-1,+1) days. The market response to other announcements (LSAPs, TAF and other liquidity facilities) is statistically insignificant. Our evidence is consistent with the existing literature on the positive impact of expansionary non-conventional monetary policy on the stock market (Rosa (2012); Wright (2012); Fiordelisi, Galloppo, and Ricci (2014); Rogers, Scotti, and Wright (2014)), and highlights the important role played by central bank liquidity swaps. Crucially, we show that it is important to account for the sentiment environment at the time when these announcements take place.

[Insert Table 1.12 around here]

1.5 Robustness checks

We conduct a host of robustness checks and our findings remain unchanged. In line with our main analysis, when we consider the impact of FFR shocks, we focus on the pre-ZLB period and use the level-based sentiment states, while for path surprises we use the ZLB sample period and changes-based states. The first two checks involve estimating the impact of FFR shocks and include the removal of FOMC meetings that coincide with employment data releases, and using an alternative sample starting point. In the third check, we use the index of Huang et al. (2015) to identify sentiment states. The fourth check considers an estimation method that is robust to the presence of outliers. The fifth and sixth checks concern the approach that we use to identify

[23] As Ait-Sahalia et al. (2012) argue, a wider post-announcement window allows for the news to be absorbed over a more extended period, which is sensible given the unprecedented nature of most of these initiatives.

sentiment states. The seventh uses additional macro-related variables for the orthogonalization of the sentiment indexes. Finally, we use a longer estimation window to investigate the impact of LSAPs and liquidity facilities announcements. The results are contained in the Appendix A.

1.5.1 Excluding employment data releases

In the early 1990s, the Fed's decisions to cut rates may have reflected an endogenous reaction to labour market conditions. Between June 1989 and September 1992 (the date of the last FFR cut associated with employment news), nearly half of the FOMC meetings coincided with the release of a worse-than-expected employment report (Bernanke and Kuttner (2005)). In order to account for the possibility that unexpected FFR changes on FOMC meetings that coincide with employment data releases may in fact reflect endogenous responses to the release of this information, we remove 9 such FOMC meetings from the sample (see Table A.2 in Appendix A). Table A.3 in the Appendix A shows that the effect of FFR surprises is conditional on the state of investor sentiment, materializing only following periods of high sentiment.

1.5.2 Sample starting in February 1994

We consider an alternative starting point for the sample period in the estimation of the effect of target rate surprises. Before 1994, there were no press releases regarding FOMC decisions and market participants had to infer whether the FOMC had taken a policy action from the signals provided by the size and type of open market operations in the days following each meeting. In a development that enhanced transparency, on February 1994 the Fed commenced the practice of issuing a statement on the day that the FOMC meeting is concluded to inform market participants about an interest rate change. We then use February 1994 as the start point of our sample, that is, the time when the Fed started to announce its policy actions, representing a shift that enhanced transparency in monetary policy making. Table A.4 in the Appendix A reports the results. Our findings are similar to those from using the sample that begins in June 1989. FFR shocks affect market-wide stock returns only following periods of high sentiment. Consistent with previous studies, the coefficient on high sentiment dummy increases in magnitude (i.e from -7.14 in Table 1.4 to -7.30 in Table A.4 for CSI).

1.5.3 Alternative sentiment measure

Huang et al. (2015) use the partial least squares (PLS) method to develop a new sentiment index, based on an extension of the BWI approach, aiming to align the investor sentiment measure with the purpose of predicting future stock returns. We construct level- and changes-based dummy variables based on the PLS index of Huang et al. (2015) using the same approach as in section 1.3.2. We then repeat the analyses for the impact of FFR shocks and path surprises and present the results in Table A.5 Panels A and B, respectively, in the Appendix A. Overall, the results are similar to those from using the other sentiment measures. The market response to FFR shocks before the ZLB materializes only following periods of high sentiment. Moreover, the impact of path surprises at the ZLB is statistically significant only during periods of decreasing sentiment.

1.5.4 Accounting for outliers

We employ the MM weighted least squares regression, using the procedure of Yohai (1987), which is robust to the presence of outliers. Tables A6 and A7 in the Appendix A report the results for the market-wide response to FFR shocks and path surprises, respectively. In line with the findings from OLS estimation, stock market returns react to FFR shocks (path surprises) only following periods of high sentiment (during periods of decreasing sentiment).

1.5.5 Monthly classification of sentiment states

In the baseline analysis using both level- and changes-based dummies, sentiment states are defined for the whole year, i.e. there is no intra-year variation. This approach is in line with Baker and Wurgler (2006) and Yu and Yuan (2011). Here, we conduct a robustness check by allowing for monthly variation in the sentiment states. Specifically, we construct a new level-based dummy, S_t^{HM}, that is equal to 1 (0) if the FOMC meeting occurred during a month that starts with high (low) sentiment level. A month is defined as starting with high (low) sentiment if the sentiment proxy at the end of the previous month is above (below) the full sample mean value. Furthermore, we construct a new changes-based dummy, S_t^{DM}, that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment month. A month is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end of that month is lower (higher) than at the end of the previous month. The results for FFR shocks and path surprises obtained using monthly classification of sentiment states are presented in Table A.8 and A9 in the Appendix A, respectively. Overall, they are similar to the results obtained using annual classification of sentiment states. However, we got weaker results (in both magnitude and significance) with the monthly change-based dummy. A plausible explanation is that, change-based dummy at the monthly frequency cannot correctly capture the sentiment correction periods, when the monetary policy mainly matters.

1.5.6 Alternative changes-based annual classification

For our benchmark analysis, we define periods of decreasing (increasing) sentiment as those years when the value of the sentiment measure in December is lower (higher) than that in the December of the previous year. We use an alternative yearly classification scheme in which a year is defined as of decreasing (increasing) sentiment if, throughout it, the average monthly change of the orthogonalized sentiment proxy is negative (positive). For the CSI and CCI measures, we first orthogonalize the monthly changes of the original indexes to the six macroeconomic variables used by Baker and Wurgler (2006), and then calculate the average value of the monthly residuals throughout each year. In the case of the BWI, we start by orthogonalizing the monthly changes of each of its five constituents, and then obtain the first principal component of the residuals, and finally calculate the average value of the principal component throughout each year. Table A.10 in the Appendix A presents the findings for the impact of path surprises on the stock market. Results from the alternative changes-based dummy are overall in line with the findings from using December-to-December changes. Stock market returns respond to monetary policy shocks during periods of decreasing sentiment only.

1.5.7 Additional variables for orthogonalization

In order to ensure that the residuals from the orthogonalizing regressions capture sentiment that is unrelated to economic fundamentals, rather than the effect of omitted variables, we use an extended set of macro-related factors for the orthogonalization. This helps us to further assess the potential of a risk-based explanation for our findings. To this end, we follow Stambaugh, Yu, and Yuan (2012) and expand the set of macro-related variables used by Baker and Wurgler (2006) by including the the default premium (BAA minus AAA corporate bond yield spread), the term premium (10-year minus 1-year Treasury bond yield spread), the real interest rate (1-month Treasury bill rate minus the monthly Consumer Price Index inflation rate), the inflation rate, and the consumption-wealth ratio (cay) defined in Lettau and Ludvigson (2001).[24] Table A.11 and A12 in the Appendix A report the results for the stock market response to FFR shocks and path surprises, respectively. The results are quantitatively similar to those we reported earlier, and indicate that our findings are robust to the use of a more extensive set of macro-variables for the orthogonalization of sentiment.

1.5.8 Longer estimation window for CAARs

We repeat the analyses for the effect of LSAPs and liquidity facilities announcements using a 90-day estimation window, instead of the 20-day window used earlier. Table A.13 in the Appendix A reports the response of stock market returns to the unconventional monetary policy announcements. Overall, the results are similar to those from using the 20-day estimation window, albeit with slightly lower CAARs.

1.6 Conclusions

This chapter shows that sentiment states strongly affect the transmission of monetary policy news to the stock market. We employ measures of monetary policy that capture conventional and non-conventional dimensions of the Fed's behaviour, along with several proxies for investor

[24]cay is obtained from Sydney Ludvigson's website, http://www.econ.nyu.edu/user/ludvigsons/.

sentiment. Our main finding is that the impact of monetary policy news is potent during the sentiment correction phase that follows overvaluation episodes. This particularly occurs, when sentiment is high at the start of the year but then declines. On the other hand, during periods of optimism build-up, the impact of monetary policy news is statistically insignificant. Specifically, during the correction phases, the excess stock market return is about 2% (1%) on the day of an unexpected cut of 25 basis points conventional (unconvnetional) monetary policy shocks. For conventional monetary policy, we also find that the impact of monetary policy shocks on market-wide stock returns is characterized by sign asymmetry. Expansionary FFR surprises significantly affect the market-wide stock returns following periods of high sentiment, however, the tightening shocks do not have a significant impact on stock returns regardless of the sentiment states. Our results still hold after we accounting for endogeneity problems. We also examine the persistence of the monetary policy impacts. We find that monetary policy surprise is predominantly contemporaneous and displays only very short-run persistence. We also show that the positive returns associated with expansionary policy shocks are broad-based across U.S. industries and their pattern is consistent with the implications of the CAPM. The industry effects are also conditional on the state of investor sentiment. Moreover, we show that the sentiment effects that we document in the relationship between monetary policy shocks and stock returns are not related to business cycle variation. For the unconventional monetary policy during the ZLB era, we find that the state of sentiment matters as well. The impact of path surprises is statistically significant only during periods when sentiment decreases. However, in contrast to the findings from FFR shocks prior to the ZLB, the effect of path surprises is not only driven by expansionary news. We show that amongst liquidity facilities and LSAP announcements, only those related to the establishment of central bank liquidity swaps matter. Conditional on the state of investor sentiment, the stock market reacted positively to these announcements. Finally, we show that our results remain strong and consistent to a host of robustness checks.

We provide a possible explanation which is related to investors' emotional state. When optimism builds-up, investors tend to behave in a manner consistent with noise trading, by relying heavily on heuristic processing of information and pushing the stock market above levels justified by fundamentals. In contrast, during correction phases they engage in more systematic processing of information and their sensitivity to news increases. An alternative explanation is centered around investor attention. Investors may pay more attention to the monetary policy news due to lose in stocks during the correction phases, which results in a significant response to expansionary monetary policy shocks. Overall, our results are consistent with a behavioural explanation.

This chapter brings together two strands of the existing literature by seeking to incorporate lessons from behavioural finance to research about the impact of monetary policy on financial markets. It contributes to the studies which seek to incorporate behavioural finance to stock market responses to news, as well as the established literature that studies the effects of the Fed's conventional and non-conventional policy actions on financial markets. Our work is also related to the literature on state dependence in the relationship between stock market and monetary policy. Several studies consider business cycle effects and show that the stock market response is stronger during recessions. In contrast, our focus is on sentiment states, which have small or zero correlation with the business cycle. Furthermore, sentiment corrections are not solely associated with bear markets but also occur during bull markets. Hence, our analysis is distinct from previous studies that condition the stock market response to policy surprises on bull-bear regimes. The results in this chapter suggest several avenues for future work. For example, one could adopt a returns decomposition approach to shed light into whether the stock market response during a sentiment correction phase is related to adjustments in expected cash flows and/or expected returns. Moreover, policy-makers when calibrating the impact of monetary surprises should be aware of the asymmetries that we document.

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Table 1.1: Descriptive statistics for FFR changes, unexpected changes and path surprises

Δi_t and Δi_t^u denote FFR target rate changes and unexpected changes, respectively, on FOMC announcement days over the full sample period (June 1989 - October 2014). $path_t$ denotes path surprises on FOMC meeting days over the zero lower bound period (January 2009 - October 2014).

	Obs	Min	Max	Mean	St.Dev.
Panel A: All meetings					
Δi_t	227	-0.75	0.75	-0.04	0.21
Δi_t^u	227	-0.42	0.17	-0.02	0.08
$path_t$	47	-0.62	0.46	-0.01	0.15
Panel B: Contractionary					
$\Delta i_t > 0$	31	0.25	0.75	0.30	0.12
$\Delta i_t^u > 0$	53	0.003	0.17	0.05	0.04
$path_t > 0$	17	0.003	0.46	0.10	0.14
Panel C: Expansionary					
$\Delta i_t < 0$	51	-0.75	-0.25	-0.34	0.14
$\Delta i_t^u < 0$	88	-0.42	-0.004	-0.09	0.09
$path_t < 0$	30	-0.62	-0.002	-0.08	0.12
Panel D: No change					
Δi_t=0	145	0.00	0.00	0.00	0.00
$\Delta i_t^u = 0$	86	0.00	0.00	0.00	0.00
$path_t = 0$	0				

Table 1.2: LSAPs and liquidity facilities announcements

This table considers announcements of expansionary nature by the Fed that reflect the initiation or continuation of Large Scale Asset Purchases (LSAPs) and liquidity facilities programmes. The liquidity facilities provided by the Fed incorporated, among other programmes, central bank liquidity swaps and the term auction facility (TAF). The source of the data is the Federal Reserve website (https://www.federalreserve.gov/monetarypolicy/).

Announcement	Obs	Date of first announcement	Date of last announcement
Liquidity facilities	46	12/12/2007	31/10/2013
Central bank liquidity swaps	13	12/12/2007	31/10/2013
Term auction facility	13	12/12/2007	28/08/2009
Other liquidity facilities	21	03/11/2008	04/12/2009
LSAPs	22	25/11/2008	30/10/2013

Table 1.3: Correlation matrix of sentiment states

This table presents correlation coefficients of the sentiment-based states, along with the business cycle and monetary cycle indicators. $S_t^{H,i}$ is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. i = CSI, CCI and BWI; where CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. $S_t^{D,i}$ is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment year. A year is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end (December) of that year is lower (higher) than at the end of the previous year. i = CSI and CCI. $NBER_t$ is a dummy variable that is equal to 1 if the FOMC meeting occurred during a U.S. recession as classified by NBER business cycle dates and 0 otherwise. The sample period is June 1989 - October 2014. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$S_t^{H,CSI}$	$S_t^{D,CSI}$	$S_t^{H,CCI}$	$S_t^{D,CCI}$	$S_t^{H,BWI}$	$NBER_t$
$S_t^{H,CSI}$	1.00					
$S_t^{D,CSI}$	0.17**	1.00				
$S_t^{H,CCI}$	0.81***	0.27***	1.00			
$S_t^{D,CCI}$	0.17***	0.86***	0.41***	1.00		
$S_t^{H,BWI}$	0.59***	0.19***	0.49***	0.05	1.00	
$NBER_t$	-0.07	0.37***	0.02	0.37***	0.05	1.00

Table 1.4: Response of stock market returns to FFR shocks before the zero lower bound - conditional upon the state of investor sentiment

Panel A of this table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: R_t=β_0+$\beta_1(1-S_t^H)\Delta i_t^u$+$\beta_2 S_t^H \Delta i_t^u$+$\varepsilon_t$, where R_t and Δi_t^u denote CRSP market returns (value-weighed and equally-weighted, alternatively) in excess of the 1-month Treasury bill rate and unexpected FFR changes, respectively. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. Panel B of this table replaces S_t^H in the above equation with S_t^D, a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment year. A year is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end (December) of that year is lower (higher) than at the end of the previous year. Panel C of this table replaces S_t^H in the above equation with S_t^{HD}, a dummy variable that is equal to 1 if the FOMC meeting occurred during a year when sentiment starts at high level but then declines, and 0 otherwise. A year is defined as of high at the start but then decreasing sentiment if the sentiment proxy at the end (December) of the previous year exceeds the full sample mean value and the sentiment proxy at the end of that year is lower than at the end of the previous year. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

		Value weighted returns				Equally weighted returns			
	Obs	β_0	β_1	β_2	$Adj.R^2$	β_0	β_1	β_2	$Adj.R^2$
Panel A: S_t^H									
CSI	180	0.21**	-0.38	−7.15***	0.14	0.16**	-0.63	−4.62**	0.10
		(0.10)	(0.86)	(2.45)		(0.07)	(0.62)	(2.26)	
CCI	180	0.20**	-0.52	−7.34***	0.14	0.15**	-0.56	−4.92**	0.11
		(0.10)	(0.83)	(2.53)		(0.07)	(0.60)	(2.30)	
BWI	180	0.23**	-0.37	−6.80***	0.14	0.18***	0.44	−5.46***	0.15
		(0.09)	(0.97)	(2.57)		(0.06)	(0.79)	(1.92)	
Panel B: S_t^D									
CSI	180	0.20**	-0.68	−4.98**	0.09	0.15**	-0.81	−3.35*	0.07
		(0.10)	(1.07)	(2.41)		(0.07)	(0.81)	(1.94)	
CCI	180	0.20**	-0.77	−4.95***	0.09	0.15**	-0.86	−3.33*	0.07
		(0.10)	(1.09)	(2.41)		(0.07)	(0.82)	(1.95)	
Panel C: S_t^{HD}									
CSI	180	0.21**	-0.21	−8.24***	0.17	0.16**	-0.37	−5.49**	0.12
		(0.09)	(0.84)	(2.42)		(0.07)	(0.61)	(2.30)	
CCI	180	0.21**	-0.25	−8.20***	0.17	0.16**	-0.40	−5.67**	0.12
		(0.09)	(0.84)	(2.43)		(0.07)	(0.61)	(2.31)	

Table 1.5: Response of stock market returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - controlling for the business cycle

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: $R_t = \beta_0 + \beta_1(1-S_t^H)(1-Rec_t)\Delta i_t^u + \beta_2(1-S_t^H)Rec_t\Delta i_t^u + \beta_3 S_t^H(1-Rec_t)\Delta i_t^u + \beta_4 S_t^H Rec_t \Delta i_t^u + \varepsilon_t$, where R_t and Δi_t^u denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate and unexpected FFR changes, respectively. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. Rec_t is a variable that captures the state of the economy, measured by the NBER business cycle chronology and the real time probability of recession. Specifically, $NBER_t$ is a dummy variable that is equal to 1 if the FOMC meeting occurred during a U.S. recession as classified by NBER business cycle dates and 0 otherwise. $Recprob_t$ is equal to the real time recession probability when the FOMC meeting takes place, obtained from the dynamic-factor Markov-Switching model of Chauvet and Piger (2008). The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	β_3	β_4	$Adj.R^2$
				Panel A: NBER recession			
CSI	180	0.21^{**}	-0.84	0.66	-8.31^{***}	-5.15	0.14
		(0.10)	(1.09)	(0.67)	(2.32)	(4.64)	
CCI	180	0.20^{**}	-1.01	0.61	-8.70^{***}	-5.18	0.14
		(0.10)	(1.04)	(0.67)	(2.39)	(4.64)	
BWI	180	0.23^{**}	-0.89	0.75	-7.73^{***}	-5.10	0.13
		(0.09)	(1.17)	(0.65)	(2.82)	(4.63)	
				Panel B: Recession probability			
CSI	180	0.21^{**}	-0.86	1.78	-7.62^{***}	-6.01	0.14
		(0.10)	(1.10)	(1.23)	(2.42)	(7.56)	
CCI	180	0.20^{**}	-1.03	1.82	-8.03^{***}	-5.79	0.14
		(0.10)	(1.06)	(1.24)	(2.59)	(7.54)	
BWI	180	0.23^{**}	-0.90	1.86	-6.91^{**}	-6.47	0.12
		(0.09)	(1.19)	(1.23)	(2.93)	(7.71)	

Table 1.6: Response of stock market returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - controlling for the monetary cycle

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: R_t=β_0+$\beta_1(1-S_t^H)(1-Eas_t)\Delta i_t^u$+$\beta_2(1-S_t^H)Eas_t\Delta i_t^u$+$\beta_3 S_t^H(1-Eas_t)\Delta i_t^u$+$\beta_4 S_t^H Eas_t\Delta i_t^u$+$\varepsilon_t$, where R_t and Δi_t^u denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate and unexpected FFR changes, respectively. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. Eas_t is a dummy variable that captures the state of the monetary cycle, being equal to 1 if the FOMC meeting occurred during a monetary easing cycle and 0 otherwise. A monetary easing cycle is defined as starting with a negative FFR target rate change and ending with a positive FFR target rate change. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	β_3	β_4	$Adj.R^2$
CSI	180	0.21**	-1.60	-0.11	0.21	−7.71***	0.15
		(0.10)	(2.46)	(0.90)	(4.11)	(2.45)	
CCI	180	0.19*	-1.64	-0.31	0.48	−7.96***	0.15
		(0.10)	(2.44)	(0.85)	(4.22)	(2.53)	
BWI	180	0.20**	11.36*	-0.68	-1.96	−8.44***	0.16
		(0.10)	(6.75)	(0.90)	(2.18)	(2.68)	

Table 1.7: Response of stock market returns to negative and positive FFR shocks before the zero lower bound, following periods of high vs. low sentiment

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: R_t=β_0+$\beta_1(1-S_t^H)\Delta i_t^{un}$ + $\beta_2(1-S_t^H)\Delta i_t^{up}$+$\beta_3 S_t^H \Delta i_t^{un}$+$\beta_4 S_t^H \Delta i_t^{up}$+$\varepsilon_t$, where R_t, Δi_t^{un} and Δi_t^{up} denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate, negative unexpected FFR changes and positive unexpected FFR changes, respectively. Negative FFR surprises are calculated as $\Delta i_t^{un} = \Delta i_t^u D_t^n$, where D_t^n is a dummy variable that is equal to 1 if $\Delta i_t^u < 0$, and 0 otherwise. Positive FFR surprises are calculated as $\Delta i_t^{up} = \Delta i_t^u D_t^p$, where D_t^p is a dummy variable that is equal to 1 if $\Delta i_t^u > 0$, and 0 otherwise. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	β_3	β_4	$Adj.R^2$
CSI	180	0.01	-1.21	-0.68	-10.11^{***}	6.81	0.22
		(0.10)	(0.84)	(4.56)	(1.51)	(6.41)	
CCI	180	0.02	-1.28	0.36	-10.06^{***}	9.41	0.22
		(0.10)	(0.84)	(3.78)	(1.51)	(7.15)	
BWI	180	0.03	-1.70	6.32	-9.50^{***}	2.38	0.19
		(0.10)	(0.97)	(6.29)	(1.85)	(5.49)	

Table 1.8: Response of stock market returns to negative and positive FFR shocks before the zero lower bound, following periods of high vs. low sentiment - excluding unscheduled FOMC meetings

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: R_t=β_0+$\beta_1(1-S_t^H)\Delta i_t^{un}$ +$\beta_2(1-S_t^H)\Delta i_t^{up}$+$\beta_3 S_t^H \Delta i_t^{un}$+$\beta_4 S_t^H \Delta i_t^{up}$+$\varepsilon_t$, where R_t, Δi_t^{un} and Δi_t^{up} denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate, negative unexpected FFR changes and positive unexpected FFR changes, respectively. Negative FFR surprises are calculated as $\Delta i_t^{un} = \Delta i_t^u D_t^n$, where D_t^n is a dummy variable that is equal to 1 if $\Delta i_t^u < 0$, and 0 otherwise. Positive FFR surprises are calculated as $\Delta i_t^{up} = \Delta i_t^u D_t^p$, where D_t^p is a dummy variable that is equal to 1 if $\Delta i_t^u > 0$, and 0 otherwise. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period includes scheduled FOMC meetings over June 1989 - December 2008. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	β_3	β_4	$Adj.R^2$
CSI	157	0.08	-0.59	0.94	-7.93^{**}	6.49	0.05
		(0.11)	(1.26)	(4.50)	(3.24)	(6.69)	
CCI	157	0.09	-0.78	0.37	-7.82^{**}	9.32	0.06
		(0.10)	(1.30)	(3.73)	(3.25)	(7.36)	
BWI	157	0.12	-0.93	6.26	-6.08^{*}	2.29	0.02
		(0.11)	(1.53)	(6.35)	(3.19)	(5.69)	

Table 1.9: Response of stock market returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - corrected for joint-response bias

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over June 1989 - December 2008 (daily data), of the following model: R_t=β_0+$\beta_1(1-S_t^H)FOMC_t$+$\beta_2(1-S_t^H)\Delta i_t^u$+$\beta_3(1-S_t^H)FOMC_t\Delta i_t^u$+$\beta_4 S_t^H FOMC_t$+$\beta_5 S_t^H \Delta i_t^u$+$\beta_6 S_t^H FOMC_t \Delta i_t^u$+$\varepsilon_t$, where R_t and Δi_t^u denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate and unexpected FFR changes, respectively. $FOMC_t$ is dummy variable that is equal to 1 on FOMC announcement days and 0 otherwise. S_t^H is a dummy variable that is equal to 1 (0) during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	β_3	β_4	β_5	β_6
CSI	4927	0.01	-0.08	-0.60^{*}	-0.33	0.33^{***}	1.83^{***}	-7.68^{***}
		(0.01)	(0.16)	(0.36)	(1.31)	(0.11)	(0.55)	(2.41)
CCI	4927	0.01	0.10	-0.60^{*}	0.10	0.30^{**}	1.91^{***}	-7.95^{***}
		(0.01)	(0.12)	(0.34)	(1.13)	(0.14)	(0.57)	(2.56)
BWI	4927	0.01	0.16	-0.48	0.18	0.30^{**}	1.89^{***}	-7.90^{***}
		(0.01)	(0.11)	(0.32)	(1.14)	(0.14)	(0.61)	(2.49)

Table 1.10: Response of stock market returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - 2-day and 3-day cumulative returns

This table presents OLS estimates with heteroscedasticity-consistent standard errors of the following model: $R_{t,t+1}$=β_0+$\beta_1(1-S_t^H)\Delta i_t^u$+$\beta_2 S_t^H \Delta i_t^u$+$\varepsilon_t$, where $R_{t,t+1}$ and Δi_t^u denote CRSP value weighted market returns in excess of the 1-month Treasury bill rate accumulated over two days (FOMC announcement day and the following day) and unexpected FFR changes, respectively. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. Panel B replaces 2-day cumulative returns with 3-day (FOMC announcement day and the following 2 days) cumulative returns, that is, $R_{t,t+2}$. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$Adj.R^2$
		Panel A: 2-day returns			
CSI	180	0.29**	-1.93	−7.79***	0.08
		(0.13)	(1.47)	(2.92)	
CCI	180	0.28**	-1.84	−8.22***	0.09
		(0.13)	(1.42)	(2.93)	
BWI	180	0.31**	-2.00	−7.42**	0.08
		(0.12)	(1.52)	(2.99)	
		Panel B: 3-day returns			
CSI	180	0.38***	-1.85	-5.45	0.03
		(0.14)	(1.74)	(3.39)	
CCI	180	0.38**	-1.92	-5.57	0.03
		(0.14)	(1.68)	(3.54)	
BWI	180	0.39***	-2.28	-4.85	0.02
		(0.14)	(1.85)	(3.37)	

Table 1.11: Response of stock market returns to path surprises at the zero lower bound, during periods of decreasing vs. increasing sentiment

Panel A of this table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: $R_t = \beta_0 + \beta_1(1 - S_t^D)path_t + \beta_2 S_t^D path_t + \varepsilon_t$, where R_t and $path_t$ denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate and path surprises, respectively. S_t^D is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment year. A year is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end (December) of that year is lower (higher) than at the end of the previous year. CSI denotes the University of Michigan's Consumer Sentiment index. The zero lower bound sample period is January 2009 - October 2014. The unscheduled meetings that were not accompanied by a FOMC statement or other information were excluded. Panel B of this table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC meeting days, of the following model: $R_t = \beta_0 + \beta_1(1 - S_t^D)path_t^n + \beta_2(1 - S_t^D)path_t^p + \beta_3 S_t^D path_t^n + \beta_4 S_t^D path_t^p + \varepsilon_t$, where $path_t^n$ and $path_t^p$ denote negative and positive path surprises, respectively. Negative path surprises are calculated as $path_t^n = path_t D_t^n$, where D_t^n is a dummy variable that is equal to 1 if $path_t < 0$, and 0 otherwise. Positive path surprises are calculated as $path_t^p = path_t D_t^p$, where D_t^p is a dummy variable that is equal to 1 if $path_t > 0$, and 0 otherwise. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	β_3	β_4	$Adj.R^2$
				Panel A			
CSI	47	0.25^{*}	0.45	-4.51^{***}			0.11
		(0.15)	(0.64)	(1.74)			
				Panel B			
CSI	47	0.35	2.71	0.04	-3.86^{**}	-7.10^{**}	0.22
		(0.24)	(4.78)	(0.98)	(1.65)	(3.50)	

Table 1.12: Response of stock market returns to LSAPs and liquidity facilities announcements, during periods of decreasing vs. increasing sentiment

This table presents the CRSP value-weighted cumulative average abnormal returns (CAARs (%)) using alternative event windows across periods of decreasing sentiment (Panel A) and increasing sentiment (Panel B). Returns are in excess of the 1-month Treasury bill rate. Abnormal returns are calculated using the constant mean model and a 20-day estimation period that ends prior to the event window. We consider announcements by the Fed over the period December 2007 - October 2014 that reflect the initiation/continuation or slowdown/stop of Large Scale Asset Purchases (LSAPs) and liquidity facilities programmes. There are 46 announcements related to liquidity facilities (LIQ_{all}), including 13 announcements about central bank liquidity swaps (CB swaps), 13 announcements about the term auction facility (TAF) and 21 announcements about other liquidity facilities (Other). 22 LSAPs-related announcements are also considered. A year is defined as of decreasing (increasing) sentiment if the University of Michigan's Consumer Sentiment index at the end (December) of that year is lower (higher) than at the end of the previous year. The statistical significance of CAARs is evaluated using the Boehmer, Masumeci, and Poulsen (1991) test statistic that accounts for event-induced increase in returns volatility. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Event window	CB swaps	TAF	Other	LIQ_{all}	LSAPs	LIQ_{all}+LSAPs
Panel A: Decreasing sentiment						
(-1, 3)	3.17	-1.92	-0.74	-0.14	1.49	-0.05
(-1, 1)	3.11**	-0.74	0.10	0.55	1.87	0.47
(0, 0)	1.51***	-0.42	-0.06	0.16	0.08	0.12
Panel B: Increasing sentiment						
(-1, 3)	0.77			0.77	-0.64	-0.36
(-1, 1)	0.22			0.22	-0.42	0.30
(0, 0)	0.96			0.96	-0.04	0.16

Figure 1.1: Actual and unexpected FFR changes

This figure plots actual and unexpected FFR changes on FOMC announcement days over the period June 1989 - October 2014. Shaded areas denote U.S recessions as classified by NBER business cycle dates.

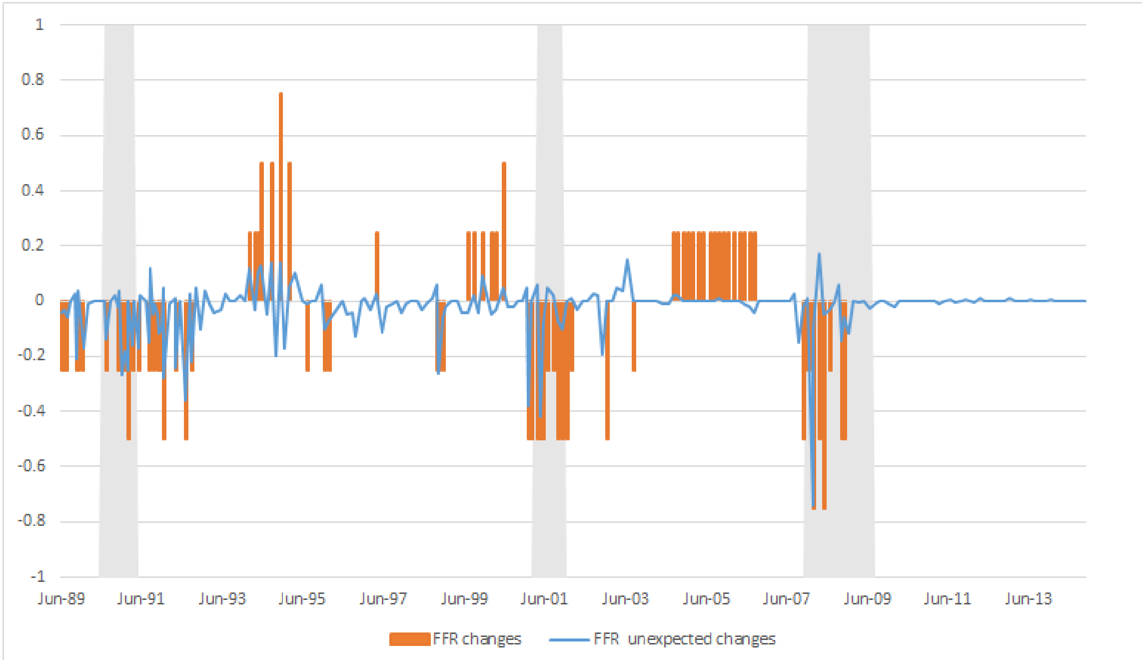


Figure 1.2: Sentiment indices

This figure plots sentiment indices using monthly data over the period December 1988 - October 2014. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. Shaded areas denote the U.S recessions as classified by NBER business cycle dates.

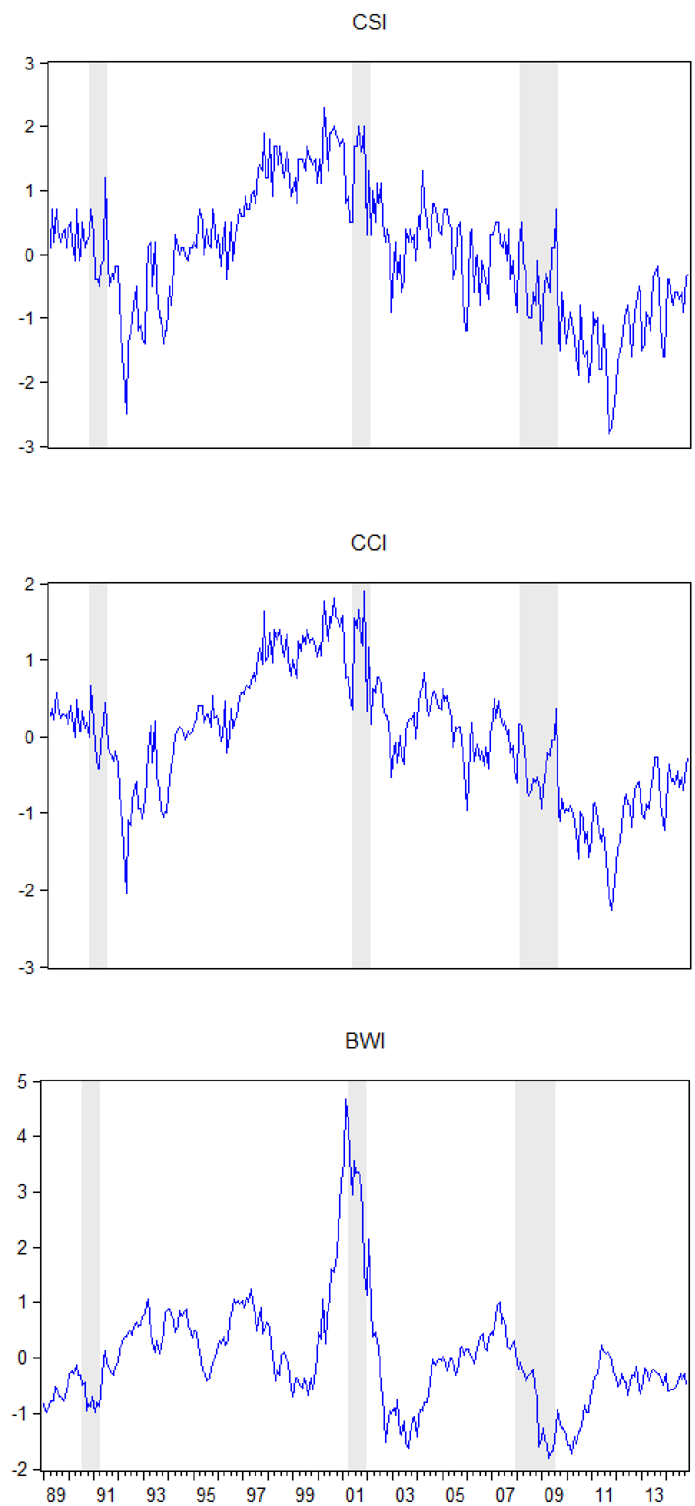


Figure 1.3: Sentiment level-based states

This figure plots level-based sentiment states, as captured by $S_t^{H,i}$, over the period December 1988 - October 2014. This dummy variable is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. i = CSI, CCI and BWI; where CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. Shaded areas denote the U.S recessions as classified by NBER business cycle dates.

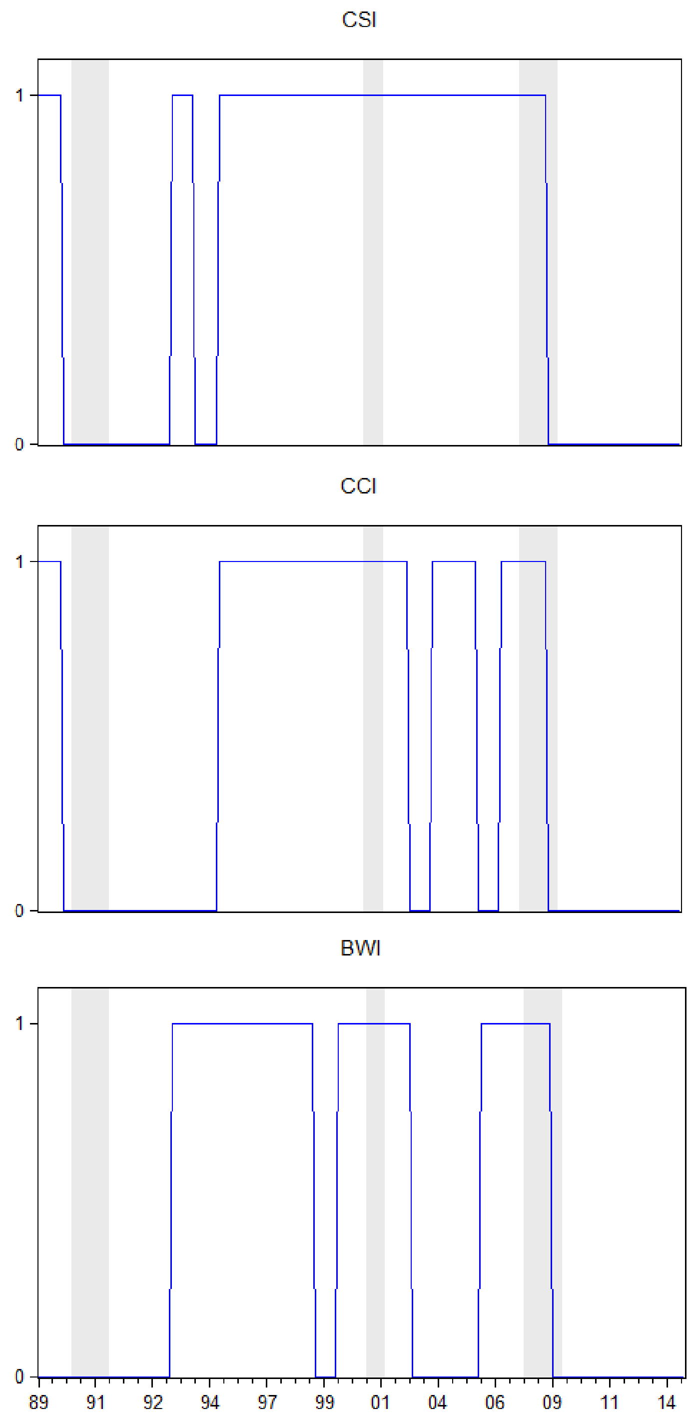


Figure 1.4: Sentiment changes-based states

This figure plots changes-based sentiment states, as captured by $S_t^{D,i}$, over the period January 1989 - October 2014. The dummy variable is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment year. A year is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end (December) of that year is lower (higher) than at the end of the previous year. i = CSI and CCI; where CSI and CCI denote the University of Michigan's Consumer Sentiment index and the U.S. Consumer Confidence index, respectively. Shaded areas denote the U.S recessions as classified by NBER business cycle dates.

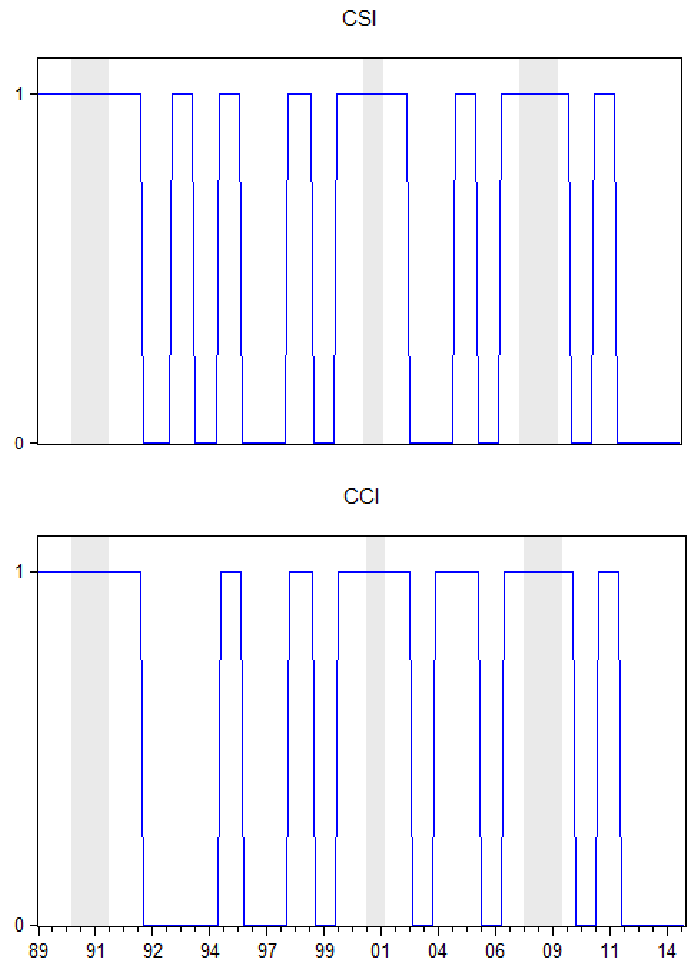


Figure 1.5: Sentiment states and bear markets

This figure plots level and changes-based interacted sentiment states (solid line), as captured by S_t^{HD}, along with a bear market indicator (dotted line). The sentiment dummy variable is equal to 1 if the FOMC meeting occurred during a year when sentiment starts at high level but then declines, and 0 otherwise. A year is defined as of high at the start but then decreasing sentiment if the CSI at the end (December) of the previous year exceeds the full sample mean value and the CSI at the end of that year is lower than at the end of the previous year. CSI denotes the University of Michigan's Consumer Sentiment index. The bear market indicator is a dummy variable that is equal to 1 when the S&P 500 stock market index is lower than its full sample 2-year moving average, and 0 otherwise. Shaded areas denote the U.S recessions as classified by NBER business cycle dates.

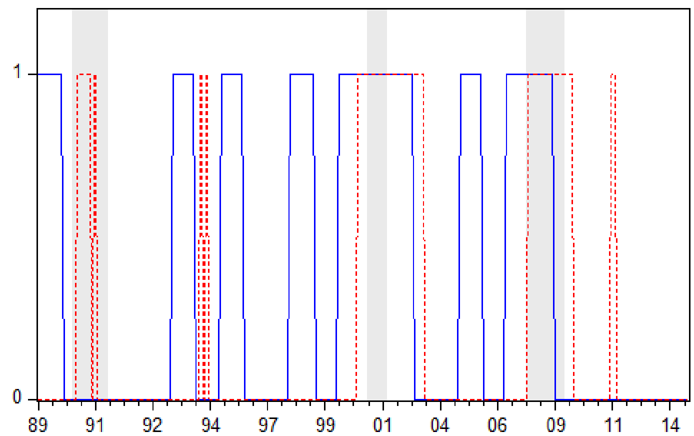


Figure 1.6: Monetary cycles

This figure plots monetary cycles, as captured by Eas_t, over the period December 1988 - October 2014. This dummy variable is equal to 1 if the FOMC meeting occurred during a monetary easing cycle and 0 otherwise. A monetary easing cycle is defined as starting with a negative FFR target rate change and ending with a positive FFR target rate change. Shaded areas denote the U.S recessions as classified by NBER business cycle dates.

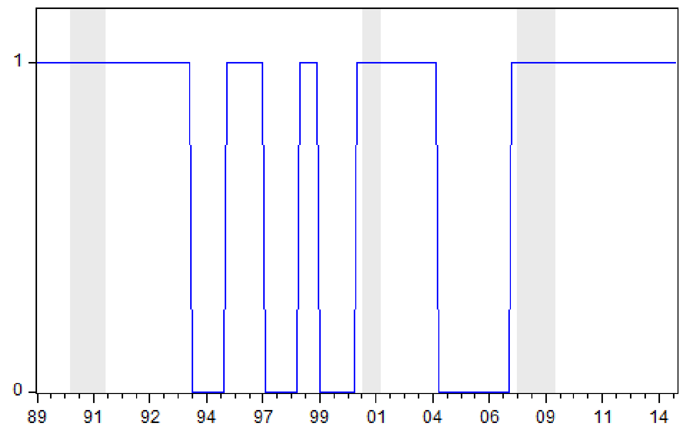


Figure 1.7: Response of industry portfolio returns to FFR shocks before the zero lower bound

This figure plots OLS estimates of the impact of unexpected FFR changes on industry portfolio returns, over FOMC announcement days, following periods of low (high) sentiment in Panel A (B), as captured by β_1 (β_2), in the following model: $R_{it}=\beta_0+\beta_1(1-S_t^H)\Delta i_t^u+\beta_2 S_t^H\Delta i_t^u+\varepsilon_t$, where R_{it} and Δi_t^u denote industry portfolio returns and unexpected FFR changes, respectively. The portfolio returns are in excess of the 1-month Treasury bill rate. We use data on 49 industry-classified portfolios, obtained from the database of K. French. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. The vertical lines represent the 95% confidence intervals associated with the estimated industry responses.

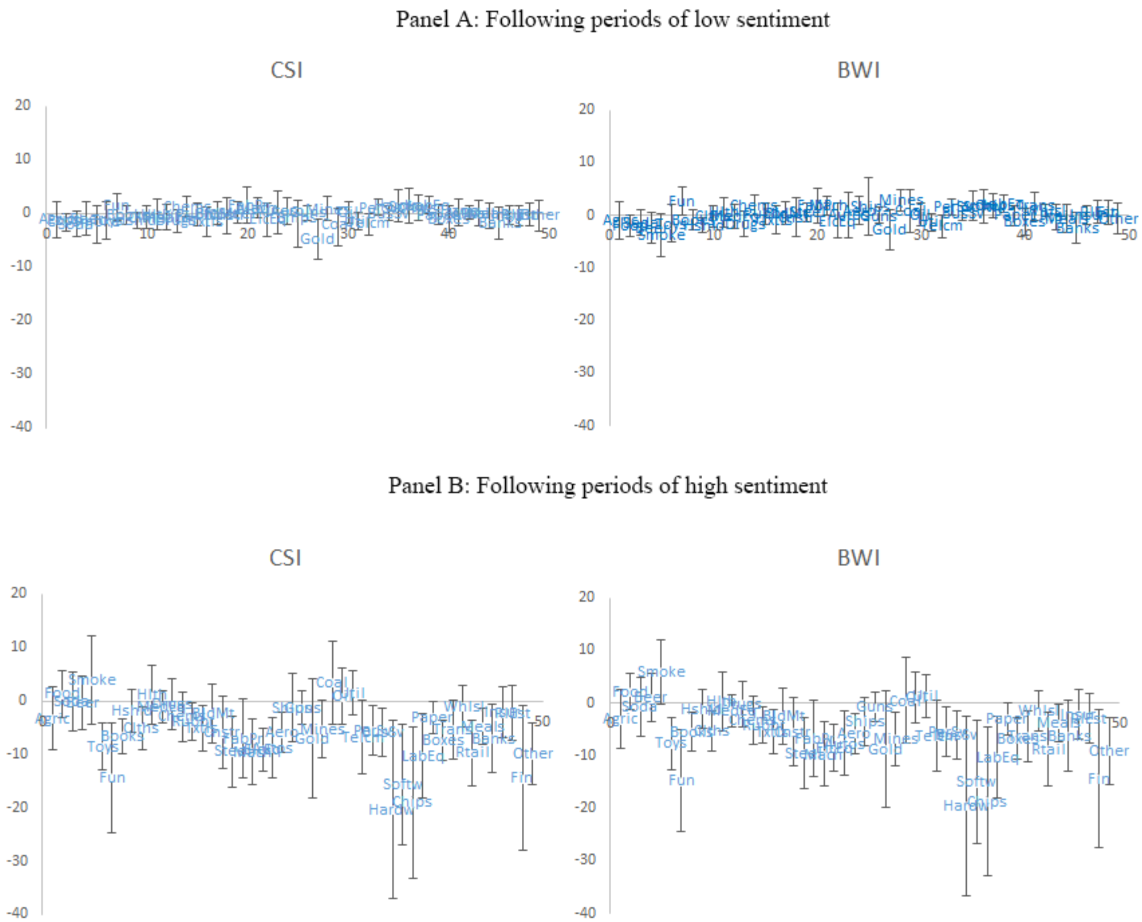


Figure 1.8: CAPM for industry portfolios on FOMC announcement days

This figure shows the fit of the CAPM for 49 industry-classified portfolios, obtained from the database of K. French, on FOMC announcement days. For each portfolio, the horizontal axis shows the average excess return earned on FOMC announcement days (in percent) whereas the vertical axis shows the excess return implied by the CAPM. The CAPM betas are estimated from a regression of the industry-classified portfolio's excess return on the excess return of the market portfolio at a daily frequency (using all days in the Fsample). The full sample period is June 1989 - October 2014, while the pre-ZLB period is June 1989 - December 2008. The results from the second-stage cross-sectional regressions are as follows: R_{FOMC} = -0.11(0.10) + 0.43(0.14)$\hat{\beta}$ for the full sample, and R_{FOMC} = -0.07(0.12) + 0.38(0.17)$\hat{\beta}$ for the pre-ZLB period, where the standard errors (in parentheses) are adjusted for the estimation error in betas following Shanken (1992). The dashed line shows the scatter plot regression line and the solid black line shows the 45-degree line.

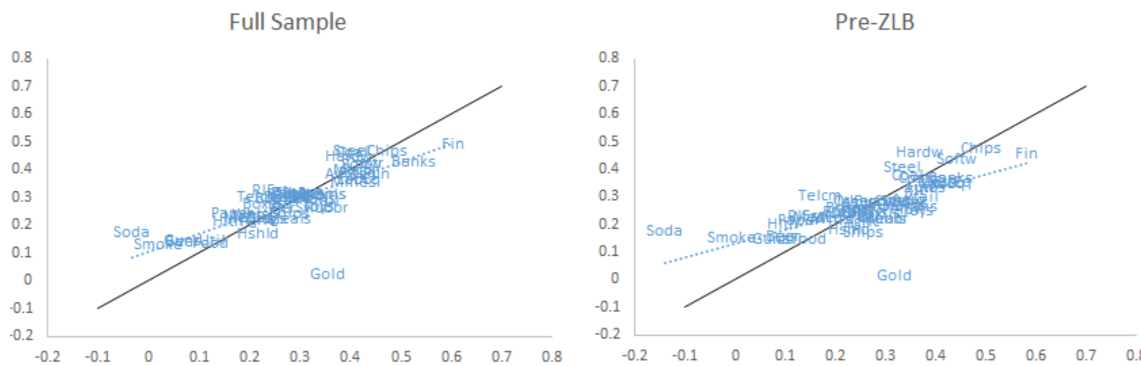
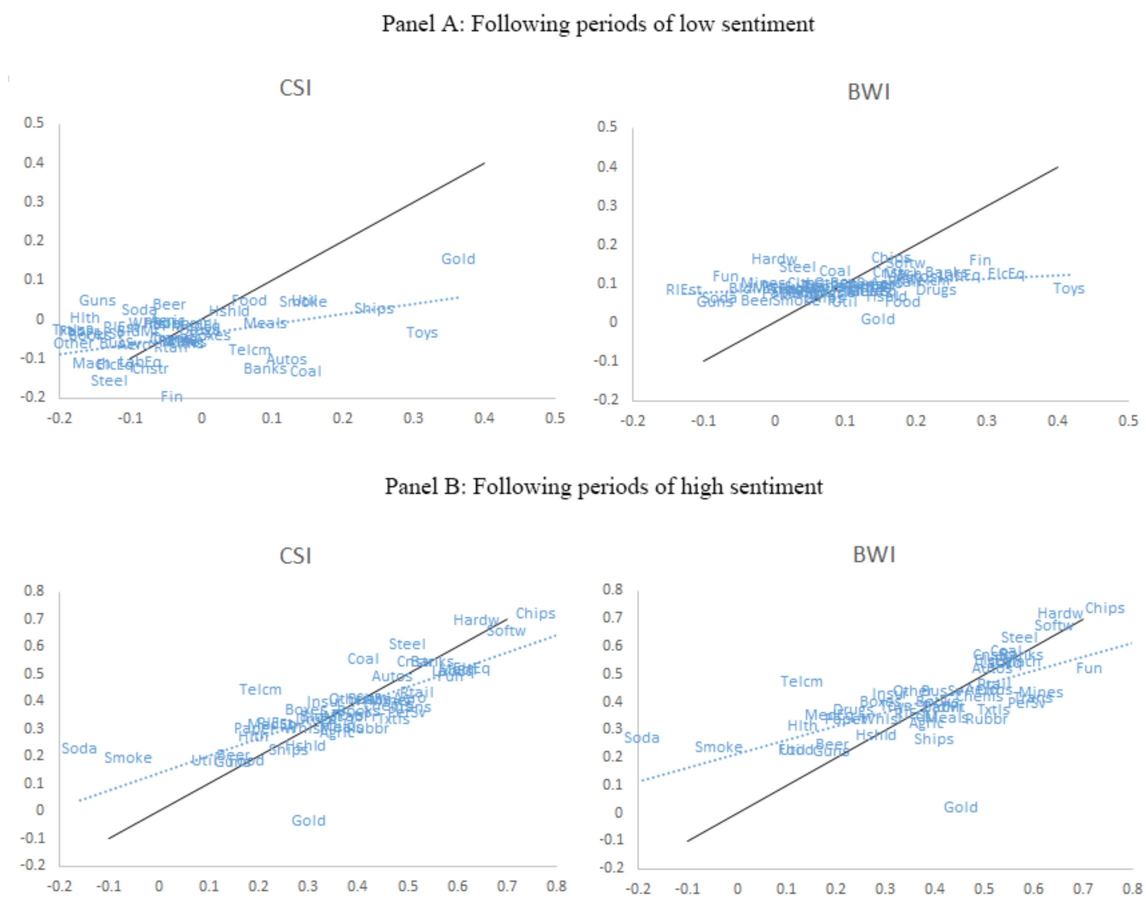


Figure 1.9: CAPM for industry portfolios on FOMC announcement days before the zero lower bound, following periods of high vs. low sentiment

This figure shows the fit of the CAPM for 49 industry-classified portfolios, obtained from the database of K. French, on FOMC announcement days following periods of high vs. low sentiment. For each portfolio, the horizontal axis shows the average excess return earned on FOMC announcement days (in percent) whereas the vertical axis shows the excess return implied by the CAPM. The CAPM betas are estimated from a regression of the industry-classified portfolio's excess return on the excess return of the market portfolio at a daily frequency (using all days in the sample). The sample period is June 1989 - December 2008. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The results from the second-stage cross-sectional regressions are as follows: R_{FOMC} = -0.17(0.16) + 0.62(0.22)$\hat{\beta}$ following periods of high sentiment, and R_{FOMC} = 0.23(0.11) - 0.30(0.12)$\hat{\beta}$ following periods of low sentiment, as defined by the CSI; R_{FOMC} = -0.11(0.20) + 0.58(0.28)$\hat{\beta}$ following periods of high sentiment, and R_{FOMC} = -0.02(0.10) + 0.13(0.13)$\hat{\beta}$ following periods of low sentiment, as defined by the BWI; where the standard errors (in parentheses) are adjusted for the estimation error in betas following Shanken (1992). The dashed line shows the scatter plot regression line and the solid black line shows the 45-degree line.



Chapter 2

Investor Sentiment States and the Cross-Sectional Stock Price Reaction to Monetary Policy

2.1 Abstract

This chapter analyzes the effect of investor sentiment states on the response of cross-sectional stock returns to monetary policy news using an event study approach over the Jun-89 to Oct-14 sample period. We demonstrate that monetary policy news affect stock portfolio returns only following periods of high sentiment or during periods of decreasing sentiment, especially for the deciles which are more sensitive to investor sentiment. Specially, FFR surprises have larger impacts on the stocks with high accruals, young stocks, stocks with high asset growth rate, stocks with low book-to-market ratio, high cash holding stocks, stocks with low gross profitability, high investment stocks, past loser stocks, stocks with high net operating assets, stocks with low asset tangibility, less profitable stocks, stocks with high return volatility, and large stocks at the pre-ZLB period. Unconventional monetary policy shocks also have larger impact on the stocks that are more exposed to investor sentiment.

2.2 Introduction

Traditional finance theory suggests that there are two main transmission channels through which monetary policy affects stock returns: the balance sheet channel and the bank lending channel. According to the balance sheet channel, monetary policy shocks can affect a firm's net cash flow by influencing consumer spending and the firm's floating-rate interest payments, and then, the firm's stock price. The bank lending channel has a more immediate effect. Monetary policy shocks will change the total supply of intermediated credit. Therefore, the level of funds that a firm can borrow from credit markets or financial intermediaries would be affected. Thus companies with different characteristics will respond differently to monetary policy shocks. A large number of previous studies investigate the impact of monetary policy shocks on cross-sectional stock returns (see Thorbecke (1997); Jensen and Mercer (2002); Kontonikas and Kostakis (2013)). However, all these studies focus on the transmission channels suggested by the classic finance theory.

In Chapter 1 of this thesis, we demonstrated that investor sentiment plays an important role in the transmission of monetary policy shocks to stock market returns. Specifically, monetary policy shocks affect market-wide stock return only following periods of high sentiment or during periods of decreasing sentiment, when stock market mispring is being corrected, as investors are more sensitive to monetary news during such periods. In fact, sentiment-driven misprices can affect not only the stock market as a whole, but also individual stocks. Having already documented the response of market-wide stock return to monetary policy shocks across sentiment states, we extend the analysis towards the response of cross-sectional stock returns.

In this chapter, we have a closer look at the influence of investor sentiment on the impact of monetary policy shocks on the cross-sectional stock returns over the period June 1989 to October 2014. The impacts of both conventional and unconventional monetary policy are investigated. We investigate the responses of 15 stock portfolio returns using the same event study methodology that we employed in Chapter 1. We first examine the sentiment sensitivity of different portfolio deciles. As discussed in previous studies, stocks with high sentiment sensitivity are more overvalued when sentiment is high, and the subsequent returns will be lower (Baker and Wurgler (2006); Lemmon and Portniaguina (2006); Stambaugh, Yu, and Yuan (2012)). We find that the young stocks, stocks with low asset tangibility, growth stocks, large stocks, low profit stocks, stocks with high return volatility, past loser stocks, stocks with high accruals, stocks with high asset growth rate, distressed stocks, stocks with low gross profitability, high investment stocks, stocks with high net operating assets and stocks hold more cash have lower average returns following periods of high sentiment. Thus, those stocks are more exposed to investor sentiment. Our findings about sentiment sensitivity of the portfolios sorted by size and book-to-market ratio are different to the findings of Baker and Wurgler (2006). A possible explanation is that sentiment sensitivity of the portfolios may change. In fact, our results show that, the long leg and short leg of portfolios sorted by total accruals, asset growth, book-to-market ratio, investment to asset, net operating assets, and size reverse at the ZLB period.

Second, consistent with our findings in Chapter 1, we demonstrate that stock portfolio returns are affected by monetary policy shocks only following periods of high sentiment or during periods of decreasing sentiment. Importantly, our findings show that short leg stocks are generally more exposed to monetary policy shocks. In other words, stocks which are more sensitive to investor sentiment are also more sensitive to monetary policy shocks. These findings can be interpreted as evidence in favour of a separate sentiment channel of the transmission of monetary policy.

This chapter contributes to the studies which investigate the role of investor sentiment in asset pricing. Our results are in line with previous studies, which find that the cross-section of future stock returns is conditional upon the begin-of-period proxies for sentiment. However, by focusing on the ZLB period, we extend previous literature by showing that the cross-sectional sentiment sensitivity may change over time. This chapter also relates to the studies which examine the relationship between monetary policy and stock returns. We extend the literature by examining the cross-sectional response of 15 portfolios.[1] Moreover, our findings are also related to the literature on state dependence in the relationship between stock returns and monetary policy. Our evidence for sentiment-dependence will be crucial to distinguish between behavioural and economic fundamentals-based explanations for the cross-sectional patterns. Specifically, previous papers that document a strong impact of monetary policy shifts on stocks of small size and high book-to-market ratio interpret their findings in the context of the credit channel of the policy transmission mechanism (Thorbecke (1997); Perez-Quiros and Timmermann (2000); Ehrmann and Fratzscher (2004); Basistha and Kurov (2008); Kontonikas and Kostakis (2013); Maio (2014)). According to the credit channel, small firms are more financially constrained, relative to large firms, since they are less well-collateralized and do not have the same ability to raise external finance (Gertler and Gilchrist (1994); Bernanke, Gertler, and Gilchrist (1996)).[2] Therefore, small stocks are expected to be more strongly affected by a monetary policy shock, in comparison to large stocks. Further, high book-to-market ratio firms are likely to be distressed and, consequently, more sensitive to changes in monetary conditions than growth firms (Kontonikas and Kostakis (2013); Maio (2014)).[3] The credit channel theory, however, neither posits a role for investor sentiment, nor does it anticipate that the response of size- and book-to-market ratio-sorted portfolios may vary across sentiment states. Moreover, it does not predict a strong reaction by growth and loser stocks to monetary policy news.[4] In fact, when one considers the impact of investor sentiment, our results show that it is the large, and low book-to-market ratio firms are more affected by monetary policy shocks, following periods of high sentiment. Thus, finding that sentiment-sensitive stocks are mostly impacted, can be interpreted as evidence in favour of a separate sentiment channel.

The rest of the chapter is organised as follows. Section 2.2 develops our hypothesis. Section

[1] Previous studies, however, mainly focus on the portfolios sorted by size, value and momentum.

[2] Small companies have limited ability to issue commercial papers and face higher agency costs of debt. Moreover, small companies have restricted access to intermediated credit, and hence on the advent of an overall reduced supply of bank loans, these companies are typically the first to have their credit lines reduced or cut. Whited and Wu (2006) and Hadlock and Pierce (2010), among others, find that size loads negatively to a composite indicator of financial constraints.

[3] Several studies have shown that the value premium is associated with relative distress. Specifically, high book-to-market (value) firms tend to have persistently lower earnings and are considered to be more financially distressed, relative to low book-to-market (growth) firms (Fama and French (1993); Fama and French (1995); Fama and French (1998)).

[4] Kontonikas and Kostakis (2013) point out that stock portfolios formed on the basis of past performance and without reference to corporate characteristics, such as momentum-sorted portfolios, cannot be used to shed light on the credit channel.

2.3 describes the data and variables employed in the empirical analysis. In Section 2.4, we present evidence on the role of investor sentiment in the impact of monetary policy shocks on different stock portfolios. Section 2.5 describes the results from various robustness checks. Finally, Section 2.6 concludes.

2.3 Data and sample

In this section we present and discuss the measures of monetary policy, investor sentiment and stock portfolios that we employ in the subsequent empirical analysis. The full sample period is June 1989 - October 2014, hence including the pre-crisis period, the financial crisis and its aftermath. Our dataset includes a set of event-dates with 204 scheduled FOMC meetings and 23 unscheduled FOMC meetings.

2.3.1 Monetary policy news

We consider both conventional and unconventional monetary policy news. We measure conventional monetary policy shocks as unexpected component of changes in the target FFR using the methodology proposed by Kuttner (2001). The unconventional monetary policy we considered is the Fed's forward guidance through FOMC statements at the ZLB. We measure the changes in forward guidance as path surprises using the methodology introduced by Gürkaynak, Sack, and Swanson (2005). We refer the reader to Section 1.3.1 for a more detailed discussion concerning the measurement of these monetary policy shocks, and for an analysis of the related descriptive statistics.

2.3.2 Investor sentiment states

In order to examine whether the relationship between cross-sectional stock returns and monetary policy shifts is conditional on the state of investor sentiment, we construct a level-based dummy variable, S_t^H, and a changes-based dummy variable, S_t^D, based on the orthogonalized sentiment indexes. We employ two proxies for investor sentiment: Baker and Wurgler's (2006, 2007) Sentiment Index (BWI) and the University of Michigan's Consumer Sentiment Index (CSI). We refer the reader to Section 1.3.2 for a more detailed discussion concerning the measurement of these variables, and for an analysis of the related descriptive statistics.

2.3.3 Stock portfolios

In order to examine the role that investor sentiment plays in the transmission of monetary policy news on cross-sectional stock returns, we consider daily returns on 15 portfolio sorts which are commonly used by previous literature: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). We obtain return data on BM/ME, Mom and Size from the database of K. French, and we construct the other 12 portfolios using the firm-level data from the merged CRSP-Compustat database.

Following Novy-Marx (2013), the sample includes all common stock (share codes 10 and 11), financial firms (those with SIC codes between 6000 and 6999) are excluded. We consider value-weighted-return of different portfolios. There portfolios are constructed using a decile sort on a signal using NYSE breakpoints. We use both annual files and quarterly files on merged CRSP-Compustat database. In order to avoid lookahead bias, for the portfolios using the annual files, accounting data for fiscal-year end of year t is matched with stock returns data from July of year t+1 until June of year t+2. These portfolios are sorted into 10 groups and rebalanced annually at the end of June. For the ones that use the quarterly files, the accounting data for a given quarter are matched to the end of the second month after which they were reported. These portfolios are sorted into 10 groups and rebalanced monthly.

We calculate Acc following the method introduced by Sloan (1996). We measure AG as the growth rate of total assets. Age is defined as the number of years since the firm's first appearance on CRSP, measured to the end of our sample. BM is book equity divided by market equity. CA is cash and marketable securities over total assets. GP is gross profits over total assets. Inv is the annual change in gross total property, plant, and equipment, plus the annual change in total inventories, divided by one-year lagged total assets. Mom is measured as stocks' cumulated past performance in the previous year by skipping the most recent month. NOA is defined as the difference on the balance sheet between all operating assets and all operating liabilities scaled by total assets. Oscore is calculated as the probability of bankruptcy in a static model using accounting variables. PPE/A is measured by property, plant and equipment over total assets. RoA is income before extraordinary items over total assets. RoB is income before extraordinary items over book value of equity. Sigma is measured by the standard deviation of monthly stock returns over the past 12 months. Size is the market value of equity. Detailed discussions about the construction of portfolios are reported in the Appendix B,

2.4 Econometric models and results

2.4.1 Investor sentiment and the long-short strategy

We begin our empirical investigation by examining the sentiment-sensitivity of different stock portfolios at the pre-ZLB period (June 1989 - December 2008). We separate our sample into two states according to the sentiment level at the end (December) of the previous year. Specifically, a year is defined as starting with high (low) sentiment if the sentiment proxy at the end of the previous year is above (below) the full sample mean value. According to Stambaugh, Yu, and Yuan (2012), short selling is the major obstacle to eliminating sentiment-driven mispricing. Overpricing should then be more prevalent than underpricing, and overpricing should be more prevalent when market-wide sentiment is high. Thus, we define the deciles with lower returns following periods of high sentiment as exhibiting higher sentiment-sensitivity because they are more overvalued. Another reason that we focus on the periods following high sentiment is that our findings in Chapter 1 show conventional monetary policy shocks affect market-wide stock returns only following periods of high sentiment

[Insert Table 2.1 around here]

Table 2.1 reports the presents the monthly average portfolio returns across sentiment states classified by CSI for the pre-ZLB periods. The first rows of Table 2.1 show that the effect of total accruals conditional on sentiment. Following periods of high sentiment, firms with high accruals earn lower returns on average than firms with low accruals.[5] Thus, stocks of firms with high accruals should have higher sentiment-sensitivity.

The next rows of Table 2.1 show that the cross-sectional effect of firm ages is conditional upon the state of investor sentiment. Specifically, youngest stocks earn 0.45% less than the top-decile Age firms following periods of high sentiment, which indicates that they are more exposed to sentiment. This is consistent with the findings of Baker and Wurgler (2006).

The next rows of Table 2.1 show that the average monthly returns following high sentiment periods is decreasing, though not monotonically, with asset growth decile. This indicates that companies that grow their total asset more are more sensitive to investor sentiment.

The next rows of Table 2.1 present the average monthly returns of stock portfolios sorted by the book-to-market ratio. The conditional cross-sectional effect is striking. The average returns increase monotonically from the growth (bottom-decile) stocks to the value (top-decile) stocks following periods of high sentiment. This is different to Baker and Wurgler (2006), who find a “U-shape" among the average monthly returns of stock portfolios sorted by the book-to-market ratio.

The next rows look at the cash. Although the returns for the top-decile is only 0.02% lower than the bottom-decile following periods of high sentiment, the conditional difference in returns on top-decile is -0.41% per month, which is much larger than that of the bottom-decile (%0.06). The results indicate that firms with larger cash to asset ratio are more exposed to investor sentiment.

The next rows examine gross profitability. Following periods of high sentiment, the average returns for the bottom-decile (top-decile) stocks is 0.91% (0.96%). The conditional differences

[5] Sloan (1996) find similar pattern, without considering the state of investor sentiment.

are the same for the two deciles. So the bottom-decile is slightly more sensitive to investor sentiment, as compared to the top-decile.

The remain results presented in the next rows show that, firms with higher past investment, lower past performance, higher net operating assets, higher O-score, less tangible assets, less profitability (measured by return-on-asset and return-on-book value of equity), and higher return volatility have lower average returns following periods of high sentiment, and thus, are more exposed to investor sentiment.

Importantly, the results in the final rows of Table 2.1 show that, following periods of high sentiment, large firms have lower average returns (0.69%) as compared to small firms (0.98%). This is in contrast to the findings of Baker and Wurgler (2006). Moreover, we got similar results with sentiment states classified by the BWI (see Table 2.2).

We then construct a long-short strategy, using the extreme deciles, 1 and 10 only. For each portfolio, we define the decile which is more exposed to investor sentiment as the short leg, and the other decile will be the long leg. According to the results reported in Table 2.3, for the pre-ZLB period, stocks with high accruals, young stocks, stocks with high asset growth rate, stocks with low book-to-market ratio, high cash holding stocks, stocks with low gross profitability, high investment stocks, past loser stocks, stocks with high net operating assets, distressed stocks, stocks with low asset tangibility, less profitable stocks, stocks with high return volatility, and large stocks are defined as the short leg.

We next examine the sentiment-sensitivity of stock portfolio deciles at the ZLB period. Because investor sentiment was always low after the ZLB was reached, following Baker and Wurgler (2006), we classify the deciles with higher average returns as with higher sentiment-sensitivity. Similarly, the deciles which are more exposed to investor sentiment are defined the short leg. The results reported in Table 2.4 show that, the sentiment sensitivity changes at the ZLB period for the portfolios sorted by total accruals, asset growth, book-to-market ratio, investment to asset, net operating assets, and size. For instance, large stocks are more exposed to investor sentiment at the pre-ZLB period, however, it is the small stocks that are more sensitive to investor sentiment at the ZLB period. Thus, large stocks is defined as the short leg (long leg) at the pre-ZLB (ZLB) period.

2.4.2 The impact of target rate surprises

We proceed by investigating the role that sentiment plays in the transmission of the conventional monetary policy shocks to cross-sectional stock returns. Specifically, we examine how FFR shocks affect the short leg/long leg of each portfolio across different sentiment states:

$$R_t = \beta_0 + \beta_1(1 - S_t^H)\Delta i_t^u + \beta_2 S_t^H \Delta i_t^u + \varepsilon_t \tag{2.1}$$

where R_t is the short leg/long leg return of each portfolio, and S_t^H is equal to one when sentiment is high at the end of the previous year. Thus, the β_2 coefficient measures the stock response to unexpected FFR changes following periods of high sentiment and the β_1 coefficient measures the stock response to unexpected FFR changes following periods of low sentiment.

[Insert Table 2.5 around here]

Table 2.5 and Table 2.6 reports the estimates of Equation 2.3 with sentiment measured by CSI and BWI, respectively. In line with the findings for market-wide stock returns in Chapter 1, the results in Table 2.5 show that the impact of FFR surprises on portfolio returns is statistically significant only when sentiment is high at the start of the year. These findings are robust to the use of BWI. In the cross-section, we find that the short leg deciles, which are more sensitive to investor sentiment, are generally more sensitive to FFR surprises following periods of high sentiment. For instance, for portfolios sorted by firm ages, the results in Table 2.5 show that the reaction of the short leg stocks to FFR surprises, conditional on the begin-of-the-year sentiment being high, is almost four times larger than the response of the long leg stocks (-11.22 vs. -3.09). The only exception is the O-score sorted portfolio. The impact of FFR shocks is larger on the long leg stocks, which are the stocks with low O-score. This may result from the multidimensional nature of the growth and distress variables mentioned by Baker and Wurgler (2006), as firms with low O-score may include high-flying growth firms, and growth stocks are more affected by FFR surprises following periods of high sentiment.

[Insert Table 2.6 around here]

On the aspect of the long-short spread, we find that the return differentials respond to unexpected FFR changes only when sentiment is high at the start of the year. The reaction of the long-short return differentials are statistically significant for the portfolios sorted by firm age, asset growth rate, book-to-market ratio, investor to asset ratio, momentum, asset tangibility, return volatility and firm size. As presented in Table 2.5, the long-short differentials decline in response to expansionary FFR surprises, driven by the stronger reaction of the short leg portfolios. For example, for the portfolios sorted by past performance, an unexpected cut of 25 basis points in the FFR is associated with about 2.5% higher return for the past-loser stocks (short leg) and 1.25% for the past-winner stocks. For the analyses based on BWI, we got similar results.

To sum up, in line with the presence of a sentiment mechanism, we find that the response of stock portfolios to monetary policy shocks is conditional on the state of investor sentiment. Conventional monetary policy shocks affect portfolio returns only following periods of high sentiment. We also find that the short leg stocks, which are more sensitive to sentiment, are also more exposed to FFR surprises.

Our evidence is in line with the event study results of Ehrmann and Fratzscher (2004) in the case of book-to-market portfolios, and Cenesizoglu (2011) for both size and book-to-market portfolios.[6] Also, our findings agree with the VAR evidence of Kontonikas and Kostakis (2013) in identifying past-loser stocks as more exposed to FFR shocks, relative to past-winner stocks.[7] Nevertheless none of these studies accounts for the role of investor sentiment and thereby average conditional patterns.

2.4.3 The impact of path surprises at the zero lower bound

We then examine the cross-sectional effect of unconventional monetary policy. We start by examining the impact of path surprises on stock returns during the ZLB era (January 2009 - October 2014). The level-based sentiment dummy variable cannot be used to identify sentiment states since it is always low throughout the ZLB period. Therefore, we employ the CSI changes-based dummy with the fowling regression[8]:

$$R_t = \beta_0 + \beta_1(1 - S_t^D)path_t + \beta_2 S_t^D path_t + \varepsilon_t \tag{2.2}$$

The results in Table 2.7 show that, consistent with the market-wide evidence in the Chapter 1, the effect of path surprise on stock portfolios materialize only during periods when sentiment is decreasing, supporting our argument of a sentiment channel. Consistent with the findings in Table 2.5, the short leg deciles are generally more sensitive to path surprises, relative to the long leg deciles. The portfolios sorted by cash to asset ratio and investment are the two of which the long leg deciles are more affected by path surprises, however, their long-short spread are insignificant.

[Insert Table 2.7 around here]

Thus, with the exception of portfolios sorted by cash to asset ratio and investment, the stocks that we expect to react more strongly to policy shocks, on the basis of high sentiment-sensitivity, do so. For some portfolios there is a pronounced dispersion in the monetary policy impact in the cross-section. For instance, during periods of decreasing sentiment, the momentum-sorted portfolio, the β_2 coefficient of the past-winner stocks (-2.75) is almost seven times smaller than that of the past-loser stock (-19.59), and not statistically different from zero. For other portfolios which has been employed in previous monetary literature (the size and book-to-market sorted portfolios), the reactions of both small and large stocks to path surprises are statistically significant, but small stocks react stronger than large stocks. Hence, the small-minus-large return differential increases in response to an unexpected decline in the path of interest rates. Expansionary path surprises also increase the value-minus-growth return differential, via the significant response of the high book-to-market stocks. These findings are consistent with previous

[6] It should be noted, though, that the results of Cenesizoglu (2011) are sensitive to the treatment of outliers.
[7] The responses of other portfolios have not been examined by previous studies.
[8] We consider only CSI changes-based dummy, see Chapter 1 for detailed explanations.

studies which examine the impact of unconventional monetary policy on stock returns. For example, Wright (2012) find that unexpected easing of monetary policy at the ZLB increases the return of the HML factor. However, they argue that it may reflect the high sensitivity of value stocks to the credit channel of the transmission mechanism. By showing that the cross-sectional repones are conditional on the state of investor sentiment, we shed light on the existence of a separate sentiment channel in the transmission of monetary policy shocks to stock returns.

Another interesting finding is that, the impact of monetary policy changes along with the changes in sentiment sensitivity. For example, the stocks with high asset growth rate are more exposed to investor sentiment at the pre-ZLB period. During the ZLB period, however, the stocks with low asset growth rate are more sensitive to investor sentiment. Our results show that, conventional monetary policy has larger impact on stocks with high asset growth rate at the pre-ZLB period, and unconventional monetary policy has larger impact on stocks with low asset growth rate at the ZLB period.

2.5 Robustness checks

We examine the robustness of our findings in a number of ways and find that the results reported in Section 3.5 are overall not sensitive to these changes. First, we employ an alternative sentiment index. Second we employ an alternative dummy variable to define sentiment states based upon a monthly classification scheme. The results are contained in the Appendix B. The reaction of stocks to monetary policy shocks is conditional upon the state of investor sentiment.

2.5.1 Alternative sentiment measure

As documented by Baker and Wurgler (2006) there is no perfect measure of investor sentiment. Different indices may capture different dimensions of investor sentiment. We employ a survey-based sentiment measure (CSI) and a sentiment index based on financial variables (BWI) in the previous section. In this section, we consider an alternative sentiment index, the U.S. Consumer Confidence Index (CCI) compiled by the Conference Board, to reassure the reader that the our results are robust across sentiment indicators.[9]

We examine the sentiment-sensitivity of different portfolio deciles for the pre-ZLB period, and present the results in Tables B.1 of the Appendix B. For the ZLB period, CCI is always at low level, so the sentiment sensitivity of different portfolio deciles are the same as the ones presented in Table 2.4. The results in Table B.1 show that the long-short strategy using CCI is not different to the ones reported in Table 2.3. We next investigate the impact of FFR shocks (for the pre-ZLB period) and path surprises (for the ZLB period) on portfolio returns across sentiment states classified by the CCI. The results are reported in Table B.3 and B.4 of the

[9]Please see Chapter 1 for detailed discussions on this sentiment measure.

Appendix B, respectively. Consistent with the baseline results, Table B.3 show that FFR shocks affect portfolio returns only following periods of high sentiment. Moreover, the short leg stocks, which are more sensitive to investor sentiment, are generally more exposed to monetary policy, excluding the portfolio sorted by O-score, which have been observed and explained in previous section.[10] Table B.4 also shows that the short leg stocks are generally more affected by path surprises shocks. In fact, because CSI and CCI show similar pattern in annual changes at the ZLB period, the results reported in Table B.4 are the same as the ones presented in Table 2.7.

2.5.2 Monthly classification of sentiment states

Similar to our analyses in Chapter 1, we employ level-based and changes-based sentiment dummy which are based upon an annual classification scheme in the baseline regressions. In order to ensure that our findings are robust to the frequency of the classification scheme, we use alternative sentiment state variables that are based upon a monthly classification of the state of investor sentiment, as in Stambaugh, Yu, and Yuan (2012). Specifically, for the analysis of the impact of target rate surprises we define a dummy variable S_t^{HM} that is equal to 1 if the FOMC meeting occurs during a month that starts with high sentiment level and 0 otherwise. A month is defined as starting with high sentiment if the sentiment proxy at the end of the previous month exceeds the full sample mean value. Table B.4 and B.5 in the Appendix B show the results using CSI and BWI, respectively. The monthly classification results are consistent with the baseline findings from annual classification of the sentiment states. In an unreported table, we also examine the impact of monthly change-based sentiment states on the transmission of path surprises to stock portfolio returns. However, although our results show a larger repones on the short-leg, most of the coefficients are insignificant. As we mentioned in Chapter 1, a plausible explanation is that, change-based dummy at the monthly frequency cannot correctly capture the sentiment correction periods, when the monetary policy mainly matters.

2.6 Conclusions

In Chapter 1, we show that there is a sentiment channel in the transmission of monetary policy to stock market. The impact of monetary policy shifts on the stock market is concentrated during the periods when the sentiment-driven mispricing is subsequently corrected, that is, following periods of high sentiment or during periods of decreasing sentiment. In this Chapter we investigate the impact of monetary policy shocks on stock portfolio returns across different sentiment states. We consider 15 portfolios which have been widely used in previous studies. We focus on the 1st and the 10th decile of each portfolio, and employ a long-short strategy, according to which the short-leg is the decile which is more exposed to investor sentiment. Following Baker

[10] For other portfolios, there are positive long-short differentials, however, not all of them are statistically significant.

and Wurgler (2006), we define a decile as more exposed to investor sentiment if the average returns of that decile is higher (lower) following periods of high (low) sentiment. Our findings show that, similar to the results on market-wide stock returns in Chapter 1, at the stock level, monetary policy shocks affect portfolio returns significantly only during the sentiment correction phases. Moreover, in the cross-section, we show that the short-leg deciles, which are hard to value and difficult to arbitrage, tend to react more strongly to both conventional and unconventional monetary policy shifts. Specifically, we find that conventional monetary policy have larger impacts on the stocks with high accruals, young stocks, stocks with high asset growth rate, stocks with low book-to-market ratio, high cash holding stocks, stocks with low gross profitability, high investment stocks, past loser stocks, stocks with high net operating assets, stocks with low asset tangibility, less profitable stocks, stocks with high return volatility, and large stocks at the pre-ZLB period. For the unconventional monetary, we also find that the response is more pronounced among the short-leg deciles, which are more exposed to investor sentiment.

The findings in this chapter enhance our argument in Chapter 1, that monetary policy shocks affect stock returns only following periods of high sentiment or during periods of decreasing sentiment. This chapter contributes to the literature which examines the impact of monetary policy shocks on the cross-sectional stock returns. Our findings cannot be explained by the traditional transmission channels of monetary policy. By showing the sentiment-based state dependence of monetary policy shocks on stock returns and the fact that stocks which are sentiment-sensitive are more exposed to monetary policy shocks, we argue that investor sentiment will affect the transmission of monetary policy to stock returns. However, it is still not clear how investor sentiment affect investors' decision-making and why the stocks which are more exposed to investor sentiment are also more exposed to monetary policy. This could be a avenue for future studies.

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Table 2.1: Portfolio average returns conditional upon the investor sentiment states based on the CSI before the zero lower bound

This table presents the average portfolio returns over months in which CSI is high at the start of the year, months in which it is low, and the difference between these two averages. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI denotes the University of Michigan's Consumer Sentiment index. The sample period is June 1989 - December 2008.

		1	2	3	4	5	6	7	8	9	10
	High	0.63	0.32	0.91	0.86	0.70	0.75	0.85	0.75	0.44	0.30
Acc	Low	0.80	0.81	0.86	0.88	0.95	1.01	1.06	1.06	1.05	1.02
	High-Low	-0.17	-0.48	0.06	-0.03	-0.25	-0.26	-0.21	-0.31	-0.61	-0.73
	High	0.35	0.26	0.89	0.86	0.48	0.97	0.68	0.68	0.85	0.80
Age	Low	0.59	1.22	0.87	1.30	0.39	0.52	0.60	0.76	0.85	0.73
	High-Low	-0.24	-0.96	0.02	-0.44	0.10	0.45	0.07	-0.07	0.00	0.07
	High	0.95	0.59	0.91	0.74	0.71	0.91	0.87	0.91	0.89	0.33
AG	Low	0.28	0.80	0.62	0.68	0.50	0.50	0.95	0.80	1.03	1.11
	High-Low	0.67	-0.21	0.29	0.06	0.22	0.41	-0.08	0.10	-0.13	-0.77
	High	0.23	0.62	0.88	0.83	1.00	1.00	1.21	1.14	1.25	1.40
BE/ME	Low	0.45	0.72	0.89	1.05	1.10	0.85	1.02	1.15	1.31	1.66
	High-Low	-0.22	-0.10	-0.02	-0.22	-0.09	0.15	0.19	-0.01	-0.06	-0.26
	High	0.80	0.40	0.64	1.05	0.67	0.60	0.68	0.81	0.82	0.78
CA	Low	0.74	0.49	0.62	0.53	0.67	0.69	0.70	1.14	1.14	1.20
	High-Low	0.06	-0.09	0.02	0.52	0.00	-0.09	-0.02	-0.33	-0.33	-0.41
	High	0.91	0.22	0.56	0.69	0.78	0.86	0.76	0.70	0.66	0.96
GP	Low	0.37	0.44	0.29	0.58	0.43	0.59	0.67	0.99	1.14	1.51
	High-Low	0.55	-0.22	0.27	0.11	0.34	0.26	0.09	-0.29	-0.47	-0.55
	High	0.82	0.68	0.77	0.94	0.98	0.85	0.70	0.70	0.45	0.44
Inv	Low	0.55	0.35	1.18	0.69	0.77	0.95	0.81	0.57	0.82	1.46
	High-Low	0.27	0.33	-0.41	0.24	0.22	-0.10	-0.11	0.13	-0.37	-1.02
	High	-0.34	0.26	0.41	0.71	0.57	0.64	0.80	1.06	0.83	1.29
Mom	Low	-0.34	0.71	0.70	0.54	0.59	0.82	0.74	0.84	0.73	1.36
	High-Low	0.00	-0.45	-0.30	0.18	-0.02	-0.18	0.06	0.23	0.10	-0.07
	High	1.04	0.79	0.97	1.10	1.12	1.14	0.99	0.84	0.93	0.79
NOA	Low	1.39	2.00	1.74	1.39	0.83	0.06	0.26	0.58	-1.14	1.83
	High-Low	-0.35	-1.20	-0.77	-0.29	0.29	1.08	0.73	0.26	2.07	-1.04
	High	0.78	0.33	0.81	0.72	0.89	0.71	0.67	0.69	0.74	0.32
Oscore	Low	1.11	0.83	0.47	0.70	0.61	0.74	0.60	0.39	0.28	0.00
	High-Low	-0.33	-0.49	0.34	0.02	0.28	-0.02	0.07	0.29	0.47	0.32
	High	0.71	0.24	0.80	0.76	0.58	0.91	0.68	0.57	0.85	1.13
PPE/A	Low	0.82	1.31	1.26	1.03	0.80	0.74	0.73	0.50	0.50	0.35
	High-Low	-0.11	-1.06	-0.46	-0.27	-0.21	0.16	-0.06	0.07	0.35	0.78
	High	0.77	0.73	1.05	1.38	1.15	0.79	0.93	0.82	0.69	1.21
RoA	Low	0.13	0.78	1.06	0.01	-0.01	0.26	0.38	1.27	1.21	1.04
	High-Low	0.64	-0.05	-0.02	1.37	1.16	0.53	0.55	-0.45	-0.52	0.16
	High	0.37	-0.14	0.55	0.52	0.83	0.56	0.82	0.88	0.87	0.82
RoB	Low	-0.18	0.17	0.38	0.62	0.56	0.57	0.63	0.76	0.83	1.36
	High-Low	0.55	-0.31	0.17	-0.10	0.27	-0.01	0.19	0.11	0.04	-0.54
	High	0.95	0.78	0.50	0.79	0.67	0.66	0.82	0.73	0.80	0.65
Sigma	Low	1.12	1.09	0.51	0.85	0.68	0.58	0.68	0.53	0.67	0.02
	High-Low	-0.17	-0.31	-0.02	-0.06	-0.02	0.08	0.14	0.20	0.14	0.63
	High	0.98	0.95	0.89	0.81	0.80	0.79	0.90	0.83	0.84	0.69
Size	Low	0.60	0.56	0.80	0.74	1.00	1.03	0.77	0.81	0.82	0.75
	High-Low	0.38	0.39	0.09	0.07	-0.19	-0.25	0.14	0.02	0.02	-0.06

Table 2.2: Portfolio average returns conditional upon investor sentiment states based on the BWI before the zero lower bound

This table presents the average portfolio returns over months in which CSI is high at the start of the year, months in which it is low, and the difference between these two averages. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. BWI denotes Baker and Wurgler's (2006, 2007) sentiment index. The sample period is June 1989 - December 2008.

		1	2	3	4	5	6	7	8	9	10
	High	0.56	0.43	0.87	0.82	0.64	0.86	0.85	0.58	0.26	0.06
Acc	Low	0.75	1.03	0.86	0.73	0.74	0.66	0.94	0.90	0.88	0.84
	High-Low	-0.19	-0.60	0.01	0.09	-0.10	0.21	-0.10	-0.31	-0.62	-0.78
	High	-0.12	0.31	0.67	0.72	0.39	1.10	0.67	0.67	0.96	0.85
Age	Low	0.95	1.45	1.15	1.19	0.90	0.65	0.65	0.74	0.74	0.72
	High-Low	-1.07	-1.14	-0.48	-0.47	-0.51	0.44	0.02	-0.07	0.23	0.12
	High	0.98	0.99	0.96	0.87	0.85	0.76	0.85	0.81	0.63	0.13
AG	Low	0.63	0.73	0.74	0.58	0.56	0.90	0.93	1.00	1.22	0.86
	High-Low	0.36	0.26	0.22	0.29	0.29	-0.14	-0.08	-0.19	-0.59	-0.72
	High	-0.23	0.25	0.63	0.82	0.91	0.95	1.10	1.17	1.29	1.38
BE/ME	Low	0.81	1.05	1.14	0.94	1.13	0.99	1.24	1.11	1.23	1.53
	High-Low	-1.04	-0.80	-0.51	-0.11	-0.22	-0.04	-0.14	0.06	0.07	-0.15
	High	0.84	0.27	0.76	0.80	0.70	0.52	0.78	1.03	0.86	0.73
CA	Low	0.73	0.42	0.51	1.10	0.92	0.72	0.59	0.91	0.91	1.33
	High-Low	0.11	-0.16	0.25	-0.30	-0.22	-0.19	0.19	0.11	-0.05	-0.61
	High	0.69	0.69	0.43	0.70	0.54	0.60	0.84	0.69	0.49	0.93
GP	Low	0.92	0.22	0.58	0.63	0.75	1.02	0.65	0.70	1.04	1.22
	High-Low	-0.22	0.47	-0.16	0.06	-0.21	-0.42	0.19	-0.01	-0.55	-0.30
	High	0.70	0.74	1.16	0.92	0.98	0.80	0.82	0.68	0.13	0.08
Inv	Low	0.83	0.70	0.53	0.85	0.90	0.93	0.63	0.65	0.95	1.25
	High-Low	-0.14	0.04	0.63	0.07	0.08	-0.13	0.19	0.03	-0.82	-1.17
	High	-0.53	0.28	0.45	0.70	0.60	0.71	0.89	1.09	0.83	1.16
Mom	Low	-0.15	0.43	0.49	0.65	0.54	0.65	0.68	0.94	0.80	1.46
	High-Low	-0.38	-0.15	-0.04	0.05	0.06	0.06	0.21	0.15	0.03	-0.30
	High	0.84	1.67	0.90	0.95	1.34	1.51	0.48	1.07	0.64	0.25
NOA	Low	1.40	0.77	1.37	1.37	0.99	0.30	1.22	0.25	0.37	1.79
	High-Low	-0.57	0.90	-0.47	-0.41	0.35	1.21	-0.74	0.83	0.27	-1.54
	High	0.72	0.60	0.69	0.57	1.06	0.83	0.62	0.48	0.62	-0.11
Oscore	Low	0.98	0.84	0.80	0.87	0.78	0.61	0.70	0.81	0.67	0.63
	High-Low	-0.25	-0.24	-0.11	-0.30	0.29	0.22	-0.08	-0.34	-0.05	-0.75
	High	0.53	0.68	0.78	0.71	0.58	0.79	0.68	0.36	0.92	1.06
PPE/A	Low	0.94	1.01	1.01	0.93	0.85	0.97	0.70	0.57	0.64	0.89
	High-Low	-0.41	-0.33	-0.22	-0.21	-0.27	-0.18	-0.02	-0.21	0.28	0.17
	High	0.89	0.63	0.50	1.07	0.53	0.90	0.74	0.56	0.93	1.14
RoA	Low	-0.15	1.00	1.63	1.13	1.27	0.46	0.90	1.16	0.66	1.20
	High-Low	1.03	-0.37	-1.13	-0.06	-0.73	0.45	-0.15	-0.60	0.26	-0.06
	High	-0.07	0.13	0.39	0.47	0.60	0.62	0.65	0.83	0.83	0.92
RoB	Low	0.60	0.44	0.65	0.61	0.84	0.50	0.92	0.97	0.90	0.94
	High-Low	-0.67	-0.31	-0.27	-0.13	-0.24	0.12	-0.27	-0.14	-0.07	-0.02
	High	1.12	1.09	0.51	0.85	0.68	0.58	0.68	0.53	0.67	0.02
Sigma	Low	0.68	0.74	0.57	0.66	0.80	0.77	0.87	0.86	1.00	1.37
	High-Low	0.43	0.35	-0.06	0.18	-0.12	-0.20	-0.20	-0.32	-0.34	-1.35
	High	0.82	0.77	0.68	0.58	0.65	0.67	0.71	0.67	0.82	0.67
Size	Low	1.00	0.98	1.07	1.01	1.04	1.02	1.05	0.99	0.86	0.73
	High-Low	-0.18	-0.22	-0.38	-0.42	-0.40	-0.35	-0.34	-0.32	-0.04	-0.06

Table 2.3: The long-short strategy before the zero lower bound

This table presents the long-short strategy for 15 portfolios. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). Deciles which are more sensitive to investor sentiment are defined as the short leg. A decile is defined as with higher sentiment sensitivity if it has lower average monthly returns during years start with high sentiment. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period is June 1989 - December 2008.

	CSI		BWI	
	Long leg	Short Leg	Long leg	Short leg
Acc	Decile 1	Decile 10	Decile 1	Decile 10
Age	Decile 10	Decile 1	Decile 10	Decile 1
AG	Decile 1	Decile 10	Decile 1	Decile 10
BE/ME	Decile 10	Decile 1	Decile 10	Decile 1
CA	Decile 1	Decile 10	Decile 1	Decile 10
GP	Decile 10	Decile 1	Decile 10	Decile 1
Inv	Decile 1	Decil 10	Decile 1	Decile 10
Mom	Decile 10	Decile 1	Decile 10	Decile 1
NOA	Decile 1	Decile 10	Decile 1	Decile 10
Oscore	Decile 1	Decile 10	Decile 1	Decile 10
PPE/A	Decile 10	Decile 1	Decile 10	Decile 1
RoA	Decile 10	Decile 1	Decile 10	Decile 1
RoB	Decile 10	Decile 1	Decile 10	Decile 1
Sigma	Decile 1	Decile 10	Decile 1	Decile 10
Size	Decile 1	Decile 10	Decile 1	Decile 10

Table 2.4: Portfolio average returns and the long-short strategy at the zero lower bound

This table presents the monthly average returns and the long-short strategy for 15 portfolios over the period January 2009 - October 2014. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). Deciles which are more sensitive to investor sentiment are defined as the short leg. A decile is defined as with higher sentiment sensitivity if it has higher average monthly returns over the sample period.

	1	2	3	4	5	6	7	8	9	10	Long leg	Short leg
Acc	1.88	1.32	1.17	1.58	1.71	1.44	1.66	1.28	1.67	1.54	Decile 10	Decile 1
Age	1.82	1.84	1.79	1.61	1.67	1.55	1.66	1.53	1.32	1.20	Decile 10	Decile 1
AG	2.04	1.82	1.19	1.54	1.70	1.27	1.26	1.47	1.68	1.55	Decile 10	Decile 1
BE/ME	1.72	1.81	1.82	1.93	1.94	1.74	1.88	1.71	1.89	2.43	Decile 1	Decile 10
CA	1.23	1.40	1.29	1.42	1.48	1.52	1.39	1.39	1.75	1.70	Decile 1	Decile 10
GP	1.64	1.44	1.68	1.66	1.49	1.38	1.56	1.45	1.42	1.53	Decile 10	Decile 1
Inv	1.54	1.55	1.83	1.80	1.03	1.63	1.36	1.62	1.39	1.24	Decile 10	Decile 1
Mom	2.42	1.85	2.01	1.70	1.90	1.63	1.53	1.39	1.39	1.49	Decile 10	Decile 1
NOA	1.85	1.38	1.70	1.45	1.27	1.39	1.20	1.60	1.37	1.53	Decile 10	Decile 1
Oscore	1.36	1.35	1.62	1.59	1.71	1.66	1.53	1.80	2.17	2.33	Decile 1	Decile 10
PPE/A	1.94	1.50	1.31	1.19	1.06	1.09	0.71	0.76	0.68	0.71	Decile 10	Decile 1
RoA	1.63	1.69	1.82	1.68	1.42	1.61	1.45	1.21	1.50	1.49	Decile 10	Decile 1
RoB	1.73	1.68	1.93	1.58	1.53	1.35	1.48	1.35	1.22	1.59	Decile 10	Decile 1
Sigma	1.17	1.45	1.44	1.56	1.67	1.84	1.98	2.05	2.31	2.30	Decile 1	Decile 10
Size	1.63	1.54	1.73	1.60	1.72	1.80	1.72	1.78	1.64	1.36	Decile 10	Decile 1

Table 2.5: Response of portfolio returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - CSI based analyses

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC meeting dates of the following model: R_t=β_0+$\beta_1(1-S_t^H)\Delta i_t^u$+$\beta_2 S_t^H \Delta i_t^u$+$\varepsilon_t$, where R_t and Δi_t^u denote portfolio returns and unexpected FFR changes, respectively. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). Deciles which are more exposed to sentiment are defined as the short leg. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value according to the University of Michigan's Consumer Sentiment Index. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. P-values from the Wald test for equality of coefficients (F-statistic) are reported in square brackets. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Portfolios	Long Leg			Short Leg			Long-Short		
	β_1	β_2	$\beta_1=\beta_2$	β_1	β_2	$\beta_1=\beta_2$	β_1	β_2	$\beta_1=\beta_2$
Acc	0.57	-10.48^{***}	[0.00]	0.06	-10.85^{***}	[0.00]	0.50	0.38	[0.95]
	(1.11)	(3.61)		(1.34)	(2.97)		(0.81)	(1.16)	
Age	-0.20	-3.09^{*}	[0.14]	-0.51	-11.20^{***}	[0.00]	0.31	8.11^{*}	[0.07]
	(0.94)	(1.79)		(1.14)	(3.80)		(0.89)	(4.34)	
AG	0.23	-2.47	[0.19]	-0.24	-11.87^{***}	[0.00]	0.47	9.40^{**}	[0.03]
	(1.03)	(1.87)		(1.28)	(3.69)		(0.61)	(4.16)	
BE/ME	0.03	-3.32^{*}	[0.15]	-0.56	-10.37^{***}	[0.00]	0.60	7.05^{***}	[0.01]
	(1.43)	(1.92)		(1.09)	(2.85)		(0.86)	(2.36)	
CA	-1.07	-3.31^{*}	[0.24]	0.16	-11.55^{***}	[0.00]	-1.22	8.23^{***}	[0.00]
	(1.02)	(1.74)		(1.33)	(3.34)		(1.00)	(2.28)	
GP	-0.35	-5.63^{***}	[0.01]	-0.33	-6.89^{***}	[0.00]	-0.03	1.26	[0.33]
	(1.08)	(1.81)		(1.12)	(1.77)		(0.55)	(1.21)	
Inv	-0.78	-2.50	[0.33]	-0.37	-10.55^{***}	[0.00]	-0.41	8.05^{**}	[0.02]
	(0.87)	(1.58)		(1.21)	(3.39)		(0.63)	(3.46)	
Mom	-0.23	-5.13^{**}	[0.08]	-0.66	-15.25^{**}	[0.02]	0.43	10.12^{**}	[0.06]
	(1.40)	(2.53)		(1.30)	(6.09)		(1.05)	(5.01)	
NOA	0.35	-8.44^{***}	[0.00]	-0.52	-9.55^{***}	[0.01]	0.88	1.08	[0.92]
	(1.23)	(2.59)		(1.19)	(3.53)		(0.60)	(2.00)	
Oscore	-0.24	-8.36^{***}	[0.00]	-0.41	-4.44^{*}	[0.11]	0.17	-3.92^{**}	[0.02]
	(1.04)	(2.12)		(1.13)	(2.38)		(0.84)	(1.53)	
PPE/A	-0.39	-1.60	[0.53]	-0.21	-13.74^{***}	[0.00]	-0.18	12.14^{**}	[0.02]
	(0.81)	(1.84)		(1.32)	(4.43)		(1.00)	(5.00)	
RoA	-0.54	-7.04^{***}	[0.00]	-0.18	-11.72^{**}	[0.02]	-0.36	4.68	[0.24]
	(1.19)	(1.93)		(1.23)	(4.80)		(0.64)	(4.28)	
RoB	-0.65	-3.76^{*}	[0.16]	-0.44	-11.81^{**}	[0.02]	-0.22	8.05	[0.14]
	(1.14)	(2.00)		(1.44)	(4.82)		(0.77)	(5.65)	
Sigma	-0.83	-0.60	[0.91]	0.53	-15.89^{***}	[0.00]	-1.36	15.28^{**}	[0.01]
	(0.78)	(1.85)		(1.48)	(5.58)		(1.35)	(6.63)	
Size	-0.70	-1.73	[0.58]	-0.51	-8.01^{***}	[0.00]	-0.19	6.27^{***}	[0.00]
	(0.72)	(1.73)		(1.03)	(2.32)		(0.93)	(1.71)	

Table 2.6: Response of portfolio returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - BWI based analyses

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC meeting dates of the following model: $R_t = \beta_0 + \beta_1 (1 - S_t^H) \Delta i_t^u + \beta_2 S_t^H \Delta i_t^u + \varepsilon_t$, where R_t and Δi_t^u denote portfolio returns and unexpected FFR changes, respectively. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). Deciles which are more exposed to sentiment are defined as the short leg. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value according to the Baker and Wurgler's (2006, 2007) sentiment index. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. P-values from the Wald test for equality of coefficients (F-statistic) are reported in square brackets. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Portfolios	Long Leg			Short Leg			Long-Short		
	β_1	β_2	$\beta_1 = \beta_2$	β_1	β_2	$\beta_1 = \beta_2$	β_1	β_2	$\beta_1 = \beta_2$
Acc	1.74^{*}	-11.03^{***}	[0.00]	0.01	-10.21^{***}	[0.00]	1.74^{**}	-0.82	[0.04]
	(1.01)	(3.29)		(1.29)	(3.04)		(0.75)	(1.07)	
Age	-0.84	-2.31	[0.45]	-0.17	-10.96^{***}	[0.00]	-0.66	8.65^{**}	[0.02]
	(1.23)	(1.58)		(1.18)	(3.68)		(0.96)	(3.94)	
AG	0.70	-2.78	[0.09]	-0.27	-11.22^{***}	[0.00]	0.97	8.44^{**}	[0.08]
	(1.10)	(1.78)		(1.35)	(3.69)		(0.68)	(4.16)	
BE/ME	0.01	-3.12	[0.18]	-0.97	-9.46^{***}	[0.00]	0.98	6.34^{***}	[0.04]
	(1.44)	(1.89)		(1.20)	(2.94)		(0.98)	(2.42)	
CA	-1.31	-2.96^{*}	[0.39]	0.65	-11.41^{***}	[0.00]	-1.93^{**}	8.45^{***}	[0.00]
	(1.04)	(1.72)		(1.30)	(3.24)		(0.99)	(2.04)	
GP	-0.76	-4.95^{***}	[0.04]	-0.10	-6.77^{***}	[0.00]	-0.66	1.81^{*}	[0.04]
	(1.22)	(1.78)		(1.12)	(1.77)		(0.63)	(1.02)	
Inv	-0.67	-2.51	[0.30]	-0.31	-10.07^{***}	[0.00]	-0.36	7.56^{**}	[0.02]
	(0.91)	(1.53)		(1.26)	(3.37)		(0.67)	(3.40)	
Mom	0.34	-5.43^{**}	[0.03]	0.18	-15.30^{**}	[0.00]	0.16	9.87^{**}	[0.04]
	(1.34)	(2.44)		(1.37)	(5.72)		(1.25)	(4.76)	
NOA	0.88	-8.52^{***}	[0.00]	-0.80	-8.81^{**}	[0.03]	1.69^{**}	0.28	[0.48]
	(1.21)	(2.49)		(1.28)	(3.51)		(0.75)	(1.84)	
Oscore	-0.61	-7.57^{***}	[0.00]	0.99	-5.59^{***}	[0.00]	-1.60	-1.99	[0.84]
	(1.30)	(2.16)		(1.11)	(2.10)		(1.46)	(1.36)	
PPE/A	-0.68	-1.25	[0.76]	-0.06	-13.18^{***}	[0.00]	-0.62	11.92^{**}	[0.01]
	(0.96)	(1.67)		(1.38)	(4.35)		(1.05)	(4.77)	
RoA	-0.69	-6.55^{***}	[0.00]	0.62	-11.89^{***}	[0.00]	-1.31	5.34	[0.09]
	(1.27)	(1.95)		(1.20)	(4.52)		(0.83)	(3.94)	
RoB	-1.17	-3.09	[0.38]	0.33	-11.95^{***}	[0.00]	-1.50	8.05^{*}	[0.05]
	(1.30)	(1.87)		(1.41)	(4.56)		(1.00)	(5.17)	
Sigma	-1.21	-0.24	[0.61]	1.91	-16.37^{***}	[0.00]	-3.13^{**}	16.13^{***}	[0.00]
	(0.90)	(1.70)		(1.45)	(5.14)		(1.55)	(5.95)	
Size	0.63	-2.97^{**}	[0.04]	-1.08	-7.06^{***}	[0.02]	1.71	4.09^{***}	[0.32]
	(1.02)	(1.37)		(1.28)	(2.36)		(1.81)	(1.56)	

Table 2.7: Response of portfolio returns to path surprises at the zero lower bound during periods of decreasing vs. increasing sentiment

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC meeting dates of the following model: $R_t = \beta_0 + \beta_1(1 - S_t^D)path_t + \beta_2 S_t^D path_t + \varepsilon_t$, where R_t and $path_t$ denote portfolio returns and path surprises, respectively. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). Deciles which are more exposed to sentiment are defined as the short leg. S_t^D is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment year. A year is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end (December) of that year is lower (higher) than at the end of the previous year according to the University of Michigan's Consumer Sentiment index. The zero lower bound sample period is January 2009 - October 2014. The unscheduled meetings that were not accompanied by a FOMC statement or other information were excluded. Standard errors are reported in parentheses. P-values from the Wald test for equality of coefficients (F-statistic) are reported in square brackets. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Portfolios	Long Leg			Short Leg			Long-Short		
	β_1	β_2	$\beta_1 = \beta_2$	β_1	β_2	$\beta_1 = \beta_2$	β_1	β_2	$\beta_1 = \beta_2$
Acc	0.41	-4.25^{**}	[0.04]	0.30	-4.16^{**}	[0.06]	0.11	-0.09	[0.80]
	(0.66)	(2.09)		(1.04)	(2.09)		(0.54)	(0.45)	
Age	0.42	-2.43^{*}	[0.08]	-0.53	-3.70^{*}	[0.19]	0.94	1.27^{*}	[0.81]
	(0.53)	(1.42)		(1.28)	(1.98)		(0.94)	(0.74)	
AG	-0.69	-2.98	[0.30]	0.96	-4.04^{**}	[0.02]	-1.65^{**}	1.06^{**}	[0.00]
	(0.96)	(1.91)		(0.78)	(1.94)		(0.72)	(0.49)	
BE/ME	-0.43	-3.02^{***}	[0.22]	0.50	-9.02^{***}	[0.00]	-0.94	6.00^{***}	[0.00]
	(0.82)	(1.86)		(1.17)	(2.52)		(1.16)	(1.53)	
CA	-0.37	-3.63^{**}	[0.08]	0.48	-3.61^{**}	[0.05]	-0.86	-0.02	[0.25]
	(0.84)	(1.58)		(0.63)	(1.75)		(0.53)	(0.53)	
GP	0.33	-3.10^{**}	[0.04]	0.00	-5.33^{***}	[0.02]	0.33	2.23^{***}	[0.01]
	(0.60)	(1.45)		(0.90)	(1.85)		(0.48)	(0.62)	
Inv	0.93	-4.75^{**}	[0.02]	0.93	-4.44^{**}	[0.01]	-1.29^{***}	-0.31	[0.22]
	(0.87)	(2.40)		(0.94)	(1.78)		(0.47)	(0.61)	
Mom	0.29	-2.75	[0.35]	0.02	-19.59^{***}	[0.00]	0.26	16.84^{***}	[0.00]
	(1.81)	(2.66)		(0.97)	(4.76)		(1.22)	(6.04)	
NOA	0.34	-3.16^{*}	[0.06]	0.48	-4.42^{**}	[0.01]	-0.14	1.27^{***}	[0.05]
	(0.83)	(1.59)		(0.66)	(1.76)		(0.62)	(0.34)	
Oscore	0.18	-2.83^{*}	[0.00]	0.85	-6.13^{***}	[0.00]	-0.67	3.31^{***}	[0.00]
	(0.64)	(1.67)		(1.17)	(1.85)		(0.67)	(1.18)	
PPE/A	-0.20	-3.04^{*}	[0.14]	0.11	-3.66^{**}	[0.06]	-0.31	0.62	[0.24]
	(1.03)	(1.59)		(1.05)	(1.65)		(0.44)	(0.52)	
RoA	0.29	-2.33	[0.15]	0.51	-5.58^{***}	[0.00]	-0.22	3.24^{***}	[0.00]
	(0.82)	(1.56)		(0.93)	(1.91)		(0.55)	(0.78)	
RoB	0.36	-2.71	[0.13]	0.37	-5.78^{***}	[0.00]	-0.01	3.07^{**}	[0.05]
	(0.77)	(1.79)		(0.81)	(1.77)		(0.66)	(1.19)	
Sigma	0.05	-2.36	[0.15]	0.93	-4.56^{*}	[0.07]	-0.87	2.20^{*}	[0.19]
	(0.54)	(1.44)		(1.61)	(2.41)		(1.71)	(1.28)	
Size	0.26	-3.84^{**}	[0.02]	1.11	-5.93^{***}	[0.00]	0.85	2.09^{***}	[0.00]
	(0.62)	(1.54)		(0.84)	(1.68)		(0.54)	(0.41)	

Chapter 3

Investor Sentiment States and the Pre-FOMC Announcement Drift

3.1 Abstract

This chapter documents a strong effect of investor sentiment states on stock returns one day before the announcement by the scheduled FOMC meetings. We find that the returns on the S&P500 index increase significantly over the pre-FOMC window only during periods of high sentiment. We also find that there is no stock price drift ahead of other macro-economic announcements. Our findings on the pre-FOMC announcement order imbalance show that there are more buyer-initiated trade than seller-initiated trade on the S&P500 constituents during periods of high sentiment. These findings provide a behavioural explanation to the pre-FOMC announcement puzzle.

3.2 Introduction

As we mentioned in previous chapters, the post-FOMC announcement response of stock returns have been examined by a large number of previous studies in the past decades (Thorbecke (1997); Ehrmann and Fratzscher (2004); Bernanke and Kuttner (2005); Maio (2014); Ozdagli (2017)). Recently, Lucca and Moench (2015) document large average excess returns on U.S.equities in anticipation of monetary policy decisions made at scheduled meetings of the FOMC in the past few decades. This phenomenon, which they refer to as the pre-FOMC announcement drift, is difficult to explain with standard asset pricing theory. Bernile, Hu, and Tang (2016) and Kurov et al. (2017) argue that the pre-FOMC drift is a result of information leakage in the embargo period (a 30-minute window) before an FOMC announcement. Lucca and Moench (2015) argue that an information leakage explanation is implausible for a longer pre-FOMC window, and hence the pre-FOMC announcement drift is a puzzle.

In this chapter, we examine the impact of investor sentiment on the pre-FOMC announcement stock price drift over the period from February 1994 to October 2015. Our study is motivated by the conjecture that there are more noise traders in the stock market when investor sentiment is high (Stambaugh, Yu, and Yuan (2012)). Many papers have shown strong evidence that investor sentiment affects stock prices (Baker and Wurgler (2006); Lamont and Stein (2006)) and investors' estimation for risk (Yu and Yuan (2011)). A large body of psychology literature also shows that high sentiment leads people to make optimistic judgments, whereas low sentiment leads people to make pessimistic ones (Bower (1981); Arkes, Herren, and Isen (1988)). Following Baker and Wurgler (2006), we define a high (low) sentiment month when the sentiment measure at the end of the previous month is above (below) the full sample mean value. We employ two alternative measures of sentiment: the University of Michigan Consumer Sentiment Index and the Sentiment Index constructed by Baker and Wurgler (2006).

We show that, the state of investor sentiment strongly affects stock returns over the pre-FOMC window, which we define as one day before the scheduled FOMC announcement day, the last trading day before investors can observe signals about policy decisions. By setting our pre-FOMC window as one day before scheduled FOMC announcement, we reveal a significant pre-FOMC effect even outside the embargo period that is connected to information leakage documented in prior studies. We find that the positive drift of the S&P500 index over the pre-FOMC window concentrates only on the sentiment-exuberance state. Specifically, in high sentiment months, the S&P500 index increases about 23 basis points in the pre-FOMC window. In contrast, in low sentiment months, FOMC meetings do not feature statistically significant pre-announcement returns.

Further, we find that the pre-FOMC drift does not contain information about the subsequent outcome of the FOMC announcement. The positive and significant pre-FOMC drift during high sentiment months occurs, regardless of whether the subsequent FOMC announcement delivers an unexpected cut or rise in the FFR. We also find a pre-FOMC effect in the short-term fixed income securities. Specifically, the yield on the 3-month U.S. Tresury bills increases about 1.5 basis point on the pre-FOMC window, during periods of high sentiment. In contrast, there is no pre-FOMC effect on long-term treasury bonds.

Moreover, other macroeconomic releases do not feature statistically significant preannouncement returns, even after we consider the state of investor sentiment. Using the Google Search Volume Index (SVI) as a proxy for investor attention, we show that, compared with other macroeconomic announcements, FOMC announcement grabs more attention among investors. Finally, we find that, the pre-FOMC drift is not related to the business cycle. It is also unrelated to the yet-to-be-realized policy decision, as measured by the unexpected change in the FFR, as defined in Kuttner (2001), or the market participants' expectation about the future path of monetary policy, as measured using the approach of Gürkaynak, Sack, and Swanson (2005).

What might explain our findings? First, it is difficult to explain the pre-FOMC drift with standard asset pricing theory. Rational explanations focus on the state of the economy and link time-varying expected returns to macroeconomic variables (See, among others, Perez-Quiros and Timmermann (2000), Chordia and Shivakumar (2002), Liu and Zhang (2008), and Maio (2013)). In order to remove the effects of business cycle variation, we orthogonalize each sentiment measure to a set of macroeconomic variables. This allows us to distinguish between behavioural and rational explanations. Moreover, our evidence also shows that, economy states, as captured by the NBER recession dummy, does not result in the positive and significant pre-FOMC stock returns during periods of high sentiment.

Second, our findings cannot be explained by the information leakage story documented in Bernile, Hu, and Tang (2016) and Kurov et al. (2017). By setting our pre-FOMC window as one day before the scheduled FOMC announcement days, we avoid the embargo period when information leakage is most likely to happen. Furthermore, we also show that stock returns do not move in the same direction as suggested by the FFR shocks on announcement days.

Third, our findings cannot be explained by the argument related to volatility or liquidity, which is used by Lucca and Moench (2015). According to Campbell and Hentschel (1992), the “volatility feedback" effect implies that if volatility is priced, an anticipated decline in volatility would decrease the required rate of return, which in turn necessitates an immediate stock price and leads to lower future returns. On the other hand, Amihud (2002) documents a negative relationship between contemporaneous unexpected illiquidity and excess returns on U.S. equities. However, our evidence shows that, during high sentiment months (when we find positive and significant pre-FOMC returns), the pre-FOMC returns remain unchanged, after controlling for the level and innovation components in volatility and liquidity.

One possible explanation is related to investors’ emotional state. Psychology literature suggests that individuals engage in more heuristic processing of information when they are in a positive emotional state. During periods when investors are in a pessimistic state, their reliance on non-systematic processing of information is likely to increase (Tiedens and Linton (2001); Mackie and Worth (1989); Bless et al. (1990); Batra and Stayman (1990)). Financial literature also documents that, there are more noise traders when sentiment is high (Stambaugh, Yu, and Yuan (2012)). [1] Essentially, excessively optimistic valuations are assigned, either by overestimating the size of future cash flows or by underestimating risk (Mian and Sankaraguruswamy (2012); Kaplanski et al. (2015)). During such phases, investors are more likely to *positively* speculate about the information contents of the forthcoming FOMC announcements. This results into the pre-FOMC positive stock price. This interpretation is consistent with our evidence of positive (negative) order imbalance over the pre-FOMC window during high (low) sentiment months. At the same time, higher risk appetite of investors during such periods is evidenced by a decline in the price (increase in the yield) of the 3-month T-bill. In other words, investors allocate capital from low risk assets into risky assets over the pre-FOMC window, during high sentiment periods.

[1] Yu and Yuan (2011) also argue that investors are less rational overall during periods of high sentiment

This chapter contributes to the developing standard of literature that how stock price changes in anticipation of macro-economy and/or monetary policy announcement (Lucca and Moench (2015); Bernile, Hu, and Tang (2016); Kurov et al. (2017)). We extend the literature by incorporating insights from behavioural finance. This chapter is the first to show that the positive drift of the S&P500 index occurs only during periods of high sentiment. Our findings of the sentiment conditionality of pre-FOMC drift, together with the inability of the rational based stories to explain the drift, points to a behavioural explanation. Our findings also relates to the studies on pre-announcement drifts of individual stock returns before earnings announcements (see, for example Lamont and Frazzini (2007)). Most of these studies point to the behavioral "attention-grabbing" effect as a potential explanation. Our results offers a new angle by considering the state of investor sentiment.

This chapter also contributes to the literature on the effect of monetary policy shifts on stock prices (Thorbecke (1997); Bernanke and Kuttner (2005); Chen (2007); Wright (2012); Swanson (2015)). These studies mainly focus on the price effect on FOMC announcement days.

The rest of the chapter proceeds as follows. Section 3.3 describes the data and variables that we employ in the empirical analysis. Section 3.4 shows evidence related to the role of investor sentiment in the pre-FOMC announcement drift. Section 3.5 discusses possible explanations. Section 3.6 concludes.

3.3 Data and sample

Our analysis focuses on stock returns before scheduled FOMC meetings across different sentiment states over the period from February 1994 to October 2015, hence including the pre-crisis period, the financial crisis and its aftermath.[2] We define the pre-FOMC window as one day before a scheduled FOMC announcement day. There are 175 scheduled FOMC announcements in our sample period. In order to ensure that our results are not affected by outliers, we exclude the top and bottom 1% of pre-FOMC returns, which finally reduces the number of pre-FOMC events to 171.

3.3.1 Investor sentiment measure

We employ two proxies for investor sentiment: Baker and Wurgler's (2006, 2007) Sentiment Index (BWI) and the University of Michigan's Consumer Sentiment Index (CSI).[3] The BWI is a

[2]Before 1994, the market participants generally became aware of policy actions on the day after the FOMC's decision, when it was implemented by the Open Market Desk (Bernanke and Kuttner (2005)). On February 1994, the Fed started to announce target FFR changes, which eliminates virtually all of the timing ambiguity associated with rate changes(Bernanke and Kuttner (2005)). Lucca and Moench (2015) also find that the pre-FOMC drift is more pronounced at the post-1994 period.

[3]We obtained CSI from the FRED databases. BWI data is available at Jeffrey Wurgler's website: http://people.stern.nyu.edu/jwurgler/.

commonly used measure of investor sentiment (Yu and Yuan (2011); Stambaugh, Yu, and Yuan (2012); Shen, Yu, and Zhao (2017)). By taking the first principal component of five financial variables that can reflect sentiment, the BWI filters out idiosyncratic noise in its constituents and captures common variation.[4] We also use one consumer confidence index, measured outside of the financial markets, as a proxy for investor optimism (see, Lemmon and Portniaguina (2006); Antoniou, Doukas, and Subrahmanyam (2013) and McLean and Zhao (2014)). The CSI is based on surveys conducted by the University of Michigan in which 500 U.S. participants are asked questions about their outlook on the economy.

To remove the effect of business cycle variation, Baker and Wurgler (2006) orthogonalize each of the constituent variables of their sentiment index with respect to a set of macroeconomic conditions before conducting the principal component analysis.[5] We obtain the orthogonalized BWI from their data set, and also regress the CSI on the same set of macroeconomic variables. The residuals from this regression capture sentiment (optimism or pessimism) that is not associated by economic fundamentals (Lemmon and Portniaguina (2006)). The orthogonalized sentiment indexes are standardized so that they have zero mean and unit variance.

[Insert Figure 3.1 around here]

Figure 3.1 plots the orthogonalized sentiment indexes. They all rise during the 1990s but start to decline from around 2000, following the culmination of the dot-com boom. Sentiment declines during the recent global financial crisis, but somewhat recovers afterward. The two indexes exhibit different dynamics. For example, the late 1990s dot-com boom episode features more prominently in the BWI, as compared with the CSI.

In order to examine whether the pre-FOMC drift is conditional on the state of investor sentiment, we construct a level-based dummy variable based on the orthogonalized sentiment indexes. The dummy variable, S_t^H, is equal to 1 (0) for the days that are in a month starting with a high (low) sentiment level. We define a month as starting with high (low) sentiment if the sentiment indicator in the previous month is above (below) the full sample mean value, following Baker and Wurgler (2006). In our empirical analysis, the loading on this dummy variable reflects the pre-FOMC drift on S&P500 returns during periods of high sentiment.

[Insert Table 3.1 around here]

[4]The BWI is formed as the first principal component of the closed-end fund discount, the number and the first-day returns of IPOs, the equity share in total new issues and the dividend premium. NYSE turnover, that featured in the set of variables used in the calculation of the sentiment index in Baker and Wurgler (2006), is dropped in the most recent update of their dataset. The updated BWI exhibits very similar behaviour over time with the earlier edition.

[5]This set of macroeconomic variables include the growth in industrial production, the real growth in durable, nondurable and services consumption, the growth in employment, and a dummy variable that indicates recessions as classified by NBER business cycle dates. It is also used by other studies to remove business cycle information from sentiment proxies (Yu and Yuan (2011); McLean and Zhao (2014); Huang et al. (2015)).

As reported in Table 3.1, the correlation coefficients between the sentiment dummies is 0.34. This indicates that, the two sentiment indicators capture different dimensions of investor sentiment.

3.3.2 Stock returns

We measure daily stock market returns using the log returns of the S&P500 index. Returns are in excess of the 1-month Treasury bill rate.[6] We obtain S&P500 index data from CRSP database.

3.3.3 Trading activity measure

Following Bernile, Hu, and Tang (2016), we measure investors' trading activity by the aggregate order imbalance, defined as (B-S)/(B+S), where B (S) is the aggregate buyer-initiated (seller-initiated) dollar trading volume (see also Barber and Odean (2007); Kaniel et al. (2008); Kelley and Tetlock (2013)). Aggregate dollar trading volume is constructed using the tick-by-tick transaction data on S&P500 constituents. List of S&P500 constituents is obtained from CRSP database. We obtain buyer-initiated and seller-initiated trading volume, as identified using the Lee and Ready's (1991) algorithm, from the Intraday Indicators by WRDS database. Following Lee and Ready (1991), a trade is defined as buyer-initiated (seller-initiated) if the trade price is above (below) the midpoint of the recent (the previous second) bid–ask quote. If the transaction price is equal to the midpoint, we define a trade as buyer-initiated (seller-initiated) if the trade price is above (below) the last executed trading price. The order imbalance data covers the period over February 1994 to December 2013 only, due to availability.

3.4 Econometric models and results

This section contains the empirical findings of this chapter. Section 3.4.1 documents excess returns on the S&P500 index ahead of FOMC announcements. Section 3.4.2 examines the pre-FOMC drift in yields of fixed income instruments, and Section 3.4.3 analyzes S&P500 returns ahead of other major macroeconomic data releases.

3.4.1 Investor sentiment and pre-FOMC stock returns

Table 3.2 shows that the average market-wide stock return over the pre-FOMC window is higher in high sentiment months than in low sentiment months. In contrast, the mean of stock returns on the days outside of the pre-FOMC window is higher in low sentiment months than in high sentiment months. The results suggest that the pre-FOMC effect is conditional upon the state of investor sentiment.

[6]Following Lucca and Moench (2015), we use the one-month Treasury bill at the beginning of each month.

[Insert Table 3.2 around here]

We formally assess, across different sentiment states, the magnitude of excess stock market returns one day ahead of the scheduled FOMC announcements. Specifically, we examine whether the pre-FOMC effect is conditional upon the state of investor sentiment. To this end, we introduce an interaction term of the pre-FOMC dummy with the previously defined level-based sentiment dummy, S_t^H, in the following regression model for excess stock returns:

$$r_t = \beta_0 + \beta_1(1 - S_t^H)FOMC_t^{pre} + \beta_2 S_t^H FOMC_t^{pre} + \varepsilon_t \tag{3.1}$$

where r_t denotes the daily market excess return and $FOMC_t^{pre}$ is a dummy variable that equals 1 on the pre-FOMC window and zero otherwise. β_1 captures the mean excess return on pre-FOMC window during periods of low sentiment, and β_2 represents the mean excess return on pre-FOMC window during periods of high sentiment.

[Insert Table 3.3 around here]

We estimate Equation 3.1 with Newey and West (1987) standard errors and report the results in Panel A of Table 3.3. It shows that, first, there is no significant pre-FOMC announcement drift during periods of low sentiment. The coefficient for mean excess return on pre-FOMC window during periods of low sentiment, as captured by β_1, is statistically insignificant using either of the two sentiment indicators. Second, the mean excess return on the pre-FOMC window during periods of high sentiment, as captured by β_2, is positive and statistically significant. Specifically, the results with sentiment states defined by CSI show that, on average, the return on the day right before the FOMC meeting during periods of high sentiment is 22 basis points. The findings are robust across the two sentiment indicators.

Panel B of Table 3.3 reports the estimates of the following equation:

$$r_t = \beta_0 + \beta_1 FOMC_t^{pre} + \varepsilon_t \tag{3.2}$$

where the constant β_0 measures the unconditional mean excess return earned on all time periods outside of the pre-FOMC window. The coefficient β_1 is the mean excess return differential on pre-FOMC window versus on other days. The results show that β_1 is positive, but statistically insignificant, which indicates that there is no significant stock price changes at our pre-FOMC window, if the state of investor sentiment is not considered. These findings reveal the important role that investor sentiment plays in the pre-FOMC drift. The price drift will stay unobserved, if we do not consider the state of investor sentiment.

Bernile, Hu, and Tang (2016) and Kurov et al. (2017) find evidence of information leakage during the embargo period before FOMC announcements. We set our pre-FOMC window as one day before scheduled FOMC announcements so as to avoid the embargo period. This setting allows us to examine the pre-FOMC announcement effect in an environment whereby information leakage induces trading is unlikely.

We further empirically examine whether the pre-FOMC drift we document contains information about the next-day FOMC announcement by allowing for the interaction between the state of sentiment with FFR surprises. To this end, we introduce a new dummy variable, Sur_t, which is equal to 1 (-1) on the pre-FOMC window if the FOMC announcement on the next day conveys negative (positive) FFR surprises and zero otherwise following Bernile, Hu, and Tang (2016). FFR surprises are calculated following Kuttner (2001).

We estimate a regression model below using daily returns that include the pre-FOMC day and all days outside the pre-FOMC window:

$$\begin{aligned} r_t = \beta_0 + \beta_1(1 - S_t^H)FOMC_t^{pre} + \beta_2 S_t^H FOMC_t^{pre} \\ + \beta_3(1 - S_t^H)Sur_t + \beta_4 S_t^H Sur_t + \varepsilon_t \end{aligned} \tag{3.3}$$

Table 3.4 shows that both β_3 and β_4 are statistically insignificant. The results indicate that the FFR surprise on the FOMC announcement day is not associated with the stock return one day before the announcement, during both high and low sentiment periods. This finding implies that the pre-FOMC drift does not contain information about the FFR surprise on the next day.

[Insert Table 3.4 around here]

3.4.2 Effects on the yields of Treasury securities

Lucca and Moench (2015) find no evidence of pre-FOMC drift on the yields of fixed income instruments. In this section, we examine whether the yields of Treasury securities change on the pre-FOMC window, when the state of investor sentiment is considered. We replace the dependent variable in Equation 3.1 with the rates on the 3-month Treasury bills and 2-, 5-, and 10-year notes. Table 3.5 reports the results. We find strong evidence of pre-FOMC increase in the yield of the 3-month treasury bill, during periods of high sentiment. This suggests that, when sentiment is high, investors move capital out of short-term treasury bills in anticipation of the scheduled FOMC announcements. On the other hand, during periods of low sentiment, there is weak evidence of pre-FOMC decrease in the yield of long term treasuries when we identify sentiment states by using CSI.

[Insert Table 3.5 around here]

3.4.3 Alternative macro-announcements

Savor and Wilson (2014) find that asset prices behave very differently on days when important macroeconomic news is scheduled for announcement. However, Lucca and Moench (2015) show that there is no significant pre-announcement drift for macroeconomic news other than the FOMC announcements. We then proceed to examine the S&P500 index return before the releases of U.S employment situation (EMPS), producer price index (PPI) report and industrial production (IP) report, conditional upon the state of investor sentiment. Both EMPS and PPI report are published monthly by the US Bureau of Labor Statistics. IP report is released monthly by the Federal Reserve Board.

We exclude from our sample the announcements which were re-scheduled.[7] We replace the $FOMC_t^{pre}$ with $EMPS_t^{pre}$, PPI_t^{pre} and IP_t^{pre} and re-estimate Equation 3.1, where the dummy variable $EMPS_t^{pre}$ (PPI_t^{pre}, IP_t^{pre}) equals 1 on the day before a scheduled announcement day of the EMPS (PPI, IP) report and 0 otherwise. The results in Table 3.6 show that none of these three macroeconomic announcements features statistically significant pre-announcement returns, even after considering the state of investor sentiment.[8]

[Insert Table 3.6 around here]

Why does the pre-announcement drift feature only for the FOMC announcement? We consider one possible explanation relates to investors' attention level. Following Da, Engelberg, and Gao (2011), we use monthly Google SVI as a proxy for investor attention. We obtain the monthly SVI via the product Google Trends (http://www.google.com/trends). The SVI for a search term is the number of searches for that term divided by its all time average. We can also compare the SVI for different terms. Figure 3.2 plots the SVI for the term “FOMC", “employment situation", “producer price index" and “industrial production". It shows that, generally, the search volume for “FOMC" is higher than the search volume for the other three terms. Thus, a simple reason that we observe pre-FOMC drift only is that, other macroeconomic announcements do not grab too much investor attention, when compared to the FOMC announcement.[9]

[Insert Figure 3.2 around here]

3.5 Further search for possible explanations

Our results so far show that there is an increase in the S&P500 index on the pre-FOMC window during periods of high sentiment. In this section, we regress the S&P500 excess returns on the pre-FOMC window during periods of high sentiment on a number of variables that could potentially explain the drift. Following Lucca and Moench (2015), the variables we consider include a recession dummy as classified by the NBER business cycle dates, a measure of FFR

[7] For example, we exclude the scheduled release of EMPS at Feb 19 2004, which was eventually delayed to Mar 18 2004.

[8] We also examine the pre-announcement effect without considering sentiment state, all the results are insignificant too, tables are available upon request.

[9] We present SVI after 2004 only, due to availability.

shocks proposed by Kuttner (2001), investors' expectations about the future path of monetary policy as measured by the first two principal components (level and slope) from the cross-section of Treasury yields (Gürkaynak, Sack, and Swanson (2005)), the level and innovation component of trading volume and implied stock market volatility (VIX). All explanatory variables, except for the NBER dummy are standardized to have zero mean and unit variance. The coefficient of each variable captures the effects that variable has on pre-FOMC returns, and the intercept captures the impact of high investor sentiment states on the pre-FOMC returns, when other variables are controlled. Thus we expect a decrease in intercept after controlling for the variables that lead to the pre-FOMC drift.

[Insert Table 3.7 around here]

The first and 7th column of Table 3.7 shows a regression of pre-FOMC returns on the NBER recession dummy during periods of high sentiment, as classified by CSI and BWI, respectively. NBER is a dummy variable that is equal to 1 if the FOMC meeting occurred during a U.S. recession as classified by NBER business cycle dates and 0 otherwise. The coefficient on the dummy is insignificant for high sentiment periods classified by CSI. Importantly, the intercept remains to be 0.20 with a standard error of 0.1. Compare to our baseline results in Panel A of Table 3.3, the pre-FOMC returns during periods of high sentiment decreases a bit, but it's still statistically significant. We obtain similar results using BWI. Those results indicate that economic cycles do not affect the pre-FOMC returns during periods of high sentiment.

In Section 3.4.1 we show that the pre-FOMC returns are not related to a dummy that captures the direction of the FFR shocks. We then proceed by examining the relationship between the stock returns on the pre-FOMC window and the FFR shocks on the announcement day. The results in the second column of Table 3.7 show that the pre-FOMC returns are not significantly related to the yet-to-be-realized FFR shocks when CSI is high. Moreover, the intercept remains at 0.23 and significant, after adding the FFR shocks as a control variable. We also obtain similarly results using BWI. These findings indicate that, the positive pre-FOMC returns during periods of high sentiment we addressed cannot be explained by the information leakage argument.

We also examine whether the pre-FOMC equity returns are related to the investors' expectations about the future path of monetary policy. Following Lucca and Moench (2015), we employ the first two principal components (level and slope) from the cross-section of daily zero-coupon Treasury bond yields for maturities from one through five years. Both level and slope are lagged two days before scheduled announcement days (that is, one day before our pre-FOMC window). The coefficients for both level and slope are negative as reported in column 3 of Table 3.7. The negative sign of the coefficients indicates that the pre-FOMC drift is stronger when investors expect a monetary easing. However, both of them are statistically insignificant. Additionally, controlling for investors' expectations about the future path of monetary policy does not reduce the magnitude or significance of the intercept. The results are robust across the two sentiment measures.

Amihud (2002) documents a negative relationship between contemporaneous unexpected illiquidity and excess returns on U.S. equities. We then investigate whether market liquidity, as proxied by trading volume, affects the pre-FOMC returns during periods of high sentiment. We regress the S&P500 excess returns on the pre-FOMC window on the level and innovation component of trading volume. The level of trading volume is lagged two days before scheduled announcement days. Specifically, following Lucca and Moench (2015), we calculate the level of trading volume as the daily trading volume divided by its prior 21-day mean. The innovation component is the residual from an AR(1) regression of the daily trading volume level on a constant and its level at the previous day. The results in column 4 show that both the lagged level and contemporaneous innovation component of trading volume do not significantly affect the pre-FOMC returns when CSI is high. They do not change the magnitude and significance of the intercept either. The intercept is still 23 basis points, which is inline with our baseline results in Panel A of Table 3.3. We obtain similar results using BWI, as reported in column 10. Thus, liquidity cannot explain the positive pre-FOMC returns during periods of high sentiment.

Previous studies find that the stock market tends to be relatively quiet – conditional volatility is abnormally low – on days preceding regularly scheduled policy announcements (Bomfim (2003)). Lucca and Moench (2015) also find that the market volatility tend to be low on the pre-FOMC window. They argue that, the “volatility feedback" effect could explain the pre-FOMC drift to some extent. According to Campbell and Hentschel (1992), the “volatility feedback" effect implies that an unexpected decline in volatility leads to a downward revision in future expected volatility, and thus to lower risk and higher contemporaneous returns. We then investigate whether the pre-FOMC returns are related to equity market uncertainty as measured by the VIX. We employ both the level and innovation component of VIX.[10]The level of VIX is lagged two days before scheduled announcement days. The results in column 5 of Table 3.7 show that, the lagged value of VIX is positive and significantly related to the pre-FOMC returns, and the innovation component is negative and significantly related to the pre-FOMC returns. These results are inline with findings of Lucca and Moench (2015), which indicate that the market volatility affect stock returns on the pre-FOMC window. However, the intercept continue to be 23 basis point and significant, which implies that there is a sentiment impact on the pre-FOMC returns, even after controlling for the impact of market volatility. The results are robust across the two sentiment measures.

Finally, we employ a regression which includes a constant and all the variables above. The results in column 6 (12) of Table 3.7 show that, when other variables are controlled, there is still a negative relationship between the stock returns and the innovation component of VIX on

[10]We obtain VIX index form the FRED database: https://fred.stlouisfed.org/. The innovation component is the residual from an AR(1) regression of the daily VIX value on a constant and its value at the previous day.

the pre-FOMC window. Importantly, the intercept remains to be 23 basis points and significant. Thus, these variables cannot fully explain the positive pre-FOMC drift during periods of high sentiment.

The results above show that changes in volatility is a factor that may affect stock returns on the pre-FOMC window during periods of high sentiment. Moreover, Chordia et al. (2002) find that trading activity affects stock returns at daily level. Using aggregate order imbalance as a proxy of trading activity, they document that positive order imbalance is associated with contemporaneous positive market-wide stock returns, while negative order imbalance is associated with negative ones. We then proceed by examining the liquidity, volatility and trading volume on the pre-FOMC window, across different sentiment states.

[Insert Table 3.8 around here]

We replace the dependent variable in Equation 3.1 with ΔTrv, ΔVIX and OIB, respectively. Where ΔTrv is the daily changes in the level of trading volume. ΔVIX is the daily changes in the VIX, and OIB is the daily order imbalance. The results in Panel A of Table 3.8 show that, during periods of high sentiment there is a significant decrease in trading volume on the pre-FOMC window. However, the results in Panel B show that VIX does not change significantly on the pre-FOMC window, during both high and low sentiment periods. The results in Panel C of Table 3.8 show that, there is a positive (negative) and significant order imbalance on the pre-FOMC window during periods of high (low) sentiment. Specifically, for high sentiment state classified by the CSI, investors' net buying is 2% higher than net selling on the pre-FOMC window, which suggests that investors' appetite for acquiring stocks becomes stronger during such periods.

The results on order imbalance, together with our findings that investors allocate assets from low risk short-term T-bills to stocks on the pre-FOMC window during periods of high sentiment, proposed a behavioral explanation to our baseline results of positive pre-FOMC stock returns during periods of high sentiment. Psychology studies show that, when individuals are in a positive emotional state, they engage in more heuristic processing of information (Tiedens and Linton (2001); Mackie and Worth (1989); Bless et al. (1990)). High sentiment also drives people to make optimistic judgments and choices (Bower (1981); Arkes, Herren, and Isen (1988)). Also, as pointed out by previous literature, investors pay more attention to their portfolios around (before or after) attention-grabbing events (see Lamont and Frazzini (2007); Barber and Odean (2007); Yuan (2015)). We thus consider the following explanation for the pre-FOMC puzzle: On the pre-FOMC window when sentiment is high, investors hold an optimistic view on the yet-to-be-realized policy decisions. Such optimistic view leads them to switch from low risk assets to stocks. It also results in more buyer-initiated trade on the pre-FOMC window, and in turn, positively affects stock price.

3.6 Additional tests with the cross-sectional stock returns

We also examine the pre-FOMC announcement drift among stock portfolio returns, conditional upon the state of investor sentiment. We replace r_t in Equation 3.1 with returns of 15 portfolios.[11] Table C.1 and C.2 in the Appendix C report the results using CSI and BWI, respectively. The results are generally in line with the ones using market-wide stock returns. There is an increase in portfolio returns on the pre-FOMC window only during periods of high sentiment. Specifically, when sentiment is high, the pre-FOMC drift is concentrated in the oldest firms, firms with most net issuance, firms with most tangible assets, firms with highest RoB (RoA) and largest firms. For portfolios sorted by past performance (LR, Mom, SR), the results tend to be a U-shape. That is, when sentiment is high, only the deciles in the middle (deciles 4, 5, 6) have positive and significant pre-FOMC returns. Generally, this evidence show that the pre-FOMC drift is more pronounced in liquid stocks.

3.7 Conclusions

In this chapter we provide a behavioural explanation of the pre-FOMC puzzle documented by Lucca and Moench (2015). We find that the pre-FOMC announcement drift in stock returns is conditional upon the state of investor sentiment. We find that the pre-FOMC announcement stock price drift materializes only during periods of high sentiment. Specifically, we find that the S&P500 index increases by 22 basis points on the day before a scheduled FOMC announcement during periods of high sentiment. In contrast, in low sentiment months, FOMC meetings do not feature statistically significant pre-announcement returns. We investigate several possible explanations for our findings and the evidence points toward a behavioral channel, which relates to the investors' optimism and their trading activity. We show that, during periods of high sentiment, investors reduce investment in risk-free assets (short-term T-bills) and increase exposures to risky assets (stocks) on the pre-FOMC window, as evidenced by more net-buying activities on the pre-FOMC window, leading to the positive pre-FOMC announcement stock returns. Moreover, we find no evidence of pre-announcement drift ahead of other macro-economic announcements, even after we consider the state of investor sentiment. One possible explanation is that investors do not pay too much attention to other macro-economic announcements, as compared to the FOMC announcements. Use Google searching volume as a proxy of investor attention, we find evidence that support our view. We also examine other explanations of the pre-FOMC drift, which have been employed by previous studies. However, our evidence show

[11] Similar to our analyses in Chapter 2, we consider the following portfolios: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size).

that none of them could explain the stock price drift on our pre-FOMC window. Specifically, we show that the pre-FOMC drift does not contain information about the subsequent outcome of the FOMC announcement. The positive and significant pre-FOMC drift during high sentiment months occurs, regardless of whether the subsequent FOMC announcement delivers an unexpected cut or rise in the FFR. Thus, the drift we document is not a result of information leakage. We also show that our findings cannot be explained by the “volatility feedback" effect.

This chapter contributes to the recent studies on the pre-FOMC announcement drift. It is the first to show the state dependence of the pre-FOMC announcement drift. Previous studies either call the pre-FOMC as a puzzle or employ a leakage-based explanation. We bring together two strands of the literature on behavioural finance and the pre-FOMC stock price drift, and provide a behavioral explanation to the pre-FOMC puzzle. We argue that the pre-FOMC drift is a result of sentiment-driven speculation among investors at the pre-FOMC window. Our findings also relates to the studies on pre-announcement drifts of individual stock returns before earnings announcements. Most of these studies point to the behavioral “attention-grabbing" effect as a potential explanation. Our results offers a new angle by considering the state of investor sentiment.

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Table 3.1: Correlation matrix of sentiment states

This table presents correlation coefficients of the dummy variables that classify sentiment states. $S_t^{H,i}$ is a dummy variable that is equal to 1 (0) if a day belongs to a month with high (low) sentiment. A high (low) sentiment month is the month when the sentiment proxy at the end of the previous month is above (below) the full sample mean value. i = CSI or BWI, where CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period is February 1994 - October 2015. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$S_t^{H,CSI}$	$S_t^{H,BWI}$
$S_t^{H,CSI}$	1.00	
$S_t^{H,BWI}$	0.34***	1.00

Table 3.2: Summary statistics

This table reports summary statistics of daily log excess return on the S&P500 index on the pre-FOMC window and for all other days. The pre-FOMC window is one day before scheduled FOMC announcements. The sample period is February 1994 to October 2015. Panels A, B and C include the full sample, high sentiment and low sentiment period, respectively. Sentiment states are classified in monthly frequency. A high (low) sentiment month is the month when the sentiment proxy at the end of the previous month is above (below) the full sample mean value. CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively.

	Pre-FOMC window					Other days				
	Obs	Mean	Min	Max	St.Dev.	Obs	Mean	Min	Max	St.Dev.
Panel A: Full sample										
	171	0.12	-2.91	3.16	0.94	5302	0.01	-9.47	10.95	1.19
Panel B: High sentiment										
CSI	98	0.23	-2.91	2.37	0.93	2971	0.00	-7.13	5.57	1.09
BWI	71	0.25	-2.91	2.37	0.90	2211	-0.01	-7.13	5.57	1.14
Panel C: Low sentiment										
CSI	73	-0.04	-2.83	3.16	0.93	2331	0.03	-9.47	10.95	1.29
BWI	100	0.02	-2.83	3.16	0.95	3091	0.03	-9.47	10.95	1.22

Table 3.3: S&P500 index returns one-day ahead of scheduled FOMC announcements during periods of high vs. low sentiment

Panel A of this table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors of the following model: r_t=β_0+$\beta_1(1-S_t^H)FOMC_t^{pre}$+$\beta_2 S_t^H FOMC_t^{pre}$+$\varepsilon_t$, where r_t denotes daily log return of the S&P500 index in excess of the 1-month Treasury bill rate. $FOMC_t^{pre}$ is a dummy variable that is equal to 1 on the pre-FOMC window and 0 otherwise. The pre-FOMC window is one day before a scheduled FOMC announcement. S_t^H is a dummy variable that is equal to 1 (0) if a day belongs to a high (low) sentiment month. A high (low) sentiment month is the month when the sentiment proxy at the end of the previous month is above (below) the full sample mean value. CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. Panel B of this table presents the estimates of the following model: r_t=β_0+$\beta_1 FOMC_t^{pre}$+ε_t. The sample period is February 1994 - October 2015. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	No. of FOMC	β_0	β_1	β_2
		Panel A: With sentiment			
CSI	5473	171	0.02	-0.05	0.22**
			(0.01)	(0.11)	(0.10)
BWI	5473	171	0.01	0.01	0.24**
			(0.01)	(0.10)	(0.11)
		Panel B: Without sentiment			
	5473	171	0.01	0.10	
			(0.01)	(0.07)	

Table 3.4: S&P500 index returns one-day ahead of scheduled FOMC announcements during periods of high vs. low sentiment - controlling for FFR surprises

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors of the following model using daily returns that include the pre-FOMC day and all days outside the pre-FOMC window: r_t=β_0+$\beta_1(1-S_t^H)FOMC_t^{pre}$+$\beta_2 S_t^H FOMC_t^{pre}$+$\beta_3(1-S_t^H)Sur_t$+$\beta_4 S_t^H Sur_t$+$\varepsilon_t$, where r_t denotes daily log return of the S&P500 index in excess of the 1-month Treasury bill rate. $FOMC_t^{pre}$ is a dummy variable that is equal to 1 on the pre-FOMC window and 0 otherwise. The pre-FOMC window is one day before scheduled FOMC announcement. S_t^H is a dummy variable that is equal to 1 (0) if a day belongs to a month with high (low) sentiment. A high (low) sentiment month is the month when the sentiment proxy at the end of the previous month is above (below) the full sample mean value. CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. Sur_t is a dummy variable that is equal to 1 (-1) on the pre-FOMC window, if the following FOMC announcement conveys a negative (positive) Federal fund rate (FFR) surprise and 0 otherwise. The sample period is February 1994 - October 2015. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	No. of FOMC	β_0	β_1	β_2	β_3	β_4
CSI	5473	171	0.01	-0.02	0.21**	-0.21	0.08
			(0.01)	(0.11)	(0.10)	(0.16)	(0.12)
BWI	5473	171	0.01	0.00	0.26**	0.11	-0.15
			(0.01)	(0.09)	(0.12)	(0.14)	(0.14)

Table 3.5: Yield changes in Treasury securities one-day ahead of scheduled FOMC announcements during periods of high vs. low sentiment

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors of the following model: Y_t=β_0+$\beta_1(1-S_t^H)FOMC_t^{pre}$+$\beta_2 S_t^H FOMC_t^{pre}$+$\varepsilon_t$, where Y_t denotes the yield changes in 3-month Treasury bills and 2-, 5-, and 10-year notes in Panels A, B, C and D, respectively. $FOMC_t^{pre}$ is a dummy variable that is equal to 1 on the pre-FOMC window and 0 otherwise. The pre-FOMC window is one day before a scheduled FOMC announcement. S_t^H is a dummy variable that is equal to 1 (0) if a day belongs to a high (low) sentiment month. A high (low) sentiment month is the month when the sentiment proxy at the end of the previous month is above (below) the full sample mean value. CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period is February 1994 - October 2015. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	No. of FOMC	β_0	β_1	β_2
		Panel A: 3-month			
CSI	5473	171	-0.001	0.006	0.014***
			(0.001)	(0.005)	(0.005)
BWI	5473	171	-0.001	0.008*	0.015**
			(0.001)	(0.005)	(0.007)
		Panel B: 2-year			
CSI	5473	171	-0.001	-0.003	0.004
			(0.001)	(0.004)	(0.004)
BWI	5473	171	-0.001	0.000	0.002
			(0.001)	(0.004)	(0.005)
		Panel C: 5-year			
CSI	5473	171	0.000	−0.011*	-0.002
			(0.001)	(0.006)	(0.004)
BWI	5473	171	0.000	-0.007	-0.004
			(0.001)	(0.005)	(0.005)
		Panel C: 10-year			
CSI	5473	171	0.000	−0.011*	-0.003
			(0.000)	(0.006)	(0.004)
BWI	5473	171	0.000	-0.007	-0.006
			(0.001)	(0.005)	(0.005)

Table 3.6: S&P500 index returns one-day ahead of other macro-announcements during periods of high vs. low sentiment

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors of the following model: $r_t = \beta_0 + \beta_1 (1 - S_t^H) ANN_{it}^{pre} + \beta_2 S_t^H ANN_t^{pre} + \varepsilon_t$, where r_t denotes daily log return of the S&P500 index in excess of the 1-month Treasury bill rate. ANN_t^{pre} denotes $EMPS_t^{pre}$, PPI_t^{pre} and IP_t^{pre} in Panels A, B and C respectively. $EMPS_t^{pre}$ is a dummy variable that is equal to 1 on the day right before a scheduled announcement day of the U.S employment situation report and 0 otherwise. PPI_t^{pre} is a dummy variable that is equal to 1 on the day preceeding a scheduled announcement day of the U.S producer price index report and 0 otherwise. IP_t^{pre} is a dummy variable that is equal to 1 on the day preceeding a scheduled announcement day of the U.S industrial production report and 0 otherwise. S_t^H is a dummy variable that is equal to 1 (0) if a day belongs to a high (low) sentiment month. A high (low) sentiment month is the month when the sentiment proxy at the end of the previous month is above (below) the full sample mean value. CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period is February 1994 - October 2015. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	No. of FOMC	β_0	β_1	β_2
		Panel A: EMPS			
CSI	5473	171	0.02	-0.17	0.08
			(0.02)	(0.13)	(0.08)
BWI	5473	171	0.02	-0.09	0.04
			(0.02)	(0.10)	(0.10)
		Panel B: PPI			
CSI	5473	171	0.02	-0.05	-0.12
			(0.02)	(0.10)	(0.09)
BWI	5473	171	0.02	-0.04	-0.16
			(0.02)	(0.09)	(0.10)
		Panel C: IP			
CSI	5473	171	0.01	0.02	0.04
			(0.01)	(0.15)	(0.09)
BWI	5473	171	0.01	-0.03	0.12
			(0.01)	(0.11)	(0.10)

Table 3.7: Modelling the pre-FOMC stock returns during periods of high sentiment

This table reports results of regressions of pre-FOMC announcement returns on various explanatory variables on the pre-FOMC window, during periods of high sentiment only. The dependent variable is log return of the S&P500 index in excess of the 1-month Treasury bill rate on the day before a scheduled FOMC announcement. NBER is a dummy variable that is equal to 1 if the FOMC meeting occurred during a U.S. recession as classified by NBER business cycle dates and 0 otherwise. FFR shock is unexpected FFR changes on the announcement day following the pre-FOMC window. Level and Slope are the first two principal components from the cross-section of daily zero-coupon bond yields for maturities from one through five years as in **?**. Both level and slope are lagged two days before scheduled announcement days. Tra Vol (lag) denotes one-day-lagged trading volume level on the S&P500 stock market index, and trading volume level is calculated as the daily trading volume divided by its prior 21-day mean. Tra Vol (Innov.) is the residual from an AR(1) regression of the trading volume level on a constant and its previous day level. VIX (lag) denotes the one-day-lagged level of the VIX index. VIX (innov.) denotes the residual from an AR(1) regression of the VIX index on a constant and its level in the previous day. VIX is the level of the VIX index at the market close two days before the scheduled meeting. CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. All explanatory variables, except for the NBER dummy, are standardized to have zero mean and unit variance. The full sample period is February 1994 - October 2015. Robust standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	CSI						BWI					
	1	2	3	4	5	6	7	8	9	10	11	12
NBER	0.43					0.27	0.44*					0.31
	(0.28)					(0.26)	(0.26)					(0.25)
FFR shock		-0.01				0.02		0.08				0.07
		(0.06)				(0.06)		(0.07)				(0.07)
Level			-0.10			-0.07			-0.07			-0.07
			(0.09)			(0.07)			(0.11)			(0.07)
Slope			-0.04			-0.07			-0.04			-0.10
			(0.13)			(0.07)			(0.15)			(0.08)
Tra Vol (lag)				-0.10		-0.08				-0.03		-0.02
				(0.11)		(0.08)				(0.12)		(0.08)
Tra Vol (Innov.)				-0.03		-0.13				-0.02		-0.13
				(0.16)		(0.09)				(0.20)		(0.09)
VIX (lag)					0.17**	0.13					0.18**	0.13*
					(0.07)	(0.08)					(0.07)	(0.07)
VIX (Innov.)					−0.67***	−0.69***					−0.66***	−0.68***
					(0.08)	(0.08)					(0.11)	(0.11)
Const.	0.20**	0.23**	0.23**	0.23**	0.23***	0.21***	0.20**	0.25**	0.25**	0.25**	0.25***	0.22***
	(0.10)	(0.09)	(0.09)	(0.09)	(0.06)	(0.09)	(0.11)	(0.11)	(0.11)	(0.11)	(0.07)	(0.08)
Obs	98	98	98	98	98	98	71	71	71	71	71	71
No. of FOMC	98	98	98	98	98	98	71	71	71	71	71	71

Table 3.8: Volatility and order imbalance one-day ahead of scheduled FOMC announcements during periods of high vs. low sentiment

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors of the following model: $Y_t = \beta_0 + \beta_1(1 - S_t^H) FOMC_t^{pre} + \beta_2 S_t^H FOMC_t^{pre} + \varepsilon_t$, where Y_t denotes the daily changes in the trading volume level, daily changes in VIX and the daily order imbalance in Panel A, B and C respectively. $FOMC_t^{pre}$ is a dummy variable that is equal to 1 on the pre-FOMC window and 0 otherwise. The pre-FOMC window is one day before scheduled FOMC announcement. S_t^H is a dummy variable that is equal to 1 (0) if a day belongs to a high (low) sentiment month. A high (low) sentiment month is the month when the sentiment proxy at the end of the previous month is above (below) the full sample mean value. CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period is February 1994 - October 2015 for Panel A and Panel B, and January 2000 - October 2015 for Panel C. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	No. of FOMC	β_0	β_1	β_2
Panel A: ΔTrv					
CSI	5473	171	1.01***	0.00	−0.05***
			(0.01)	(0.01)	(0.02)
BWI	5473	171	1.01***	0.00	−0.06***
			(0.01)	(0.01)	(0.02)
Panel B: ΔVIX					
CSI	5473	171	-0.004	0.24	0.08
			(0.02)	(0.16)	(0.11)
BWI	5473	171	-0.004	0.19	0.09
			(0.02)	(0.14)	(0.13)
Panel C: Order imbalance					
CSI	5011	156	0.05***	−0.04***	0.02***
			(0.01)	(0.01)	(0.005)
BWI	5011	156	0.05***	−0.01**	0.01**
			(0.01)	(0.005)	(0.005)

Figure 3.1: Sentiment indices

This figure plots sentiment indices using monthly data over the period January 1994 - September 2015. CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively.

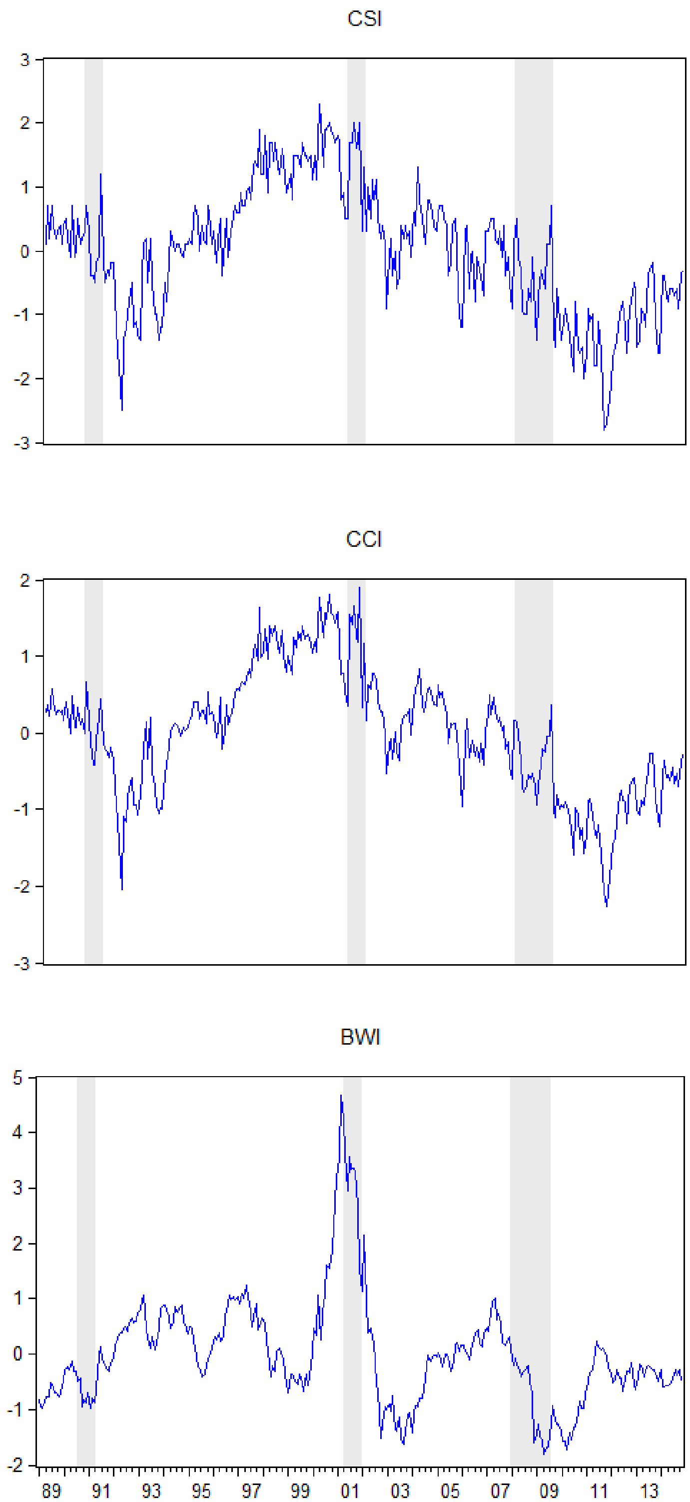
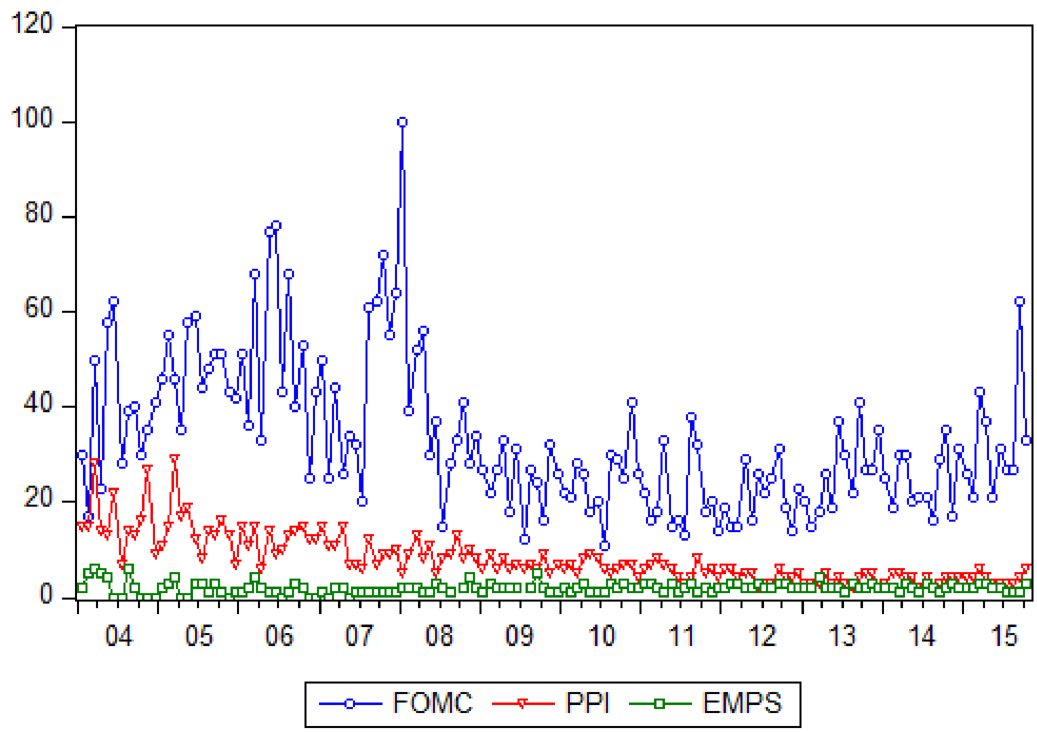


Figure 3.2: Google Searching Volume Index

This figure plots the monthly Google Searching Volume Index (SVI) for the term “FOMC", “employment situation", “producer price index" and “industrial production" respectively, over the period January 2004 - September 2015.



Chapter 4

Conclusions

4.1 Outline

This thesis examines the *post* FOMC announcement impact of U.S. conventional and unconventional monetary policy on the U.S. market-wide (see Chapter 1) and cross-sectional (see Chapter 2) stock returns over the Jun-89 to Dec-14 sample. It also examines the impact of investor sentiment states on the market-wide stock price drift *before* the scheduled FOMC announcement (see Chapter 3). We conclude this thesis by outlining in detail the contribution of each chapter to the empirical literature. We also summarise potential avenues for future research.

4.2 Contribution of each chapter to the empirical literature

In Chapter 1 we investigate how investor sentiment states affect the response of market-wide stock returns to monetary policy shocks. We find that, for the pre-ZLB period, FFR shocks affect stock market returns only during the sentiment-correction periods, that is, when sentiment is high at the start of the year but then falls. During periods of sentiment build-up, however, the impact of FFR shocks is insignificant. The sentiment effects are not driven by economic recessions, however, we find that the sentiment-based state dependence in the response of market-wide stock returns to FFR shocks is stronger during monetary policy easing cycles. We also find that the market response following periods of high sentiment is significant for expansionary FFR surprises, but not tightening surprises. Third, our evidence indicates that accounting for endogeneity does not alter our conclusions. Fourth, the effect of FFR surprises is predominantly contemporaneous and displays only very short-run persistence. Fifth, the positive returns associated with expansionary policy shocks are broad-based across U.S. industries and their pattern is consistent with the implications of the CAPM. The industrial effects are also conditional on the state of investor sentiment.

For the unconventional monetary policy at the ZLB period, we find that the impact of path surprises is statistically significant only during periods when sentiment decreases. In contrast to the findings from FFR shocks prior to the ZLB, the effect of path surprises is not only driven by expansionary news. We show that amongst liquidity facilities and LSAP announcements, only those related to the establishment of central bank liquidity swaps matter. Conditional on the state of investor sentiment, the stock market reacted positively to these announcements. Finally, we show that our results remain strong and consistent to a host of robustness checks. A possible explanation for these findings relates to the investors' emotional state. When optimism builds-up, investors tend to behave in a manner consistent with noise trading, by relying heavily on heuristic processing of information and pushing the stock market above levels justified by fundamentals. In contrast, during correction phases they engage in more systematic processing of information and their sensitivity to news increases. Overall, our results are consistent with a behavioural explanation.

Overall, Chapter 1 contributes to the existing empirical literature that seeks to incorporate findings from behavioural finance to examine the stock market reaction to news, as well as the established literature that studies the effects of the Fed's conventional and non-conventional policy actions on financial markets. We develop a new measure of sentiment states, based upon changes in sentiment and show that it reveals important information about the trading behaviour of investors during periods of sentiment adjustment. Hence, we extend the previous literature on the asset pricing implications of sentiment, which overlooks the dynamic behaviour of sentiment. Our work is also related to the literature on state dependence in the relationship between stock market and monetary policy. Several studies consider business cycle effects and show that the stock market response is stronger during recessions ((Basistha and Kurov (2008); Perez-Quiros and Timmermann (2000)). In contrast, our focus is on sentiment states, which have small or zero correlation with the business cycle. Furthermore, sentiment corrections are not solely associated with bear markets but also occur during bull markets. Hence, our analysis is distinct from previous studies that condition the stock market response to policy surprises on bull-bear regimes (Chen (2007); Jansen and Tsai (2010); Kurov (2010)).

This chapter also relates to a recent study by Mian and Sankaraguruswamy (2012), who examine whether stock price changes in response to firm-specific earnings surprises are affected by lagged sentiment. They conclude that behavioral biases affect how information is impounded into stock prices. Our work has a different angle by focusing on market-wide news that stem from shifts in monetary policy, as opposed to firm-specific news. Another related recent study is that of Garcia (2013), who also argues that investors' sensitivity to news may be state dependent. In Garcia's (2013) analysis, however, this is related to the state of the business cycle, with the sensitivity to news being stronger during economic downturns; whereas we focus on sentiment downturns that, as we argue above, are distinct from recessions. Finally, this chapter extends previous work by Bernanke and Kuttner (2005), Lucca and Moench (2015) and Savor and Wilson (2014), among others, who find that the CAPM performs well on days associated with monetary policy news. We show that the CAPM does a good job in explaining the observed cross-industry variation of FOMC announcement-day returns only during sentiment-correction phases. Different from our event study analysis, Antoniou et al. (2015) use monthly data for asset-pricing tests and show that the security market line is positively slopped only following low sentiment periods.

In Chapter 2 we analyze the impact of investor sentiment states on the response of cross-sectional stock returns to monetary policy news using an event study approach over the Jun-89 to Oct-14 sample period. We consider 15 portfolio sorts which are commonly used by previous literature. Our results show that, in line with our results on market-wide stock returns in Chapter 1, conventional monetary policy news affect the cross-sectional stock returns only following periods of high sentiment. Unconventional monetary policy affect cross-sectional stock returns only during periods of decreasing sentiment. Importantly, the effect of monetary policy shocks differs across the cross-section of stocks. We find that stocks which are more sensitive to investor sentiment, are also more sensitive to monetary policy shocks.

This chapter enhances our argument in Chapter 1, that monetary policy shocks affect stock returns only following periods of high sentiment or during periods of decreasing sentiment. Also, previous studies that examine the impact of monetary policy shocks on the cross-sectional stock returns mainly focus on portfolios constructed on the basis of fundamental characteristics. Foe example, Thorbecke (1997) examine size portfolios, Jensen et al. (1997) and Maio (2014) consider value and size anomalies, Kontonikas and Kostakis (2013) investigate portfolios sorted by past performance. In this chapter, we extend the literature by investigating the responses of 15 stock portfolios. In addition, our evidence that the region of the cross-section of stocks that are more exposed to investor sentiment are also likely to be more sensitive to monetary policy news indicates the existence of a sentiment channel in the transmission of monetary policy shocks to stock returns.

In Chapter 3, we examine the impact of investor sentiment on the pre-FOMC announcement stock price drift over the period from February 1994 to October 2015. We show that, the state of investor sentiment strongly affects stock returns over the pre-FOMC window, which we define as one day before the scheduled FOMC announcement day, the last trading day before investors can observe signals about policy decisions. We find that the positive drift of the S&P500 index over the pre-FOMC window concentrates only on the sentiment-exuberance state. We investigate several possible explanations for our findings and the evidence points toward a behavioral channel, which relates to the investors' optimism and their trading activity. During periods of high sentiment, investors reduce investment in risk-free assets (short-term T-bills) and increase exposures to risky assets (stocks) on the pre-FOMC window, as evidenced by more net-buying activities on the pre-FOMC window, leading to the positive pre-FOMC announcement stock returns.

Chapter 3 contributes to the developing standard of literature that how stock price changes in anticipation of macro-economy and/or monetary policy announcement (Lucca and Moench

(2015); Bernile, Hu, and Tang (2016); Kurov et al. (2017)). We extend the literature by incorporating insides behavioural finance. This chapter is the first to show that the positive drift of the S&P500 index occurs only during periods of high sentiment. Our findings of the sentiment conditionality of pre-FOMC drift, together with the inability of the rational based stories to explain the drift, points to a behavioural explanation. Our findings also relates to the studies on pre-announcement drifts of individual stock returns before earnings announcements (see, for example Lamont and Frazzini (2007)). Most of these studies point to the behavioral "attention-grabbing" effect as a potential explanation. Our results offers a new angle by considering the state of investor sentiment.

This chapter also contributes to the literature on the effect of monetary policy shifts on stock prices (Thorbecke (1997); Bernanke and Kuttner (2005); Chen (2007); Wright (2012); Swanson (2015)). These studies mainly focus on the price effect on FOMC announcement days.

4.3 Avenues for future research

There are several potential avenues for future research following this thesis. Our results in Chapter 1 and 2 show that monetary policy shocks affect both market-wide and cross-sectional stock returns only following periods of high sentiment of during periods of decreasing sentiment. These findings shed important light into a sentiment channel in the monetary policy transmission mechanism. For future research, it would be interesting to investigate the dynamic relationship between monetary policy shocks and other asset prices (i.e. the corporate bond returns), conditional upon the state of investor sentiment.

Previous studies demonstrate that the U.S. monetary policy have impact on foreign stock returns (Hayo et al. (2010); Chortareas and Noikokyris (2017)). Because our evidence shows that the U.S. investor sentiment plays an important role in the transmission of monetary policy shocks to stock returns. It will be interesting to check whether the U.S. or domestic investor sentiment states affect the global impact of the U.S. conventional and unconventional monetary policy.

Additionally, in Chapter 3 we provide a behavioural explanation to the pre-FOMC puzzle documented by Lucca and Moench (2015). We show that there is an increase in the U.S. stock market returns one-day before the scheduled FOMC announcement days, only during periods of high sentiment. In fact, according to Lucca and Moench (2015), international stock market indices also feature significant pre-FOMC announcement drift. Thus, examine the impact of the U.S. or domestic investor sentiment states on the international pre-FOMC puzzle will be another possible avenue for future research.

Lastly, all the event studies we employed in this thesis are based on daily data. A future investigation may consider expanding the analyses to include regressions based on intra-day data around the FOMC announcements.

Appendix A

Appendix for Chapter 1

Table A.1: FOMC meetings with negative and positive FFR shocks across sentiment states

This table shows the number of FOMC meetings associated with negative and positive unexpected FFR changes across sentiment states over the full sample period (June 1989 - October 2014. Δi_t^u denotes unexpected FFR changes. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. S_t^D is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment year. A year is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end (December) of that year is lower (higher) than at the end of the previous year. S_t^{HD} is a dummy variable that is equal to 1 if the FOMC meeting occurred during a year when sentiment starts at high level but then declines, and 0 otherwise. A year is defined as of high at the start but then decreasing sentiment if the sentiment proxy at the end (December) of the previous year exceeds the full sample mean value and the sentiment proxy at the end of that year is lower than at the end of the previous year. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively.

		S_t^H	1-S_t^H	S_t^D	1-S_t^D	S_t^{HD}	1-S_t^{HD}
	CSI	55	33	58	30	36	52
$\Delta i_t^u < 0$	CCI	49	39	57	31	35	53
	BWI	48	40				
	CSI	32	21	29	24	22	31
$\Delta i_t^u > 0$	CCI	27	26	29	24	22	31
	BWI	26	27				

Table A.2: List of unscheduled FOMC meetings and meetings associated with employment report releases before the zero lower bound

This table presents the dates of unscheduled FOMC meetings and meetings associated with employment report releases, along with the corresponding FFR target rate changes (Δi_t) and unexpected changes (Δi_t^u) expressed in basis points. The sample period is June 1989 - December 2008. During the zero lower bound period (January 2009 - October 2014) several unscheduled meetings occurred that were not accompanied by a FOMC statement or other information.

Date	Δi_t	Δi_t^u	Employment	Unscheduled
05/06/1989	-25	-4	No	Yes
07/07/1989	-25	-3	Yes	No
26/07/1989	-25	-6	No	Yes
16/10/1989	-25	-21	No	Yes
06/11/1989	-25	4	Yes	Yes
13/07/1990	-25	-14	No	Yes
29/10/1990	-25	-2	No	Yes
07/12/1990	-25	-27	Yes	Yes
08/01/1991	-25	-18	No	Yes
01/02/1991	-50	-25	Yes	Yes
08/03/1991	-25	-16	Yes	Yes
30/04/1991	-25	-17	No	Yes
06/08/1991	-25	-15	Yes	Yes
13/09/1991	-25	-5	No	Yes
31/10/1991	-25	-5	No	Yes
06/12/1991	-25	-9	Yes	Yes
20/12/1991	-50	-28	No	Yes
09/04/1992	-25	-24	No	Yes
02/07/1992	-50	-36	Yes	No
04/09/1992	-25	-22	Yes	Yes
18/04/1994	25	10	No	Yes
15/10/1998	-25	-26	No	Yes
03/01/2001	-50	-38	No	Yes
18/04/2001	-50	-42	No	Yes
17/09/2001	-50	-32	No	Yes
22/01/2008	-75	-74	No	Yes
08/10/2008	-50	-14	No	Yes

Table A.3: Response of stock market returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - excluding employment releases

This table presents OLS estimates with heteroscedasticity-consistent standard errors, excluding meetings that coincide with employment report releases, of the following model: R_t=β_0+$\beta_1(1-S_t^H)\Delta i_t^u$+$\beta_2 S_t^H \Delta i_t^u$+$\varepsilon_t$, where R_t and Δi_t^u denote CRSP value weighted market returns in excess of the 1-month Treasury bill rate and unexpected FFR changes, respectively. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period includes FOMC meetings over June 1989 - December 2008, excluding meetings associated with the release of employment reports, as well as the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$Adj.R^2$
CSI	171	0.22^{**}	-1.52	-7.03^{***}	0.14
		(0.10)	(1.44	(2.44)	
CCI	171	0.21^{**}	-1.67	-7.21^{***}	0.14
		(0.10)	(1.36)	(2.58)	
BWI	171	0.24^{**}	-1.46	-6.78^{***}	0.14
		(0.09)	(1.47)	(2.57)	

Table A.4: Response of stock market returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - sample commences in February 1994

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: $R_t = \beta_0 + \beta_1(1 - S_t^H)\Delta i_t^u + \beta_2 S_t^H \Delta i_t^u + \varepsilon_t$, where R_t and Δi_t^u denote CRSP value weighted market returns in excess of the 1-month Treasury bill rate and unexpected FFR changes, respectively. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period includes FOMC meetings over February 1994 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$Adj.R^2$
CSI	125	0.27^{**}	-1.67	-7.30^{***}	0.16
		(0.12)	(2.55)	(2.67)	
CCI	125	0.26^{**}	-1.99	-7.48^{***}	0.16
		(0.12)	(2.26)	(2.78)	
BWI	125	0.27^{**}	1.64	-6.69^{**}	0.15
		(0.11)	(5.17)	(2.62)	

Table A.5: Response of stock market returns to FFR shocks and path surprises - sentiment states defined by PLS sentiment index

Panel A of this table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: R_t=β_0+$\beta_1(1-S_t^H)\Delta i_t^u$+$\beta_2 S_t^H \Delta i_t^u$+$\varepsilon_t$, where R_t and Δi_t^u denote CRSP value weighted market returns in excess of the 1-month Treasury bill rate and unexpected FFR changes, respectively. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. The sample period used in Panel A includes FOMC meetings before the zero lower bound (June 1989 - December 2008), with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Panel B presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC meeting days of the following model: R_t=β_0+$\beta_1(1-S_t^D)path_t$+$\beta_2 S_t^D path_t$+ε_t, where $path_t$ denotes path surprises. S_t^D is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment year. A year is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end (December) of that year is lower (higher) than at the end of the previous year. The zero lower bound sample period used in Panel B is January 2009 - October 2014. PLS denotes the sentiment index developed by Huang et al. (2015). Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$Adj.R^2$
Panel A: FFR shocks					
PLS	180	0.23^{**}	-1.25	-9.81^{***}	0.16
		(0.10)	(1.39)	(1.57)	
Panel B: Path surprises					
PLS	47	0.32^{*}	-4.37	-2.42^{*}	0.04
		(0.16)	(4.04)	(1.36)	

Table A.6: Response of stock market returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - robust estimates

This table presents MM weighted least squares estimates using the procedure of Yohai (1987), which is robust to the presence of outliers, over FOMC announcement days, of the following model: R_t=β_0+$\beta_1(1-S_t^H)\Delta i_t^u$+$\beta_2 S_t^H \Delta i_t^u$+$\varepsilon_t$, where R_t and Δi_t^u denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate and unexpected FFR changes, respectively. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$Adj.R^2$
CSI	178	0.16^{**}	-0.49	-6.85^{***}	0.16
		(0.07)	(0.97)	(1.00)	
CCI	179	0.14^{**}	-0.64	-7.55^{***}	0.19
		(0.07)	(0.94)	(1.03)	
BWI	178	0.17^{**}	-0.74	-5.39^{***}	0.10
		(0.07)	(1.01)	(1.00)	

Table A.7: Response of stock market returns to path surprises at the zero lower bound, during periods of decreasing vs. increasing sentiment - robust estimates

This table presents MM weighted least squares estimates using the procedure of Yohai (1987), which is robust to the presence of outliers, over FOMC announcement days, of the following model: $R_t = \beta_0 + \beta_1 (1 - S_t^D) path_t + \beta_2 S_t^D path_t + \varepsilon_t$, where R_t and $path_t$ denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate and path surprises, respectively. S_t^D is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment year. A year is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end (December) of that year is lower (higher) than at the end of the previous year. CSI denotes the University of Michigan's Consumer Sentiment index. The zero lower bound sample period is January 2009 - October 2014. The unscheduled meetings that were not accompanied by a FOMC statement or other information were excluded. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$Adj.R^2$
CSI	47	0.17	0.56	-3.37^{**}	0.16
		(0.16)	(1.66)	(1.39)	

Table A.8: Response of stock market returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - monthly classification of sentiment states

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: R_t=β_0+$\beta_1(1-S_t^{HM})\Delta i_t^u$+$\beta_2 S_t^{HM}\Delta i_t^u$+$\varepsilon_t$, where R_t and Δi_t^u denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate and unexpected FFR changes, respectively. S_t^{HM} is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a month that starts with high (low) sentiment level. A month is defined as starting with high (low) sentiment if the sentiment proxy at the end of the previous month is above (below) the full sample mean value. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$Adj.R^2$
CSI	180	0.23^{***}	-0.23	-6.95^{***}	0.14
		(0.09)	(1.37)	(2.09)	
CCI	180	0.24^{**}	-0.41	-6.39^{***}	0.13
		(0.10)	(1.46)	(2.19)	
BWI	180	0.23^{**}	0.07	-6.22^{**}	0.13
		(0.09)	(1.66)	(2.39)	

Table A.9: Response of stock market returns to path surprises at the zero lower bound, during periods of decreasing vs. increasing sentiment - monthly classification of sentiment states

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: R_t=β_0+$\beta_1(1-S_t^{DM})path_t$+$\beta_2 S_t^{DM} path_t$+$\varepsilon_t$, where R_t and $path_t$ denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate and path surprises, respectively. S_t^{DM} is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment month. A month is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end of that month is lower (higher) than at the end of the previous month. CSI and CCI denote the University of Michigan's Consumer Sentiment index and the U.S. Consumer Confidence index, respectively. The zero lower bound sample period is January 2009 - October 2014. The unscheduled meetings that were not accompanied by a FOMC statement or other information were excluded. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$Adj.R^2$
CSI	47	0.32^*	-1.66	-2.69^*	0.04
		(0.16)	(2.17)	(1.43)	
CCI	47	0.32^*	-0.68	-2.98^*	0.05
		(0.16)	(1.54)	(1.62)	

Table A.10: Response of stock market returns to path surprises at the zero lower bound, during periods of decreasing vs. increasing sentiment - alternative changes-based sentiment dummy

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: R_t=β_0+$\beta_1(1-S_t^D)path_t$+$\beta_2 S_t^D path_t$+ε_t, where R_t and $path_t$ denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate and path surprises, respectively. S_t^D is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment year. A year is defined as of decreasing (increasing) sentiment if, throughout it, the average monthly change of the sentiment proxy is negative (positive). CSI and BWI denote the University of Michigan's Consumer Sentiment index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The zero lower bound sample period is January 2009 - October 2014. The unscheduled meetings that were not accompanied by a FOMC statement or other information were excluded. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$Adj.R^2$
CSI	47	0.39**	-1.19	−12.32*	0.20
		(0.16)	(1.10)	(6.88)	
BWI	47	0.36**	-1.16	−11.23*	0.19
		(0.17)	(1.15)	(5.78)	

Table A.11: Response of stock market returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - alternative orthogonalization

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: R_t=β_0+$\beta_1(1-S_t^H)\Delta i_t^u$+$\beta_2 S_t^H \Delta i_t^u$+$\varepsilon_t$, where R_t and Δi_t^u denote CRSP value weighted market returns in excess of the 1-month Treasury bill rate and unexpected FFR changes, respectively. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CSI, CCI and BWI denote the University of Michigan's Consumer Sentiment index, the U.S. Consumer Confidence index and Baker and Wurgler's (2006, 2007) sentiment index, respectively. The additional macro-related variables used for the orthogonalization of the sentiment indices include: the default premium, the term premium, the real interest rate, the inflation rate, and the consumption-wealth ratio. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$Adj.R^2$
CSI	180	0.21^{**}	0.14	-9.35^{***}	0.21
		(0.10)	(1.24)	(1.58)	
CCI	180	0.22^{**}	-0.42	-7.62^{***}	0.15
		(0.10)	(0.83)	(2.50)	
BWI	180	0.24^{***}	-0.35	-7.10^{***}	0.14
		(0.09)	(0.89)	(2.61)	

Table A.12: Response of stock market returns to path surprises at the zero lower bound, during periods of decreasing vs. increasing sentiment - alternative orthogonalization

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC announcement days, of the following model: R_t=β_0+$\beta_1(1-S_t^D)path_t$+$\beta_2 S_t^D path_t$+ε_t, where R_t and $path_t$ denote CRSP value-weighted market returns in excess of the 1-month Treasury bill rate and path surprises, respectively. S_t^D is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment year. A year is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end (December) of that year is lower (higher) than at the end of the previous year. CSI and CCI denote the University of Michigan's Consumer Sentiment index and the U.S. Consumer Confidence index, respectively. The additional macro-related variables used for the orthogonalization of the sentiment indices include: the default premium, the term premium, the real interest rate, the inflation rate, and the consumption-wealth ratio. The zero lower bound sample period is January 2009 - October 2014. The unscheduled meetings that were not accompanied by a FOMC statement or other information were excluded. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$Adj.R^2$
CSI	47	0.23	0.62	-4.56^{**}	0.12
		(0.15)	(0.62)	(1.74)	
CCI	47	0.25^{*}	0.45	-4.51^{**}	0.11
		(0.15)	(0.64)	(1.74)	

Table A.13: Response of stock market returns to LSAPs and liquidity facilities announcements, during periods of decreasing vs. increasing sentiment - longer estimation window

This table presents the CRSP value-weighted cumulative average abnormal returns (CAARs (%)) using alternative event windows across periods of decreasing sentiment (Panel A) and increasing sentiment (Panel B). Returns are in excess of the 1-month Treasury bill rate. Abnormal returns are calculated using the constant mean model and a 90-day estimation period that ends prior to the event window. We consider announcements of expansionary nature by the Fed over the period December 2007 - October 2013 that reflect the initiation or continuation of Large Scale Asset Purchases (LSAPs) and liquidity facilities programmes. There are 46 announcements related to liquidity facilities (LIQ_{all}), including 13 announcements about central bank liquidity swaps (CB swaps), 13 announcements about the term auction facility (TAF) and 21 announcements about other liquidity facilities (Other). 22 LSAPs-related announcements are also considered. A year is defined as of decreasing (increasing) sentiment if the University of Michigan's Consumer Sentiment index at the end (December) of that year is lower (higher) than at the end of the previous year. The statistical significance of CAARs is evaluated using the Boehmer, Masumeci, and Poulsen (1991) test statistic that accounts for event-induced increase in returns volatility.. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Event window	CB swaps	TAF	Other	LIQ_{all}	LSAPs	LIQ_{all}+LSAPs
Panel A: Decreasing sentiment						
(-1, 3)	2.81	-2.02	-0.66	-0.23	2.37	-0.02
(-1, 1)	2.90**	-0.80	0.15	0.50	2.40	0.49
(0, 0)	1.44**	-0.44	-0.04	0.14	0.25	0.13
Panel B: Increasing sentiment						
(-1, 3)	0.76			0.76	-0.15	0.03
(-1, 1)	0.21			0.21	-0.13	-0.06
(0, 0)	0.96			0.96	0.06	0.24

Appendix B

Appendix for Chapter 2

Portfolio constructions

In order to examine the role that investor sentiment plays in the transmission of monetary policy news on cross-sectional stock returns, we consider daily returns on 15 portfolio sorts which are commonly used by previous literature: accruals (Acc), asset growth (AG), firm age (Age)), book-to-market ratio (BM), cash to asset (CA), gross profitability (GP), investment-to-assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size).

Age

Firm age is the first company characteristic we consider. Recent study of Hadlock and Pierce (2010) suggests that firm age is an useful predictor of financial constraint levels, and the relationship between monetary policy and financial constraint has been well documented (see Basistha and Kurov, 2008;Kontonikas and Kostakis, 2013). Moreover, according to Baker and Wurgler (2006), firm age is also an important variable to use for examining the relationship between investor sentiment and stock returns. They find that young stocks are more sensitive to investor sentiment compare to old stocks.

Following Baker and Wurgler (2006), we define firm age as the number of years since the firm's first appearance on CRSP, measured to the end of our sample, rebalanced annually at the end of June. Decile 1 represents the youngest group, while Decile 10 represents the oldest group.

Asset tangibility

We then consider asset tangibility. As mentioned by Baker and Wurgler (2006), tangibility may proxy for the difficulty of valuation. Firms with more intangible assets are more sensitive to fluctuations in sentiment since they are more difficult to value.

We measure asset tangibility as property, plant and equipment (data item PPEGT) over total assets (data item AT), rebalanced annually at the end of June. Decile 1 is the group that with least tangible asset, while Decile 10 is the group that with most tangible asset.

Value

Previous literature on monetary policy indicate that value is an important characteristic to help examine the balance sheet channel of the transmission of monetary policy (Kontonikas and Kostakis, 2013). On the other hand, literature on invertor sentiment suggest that growth firms are relatively hard to arbitrage, and so they are most affected by sentiment (Baker and Wurgler, 2006).

The value characteristic we consider is book-to-market ratio (BE/ME). Following Fama and French (1993), BE/ME is measured as book equity from the previous fiscal year divided by market equity from December of the previous year. Specifically, book equity is stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available, data item TXDITC), minus the book value of preferred stock. We measure stockholders' equity as book value of assets (data item AT) minus total liabilities (data item LT). For the book value of preferred stock, we use the redemption (data item PSTKRV), liquidation (data item PSTKL), or par value (data item UPSTK) in that order , depending on availability. Market equity is the market price times shares outstanding. Portfolios are rebalanced annually at the end of June. Decile 1 represents the group with lowest $BE/ME/$ (growth stocks) while Decile 10 represents the group with largest $BE/ME/$ (value stocks).

Size

Firm size is another company characteristic we consider. On one hand, size premium has been well documented in the asset pricing literature. Using a VAR approach, previous studies on monetary policy find that small stocks are more exposed to monetary policy shocks (see Thorbecke, 1997;Kontonikas and Kostakis, 2013). On the other hand, as Lee et al. (1991) state, small stocks are disproportionately held by individuals as opposed to institutions, thus, firm size represents a natural variable to use for examining the relationship between investor sentiment and stock returns. Lemmon and Portniaguina (2006) find that stocks have lower return following periods of high investor sentiment, and smaller stocks are more affected. Baker and Wurgler (2006) also find low subsequent stock return following periods of high sentiment, but there is no significant size effects. However, they find that following periods of low sentiment, smaller stocks are more exposed to investor sentiment.

Following Fama and French (1993), we construct size-sorted portfolio at the end of each June using the CRSP end of June price times shares outstanding, rebalanced annually. Decile 1 represents the smallest group, while Decile 10 represents the largest group.

Return volatility

We then consider return volatility. Drechsler et al. (2014) find that expansionary monetary policy result in higher volatility. Literature on investor sentiment also document that stocks with high return volatility are more sensitive to sentiment fluctuation (see Baker and Wurgler, 2006; Chung, Hung, and Yeh, 2012).

Following Baker and Wurgler (2006) we measure return volatility (*Sigma*) as the standard deviation of monthly stock returns over the 12 months ending in June of year t, for firms with at least 10 return observations. Rebalanced annually at the end of June. Decile 1 represents the group with lowest *Sigma*, while Decile 10 represents the group with highest *Sigma*.

Momentum

The momentum effect, which refers to the phenomenon that high past recent returns forecast high future returns, discovered by Jegadeesh and Titman (1993), is one of the well documented anomalies in asset pricing literature. Studies on monetary policy find that past losers are more affected by policy shocks (Kontonikas and Kostakis, 2013). Antoniou, Doukas, and Subrahmanyam (2013) also prove that the momentum effect is stronger when sentiment is high, and they suggest this is because of the slow spread of bad news during high-sentiment periods.

We construct momentum portfolio following Jegadeesh and Titman (1993). At the end of each month, stocks are sorted based on their cumulated return from month t-12 to month t-2, rebalanced monthly. Decile 1 represents past losers, while Decile 10 represents past winners.

Accruals

Accruals is another firm characteristic we consider. Sloan (1996) find that a firms with high accruals generally earn lower returns on average than firms with low accruals. They suggest that investors overestimate the persistence of the accrual component of earnings when forming earnings expectations. Recent study on investor sentiment also prove that stock returns of firms with high accruals are more exposed to investor sentiment (Stambaugh, Yu, and Yuan, 2012).

We construct portfolios sorted by accruals following Sloan (1996):

$$Accruals = \frac{\Delta ACT - \Delta CHE - \Delta LCT + \Delta DLC + \Delta TXP - \Delta DP}{(AT + AT_{-1})/2} \tag{B.1}$$

where ΔACT is the annual change in total current assets, ΔCHE is the annual change in total cash and short-term investments, ΔLCT is the annual change in current liabilities, ΔDLC is the annual change in debt in current liabilities, ΔTXP is the annual change in income taxes payable, ΔDP is the annual change in depreciation and amortization, and $(AT + AT_{-1})/2$ is average total assets over the last two years. Rebalanced annually at the end of June. Decile 1 represents the group with least accruals, while Decile 10 represents the group with most accruals.

Asset growth

We also consider the impact of monetary policy on stocks sorted by asset growth rate across sentiment states. Cooper, Gulen, and Schill (2008) find that a firm's annual asset growth rate is a strong predictor of the cross-section of U.S. stock returns. Firms with high asset growth rate earn lower subsequent returns. Stambaugh, Yu, and Yuan (2012) also find that firms with high asset growth rate are more sensitive to investor sentiment fluctuations.

Following Cooper, Gulen, and Schill (2008), we measure asset growth as the growth rate of total assets (data item AT) in the previous fiscal year. Portfolios are formed on the end of June, rebalanced annually. Decile 1 represents the group with lowest asset growth rate, while Decile

10 represents the group with highest asset growth rate.

Distress

We then consider financial distress. Literature on monetary policy indicate that distressed companies should be more sensitive to monetary news that may affect their cash flows. Stambaugh, Yu, and Yuan (2012) find that distressed stocks are more exposed to investor sentiment.

The distress measure we consider is the O-score of Ohlson (1980). The O-score is calculated as the probability of bankruptcy in a static model:

$$\begin{aligned} O-score = &-1.32 - 0.407 log(ADJASSET/CPI) + 6.03TLTA - 1.43WCTA + 0.076CLCA \\ &- 1.72OENEG - 2.37NITA - 1.83FUTL + 0.285INTWO - 0.521CHIN \end{aligned} \tag{B.2}$$

where ADJASSET is adjusted total assets calculated as total assets plus 10% of the difference between market equity and book equity (ME-BE) following Campbell, Hilscher, and Szilagyi (2008) to ensure that assets are not too close to zero. CPI is the consumer price index. TLTA is the leverage ratio defined as the book value of debt (data item DLCQ plus data item DLTTQ) divided by ADJASSET. WCTA is working capital divided by market assets (data item ACTQ - data item LCTQ)/ADJASSET. CLCA is current liabilities (data item LCTQ) divided by current assets (data item ACTQ). OENEG is one if total liabilities (data item LTQ) exceeds total assets (data item ATQ) and is zero otherwise. NITA is net income (data item NIQ) divided by assets, ADJASSET. FUTL is the fund provided by operations (data item PIQ) divided by liabilities (data item LTQ). INTWO is equal to one if net income (data item NIQ) is negative for the last two quarters and zero otherwise. CHIN is $(NI_t$-$NI_{t-1})$/$(|NI_t|$+$|NI_{t-1}|)$, where NI t is net income (data item NIQ) for the most recent quarter (Chen, Novy-Marx, and Zhang, 2011). Rebalanced monthly. Decile 1 represents the group with lowest O-score, while Decile 10 represents the group with largest O-score.

Gross profitability

Gross profitability is another firm characteristic we consider. As suggested by Novy-Marx (2013), gross profits scaled by assets is the cleanest accounting measure of true economic profitability. Moreover, Stambaugh, Yu, and Yuan (2012) find that less profitable stocks are more exposed to investor sentiment fluctuations.

We measure gross profitability as gross profits (data item GP) divided by the total assets (data item AT) following Novy-Marx (2013). Portfolios are formed on the end of June, rebalanced annually. Decile 1 represents the least profitable stocks, while Decile 10 represents the most profitable stocks.

Investment-to-assets

Another firm characteristic we consider is the investment-to-assets ratio. Titman, Tompaidis, and Tsyplakov (2004) show that there is an investment anomaly in the stock market, subsequent returns are lower for firms with higher past investment. Stambaugh, Yu, and Yuan (2012) examine the predict power of investor sentiment on stocks sorted by investment-to-assets, however, they do not find a significant difference between the high past investment group and the low past investment group.

Investment-to-assets is measured as the annual change in gross property, plant, and equipment (data item PPEGT) plus the annual change in inventories (data item INVT) scaled by the lagged book value of assets (AT) following Lyandres, Sun, and Zhang (2007). Portfolios are formed on the end of each June, rebalanced annually. Decile 1 represents the group with lowest investment-to-assets ratio, while Decile 10 represents the group with highest investment-to-assets ratio.

Profitability

We also consider profitability. According to Fama and French (2006), profitability is a positive predictor of future stock returns. Stambaugh, Yu, and Yuan (2012) find that less profitable firms are more exposed to sentiment fluctuations.

Profitability characteristics include return on book value of equity and return on assets. Following Chen, Novy-Marx, and Zhang (2011), we measure return on book equity as income before extraordinary items (data item IBQ) divided by one-quarter lagged book value of equality. The quarterly book equity is measured in the same way following Fama and French (1993). We measure return on assets as income before extraordinary items (data item IBQ) divided by one-quarter lagged total assets (data item ATQ). Portfolios are rebalanced monthly. Decile 1 represents the group with lowest $RoB(RoA)$ ratio, while Decile 10 represents the group with highest $RoB(RoA)$ ratio.

Net Operating Assets

Hirshleifer et al. (2004) find that firms with higher net operating assets predicts lower future returns. In the study of Stambaugh, Yu, and Yuan (2012), they find that stock returns of firms with higher net operating assets are more sensitive to investor sentiment fluctuations.

We measure net operating asset as the difference on the balance sheet between all operating assets (OA) and all operating liabilities (OL) scaled by total assets (data item AT) following Hirshleifer et al. (2004):

$$OA = AT - CHE \tag{B.3}$$

$$OL = AT - DLC - DLTT - MIB - UPSTK - CEQ \tag{B.4}$$

where AT is total assets, CHE is cash and short term investment, DLC is Debt included in current liabilities, DLTT is long term debt, MIB is minority interests, UPSTK is preferred stocks and CEQ is common equity. Portfolios are formed on the end of each June, rebalanced annually. Decile 1 represents the group with lowest net operating asset, while Decile 10 represents the group with highest net operating asset.

Cash-to-asset

Finally, we consider the cash-to-asset ratio. The cash holding effect documented by Palazzo

(2012) indicates that firms with high cash-to-assets ratios outperform firms with low cash ratios, even after adjusting for the Fama and French's (1993) three factors. Moreover, Li and Luo (2016) find that the cash holding effect varies significantly across sentiment states.

We construct portfolios sorted by the cash-to-asset ratio following by Palazzo (2012). The cash-to-asset ratio is measured as cash and marketable securities (data item CHEQ) over total assets (data item ATQ). Rebalanced monthly. Decile 1 represents the group with lowest cash-to-assets ratio, while Decile 10 represents the group with highest cash-to-assets ratio.

Table B.1: Portfolio average returns conditional upon the investor sentiment states based on the CCI and the long-short strategy before the zero lower bound

This table presents the average portfolio returns over months in which CCI is high at the start of the year, months in which it is low, and the difference between these two averages. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). Deciles which are more sensitive to investor sentiment are defined as the short leg. A decile is defined as with higher sentiment sensitivity if it has lower average monthly returns during years start with high sentiment. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value. CCI denotes the U.S. Consumer Confidence index. The sample period is June 1989 - December 2008.

		1	2	3	4	5	6	7	8	9	10	Long leg	Short leg
Acc	High	0.48	0.66	0.74	0.81	0.62	0.72	0.79	0.59	0.35	0.21	Decile 1	Decile 10
	Low	1.47	1.14	1.20	1.2	1.29	1.22	1.40	1.17	1.35	1.28		
	High-Low	-0.99	-0.48	-0.46	-0.39	-0.67	-0.50	-0.61	-0.58	-1.00	-1.07		
Age	High	0.06	0.60	0.93	0.72	0.37	1.01	0.61	0.61	0.78	0.72	Decile 10	Decile 1
	Low	1.49	1.64	1.30	1.57	1.18	1.17	1.25	1.27	1.21	1.10		
	High-Low	-1.42	-1.04	-0.37	-0.85	-0.80	-0.16	-0.65	-0.66	-0.43	-0.38		
AG	High	0.66	0.66	0.82	0.67	0.60	0.79	0.84	0.95	0.92	0.27	Decile 1	Decile 10
	Low	1.59	1.60	1.15	1.24	1.29	1.15	1.16	1.18	1.34	1.27		
	High-Low	-0.94	-0.95	-0.33	-0.57	-0.69	-0.35	-0.32	-0.22	-0.42	-1.00		
BE/ME	High	0.59	0.80	0.87	0.63	0.71	0.83	0.52	0.80	0.86	0.77	Decile 10	Decile 1
	Low	1.28	1.21	1.28	1.31	1.29	1.35	1.23	1.14	1.56	1.52		
	High-Low	-0.69	-0.41	-0.41	-0.68	-0.58	-0.52	-0.71	-0.33	-0.70	-0.75		
CA	High	0.80	0.18	0.56	0.96	0.57	0.54	0.57	0.84	0.70	0.78	Decile 1	Decile 10
	Low	1.06	1.07	1.09	1.23	1.17	1.20	1.20	1.33	1.56	1.47		
	High-Low	-0.26	-0.89	-0.54	-0.27	-0.60	-0.67	-0.63	-0.49	-0.85	-0.69		
GP	High	0.72	0.28	0.41	0.56	0.60	0.79	0.61	0.54	0.70	1.05	Decile 10	Decile 1
	Low	1.23	1.17	1.22	1.28	1.25	1.17	1.33	1.24	1.22	1.42		
	High-Low	-0.51	-0.89	-0.81	-0.72	-0.64	-0.38	-0.72	-0.71	-0.53	-0.37		
Inv	High	0.75	0.71	0.69	0.80	0.89	0.85	0.77	0.58	0.43	0.36	Decile 1	Decile 10
	Low	1.22	1.18	1.56	1.43	1.11	1.34	1.08	1.27	1.10	1.27		
	High-Low	-0.47	-0.47	-0.87	-0.63	-0.23	-0.49	-0.31	-0.68	-0.67	-0.91		
Mom	High	-0.9	-0.06	0.20	0.61	0.49	0.58	0.79	1.06	0.76	1.23	Decile 10	Decile 1
	Low	1.51	1.52	1.48	1.29	1.34	1.28	1.21	1.23	1.26	1.56		
	High-Low	-2.41	-1.59	-1.28	-0.68	-0.85	-0.70	-0.42	-0.17	-0.50	-0.33		
NOA	High	0.82	0.84	0.64	0.75	0.77	0.71	0.70	0.31	0.95	-0.16	Decile 1	Decile 10
	Low	1.45	1.39	1.39	1.29	1.00	1.30	0.97	1.24	1.21	1.07		
	High-Low	-0.63	-0.55	-0.74	-0.54	-0.23	-0.59	-0.27	-0.93	-0.26	-1.23		
Oscore	High	0.75	0.64	0.73	0.58	0.83	0.56	0.55	0.42	0.51	-0.08	Decile 1	Decile 10
	Low	1.22	1.18	1.26	1.34	1.34	1.37	1.25	1.45	1.51	1.60		
	High-Low	-0.47	-0.54	-0.53	-0.75	-0.51	-0.81	-0.69	-1.03	-1.00	-1.68		
PPE/A	High	0.62	0.60	0.73	0.74	0.51	0.86	0.56	0.31	0.74	1.10	Decile 10	Decile 1
	Low	1.49	1.47	1.36	1.33	1.27	1.25	1.18	1.18	1.14	0.95		
	High-Low	-0.86	-0.87	-0.63	-0.59	-0.76	-0.39	-0.61	-0.86	-0.40	0.15		
RoA	High	-0.05	0.14	0.34	0.64	0.46	0.82	0.60	0.66	0.83	0.96	Decile 10	Decile 1
	Low	1.35	1.26	1.45	1.43	1.10	1.34	1.22	1.13	1.30	1.28		
	High-Low	-1.40	-1.12	-1.11	-0.79	-0.64	-0.52	-0.62	-0.46	-0.47	-0.32		
RoB	High	-0.05	0.01	0.35	0.35	0.72	0.40	0.68	0.85	0.88	0.95	Decile 10	Decile 1
	Low	1.36	1.29	1.41	1.29	1.27	1.19	1.26	1.20	1.08	1.38		
	High-Low	-1.41	-1.28	-1.06	-0.94	-0.55	-0.79	-0.59	-0.35	-0.20	-0.43		
Size	High	0.76	0.71	0.65	0.61	0.60	0.63	0.78	0.68	0.77	0.63	Decile 1	Decile 10
	Low	1.64	1.42	1.58	1.41	1.58	1.55	1.43	1.48	1.36	1.15		
	High-Low	-1.08	-0.71	-0.93	-0.80	-0.98	-0.92	-0.65	-0.8	-0.60	-0.51		
Sigma	High	0.94	0.95	0.45	0.83	0.61	0.56	0.68	0.37	0.58	0.31	Decile 1	Decile 10
	Low	1.08	1.17	1.14	1.15	1.41	1.39	1.46	1.71	1.84	1.86		
	High-Low	-0.14	-0.22	-0.69	-0.33	-0.81	-0.83	-0.78	-1.33	-1.26	-1.56		

Table B.2: Response of portfolio returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - CCI based analyses

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC meeting dates of the following model: $R_t = \beta_0 + \beta_1 (1 - S_t^H) \Delta i_t^u + \beta_2 S_t^H \Delta i_t^u + \varepsilon_t$, where R_t and Δi_t^u denote portfolio returns and unexpected FFR changes, respectively. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). Deciles which are more exposed to sentiment are defined as the short leg. S_t^H is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a year that starts with high (low) sentiment level. A year is defined as starting with high (low) sentiment if the sentiment proxy at the end (December) of the previous year is above (below) the full sample mean value according to the U.S. Consumer Confidence index. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. P-values from the Wald test for equality of coefficients (F-statistic) are reported in square brackets. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Portfolios	Long Leg			Short Leg			Long-Short		
	β_1	β_2	$\beta_1 = \beta_2$	β_1	β_2	$\beta_1 = \beta_2$	β_1	β_2	$\beta_1 = \beta_2$
Acc	0.55	-11.05^{***}	[0.00]	-0.14	-11.20^{***}	[0.00]	0.68	0.15	[0.69]
	(1.06)	(3.69)		(1.30)	(3.07)		(0.79)	(1.19)	
Age	-0.42	-2.98	[0.20]	-0.48	-11.81^{***}	[0.00]	0.06	8.83^{**}	[0.04]
	(0.93)	(1.86)		(1.09)	(3.89)		(0.78)	(4.40)	
AG	0.24	-2.63	[0.17]	-0.35	-12.37^{***}	[0.00]	0.60	9.73^{**}	[0.03]
	(0.98)	(1.97)		(1.23)	(3.79)		(0.59)	(4.31)	
BE/ME	0.03	-3.32^{*}	[0.15]	-0.76	-10.67^{***}	[0.00]	0.76	7.21^{***}	[0.01]
	(1.43)	(1.92)		(1.07)	(2.95)		(0.82)	(2.44)	
CA	-1.13	-3.36^{*}	[0.26]	0.02	-12.03^{***}	[0.00]	-1.15	8.66^{***}	[0.00]
	(0.97)	(1.82)		(1.28)	(3.43)		(0.96)	(2.30)	
GP	-0.45	-5.80^{***}	[0.01]	-0.53	-7.00^{***}	[0.00]	0.08	1.21	[0.41]
	(1.05)	(1.90)		(1.10)	(1.85)		(0.54)	(1.28)	
Inv	-0.74	-2.63	[0.30]	-0.43	-11.03^{***}	[0.00]	-0.32	8.40^{**}	[0.02]
	(0.83)	(1.65)		(1.15)	(3.46)		(0.61)	(3.57)	
Mom	-0.29	-5.32^{**}	[0.08]	-0.68	-16.02^{**}	[0.01]	0.39	10.70^{**}	[0.04]
	(1.34)	(2.65)		(1.26)	(6.26)		(1.03)	(5.14)	
NOA	0.24	-8.81^{***}	[0.00]	-0.59	-9.97^{***}	[0.01]	0.82	1.16	[0.87]
	(1.19)	(2.68)		(1.14)	(3.67)		(0.59)	(2.10)	
Oscore	-0.41	-8.60^{***}	[0.00]	-0.23	-4.87^{**}	[0.08]	-0.17	-3.73^{**}	[0.05]
	(1.02)	(2.19)		(1.08)	(2.44)		(0.85)	(1.61)	
PPE/A	-0.55	-1.47	[0.56]	-0.41	-14.24^{***}	[0.00]	-0.14	12.77^{**}	[0.02]
	(0.79)	(1.91)		(1.29)	(4.58)		(0.96)	(5.13)	
RoA	-0.71	-7.20^{***}	[0.00]	-0.05	-12.50^{**}	[0.01]	-0.66	5.31	[0.18]
	(1.15)	(2.01)		(1.17)	(4.90)		(0.66)	(4.40)	
RoB	-0.82	-3.73^{*}	[0.20]	-0.31	-12.58^{**}	[0.01]	-0.52	8.86	[0.11]
	(1.11)	(2.10)		(1.37)	(4.93)		(0.58)	(5.79)	
Sigma	-0.97	-0.42	[0.78]	0.57	-16.83^{***}	[0.00]	-1.56	16.41^{**}	[0.01]
	(0.77)	(1.91)		(1.41)	(5.66)		(1.30)	(6.71)	
Size	-0.60	-1.90	[0.50]	-0.71	-8.17^{***}	[0.00]	0.11	6.27^{***}	[0.00]
	(0.69)	(1.80)		(1.01)	(2.42)		(0.94)	(1.80)	

Table B.3: Response of portfolio returns to path surprises at the zero lower bound during periods of decreasing vs. increasing sentiment - CCI based analyses

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC meeting dates of the following model: $R_t = \beta_0 + \beta_1(1 - S_t^D)path_t + \beta_2 S_t^D path_t + \varepsilon_t$, where R_t and $path_t$ denote portfolio returns and path surprises, respectively. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). Deciles which are more exposed to sentiment are defined as the short leg. S_t^D is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a decreasing (increasing) sentiment year. A year is defined as of decreasing (increasing) sentiment if the sentiment proxy at the end (December) of that year is lower (higher) than at the end of the previous year according to the U.S. Consumer Confidence index. The zero lower bound sample period is January 2009 - October 2014. The unscheduled meetings that were not accompanied by a FOMC statement or other information were excluded. Standard errors are reported in parentheses. P-values from the Wald test for equality of coefficients (F-statistic) are reported in square brackets. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Portfolios	Long Leg			Short Leg			Long-Short		
	β_1	β_2	$\beta_1 = \beta_2$	β_1	β_2	$\beta_1 = \beta_2$	β_1	β_2	$\beta_1 = \beta_2$
Acc	0.41	-4.25^{**}	[0.04]	0.30	-4.16^{**}	[0.06]	0.11	-0.09	[0.80]
	(0.66)	(2.09)		(1.04)	(2.09)		(0.54)	(0.45)	
Age	0.42	-2.43^{*}	[0.08]	-0.53	-3.70^{*}	[0.19]	0.94	1.27^{*}	[0.81]
	(0.53)	(1.42)		(1.28)	(1.98)		(0.94)	(0.74)	
AG	-0.69	-2.98	[0.30]	0.96	-4.04^{**}	[0.02]	-1.65^{**}	1.06^{**}	[0.00]
	(0.96)	(1.91)		(0.78)	(1.94)		(0.72)	(0.49)	
BE/ME	-0.43	-3.02^{***}	[0.22]	0.50	-9.02^{***}	[0.00]	-0.94	6.00^{***}	[0.00]
	(0.82)	(1.86)		(1.17)	(2.52)		(1.16)	(1.53)	
CA	-0.37	-3.63^{**}	[0.08]	0.48	-3.61^{**}	[0.05]	-0.86	-0.02	[0.25]
	(0.84)	(1.58)		(0.63)	(1.75)		(0.53)	(0.53)	
GP	0.33	-3.10^{**}	[0.04]	0.00	-5.33^{***}	[0.02]	0.33	2.23^{***}	[0.01]
	(0.60)	(1.45)		(0.90)	(1.85)		(0.48)	(0.62)	
Inv	0.93	-4.75^{**}	[0.02]	0.93	-4.44^{**}	[0.01]	-1.29^{***}	-0.31	[0.22]
	(0.87)	(2.40)		(0.94)	(1.78)		(0.47)	(0.61)	
Mom	0.29	-2.75	[0.35]	0.02	-19.59^{***}	[0.00]	0.26	16.84^{***}	[0.00]
	(1.81)	(2.66)		(0.97)	(4.76)		(1.22)	(6.04)	
NOA	0.34	-3.16^{*}	[0.06]	0.48	-4.42^{**}	[0.01]	-0.14	1.27^{***}	[0.05]
	(0.83)	(1.59)		(0.66)	(1.76)		(0.62)	(0.34)	
Oscore	0.18	-2.83^{*}	[0.00]	0.85	-6.13^{***}	[0.00]	-0.67	3.31^{***}	[0.00]
	(0.64)	(1.67)		(1.17)	(1.85)		(0.67)	(1.18)	
PPE/A	-0.20	-3.04^{*}	[0.14]	0.11	-3.66^{**}	[0.06]	-0.31	0.62	[0.24]
	(1.03)	(1.59)		(1.05)	(1.65)		(0.44)	(0.52)	
RoA	0.29	-2.33	[0.15]	0.51	-5.58^{***}	[0.00]	-0.22	3.24^{***}	[0.00]
	(0.82)	(1.56)		(0.93)	(1.91)		(0.55)	(0.78)	
RoB	0.36	-2.71	[0.13]	0.37	-5.78^{***}	[0.00]	-0.01	3.07^{**}	[0.05]
	(0.77)	(1.79)		(0.81)	(1.77)		(0.66)	(1.19)	
Sigma	0.05	-2.36	[0.15]	0.93	-4.56^{*}	[0.07]	-0.87	2.20^{*}	[0.19]
	(0.54)	(1.44)		(1.61)	(2.41)		(1.71)	(1.28)	
Size	0.26	-3.84^{**}	[0.02]	1.11	-5.93^{***}	[0.00]	0.85	2.09^{***}	[0.00]
	(0.62)	(1.54)		(0.84)	(1.68)		(0.54)	(0.41)	

Table B.4: Response of portfolio returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - monthly classification of sentiment states (CSI)

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC meeting dates of the following model: R_t=β_0+$\beta_1(1-S_t^{HM})\Delta i_t^u$+$\beta_2 S_t^{HM}\Delta i_t^u$+$\varepsilon_t$, where R_t and Δi_t^u denote portfolio returns and unexpected FFR changes, respectively. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). Deciles which are more exposed to sentiment are defined as the short leg. S_t^{HM} is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a month that starts with high (low) sentiment level. A month is defined as starting with high (low) sentiment if the sentiment proxy at the end of the previous month is above (below) the full sample mean value according to the University of Michigan's Consumer Sentiment Index. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. P-values from the Wald test for equality of coefficients (F-statistic) are reported in square brackets. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Portfolios	Long Leg			Short Leg			Long-Short		
	β_1	β_2	$\beta_1=\beta_2$	β_1	β_2	$\beta_1=\beta_2$	β_1	β_2	$\beta_1=\beta_2$
Acc	0.01	-9.36^{***}	[0.00]	-0.56	-9.68^{***}	[0.00]	0.57	0.32	[0.85]
	(1.60)	(3.49)		(1.81)	(2.85)		(0.85)	(1.11)	
Age	-0.11	-3.02^{**}	[0.13]	-0.59	-10.57^{***}	[0.01]	0.48	7.55^{*}	[0.10]
	(1.29)	(1.48)		(1.75)	(3.48)		(0.93)	(4.21)	
AG	0.20	-2.31	[0.22]	-0.65	-10.87^{***}	[0.00]	0.85	8.57^{**}	[0.06]
	(1.47)	(1.48)		(1.76)	(3.51)		(0.73)	(4.10)	
BE/ME	-0.15	-2.97^{**}	[0.22]	-0.53	-9.90^{***}	[0.00]	0.39	6.92^{***}	[0.00]
	(2.06)	(1.18)		(1.56)	(2.55)		(1.07)	(2.18)	
CA	-0.96	-3.30^{**}	[0.22]	-0.12	-10.67^{***}	[0.00]	-0.84	7.37^{***}	[0.00]
	(1.50)	(1.27)		(1.84)	(3.12)		(1.13)	(2.36)	
GP	-0.54	-5.18^{***}	[0.02]	-0.31	-6.58^{***}	[0.00]	-0.23	1.40	[0.20]
	(1.60)	(1.32)		(1.47)	(1.47)		(0.73)	(1.06)	
Inv	-0.95	-2.24^{*}	[0.46]	-0.49	-9.90^{***}	[0.00]	-0.46	7.66^{**}	[0.02]
	(1.29)	(1.22)		(1.76)	(3.08)		(1.09)	(3.21)	
Mom	-0.62	-4.49^{**}	[0.16]	0.03	-15.17^{**}	[0.01]	-0.66	10.68^{**}	[0.02]
	(1.90)	(2.12)		(3.03)	(5.09)		(1.95)	(4.43)	
NOA	0.16	-7.83^{***}	[0.00]	-0.92	-8.70^{***}	[0.01]	1.08	0.87	[0.92]
	(1.71)	(2.29)		(1.61)	(3.32)		(0.62)	(1.91)	
Oscore	-0.10	-8.08^{***}	[0.00]	-0.75	-3.90^{**}	[0.08]	0.65	-4.18^{***}	[0.00]
	(1.43)	(1.79)		(1.92)	(1.79)		(1.18)	(1.20)	
PPE/A	-0.54	-1.39	[0.65]	-0.28	-12.98^{***}	[0.00]	-0.26	11.59^{**}	[0.02]
	(1.37)	(1.37)		(1.79)	(4.18)		(1.11)	(4.89)	
RoA	-0.39	-6.86^{***}	[0.00]	-0.72	-10.61^{**}	[0.04]	0.33	3.75	[0.42]
	(1.59)	(1.49)		(1.82)	(4.59)		(0.83)	(4.19)	
RoB	-0.54	-3.71^{**}	[0.14]	-0.78	-10.90^{**}	[0.04]	0.24	7.18	[0.21]
	(1.53)	(1.63)		(1.95)	(4.57)		(0.90)	(5.54)	
Sigma	-0.40	-1.03	[0.75]	-0.30	-14.23^{***}	[0.00]	-0.10	13.20^{*}	[0.06]
	(1.14)	(1.63)		(2.25)	(5.45)		(1.84)	(6.70)	
Size	-0.79	-1.59	[0.66]	-0.15	-7.97^{***}	[0.00]	-0.64	6.39^{***}	[0.00]
	(1.23)	(1.35)		(1.58)	(1.81)		(1.01)	(1.54)	

Table B.5: Response of portfolio returns to FFR shocks before the zero lower bound, following periods of high vs. low sentiment - monthly classification of sentiment states (BWI)

This table presents OLS estimates with heteroscedasticity-consistent standard errors, over FOMC meeting dates of the following model: $R_t = \beta_0 + \beta_1(1 - S_t^{HM})\Delta i_t^u + \beta_2 S_t^{HM}\Delta i_t^u + \varepsilon_t$, where R_t and Δi_t^u denote portfolio returns and unexpected FFR changes, respectively. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). Deciles which are more exposed to sentiment are defined as the short leg. S_t^{HM} is a dummy variable that is equal to 1 (0) if the FOMC meeting occurred during a month that starts with high (low) sentiment level. A month is defined as starting with high (low) sentiment if the sentiment proxy at the end of the previous month is above (below) the full sample mean value according to the Baker and Wurgler's (2006, 2007) sentiment index. The sample period includes FOMC meetings over June 1989 - December 2008, with the exception of the 17 September 2001 meeting and the 22 January 2008 meeting. Standard errors are reported in parentheses. P-values from the Wald test for equality of coefficients (F-statistic) are reported in square brackets. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Portfolios	Long Leg			Short Leg			Long-Short		
	β_1	β_2	$\beta_1=\beta_2$	β_1	β_2	$\beta_1=\beta_2$	β_1	β_2	$\beta_1=\beta_2$
Acc	1.00	-8.75^{***}	[0.01]	-0.09	-8.74^{***}	[0.01]	1.09	-0.01	[0.38]
	(1371)	(3.46)		(1.73)	(3.10)		(0.78)	(1.04)	
Age	-0.49	-2.36^{*}	[0.37]	-0.43	-9.29^{**}	[0.03]	-0.05	6.93^{*}	[0.08]
	(1.75)	(1.22)		(1.83)	(3.64)		(1.15)	(3.85)	
AG	1.01	-2.52^{*}	[0.09]	-0.58	-9.50^{**}	[0.03]	-1.59^{*}	6.98^{*}	[0.18]
	(1.63)	(1.42)		(1.91)	(3.67)		(0.82)	(3.93)	
BE/ME	-0.82	-2.10	[0.62]	-0.65	-8.51^{***}	[0.00]	-0.18	6.41^{***}	[0.00]
	(2.17)	(1.47)		(1.82)	(2.79)		(1.19)	(2.02)	
CA	-0.68	-3.17^{***}	[0.22]	0.22	-9.44^{***}	[0.01]	0.90	6.27^{**}	[0.01]
	(1.72)	(1.18)		(1.77)	(3.53)		(0.76)	(2.79)	
GP	-0.75	-4.38^{***}	[0.11]	-0.84	-5.33^{***}	[0.07]	0.09	0.95	[0.01]
	(1.73)	(1.57)		(1.52)	(1.98)		(0.90)	(1.05)	
Inv	-0.65	-2.27^{**}	[0.39]	0.26	-9.12^{***}	[0.00]	0.92	6.85^{**}	[0.02]
	(1.49)	(1.14)		(1.94)	(3.11)		(1.22)	(3.02)	
Mom	0.84	-4.98^{**}	[0.03]	0.68	-13.51^{***}	[0.02]	0.15	8.53^{*}	[0.08]
	(1.76)	(2.19)		(3.49)	(5.18)		(2.33)	(4.37)	
NOA	0.94	-7.27^{***}	[0.00]	-1.04	-7.54^{**}	[0.08]	1.98^{**}	0.27	[0.35]
	(1.77)	(1.77)		(1.87)	(3.21)		(0.87)	(1.62)	
Oscore	-0.61	-6.61^{***}	[0.00]	1.09	-4.75^{***}	[0.03]	-1.70	-1.86^{*}	[0.94]
	(1.74)	(2.25)		(2.06)	(1.66)		(1.91)	(1.06)	
PPE/A	-0.48	-1.31	[0.67]	-0.61	-10.98^{**}	[0.03]	0.13	9.67^{**}	[0.06]
	(1.64)	(1.19)		(1.86)	(4.45)		(1.05)	(4.86)	
RoA	-0.48	-5.89^{***}	[0.03]	0.06	-9.77^{**}	[0.04]	-0.53	3.88	[0.00]
	(1.73)	(1.90)		(1.86)	(4.47)		(1.12)	(3.61)	
RoB	-0.90	-3.02^{**}	[0.35]	-0.29	-9.83^{**}	[0.05]	-0.61	6.81	[0.14]
	(1.79)	(1.53)		(1.90)	(4.55)		(1.20)	(4.93)	
Sigma	-0.38	-0.96	[0.76]	1.51	-13.56^{**}	[0.00]	-1.89	12.60^{**}	[0.02]
	(1.45)	(1.35)		(2.23)	(5.38)		(2.05)	(6.22)	
Size	1.28	-2.93^{***}	[0.02]	-0.55	-6.61^{***}	[0.03]	1.83	3.68^{**}	[0.00]
	(1.56)	(0.91)		(2.00)	(2.08)		(2.16)	(1.52)	

Appendix C

Appendix for Chapter 3

Table C.1: Portfolio returns one-day ahead of scheduled FOMC announcements during periods of high vs. low sentiment - sentiment states classified by the CSI

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors of the following model: r_t=β_0+$\beta_1(1-S_t^H)FOMC_t^{pre}$+$\beta_2 S_t^H FOMC_t^{pre}$+$\varepsilon_t$, where r_t denotes daily log return of different portfolios in excess of the 1-month Treasury bill rate. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). $FOMC_t^{pre}$ is a dummy variable that is equal to 1 on the pre-FOMC window and 0 otherwise. The pre-FOMC window is one day before a scheduled FOMC announcement. S_t^H is a dummy variable that is equal to 1 (0) if a day belongs to a high (low) sentiment month. A high (low) sentiment month is the month when the sentiment proxy at the end of the previous month is above (below) the full sample mean value. The sentiment indicator is the University of Michigan's Consumer Sentiment index. The sample period is February 1994 - October 2015. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Decile 1		Decile 2		Decile 3		Decile 4		Decile 5		Decile 6		Decile 7		Decile 8		Decile 9		Decile 10	
	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2
Age	-0.008	0.034	-0.022	-0.036	-0.063	-0.010	-0.097	0.149	-0.058	0.097	0.084	0.074	-0.123	0.203*	-0.017	0.110	-0.008	0.218**	0.073	0.294***
	(0.122)	(0.165)	(0.124)	(0.164)	(0.121)	(0.155)	(0.134)	(0.156)	(0.110)	(0.129)	(0.104)	(0.113)	(0.105)	(0.111)	(0.090)	(0.094)	(0.097)	(0.085)	(0.082)	(0.102)
PPE/A	-0.008	0.128	0.001	0.086	0.020	0.119	0.041	0.163	-0.088	0.103	-0.011	0.226**	0.014	0.227**	-0.047	0.212**	-0.023	0.188**	0.073	0.295**
	(0.119)	(0.155)	(0.109)	(0.155)	(0.082)	(0.111)	(0.090)	(0.104)	(0.101)	(0.115)	(0.104)	(0.113)	(0.099)	(0.108)	(0.090)	(0.095)	(0.092)	(0.083)	(0.124)	(0.116)
RoB	-0.014	-0.039	0.030	0.134	0.021	0.113	-0.070	0.122	-0.024	0.131	-0.010	0.149	-0.069	0.220**	-0.016	0.159	0.016	0.227**	0.017	0.198*
	(0.138)	(0.197)	(0.126)	(0.125)	(0.107)	(0.122)	(0.102)	(0.103)	(0.096)	(0.106)	(0.111)	(0.141)	(0.097)	(0.102)	(0.099)	(0.109)	(0.090)	(0.112)	(0.094)	(0.108)
Size	-0.008	-0.135	0.045	-0.080	0.028	-0.089	0.056	0.003	0.012	-0.028	0.001	-0.025	-0.028	-0.004	-0.039	0.083	-0.028	0.140	0.010	0.245**
	(0.107)	(0.089)	(0.142)	(0.114)	(0.138)	(0.128)	(0.129)	(0.126)	(0.123)	(0.129)	(0.113)	(0.117)	(0.110)	(0.117)	(0.106)	(0.115)	(0.100)	(0.113)	(0.094)	(0.115)
Mom	-0.072	-0.028	-0.011	0.154	-0.010	0.151	-0.032	0.170	0.003	0.161	0.005	0.220**	0.042	0.133	-0.004	0.238**	0.066	0.200*	-0.134	0.117
	(0.179)	(0.174)	(0.136)	(0.136)	(0.119)	(0.104)	(0.102)	(0.123)	(0.102)	(0.108)	(0.096)	(0.089)	(0.093)	(0.087)	(0.095)	(0.101)	(0.102)	(0.107)	(0.150)	(0.170)
Acc	0.040	0.144	-0.030	0.180	0.056	0.324***	-0.027	0.070	0.024	0.259**	-0.046	0.112	-0.013	0.090	0.004	0.150	-0.042	0.135	-0.019	-0.102
	(0.137)	(0.143)	(0.120)	(0.131)	(0.102)	(0.117)	(0.084)	(0.106)	(0.090)	(0.112)	(0.094)	(0.094)	(0.090)	(0.123)	(0.093)	(0.107)	(0.105)	(0.130)	(0.119)	(0.146)
BM/ME	0.033	0.135	0.004	0.142	-0.025	0.212**	-0.057	0.226*	0.000	0.221**	-0.028	0.154	-0.020	0.175	-0.049	0.211**	-0.065	0.165	-0.099	0.105
	(0.100)	(0.133)	(0.092)	(0.108)	(0.097)	(0.100)	(0.105)	(0.118)	(0.101)	(0.108)	(0.103)	(0.098)	(0.102)	(0.112)	(0.112)	(0.093)	(0.128)	(0.116)	(0.147)	(0.099)
CA	-0.023	0.073	0.064	0.243***	0.025	0.124	0.028	0.173*	0.019	0.263**	-0.030	0.203**	-0.031	0.268**	0.038	0.194*	-0.109	0.160	0.000	0.025
	(0.104)	(0.095)	(0.092)	(0.093)	(0.090)	(0.093)	(0.093)	(0.093)	(0.098)	(0.116)	(0.095)	(0.099)	(0.099)	(0.106)	(0.091)	(0.101)	(0.095)	(0.114)	(0.131)	(0.164)
GP	0.047	0.237*	-0.032	0.086	-0.017	0.157	-0.060	0.214**	-0.010	0.248**	0.024	0.102	-0.085	0.137	0.057	0.135	0.004	0.150	0.034	0.195
	(0.102)	(0.128)	(0.102)	(0.093)	(0.114)	(0.098)	(0.115)	(0.097)	(0.107)	(0.106)	(0.094)	(0.124)	(0.109)	(0.142)	(0.094)	(0.120)	(0.096)	(0.132)	(0.095)	(0.116)
Inv	-0.024	0.235**	-0.023	0.161*	0.058	0.190	-0.010	0.231*	0.042	0.212*	-0.008	0.060	0.004	0.219*	0.043	0.121	-0.072	0.054	0.002	0.073
	(0.091)	(0.113)	(0.096)	(0.097)	(0.095)	(0.120)	(0.093)	(0.123)	(0.096)	(0.121)	(0.092)	(0.126)	(0.095)	(0.117)	(0.108)	(0.128)	(0.117)	(0.113)	(0.143)	(0.125)
AG	-0.003	0.194**	-0.042	0.183*	-0.008	0.207**	0.040	0.146	-0.053	0.138	-0.014	0.183*	0.061	0.305***	0.012	0.342**	-0.024	0.092	0.001	0.008
	(0.119)	(0.098)	(0.110)	(0.109)	(0.095)	(0.101)	(0.095)	(0.103)	(0.089)	(0.097)	(0.093)	(0.107)	(0.097)	(0.099)	(0.102)	(0.140)	(0.108)	(0.137)	(0.115)	(0.155)
NOA	-0.015	0.094	0.012	0.233**	-0.010	0.241**	0.034	0.249***	0.009	0.192*	0.008	0.176*	0.048	0.194*	-0.061	0.129	0.011	0.138	-0.017	0.035
	(0.128)	(0.148)	(0.098)	(0.116)	(0.093)	(0.111)	(0.094)	(0.092)	(0.095)	(0.105)	(0.084)	(0.096)	(0.092)	(0.115)	(0.102)	(0.139)	(0.105)	(0.122)	(0.112)	(0.130)
Oscore	-0.022	0.197	0.021	0.168	0.014	0.126	-0.009	0.143	-0.059	0.099	-0.035	0.111	0.013	0.133	-0.016	-0.005	-0.011	0.027	-0.056	-0.095
	(0.101)	(0.126)	(0.090)	(0.103)	(0.099)	(0.103)	(0.086)	(0.089)	(0.098)	(0.092)	(0.093)	(0.095)	(0.094)	(0.111)	(0.104)	(0.093)	(0.117)	(0.104)	(0.130)	(0.134)
RoA	0.015	-0.083	0.026	0.172	0.021	0.135	-0.034	0.297***	0.016	0.105	-0.043	0.156	0.011	0.208*	-0.031	0.194*	-0.023	0.170	0.010	0.190
	(0.139)	(0.198)	(0.127)	(0.119)	(0.105)	(0.108)	(0.098)	(0.111)	(0.093)	(0.107)	(0.101)	(0.110)	(0.101)	(0.109)	(0.097)	(0.103)	(0.093)	(0.106)	(0.100)	(0.123)
Sigma	0.032	0.163*	0.021	0.238**	0.038	0.358***	0.041	0.195**	-0.021	0.180*	-0.136	0.148	-0.085	-0.010	-0.098	0.118	-0.128	-0.175	0.085	0.082
	(0.072)	(0.092)	(0.083)	(0.100)	(0.093)	(0.095)	(0.101)	(0.095)	(0.114)	(0.108)	(0.119)	(0.121)	(0.123)	(0.140)	(0.158)	(0.149)	(0.160)	(0.184)	(0.177)	(0.220)

Table C.2: Portfolio returns one-day ahead of scheduled FOMC announcements during periods of high vs. low sentiment - sentiment states classified by the BWI

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors of the following model: $r_t=\beta_0+\beta_1(1-S_t^H)FOMC_t^{pre}+\beta_2 S_t^H FOMC_t^{pre}+\varepsilon_t$, where r_t denotes daily log return of different portfolios in excess of the 1-month Treasury bill rate. Portfolios formed on the following characteristics are considered: Accruals (Acc), asset growth (AG), firm age (Age), book-to-market ratio (BM/ME), cash to asset (CA), gross profitability (GP), investment to assets (Inv), momentum (Mom), net operating assets (NOA), O-score of Ohlson (1980) (Oscore), asset tangibility (PPE/A), return on assets (RoA), return on book value of equity (RoB), return volatility (Sigma) and market value of equity (Size). $FOMC_t^{pre}$ is a dummy variable that is equal to 1 on the pre-FOMC window and 0 otherwise. The pre-FOMC window is one day before a scheduled FOMC announcement. S_t^H is a dummy variable that is equal to 1 (0) if a day belongs to a high (low) sentiment month. A high (low) sentiment month is the month when the sentiment proxy at the end of the previous month is above (below) the full sample mean value. The sentiment indicator is Baker and Wurgler's (2006, 2007) sentiment index. The sample period is February 1994 - October 2015. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Decile 1		Decile 2		Decile 3		Decile 4		Decile 5		Decile 6		Decile 7		Decile 8		Decile 9		Decile 10	
	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2	β_1	β_2
Age	-0.112	0.100	-0.138	0.053	-0.184	0.066	-0.177	0.140	-0.085	0.074	0.042	0.108	-0.112	0.105	-0.021	0.078	-0.089	0.216***	-0.007	0.293***
	(0.147)	(0.133)	(0.144)	(0.135)	(0.144)	(0.127)	(0.151)	(0.137)	(0.128)	(0.110)	(0.114)	(0.104)	(0.117)	(0.104)	(0.107)	(0.083)	(0.110)	(0.082)	(0.091)	(0.088)
PPE/A	-0.123	0.175	-0.043	0.094	-0.079	0.166*	-0.025	0.179*	-0.121	0.075	-0.071	0.205**	0.060	0.135	-0.073	0.16*	-0.068	0.164**	-0.023	0.306***
	(0.131)	(0.133)	(0.120)	(0.131)	(0.092)	(0.094)	(0.096)	(0.095)	(0.112)	(0.103)	(0.113)	(0.104)	(0.114)	(0.096)	(0.104)	(0.086)	(0.114)	(0.071)	(0.147)	(0.103)
RoA	-0.045	-0.011	-0.007	0.156	0.000	0.120	-0.144	0.288***	-0.034	0.117	-0.073	0.124	-0.054	0.202**	-0.066	0.158*	-0.045	0.133	-0.068	0.198*
	(0.165)	(0.161)	(0.151)	(0.107)	(0.126)	(0.094)	(0.111)	(0.097)	(0.109)	(0.092)	(0.122)	(0.093)	(0.117)	(0.096)	(0.109)	(0.094)	(0.104)	(0.095)	(0.107)	(0.11)
RoB	-0.054	-0.003	-0.010	0.135	-0.058	0.147	-0.137	0.119	-0.056	0.112	-0.031	0.120	-0.042	0.120	-0.054	0.139	-0.041	0.211**	-0.074	0.216**
	(0.167)	(0.158)	(0.151)	(0.109)	(0.124)	(0.105)	(0.118)	(0.093)	(0.117)	(0.090)	(0.129)	(0.118)	(0.115)	(0.091)	(0.107)	(0.101)	(0.100)	(0.098)	(0.102)	(0.097)
Size	-0.007	-0.102	-0.002	-0.010	-0.011	-0.027	0.032	0.036	-0.042	0.023	-0.054	0.022	-0.076	0.025	-0.102	0.096	-0.094	0.143	-0.051	0.226**
	(0.142)	(0.070)	(0.182)	(0.097)	(0.173)	(0.108)	(0.162)	(0.105)	(0.152)	(0.108)	(0.142)	(0.095)	(0.137)	(0.096)	(0.128)	(0.097)	(0.120)	(0.095)	(0.104)	(0.101)
GP	-0.093	0.289***	-0.025	0.049	-0.038	0.125	-0.135	0.194**	-0.078	0.228**	-0.068	0.149	-0.118	0.100	0.011	0.148	-0.008	0.118	-0.058	0.218**
	(0.117)	(0.107)	(0.124)	(0.083)	(0.138)	(0.090)	(0.136)	(0.090)	(0.126)	(0.095)	(0.109)	(0.103)	(0.120)	(0.123)	(0.105)	(0.104)	(0.097)	(0.116)	(0.103)	(0.103)
Inv	-0.083	0.207**	-0.047	0.128	-0.008	0.203**	-0.050	0.195*	-0.045	0.230**	-0.051	0.074	-0.056	0.205**	-0.013	0.141	-0.089	0.032	-0.081	0.116
	(0.103)	(0.096)	(0.105)	(0.092)	(0.106)	(0.103)	(0.095)	(0.109)	(0.109)	(0.103)	(0.099)	(0.109)	(0.106)	(0.102)	(0.129)	(0.107)	(0.139)	(0.102)	(0.179)	(0.108)
Mom	-0.138	0.009	-0.082	0.162	-0.010	0.107	-0.089	0.156	-0.013	0.130	-0.042	0.196**	-0.002	0.140*	-0.032	0.193**	0.033	0.188**	-0.226	0.116
	(0.216)	(0.152)	(0.167)	(0.116)	(0.145)	(0.093)	(0.125)	(0.101)	(0.123)	(0.093)	(0.116)	(0.079)	(0.112)	(0.078)	(0.108)	(0.092)	(0.120)	(0.095)	(0.182)	(0.143)
NOA	-0.106	0.131	-0.059	0.224**	-0.055	0.205**	-0.034	0.240***	-0.055	0.190**	-0.051	0.174**	0.087	0.125	-0.158	0.149	-0.047	0.147	-0.062	0.054
	(0.136)	(0.135)	(0.109)	(0.102)	(0.108)	(0.095)	(0.104)	(0.086)	(0.107)	(0.094)	(0.098)	(0.082)	(0.107)	(0.097)	(0.116)	(0.115)	(0.118)	(0.107)	(0.136)	(0.108)
Acc	-0.036	0.173	-0.108	0.180	-0.005	0.296***	-0.044	0.056	-0.004	0.216**	-0.077	0.091	-0.049	0.089	-0.064	0.161*	-0.095	0.126	-0.111	-0.010
	(0.157)	(0.129)	(0.138)	(0.115)	(0.118)	(0.102)	(0.100)	(0.088)	(0.102)	(0.097)	(0.107)	(0.087)	(0.104)	(0.102)	(0.101)	(0.096)	(0.115)	(0.114)	(0.137)	(0.125)
BM	-0.059	0.176	-0.072	0.161*	-0.026	0.146	-0.083	0.167	-0.046	0.195**	-0.088	0.148*	-0.044	0.139	-0.073	0.157*	-0.057	0.095	-0.127	0.070
	(0.111)	(0.113)	(0.102)	(0.095)	(0.108)	(0.093)	(0.124)	(0.102)	(0.122)	(0.092)	(0.124)	(0.086)	(0.128)	(0.092)	(0.138)	(0.085)	(0.164)	(0.096)	(0.184)	(0.094)
CA	-0.112	0.113	0.038	0.213***	-0.018	0.128	-0.081	0.215**	0.004	0.206**	-0.042	0.148	-0.087	0.228**	-0.015	0.191**	-0.166	0.128	-0.068	0.069
	(0.127)	(0.083)	(0.110)	(0.081)	(0.105)	(0.083)	(0.101)	(0.087)	(0.118)	(0.097)	(0.112)	(0.088)	(0.113)	(0.094)	(0.105)	(0.088)	(0.106)	(0.100)	(0.134)	(0.148)
Oscore	-0.080	0.181	-0.014	0.153*	-0.046	0.140	-0.039	0.123	-0.110	0.094	-0.054	0.085	-0.016	0.122	-0.066	0.029	-0.076	0.064	-0.055	-0.085
	(0.107)	(0.112)	(0.101)	(0.092)	(0.118)	(0.090)	(0.103)	(0.078)	(0.116)	(0.082)	(0.112)	(0.083)	(0.114)	(0.092)	(0.125)	(0.085)	(0.149)	(0.087)	(0.166)	(0.108)
AG	-0.036	0.165*	-0.025	0.108	-0.042	0.173*	-0.029	0.168*	-0.075	0.101	-0.128	0.213**	-0.039	0.312**	-0.063	0.307**	-0.083	0.104	-0.063	0.054
	(0.138)	(0.097)	(0.136)	(0.094)	(0.102)	(0.095)	(0.105)	(0.093)	(0.106)	(0.084)	(0.099)	(0.096)	(0.113)	(0.087)	(0.109)	(0.121)	(0.117)	(0.120)	(0.131)	(0.129)
Sigma	0.006	0.146*	-0.018	0.208**	-0.004	0.301***	-0.018	0.197**	-0.123	0.201**	-0.202	0.119	-0.117	-0.008	-0.155	0.101	-0.205	-0.104	-0.059	0.190
	(0.077)	(0.081)	(0.089)	(0.090)	(0.111)	(0.084)	(0.118)	(0.087)	(0.135)	(0.097)	(0.146)	(0.103)	(0.155)	(0.113)	(0.183)	(0.138)	(0.192)	(0.154)	(0.211)	(0.182)

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