Investor Sentiment regimes, Monetary Policy Shocks, and Stock Price Reaction

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Abstract

We investigate whether and how the state of investor sentiment affects the impact of monetary policy shocks on the stock market return and the cross-section of stock returns. We find that stock returns show a strong and significantly positive response to expansionary surprises in the Federal funds rate when the start-of-the-year investor sentiment is high. This effect is particularly strong for stocks with large size, low book-to-market value and low past returns. Moreover, we find that stock prices significantly respond to non-conventional monetary policy announcements.

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1 Introduction

Behavioral theory and empirical studies have established strong evidence for the effect of investor sentiment on stock returns (e.g., Lee et al., 1991; Kumar and Lee, 2006; Baker and Wurgler, 2006; Stambaugh et al., 2012). Financial economists also document that monetary policy shocks have significant impacts on the stock market. Thorbecke (1997), Ehrmann and Fratzscher (2004), Bernanke and Kuttner (2005), Kontonikas and Kostakis (2013) show that, in line with the present value argument, cuts in unexpected Federal funds rate (FFR) are positively related to stock returns. Theoretically, there are two channels through which monetary policy could affect stock price. First, changes in FFR could change investors' expectation about future cash flows. Second, it will change the cost of capital: it may affect the real interest rate that is used to discount the future cash flow or the risk premium associated with holding stocks (Bernanke and Kuttner, 2005; Maio, 2014).

Monetary policy shocks also exert impacts on investor sentiment. For example, Kurov (2010) finds that expansionary monetary policy shocks increase investor sentiment, especially during bear markets. He also documents that stocks that are more sensitive to investor sentiment changes are also more sensitive to monetary policy shocks. However, there is little research investigating the role investor sentiment plays in the transmission of monetary policy effects to stocks.

In this paper, we examine, across different states of investor sentiment, the responses of the stock market return and the cross-section of stock returns to monetary policy shocks on the meeting days of the Federal Open Market Committee (FOMC). Our goal is to understand whether the impacts of unanticipated monetary policy shifts on the returns of the stock market and the cross-section of stocks differ across different states of investor sentiment. Baker and Wurgler (2006) find that the cross-section of expected stock returns depend on beginning-of-period proxies for sentiment. Yu and Yuan (2011) document that the stock markets expected excess return only shows a positive relation to the markets conditional variance in low-sentiment periods. To our knowledge, this paper is the first to link investor sentiment to the state dependence of monetary policy impacts on stock returns. We also contribute to the literature by revealing that the effect of monetary policy shifts on the cross-section of stock returns is conditional upon investor sentiment-based regimes.

Prior studies on the state dependence of monetary policy impacts generally focus on the state of the macroeconomy. In this study, however, we separate the state of investor sentiment into high-sentiment and low-sentiment regimes according to the beginning-of-year value of investor sentiment. We consider three different sentiment indices with each being orthogonalized to a set of macroeconomic variables, thereby removing the variation due to economic components. We use three monthly measures of investor sentiment: the University of Michigan Consumer Sentiment Index (CSI), the U.S. Consumer Confidence Index (CCI) and the Sentiment Index constructed by Baker and Wurgler (BWI). We define a year as high sentiment if the sentiment indicator at the end of the previous year exceeds the full sample median value.

We first use daily returns on the CRSP value-weighted market index in excess of the treasury bill rate as a proxy for the excess market portfolio returns and examine the market-wide response of stocks to FFR shocks on FOMC meeting days, separating periods of high versus low sentiment. The daily return is measured between the FOMC meeting day and the previous trading day. We employ an event study approach following

Bernanke and Kuttner (2005) to examine the response of stock returns to monetary policy shocks, which we construct using FFR futures contracts.

We find that, when sentiment is high at the start of the year, excess stock market returns respond positively to monetary easing shocks in the form of unexpected FFR cuts. Specifically, in response to an unexpected cut in the FFR of 25 basis points, excess stock market return increases by about 2% in a day. In contrast, in months when sentiment is low at the start of the year, the impact of monetary policy shocks on excess stock market returns is insignificant. Our findings are robust to the use of alternative sentiment indicators, and are similar during the period before the 2007-2008 financial crisis. Our finding that the stock market return only reacts to expansionary FFR shocks when sentiment is high at the beginning of the year has important implications.

As depicted in Figure 2 and documented by Chung et al. (2012), high sentiment levels, typically occurring near business cycle peaks, tend to be followed by negative changes in sentiment throughout economic contractions. We also examine how changes in investor sentiment affect the relationship between FFR shocks and stock market returns. A decreasing sentiment period is definded as years when the value of the sentiment proxy at December is lower than the value at December of the previous year. We find that during periods when investor sentiment is decreasing stock market returns respond positively to an expansionary monetary policy shock. We then analyze the joint effect of sentiment level and changes on the relationship between stock market returns and monetary policy shocks. We find that the effect of policy shifts is stronger during years that sentiment started at high levels but then subsequently declined.

Next, we examine the cross-sectional variation in the response of stock returns to monetary policy shocks by analyzing returns of value-weighted stock portfolios sorted by size, value and momentum. In line with our findings on the market level, the impact of FFR surprises on portfolio returns tend to be statistically significant only when sentiment is high at the start of the year. Importantly, the effect of monetary policy shocks differs across the cross-section of stocks: large, growth and loser stocks are significantly more exposed to policy shifts solely when sentiment is high at the start of the year. The return differentials on the long-short strategies decline in response to expansionary surprises due to the stronger response of the short-leg portfolios (large, growth and loser).

We expand our analysis to analyze the responses of the size (SMB) and value (HML) factor portfolios of Fama and French (1993), and momentum (MOM) factor portfolio of Carhart (1997). Again, the factor returns on SMB, HML and MOM are positively related to unexpected FFR changes only when start-of-the year sentiment is high. We further analyze the responses of value-weighted returns of two-way sorted portfolios: 25 size-value portfolios and 25 size-momentum portfolios. We find that when sentiment is high at the start of the year, within each size quintile the impact of policy shocks is generally stronger for growth than value stocks, and for loser than winner stocks. Our findings are consistent with the notion of overpricing during sentiment build-up period, which is followed by subsequent pricing corrections. Our evidence suggests that the pricing correction of growth and loser stocks are large relative to value and winner stocks during priods of decreasing sentiment. When an expansionary monetary policy shock occurs, these stocks benefit with strong reactions. On the other hand, liquidity may play a more important role for the strong reaction of large size stocks, since as pointed out by Amihud (2002) that large size stocks are more liquid than smaller ones.

Finally, we examine the impact of non-conventional monetary policy announcements. We consider only announcements of expansionary nature, that is, related to the initiation or continuation of Large-Scale Asset Purchases (LSAPs) and liquidity facilities programmes. We estimate ARs adopting a constant mean model (MacKinlay, 1997). The mean is calculated using a 20-day estimation period, ending 2 days before the announcement. We find that cumulative average abnormal returns (CAARs) of the stock market increase and the CAARs are strongly significant around liquidity swaps announcements only during periods of decreasing sentiment.

We conduct a host of robustness checks including adopting an estimation method which is robust to the presence of outliers, removing FOMC meetings that coincide with employment data releases, using an alternative starting point for our estimation sample, and using returns of industry portfolios. All our findings remain strong and consistent, and do not change our conclusions.

The rest of the paper proceeds as follows. Section 2 develops our hypotheses. Section 3 describes the data and variables employed in the empirical analysis. In Section 4, we present evidence on the role of investor sentiment in the impact of monetary policy shocks on the U.S. stock market and different stock portfolios. Section 5 describes the results from various robustness checks. Finally, Section 6 concludes.

2 Hypothesis development

In this paper, we posit that the state of investor sentiment may affect the way by which investors react to monetary policy news, and hence stock returns. Specifically, we hypothesize that monetary policy shocks have a larger impact on stock returns when sentiment is high at the start of the year. Our hypothesis is based on the following arguments.

First, the effect of monetary policy shocks on stock returns is state dependent. For example, Chen (2007) finds that the effect of monetary policy surprises on stock returns is much larger in bear markets than that in bull markets. Similarly, Basistha and Kurov (2008) find that the reaction of stock prices to monetary policy news is much stronger in recessions and in tight credit market conditions than in good economic times. As Chen (2007) states "according to recent theoretical models with agency costs of financial intermediation, people show that when there is information asymmetry in financial markets, agents may behave as if they are constrained financially". Thus, monetary policy may have greater effects in "bad times". However, Kontonikas et al. (2013) show that stock returns are not positively related to unexpected FFR cuts during the financial crisis, which is an extreme "bad time". They argue that this may be because investors treat those cuts as signals of worse future condition, which indicates that investors are not confident about the market.

Second, many studies document that investor sentiment affects asset prices (see, e.g., Lemmon and Portniaguina, 2006, and Kumar and Lee, 2006). Baker and Stein (2004) find that an increase in investor sentiment leads to an increase in market liquidity and stock prices. Baker and Wurgler (2006) show that investor sentiment predict the cross-section of stock returns. Such return predictive power, however, is state dependent. Chung et al. (2012) demonstrate that only during economic expansions does investor sentiment perform well in predicting the cross-section of stock returns. Yu and Yuan (2011) find a positive risk-return relation in the low-sentiment periods, but a weak relation in the high-sentiment periods in the U.S. stock market. Stambaugh et al. (2012) argue that the profitability of 11 anomalies reflects mispricing, and show that the profitability of the long-short and the short-legs of the anomaly strategies are stronger in months following high levels of sentiment. They attribute such higher profitability to stronger declines in the short-leg of each of the anomaly strategies.

Intuitively, when beginnng-of-period sentiment is hign or when sentiment is declining, investors are likely to face the arrival of good monetary policy news, [1]while when beginnng-of-period sentiment is low, investor may not be confident enough about the good monetary news. Thus, it is natural to observe larger monetary policy impact on stocks when beginnng-of-period sentiment is hign or when sentiment is declining. This is also consistent with previous studies which find larger monetary policy impact during "bad times". As Yu and Yuan (2011) mentioned, there are more sentiment-driven investors when sentiment is high. It is also proved that when investor sentiment is high, the aggregate mispricing will be high and that high sentiment is usually followed by low stock returns (Baker and Wurgler, 2006), thus high sentiment, generally will be followed by a downside stock market condition, which is also a period of "bad time", then there will be larger impact of monetary policy.

3 Data

3.1 Conventional monetary policy

The conduct of monetary policy during the sample period June 1989–October 2014 is characterised by the targeting of the Fed funds rate (FFR), 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 sample period includes 227 FOMC meetings, 23 of which were unscheduled.[2] In line with Bernanke and Kuttner

[1]As Bernanke and Kuttner 2005 state, investors react to good monetary news rather than bad news

[2]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 ambiguity existed about the dates of open market operations. In February 1994 the Fed started to announce target FFR changes, a develop-

(2005), the unscheduled FOMC meeting that occurred in the aftermath of the 11 September 2001 attacks (17 September 2001) is excluded from the sample. We also excluded unscheduled meetings that were not accompanied by a FOMC statement or other information.[3] Finally, we removed the most prominent outlier, as identified by the difference in fits statistic of Welsch and Kuh (1977), that corresponds to the FOMC meeting of 22 January 2008.[4]

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

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

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.[5]

This proxy of monetary policy shocks has been used extensively in previous studies that analyze the response of stocks to monetary policy shifts (Bernanke and Kuttner, 2005; Kurov, 2010; Kontonikas et al., 2013). The source of the futures data is Bloomberg, while data on the FFR is obtained from the Federal Reserve Economic Database (FRED) maintained by the Federal Reserve Bank of St. Louis.

ment that enhanced transparency in monetary policy. The corresponding dates are obtained from the Federal Reserve website at http://www.federalreserve.gov/monetarypolicy/fomccalendars.htm.

[3] A number of such meetings occur in the latter part of the sample, from January 2008 onwards. These meetings are just dated and no further information, related to the FFR or QE, is provided at the Federal Reserve website.

[4] 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.

[5] 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.

Figure 1 plots actual and unexpected changes in the target FFR on FOMC meeting dates. Typically, large expansionary monetary policy shocks (unexpected declines in the FFR) materialize during, or near, periods of economic slowdown. Descriptive statistics in Table 1 indicate that the average FFR change is equal to -0.04%, ranging from a minimum of -0.75% to a maximum of 0.75%. 82 FOMC meetings are associated with FFR changes, 51 of which are of expansionary nature ($\Delta i<0$), while 31 are contractionary ($\Delta i>0$).

During October 2008, in the aftermath of the Lehman Brother's collapse, the Fed reduced the FFR from 2% to 1%. This was followed by another major decrease in the FFR at the FOMC meeting of 16 December 2008, from 1% to the range of 0%–0.25%. Ever since, and until the end of the sample period, there are no further rate changes and the volatility of FFR shocks dies out. When we estimate the impact of FFR shocks on the stock market across sentiment regimes, we utilize both the full sample period and a pre-crisis period (June 1989–August 2007) in an effort to account for the effect of the financial crisis and the subsequent non-conventional policies adopted by the Fed.[6]

3.2 Non-conventional monetary policy

In order to alleviate the constraint to monetary stimulus that the ZLB posed, the Fed provided frequent assurances to the public and financial markets about its intention to keep the policy rate at near zero in the future, which is known as "forward guidance" (Bernanke, 2013; Doh and Connolly, 2013).[7] Moreover, the Fed significantly expanded its

[6] In line with Kontonikas et al. (2013), among other studies, we date the start of the financial crisis to September 2007. By the end of the summer of 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.

[7] At the beginning, 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

balance sheet through the provision of non-sterilized liquidity facilities, that were heavily used in autumn 2008, and large scale purchases of mainly mortgage backed securities and Treasury bonds. Fed's non-conventional policy actions aimed to improve financial markets conditions and put downward pressure on long-term borrowing costs.

In our empirical analysis, we examine the impact of non-conventional monetary policy announcements on stock returns, while accounting for the role of investor sentiment. Specifically, we measure the reaction of stock returns to the announcement of Large Scale Asset Purchases (LSAPs) and liquidity facilities that included dollar and foreign currency liquidity swaps between the Fed and other central banks.[8] Unlike FFR changes, for which we can use market-based expectations to isolate their surprise component, direct measures of expectations on LSAPs and liquidity facilities announcements are not available. Hence, in line with most previous related studies we will not attempt to measure shocks in non-conventional policies (Gagnon et al., 2011; Ait-Sahalia et al., 2012; Fiordelisi et al., 2014; Ricci, 2015).[9]

3.3 Investor sentiment measures

We use three monthly measures of investor sentiment: the University of Michigan's Consumer Sentiment Index (CSI), the U.S. Consumer Confidence Index (CCI) and Baker

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.

[8]The liquidity facilities provided by the Fed incorporated: central bank liquidity swaps; 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 and term auction facility.

[9]Two notable exceptions, in the sense that they try to identify non-conventional policy shocks, are Rosa (2012) and Wright (2012). Rosa (2012) 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. Wright (2012) employs two approaches: a structural VAR with daily data and a heteroskedasticity-based identification strategy (Rigobon and Sack, 2004); an intraday event study whereas changes in long-term bond futures rates are used to quantify monetary policy surprises during the period of unconventional policy.

and Wurgler's (2006) Sentiment Index (BWI).[10] The use of alternative proxies of investor sentiment is consistent with the idea that a single perfect measure of sentiment does not exist and it is therefore important to capture different dimensions of it (Lutz, 2015). The CSI is based upon surveys conducted by the University of Michigan through telephone interviews during which 500 U.S. participants are asked questions about their outlook on the economy. The CCI is also an economic survey-based measure compiled by the Conference Board. However, it uses a larger pool of respondents (5000) and somewhat different questions, as compared to the CSI. Both indices have been frequently employed in previous studies as proxies of investor sentiment (Lemmon and Portniaguina, 2006; McLean and Zhao, 2014). The BWI is another commonly used measure of investor sentiment (Yu and Yuan, 2011; Stambaugh et al., 2012), formed as the first principal component of six measures of investor sentiment: the closed-end fund discount, the number and the first-day returns of IPOs, the turnover of NYSE, the equity share in total new issues and the dividend premium. By taking the first principal component, the BWI filters out idiosyncratic noise in its constituents and captures common variation. Data on the BWI is available until December 2010, hence this measure of sentiment will only be used for our pre-crisis estimations in the next section.

All sentiment measures are orthogonalized with respect to macroeconomic conditions so that we can capture "pure" sentiment that is not related to shifts in economic fundamentals. Specifically, in order to calculate the orthogonalized version of their index, which we employ in this study, Baker and Wurgler (2006) regress each of the component variables on a set of macroeconomic indicators. The residuals from these regressions are then used for the calculation of the principal component that represents the BWI.

[10]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/.

The following six macro-variables are employed: the growth in industrial production, the 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. Following Baker and Wurgler (2006), we also orthogonalize the CSI and the CCI, using the same six macroeconomic indicators.

Figure 2 plots the three orthogonalized sentiment indices.[11] They all show declines in sentiment during, or near, economic contractions. However, the BWI exhibits rather different dynamics over time, for instance, increasing significantly at the late 1990s, capturing the "dot-com boom" stock market episode. The differences between the BWI and the survey-based measures of sentiment are also apparent in Table 2 that reports the correlation coefficients between the three indices. While the CCI and CSI are highly correlated, BWI is weakly and negatively correlated with both, indicating that different dimensions of sentiment are captured.

3.4 Stock returns

We use market-wide and portfolio returns in excess of the 1-month Treasury bill rate. Returns are measured between the FOMC meeting day and the previous trading day. Market-wide returns are proxied by the CRSP value-weighted market returns. We consider portfolios of stocks sorted according to three characteristics: size (s), as proxied by the firm's market value; value (bm), as measured by the book-to-market ratio; and momentum (m), which captures past performance based upon returns from month $t-12$ to month $t-2$. For each characteristic, value-weighted returns on 10 portfolio groups are available. Decile 1 (10) denotes the portfolio group with the lowest (highest) characteristic. For

[11] The indices are standardized so that they have zero mean and unit variance (Lutz, 2015).

example, the size-sorted portfolios $s1$ and $s10$ correspond to the firms with the smallest and largest market value, respectively. The source of the stock market data is WRDS for CRSP market returns and Kenneth French's online data library for size, value and past performance-related portfolio returns, and the 1-month Treasury bill rate.

4 Econometric models and results

4.1 The impact of FFR shocks

4.1.1 Market response

We begin our empirical investigation by examining the market-wide response of stocks to FFR shocks on FOMC meeting days conditional upon the state of the level of sentiment. This is accomplished by interacting the FFR surprises with S_t^H, that is, a dummy variable that is equal to 1 if the FOMC meeting occurred during years that start with high sentiment levels and 0 otherwise. In line with Baker and Wurgler (2006), a year is defined as of high sentiment if the sentiment indicator at the end of the previous year exceeds the full sample median value. The following regression model for excess stock returns is estimated:

$$R_t = \beta_0 + \beta_1(1 - S_t^H)\Delta i_t^u + \beta_2 S_t^H \Delta i_t^u + \varepsilon_t \tag{3}$$

where R_t denotes CRSP value-weighted market returns between the FOMC meeting day and the previous trading day in excess of the 1-month Treasury bill rate.

Table 3 reports the Ordinary Least Squares (OLS) with Newey and West (1987) standard errors estimates of Equation 3 across the full sample (Panel A) and pre-crisis (Panel

B) periods. The full sample stock market reaction to unexpected FFR changes when sentiment is high at the beginning of the year, as captured by β_2, is dominant both in terms of magnitude and statistical significance. The results are quite similar across the two survey-based sentiment indicators. The Wald test for equal stock market reaction to monetary policy shocks over different sentiment states (H_0: $\beta_1 = \beta_2$) strongly rejects the null hypothesis. The negative sign of β_2 indicates that when start of the year sentiment is high, excess stock market returns respond positively to monetary easing shocks. Specifically, the results imply an about 2% excess stock market return in response to an unexpected 25 basis points cut in the FFR. The pre-crisis results in Table 3 offer similar insights indicating that the effect of FFR shocks on stock returns is remarkably strong over time and robust to the use of alternative sentiment indicators.

Bernanke and Kuttner (2005) show that the stock market response to FFR changes is asymmetric, primarily driven by expansionary surprises. Motivated by their analysis, we separate FFR shocks into positive (contractionary) and negative (expansionary) and estimate the following regression model to examine whether the sentiment-dependent effect of FFR shocks on the stock market also exhibits such an asymmetry:

$$R_t = \beta_0 + \beta_1(1 - S_t^H)\Delta i_t^{un} + \beta_2(1 - S_t^H)\Delta i_t^{up} + \beta_3 S_t^H \Delta i_t^{un} + \beta_4 S_t^H \Delta i_t^{up} + \varepsilon_t \qquad (4)$$

where Δi_t^{un} and Δi_t^{up} denote negative and positive unexpected FFR changes, respectively.

Table 4 reports OLS estimates of Equation 4. They show that the reaction of stock market returns to FFR shocks only materializes when sentiment is high at the beginning of the year and solely in response to expansionary shifts. This effect is captured by β_3, which is negative and significant at the 1% level across all alternative specifications. These findings suggest that the state of investor sentiment plays an important role in the transmission of expansionary monetary policy shocks to the stock market, while contractionary shocks do not matter.

As shown in Figure 2, high sentiment levels, typically occurring near business cycle peaks, tend to be followed by negative changes in sentiment throughout economic contractions.[12] Given the evidence in Table 3 about the importance of the *level* of sentiment, this prompts us to examine how *changes* in investor sentiment affect the relationship between FFR shocks and stock market returns. To do so, we we replace the sentiment level-based dummy variable of Equation 3 with a dummy variable that is based upon changes in sentiment and estimate Equation 5:

$$R_t = \beta_0 + \beta_1(1 - S_t^D)\Delta i_t^u + \beta_2 S_t^D \Delta i_t^u + \varepsilon_t \tag{5}$$

where S_t^D is a dummy variable that is equal to 1 during decreasing sentiment periods, that is, years when the value of the sentiment proxy at December is lower than the value at December of the previous year.[13]

The results in Table 5 indicate that during periods of decreasing investor sentiment stock market returns respond positively to an expansionary monetary policy shock. The rejection of the null hypothesis of similar stock market reaction across different sentiment regimes is stronger in the pre-crisis sample. The magnitude of the coefficient that captures decreasing sentiment periods (β_2) is smaller than in Table 3, where sentiment level-based

[12]See Chung et al. (2012) for econometric evidence linking developments in orthogonalized sentiment with the business cycle.

[13]The correlation between the two sentiment dummies, S_t^H and S_t^D, is positive, ranging from 0.5 in the case of the BWI to 0.1 for CSI.

states are utilised. Nevertheless, the key message is the same, that is, the state of investor sentiment significantly influences the way in which the stock market responds to monetary policy surprises.

Finally, in order to investigate an alternative classification of sentiment regimes that accounts for the joint effect of sentiment level and changes on the relationship between stock market returns and monetary policy shocks, we estimate Equation 6:

$$R_t = \beta_0 + \beta_1(1 - S_t^{HD})\Delta i_t^u + \beta_2 S_t^{HD} \Delta i_t^u + \varepsilon_t \tag{6}$$

where S_t^{HD} is a dummy variable that is equal to 1 if the FOMC meeting occurred during a year of high and decreasing sentiment and 0 otherwise. A year is defined as of high and decreasing sentiment if the sentiment proxy at the end (December) of the previous year exceeds the full sample median value and the sentiment proxy at the end (December) of that year is lower than at the end (December) of the previous year.

The results are reported in Table 6. They provide further evidence on the importance of sentiment-related regimes for the transmission of monetary policy shocks to the stock market. In particular, we find that the effect of policy shifts is stronger during years that sentiment started at high levels but then subsequently declined. Estimates of the coefficient coefficient of interest (β_2) are similar in statistical significance and very close in magnitude to those reported in Table 3, across alternative proxies of sentiment and sample periods. The Wald test for equality of coefficients strongly supports the notion of sentiment-based regimes .

Summarising our findings for the market-wide response, they are broadly consistent with previous studies that identify state dependence in the reaction of stocks to monetary policy shifts (Chen, 2007; Basistha and Kurov, 2008; Jansen and Tsai, 2010; Kontonikas et al., 2013). However, they extend this literature in important new dimensions. This is accomplished by examining the role of sentiment-based regimes, by considering alternative investor sentiment indicators, orthogonalized so that they capture “excessive” sentiment that is unwarranted by economic fundamentals, and alternative criteria to identify regimes. Moreover, by accounting for asymmetries driven by the type of monetary policy shocks over a longer sample period and a period that excludes the recent financial crisis and its aftermath.

4.1.2 Response of the cross-section of stocks

Having established that investor sentiment is a factor that affects the market-wide reaction to monetary policy shocks, we now turn our attention to the response of different types of stocks. Tables 7 reports OLS estimates of Equation 3, replacing market-wide returns with returns on stock portfolios formed on the basis of size, value and momentum. Decile 1 denotes the smallest ($s1$), growth ($bm1$) and loser ($m1$) stocks, while decile 10 represents the largest ($s10$), value ($bm10$) and winner ($m10$) stocks. In line with the market-wide findings in Table 3, estimates of the impact of FFR surprises on portfolio returns tend to be statistically significant only when sentiment is high at the start of the year. This result is robust to the use of alternative sentiment indicators, both in the full sample and the pre-crisis estimations.

Importantly, we provide evidence consistent with the idea that the effect of monetary policy shocks differs across the cross-section of stocks, with investor sentiment determining the strength of the transmission. In particular, large, growth and loser stocks are significantly more exposed to policy shifts solely when sentiment is high at the start of the year. For instance, using the CCI sentiment measure, the full sample estimate of the growth stocks reaction to FFR surprises, conditional upon beginning of year sentiment being high, is about four times larger than the corresponding response of value stocks (-11.25 vs. -2.68). Results for the remaining deciles indicate the presence of a trend, whereby moving from larger, growth and loser towards smaller, value and winner portfolios, the monetary policy impact generally decreases in magnitude, albeit not strictly monotonically. Figure 3 visualizes this pattern by plotting OLS estimates of the β_2 coefficient in Equation (3) across the 10 deciles of portfolio returns.

Defining small, value and winner as the long-leg portfolio returns, whereas large, growth and loser are the short-leg returns, our results indicate that the small-large ($s1$-$s10$), value-growth ($bm10$-$bm1$) and winner-loser ($m10$-$m1$) returns differentials significantly react to unexpected FFR changes only when sentiment is high at the start of the year. Specifically, they decline in response to expansionary surprises with the result being driven by the stronger response of the short-leg of the returns differential. For example, considering the pre-crisis BWI case estimates in Table 7, given that an unexpected 100 basis points cut in the FFR is associated with 13.00% higher return for the growth stocks and 4.61% for the value stocks, the value-growth returns differential decreases. In order to further explore the impact of monetary policy shocks across sentiment states, we then use the size (SMB) and value (HML) factors of Fama and French (1993) and the momentum (MOM) factor of Carhart (1997), in turn, as the dependent variable. The results are reported in Table 8 and show that, consistently with the extreme deciles portfolio returns differentials results in Table 7, SMB, HML and MOM are positively related to unexpected FFR changes only when start of the year sentiment is high.

To gain further insights in the interaction of the size and value premiums, Table 9 present OLS estimates of the β_2 coefficient in Equation 3 using as a dependent variable the returns on double-sorted size and book-to-market portfolios. The evidence is consistent with the existence of a value gradient with respect to FFR surprises. Specifically, when sentiment is high at the start of the year, within each size quintile the impact of policy shocks is generally stronger for growth than value stocks. For instance, the pre-crisis OLS estimates for the CSI sentiment measure in Table 8 show that within the largest size quintile ($s5$), the highest value portfolio returns ($bm5$) increase by 3.92% in response to an expansionary FFR surprise, while the lowest value ($bm1$) portfolio returns increase by 11.27%. Thus, the value-growth monetary policy impact differential is not related to size effects. Evidence for a size gradient is not as consistent, but the general tendency is for the monetary policy effect to strengthen as we move towards higher size quintiles.

A similar analysis is conducted for the double-sorted size and momentum portfolios in order to examine whether the winner-loser differential response to unexpected FFR changes is pervasive across size quintiles. The results in Table 10 suggest that the policy impact differential is independent of size effects since within each size quintile portfolio, returns of loser stocks tend to be more sensitive to monetary policy shocks than winners. Focusing on the pre-crisis OLS estimates in the case of the CCI sentiment proxy, for example, the results in Table 9 indicate that within the smallest size quintile, the loser portfolio returns ($m5$) response to an unexpected FFR decline is stronger (8.67%) than the winner's response (3.71%).

Overall, we identify heterogeneity in the response of stocks to monetary policy shocks with large, growth and loser stocks reacting more significantly when sentiment is high at the start of the year. With regards to previous related event studies, our findings are in line, to some extent, with Cenesizoglu (2011) by documenting a stronger response of large and growth stocks to monetary policy shocks.[14] On the other hand, they are in contrast with Ehrmann and Fratzscher (2004) and Jansen and Tsai (2010) who find that small stocks are more significantly affected by FFR surprises. Unlike all these studies, however, our analysis reveals that the effect of policy shifts on the cross-section of stocks is conditional upon investor sentiment-based regimes.

To gain a better understanding on how such state-dependence may arise, we should recall that high sentiment levels tend to be materialise near business cycle peaks, followed by negative changes in sentiment as the economy contracts. Sentiment waves can generate mispricing and subsequent corrections, especially affecting stocks whose valuations are more subjective and difficult to arbitrage, such as growth stocks (Baker and Wurgler, 2006). Stambaugh et al. (2012) points out that the combination of sentiment-driven investors and impediments to short selling can cause prices to depart from fundamentals. He finds that loser stocks, amongst others, are also highly exposed to mispricing. When sentiment is high, growth and loser stocks subsequently underperform relative to their value and winner counterparts. Given that stocks mainly react to expansionary surprises, our evidence is consistent with the conjecture that monetary policy easing puts a break to the price declines that growth and loser stocks exhibit in the aftermath of high sentiment episodes.

The stronger response of large stocks to FFR surprises is more challenging to interpret since, on the one hand, they should be less affected by the aforementioned sentiment-mispricing channel (Baker and Wurgler, 2006) and on the other hand, the credit channel of the monetary policy transmission mechanism is consistent with a stronger response of

[14] The results of Cenesizoglu (2011) are conditional upon the treatment of outliers. Accounting for outliers, the differential response of smallest and largest stocks becomes statistically insignificant, while in the case of value and growth stocks the opposite is true.

small stocks (Ehrmann and Fratzscher, 2004; Kontonikas and Kostakis, 2013). To appreciate this important finding, it is essential that liquidity is taken into consideration. Specifically, large stocks are more liquid than smaller ones (Amihud, 2002). FOMC meeting days are important dates for the calendar of institutional investors, who typically hold large stocks (Lee et al., 1991; Lemmon and Portniaguina, 2006), and tend to be associated with higher trading activity (Lucca and Moench, 2015; Florackis et al., 2014). If monetary shifts affect the liquidity of large stocks more significantly, as compared to that of small stocks, then an expansionary shock will render large stocks even closer substitutes to other highly liquid instruments, such as government bonds, reducing the premium required to hold them. Hence, the price of large stocks increase more than that of small stocks in response to an expansionary policy shock.

Moreover, as Nyborg and Östberg (2014) demonstrate, banks use highly liquid stocks to engage in "liquidity pullback" and portfolio rebalancing during periods of distress, characterised by tightening funding conditions and increased market uncertainty. Since high sentiment levels tend to be followed by falling sentiment, as the economy and financial market conditions deteriorate, our state-dependent findings suggest that during such periods banks and other institutional investors heavily use large stocks in response to monetary policy shocks. Finally, it appears that trading in small stocks on FOMC meeting days does not exhibit an overall direction that is as consistent as in the case of large stocks and therefore does not lead to strongly positive or negative returns.

4.2 The impact of non-conventional monetary policy announcements

Having demonstrated the role of investor sentiment in the impact of conventional monetary policy shocks on stock returns in Section 4.1, we now turn our attention to the recent non-conventional policies. In line with several previous studies on the impact of non-conventional policy announcements (Ait-Sahalia et al., 2012; Fiordelisi et al., 2014; Ricci, 2015), we adopt an event study approach where abnormal returns (ARs) are calculated and evaluated in short windows surrounding these announcements. Keeping the event window narrow helps the identification since it avoids contaminating the analysis of the impact of a particular announcement with that of previous and subsequent announcements (Ait-Sahalia et al., 2012). We focus on the following event windows: 5-day (-1,+3), 3-day (-1,+1) and one-day (0,0).

To define the events, we consider monetary policy shifts of expansionary nature, that is, announcements related to the initiation or continuation of LSAPs and liquidity facilities programmes. The first such event occurs in December 2007 and the last one in October 2013. We further classify the events according to the state of investor sentiment during the time that they occurred and then conduct the event study across each sentiment state. The period of non-conventional monetary policy announcements is characterised by no-change in the variable capturing the level of sentiment ($S_t^H = 0$). Hence, to identify sentiment-based regimes we use the variable that captures changes in sentiment (S_t^D) since, unlike the sentiment level dummy, it exhibits some variation over the period of non-conventional monetary policy announcements. Moreover, since BWI ends in 2010, and CSI and CCI share a very similar pattern, we only consider the former proxy of investor sentiment in our analysis. This part of the analysis has limited sample When comparing the effect of non-conventional policy announcements with that of FFR surprises. For example, there are only 13 events related to central bank liquidity swaps announcements, 8 of which occur during periods of decreasing sentiment while the remaining 5 occur during periods of increasing sentiment.

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 et al. (1991) test statistic that addresses the event-induced increase in return volatility (Ricci, 2015). To do so, we first obtain the cumulative standardized abnormal returns (CSARs):

$$CSAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} \frac{AR_{i,t}}{S(AR_i)} \tag{9}$$

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

$$T = \frac{\frac{1}{N}\sum_{i=1}^{N} CSAR_i(t_1, t_2)}{\sqrt{\frac{1}{N(N-1)}[CSAR_i(t_1, t_2) - \frac{1}{N}\sum_{i=1}^{N} CSAR_i(t_1, t_2)]^2}} \tag{10}$$

where N is the number of observations in the sample.

The results in Table 11 indicate that the stock market benefited from the establishment of the US dollar and foreign-currency liquidity lines by the Fed. However, the market response tends to be positive but statistically insignificant (Results available upon request) when we analyze the announcements related to LSAPs and liquidity facilities other than central bank liquidity swaps. The insignificant market response may reflect an identification problem related to the lack of expectations data on non-conventional policies (Ait-Sahalia et al., 2012). In particular, if non-conventional policy announcements were anticipated then they may affect the stock market prior to the event window, thereby attenuating the significance of the announcement's effects. Overall, 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 et al., 2014; Rogers et al., 2014) and highlights the important role of central bank liquidity swaps. In line with the findings from conventional monetary policy analysis, we find that the state of investor sentiment is also crucial for non-conventional policies. In particular, CAARs are positive and significant only during periods of decreasing sentiment.

The results of portfolio returns in Table 12 suggest that the cross-sectional effects of non-conventional monetary policy announcements are not easy to ascertain. In contrast to the insights from conventional monetary policy analysis, when sentiment is decreasing small stocks tend to be more exposed to central bank liquidity swaps announcements. However, the differential in the small-large return responses is insignificant. In the case of value-sorted portfolios, the evidence on the effects of non-conventional policy is even more contrasting to that from conventional policy shocks. The value-growth return differential increases in response to an expansionary non-conventional policy announcement, reflecting the stronger reaction the long-leg of the return differential, that is, value stocks. This finding is consistent with the evidence in Wright (2012) regarding the impact of non-conventional monetary policy shocks on the HML factor. Finally, both loser and winner stocks significantly respond to central bank liquidity swaps announcements during periods of decreasing sentiment, with the former exhibiting a larger impact magnitude, as in the case of conventional policy surprises. The differential of winner-loser return response is insignificant, however.

5 Robustness checks

We examine the robustness of our key findings in a number of ways and find that the results reported in Section 4 are overall not sensitive to these changes. First, we utilise an estimation method which is robust to the presence of outliers. Second, we remove FOMC meetings that coincide with employment data releases. Third, we consider an alternative starting point for our estimation sample. Fourth, we employ an alternative dummy variable to classify sentiment states based upon a monthly classification scheme. Fifth, we replace value weighted market returns with equally-weighted returns. Sixth and seventh, we use data on liquidity-sorted portfolios and industry portfolios, respectively. Eighth, we use a longer estimation window to investigate of the impact of non-conventional monetary policy announcements. The results are contained in the Appendix.

5.1 Robust estimation

We employ the MM weighted least squares regression, using the procedure of Yohai (1987), which is robust to the presence of outliers. Table A1 and Table A2 in the Appendix report the results for market-wide response to monetary policy shocks and the reaction of the cross-section of stocks, respectively. The robust estimation results are consistent with the baseline findings from OLS estimation in Tables 3 and 7. Stocks react to monetary policy shocks only when sentiment is high at the start of the year, with large, growth and loser stocks displaying the strongest response.

5.2 Excluding employment data releases

In the early 1990s, the Feds 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 A3 in the Appendix for the dates). Our findings are not sensitive to the exclusion of employment data release dates. In the Appendix, Table A4 shows the market-wide results and Table A5 reports the results for size, value and past performance-sorted portfolios.

5.3 Sample starts at February 1994

We consider an alternative start for the sample period in February 1994 when the Fed started to announce target FFR changes, representing a shift that enhanced transparency in monetary policy making. Tables A6 and Table A7 in the Appendix, respectively, report the results for the market as a whole and the cross-section of stocks. Our findings hold and are similar to those from the baseline estimations where the sample begins in June 1989 and identify an important role for sentiment-based regimes in the transmission of monetary policy shocks to the stock market and uncovering significant heterogeneity in the response of different types of stocks.

5.4 Monthly classification of sentiment state

We use an alternative sentiment state variable that is based upon a monthly classification of investor sentiment. We define a dummy variable S_t^{HM} that is equal to 1 if the FOMC meeting occurrs during a high sentiment month and 0 otherwise. A month is defined as of high sentiment if the sentiment proxy at the end of the previous month exceeds the full sample median value. The responses of market-wide and portfolio returns to FFR shocks with monthly classification of sentiment dummy are reported in Table A8 and Table A9 of the Appendix, respectively. Although there are some mild differences in the magnitude of the coefficients, the results are overall similar to the results from using an annual classification scheme for the sentiment dummy. That is, FFR shocks strongly affect stock returns when sentiment is high at the start of the period.

5.5 Equally-weighted market returns

We employ CRSP equally-weighted market returns to examine whether the market-wide response that we identify earlier may be driven by the effect of large stocks. The results in Table A10 in the Appendix show that the magnitude of the estimated β_2 coefficient is lower, as compared with the finding in Table 3, but the effect of FFR surprises on equally-weighted market returns when sentiment is hight at the start of the year is strong and significant. Thus, the channel of liquidity effects operating though large stocks cannot fully explain the market-wide response. These findings suggest that the sentiment-mispricing channel is operational not only at stock portfolio level but also at the market level.

5.6 Liquidity portfolios

To verify our liquidity-based explanation for the stronger response of large stocks in the benchmark results, we analyze the return resposes across 10 portfolios sorted by stock liquidity. To this end, we sort stocks in ascending order on the basis of the illiquidity ratio of Amihud (2002)) ($Illiq$), the Amivest liquidity ratio (Liq), and the turnover rate (Tr). Thus, decile 1 portfolios, $Illiq1$, $Liq1$ and $Tr1$, contain, respectively, the most liquid stocks based on the Amihud ratio, and the most illiquid portfolio according to the Amivest ratio and the turnover rate; decile 10 portfolios, $Illiq10$, $Liq10$ and $Tr10$, contain, respectively, the most illiquid stocks based on the Amihud ratio, and the most liquid portfolio according to the Amivest ratio and the turnover rate, respectively.

The results in Table A11 of the Appendix confirm that sentiment and liquidity interact in a manner consistent with the baseline results when we use size to sort stocks. Specifically, liquid stocks ($Illiq1$, $Liq10$ and $Tr10$) are significantly more exposed to monetary policy shocks, as compared to illiquid stocks ($Illiq10$, $Liq1$ and $Tr1$). This finding is in line with previous evidence by Florackis et al. (2014) for the case of the UK market. Moreover, we find that the state of investor sentiment determines the strength of the impact of monetary policy shocks on liquidity-sorted portfolios, whereby the effect is significant only when sentiment is high at the start of the year.

5.7 Industry portfolios

To further expand the analysis on the impact of FFR surprises on the cross-section of stock returns, we examine the return response of different industrial sectors using data on 10 industry portfolios: non-durables, durables, manufacturing, energy, hi-technology, telecommunications, shops, health care, utilities and other. The results in Table A12 in the Appendix indicate that, in line with the baseline evidence, the reaction of industry-based returns to monetary policy shocks is typically stronger when sentiment is high at the start of the year. Moreover, there exists significant heterogeneity in the response of different industries to FFR surprises: high-tech stocks exhibit the strongest reaction to policy shocks, followed by durables, telecoms and shops, while the energy sector is one of the least responsive industries. This pattern of heterogeneity is consistent with the evidence in previous studies (Bernanke and Kuttner, 2005; Ehrmann and Fratzscher, 2004; Basistha and Kurov, 2008; Kontonikas et al., 2013).

5.8 Longer estimation window

We repeat the analysis for the effect of non-conventional monetary policy announcements using a 90-day estimation window, instead of the 20-day window used for the baseline results. Tables A13 and A14 report, respectively, the the responses of market-wide and portfolios-based returns to the announcement of central bank liquidity swaps. The overall the results are similar to those from the 20-day estimation window, albeit with slightly lower CAARs.

6 Conclusions

This paper investigates the role of investor sentiment in the transmission of monetary policy shocks on stock returns between 1989 and 2014. We document that the state of investor sentiment, orthogonalized with respect to several macroeconomic conditions, affects the impact of monetary policy surprises on stock returns. Specifically, stock market returns increase following an unexpected cut in the FFR when sentiment is high at the start of the year, especially in the pre-crisis period. Our evidence also shows that non-conventional monetary policy announcements are followed by increases in the stock market returns but the response is dependent upon the state of sentiment. Our findings extend the literature on the state dependence of monetary policy impact. We also examine whether and how the state of investor sentiment may affect the return responses of different stock portfolios to monetary policy shocks. Similar to our findings for the stock market level, portfolio returns are more affected by monetary policy only when sentiment is high at the start of the year. Furthermore, large, growth and loser stocks show stronger responses to conventional policy shocks than small, value and winner stocks.

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Table 1: Descriptive statistics for FFR changes and unexpected changes

Δi and Δi_t^u denote FFR target rate changes and unexpected changes, respectively, on FOMC meeting dates over the period of June 1989 - October 2014.

	Obs	Min	Max	Mean	St.Dev.
Panel A: All meetings					
Δi	227	-0.75	0.75	-0.04	0.21
Δi_t^u	227	-0.42	0.17	-0.02	0.08
Panel B: Contractionary					
$\Delta i>0$	31	0.25	0.75	0.30	0.12
Δi_t^u	31	-0.05	0.14	0.02	0.05
Panel C: Expansionary					
$\Delta i<0$	51	-0.75	-0.25	-0.34	0.14
Δi_t^u	51	-0.42	0.17	-0.10	0.13
Panel D: No change					
$\Delta i=0$	145	0.00	0.00	0.00	0.00
Δi_t^u	145	-0.20	0.12	0.00	0.04

Table 2: Correlation matrix of sentiment indices

This table presents the correlation coefficients of the first difference (Δ) in the sentiment indices. 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 full sample period is January 1989 - October 2014 and the pre-crisis period is January 1989 to August 2007. P-values are reported in parentheses. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

Panel A:Full sample			
	ΔCSI	ΔCCI	
ΔCSI	1.000***		
	(0.000)		
ΔCCI	0.914***	1.000***	
	(0.000)	(0.000)	
Panel B:Pre-crisis			
	ΔCSI	ΔCCI	ΔBWI
ΔCSI	1.000***		
	(0.000)		
ΔCCI	0.918***	1.000***	
	(0.000)	(0.000)	
ΔBWI	−0.109*	-0.080	1.000***
	(0.077)	(0.195)	(0.000)

Table 3: Response of stock market returns to FFR shocks during periods of high vs. low sentiment

This table presents OLS estimates with heteroscedasticity and autocorrelation 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 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 if the FOMC meeting occurred during a high sentiment year and 0 otherwise. A year is defined as of high sentiment if the sentiment proxy at the end (December) of the previous year exceeds the full sample median 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 A and B include the full sample (June 1989 - October 2014) and pre-crisis (June 1989 - August 2007) FOMC meetings, respectively, with the exception of the 17 September 2001 meeting, the 22 January 2008 meeting and the unscheduled meetings that were not accompanied by a FOMC statement or other information. Standard errors are reported in parentheses. P-values from the Wald test for equality of coefficients (F-statistic) in square brackets. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$\beta_1 = \beta_2$	$Adj.R^2$
Panel A: Full sample						
CSI	227	0.23***	-0.70	−7.25***	[0.00]	0.10
		(0.09)	(0.84)	(2.58)		
CCI	227	0.24***	-0.64	−7.58***	[0.00]	0.11
		(0.09)	(0.83)	(2.57)		
Panel B: Pre-crisis						
CSI	168	0.16*	-0.92	−8.91***	[0.00]	0.25
		(0.07)	(0.95)	(1.17)		
CCI	168	0.16*	-0.88	−9.31***	[0.00]	0.27
		(0.09)	(0.81)	(1.68)		
BWI	168	0.13	-0.73	−9.14***	[0.00]	0.28
		(0.09)	(0.76)	(1.73)		

Table 4: Response of stock market returns to negative and positive FFR shocks during periods of high vs. low sentiment

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors, over FOMC meeting dates of the following model: $R_t = \beta_0 + \beta_1(1 - S_t^H)\Delta i_t^{un} + \beta_2(1 - S_t^H)\Delta i_t^{up} + \beta_3 S_t^H \Delta i_t^{un} + \beta_4 S_t^H \Delta i_t^{up} + \varepsilon_t$, 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. S_t^H is a dummy variable that is equal to 1 if the FOMC meeting occurred during a high sentiment year and 0 otherwise. A year is defined as of high sentiment if the sentiment proxy at the end (December) of the previous year exceeds the full sample median 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 A and B include the full sample (June 1989 - October 2014) and pre-crisis (June 1989 - August 2007) FOMC meetings, respectively, with the exception of the 17 September 2001 meeting, the 22 January 2008 meeting and the unscheduled meetings that were not accompanied by a FOMC statement or other information. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

	Obs	β_1	β_2	β_3	β_4	$Adj.R^2$
			Panel A: Full sample			
CSI	227	-1.02	-1.21	-9.85^{***}	9.47	0.16
		(0.81)	(3.73)	(1.49)	(6.85)	
CCI	227	-0.95	-1.28	-10.16^{***}	9.14	0.17
		(0.81)	(3.75)	(1.43)	(7.02)	
			Panel B: Pre-crisis			
CSI	168	-1.23	-0.74	-10.13^{***}	1.29	0.26
		(0.81)	(3.77)	(1.47)	(6.41)	
CCI	168	-1.14	-0.87	-10.43^{***}	0.33	0.27
		(0.81)	(3.78)	(1.40)	(6.64)	
BWI	168	-1.06	0.27	-9.68^{***}	-4.06	0.28
		(0.81)	(3.42)	(1.53)	(-10.53)	

Table 5: Response of stock market returns to FFR shocks during periods of decreasing vs. increasing sentiment

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors, over FOMC meeting dates of the following model: $R_t = \beta_0 + \beta_1(1 - S_t^D)\Delta i_t^u + \beta_2 S_t^D \Delta i_t^u + \varepsilon_t$, 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^D is a dummy variable that is equal to 1 if the FOMC meeting occurred during a decreasing sentiment year and 0 otherwise. A year is defined as of decreasing sentiment if the sentiment proxy at the end (December) of that year is lower than at the end (December) 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. Panel A and B include the full sample (June 1989 - October 2014) and pre-crisis (June 1989 - August 2007) FOMC meetings, respectively, with the exception of the 17 September 2001 meeting, the 22 January 2008 meeting and the unscheduled meetings that were not accompanied by a FOMC statement or other information. Standard errors are reported in parentheses. P-values from the Wald test for equality of coefficients (F-statistic) in square brackets. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$\beta_1 = \beta_2$	$Adj.R^2$
			Panel A: Full sample			
CSI	227	0.24***	-1.42	-4.59^{*}	[0.26]	0.06
		(0.09)	(1.36)	(2.45)		
CCI	227	0.23***	-0.69	-4.85^{**}	[0.09]	0.07
		(0.09)	(1.08)	(2.36)		
			Panel B: Pre-crisis			
CSI	168	0.13	-0.78	-5.81^{**}	[0.04]	0.16
		(0.09)	(1.05)	(2.29)		
CCI	168	0.13	-0.87	-5.74^{**}	[0.04]	0.16
		(0.09)	(1.06)	(2.29)		
BWI	168	0.12	-0.62	-8.26^{***}	[0.00]	0.24
		(0.09)	(0.91)	(2.09)		

Table 6: Response of stock market returns to FFR shocks during periods of high and decreasing sentiment

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors, over FOMC meeting dates of the following model: $R_t = \beta_0 + \beta_1(1 - S_t^{HD})\Delta i_t^u + \beta_2 S_t^{HD} \Delta i_t^u + \varepsilon_t$, 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^{HD} is a dummy variable that is equal to 1 if the FOMC meeting occurred during a high and decreasing sentiment year and 0 otherwise. A year is defined as of high and decreasing sentiment if the sentiment proxy at the end (December) of the previous year exceeds the full sample median value and the sentiment proxy at the end (December) of that year is lower than at the end (December) 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. Panel A and B include the full sample (June 1989 - October 2014) and pre-crisis (June 1989 - August 2007) FOMC meetings, respectively, with the exception of the 17 September 2001 meeting, the 22 January 2008 meeting and the unscheduled meetings that were not accompanied by a FOMC statement or other information. Standard errors are reported in parentheses. P-values from the Wald test for equality of coefficients (F-statistic) in square brackets. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

	Obs	β_0	β_1	β_2	$\beta_1 = \beta_2$	$Adj.R^2$
Panel A: Full sample						
CSI	227	0.25***	-0.81	−7.84***	[0.00]	0.11
		(0.09)	(0.92)	(2.70)		
CCI	227	0.25***	-0.43	−8.18***	[0.00]	0.12
		(0.09)	(0.84)	(2.50)		
Panel B: Pre-crisis						
CSI	168	0.15*	-0.63	−10.24***	[0.00]	0.29
		(0.08)	(0.84)	(1.43)		
CCI	168	0.15*	-0.68	−10.15***	[0.00]	0.29
		(0.08)	(0.85)	(1.45)		
BWI	168	0.13	-0.62	−10.09***	[0.00]	0.29
		(0.08)	(0.80)	(1.37)		

Table 7: Response of size, value and momentum sorted portfolio returns to FFR shocks during periods of high vs. low sentiment

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors, over FOMC meeting dates of 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 portfolio returns and unexpected FFR changes, respectively. The criteria used to sort stocks in portfolios are size (s), proxied by market capitalization, value (bm), measured by the book-to-market ratio, and momentum (m), captured by past performance based on returns from month t-12 to month t-2. $s1$, $bm1$ and $m1$ denote the decile 1 portfolios, that is, the smallest, growth and loser portfolio, respectively. $s10$, $bm10$ and $m10$ denote the decile 10 portfolios, that is, the largest, value and winner portfolio, respectively. Decile 1 and 10 returns are in excess of the 1-month Treasury bill rate. S_t^H is a dummy variable that is equal to 1 if the FOMC meeting occurred during a high sentiment year and 0 otherwise. A year is defined as of high sentiment if the sentiment proxy at the end (December) of the previous year exceeds the full sample median 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 A and B include the full sample (June 1989 - October 2014) and pre-crisis (June 1989 - August 2007) FOMC meetings, respectively, with the exception of the 17 September 2001 meeting, the 22 January 2008 meeting and the unscheduled meetings that were not accompanied by a FOMC statement or other information. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

		β_1	β_2	$Adj.R^2$		β_1	β_2	$Adj.R^2$		β_1	β_2	$Adj.R^2$
Panel A: Full sample												
	$s1$	-0.82	-1.48	0.00	$bm1$	-0.96	−10.69***	0.17	$m1$	-1.40	−14.80*	0.10
		(0.69)	(1.79)			(0.91)	(3.46)			(1.40)	(7.82)	
CSI	$s10$	-0.82	−8.19***	0.13	$bm10$	-0.62	-2.25	0.00	$m10$	-0.64	−5.19**	0.03
		(0.84)	(2.70)			(1.35)	(1.73)			(1.12)	(2.57)	
	$s1-s10$	-0.01	6.70***	0.14	$bm10-bm1$	0.34	8.45***	0.16	$m10-m1$	0.76	9.61	0.06
		(0.70)	(1.86)			(0.86)	(2.59)			(1.06)	(6.61)	
	$s1$	-0.76	-1.60	0.00	$bm1$	-0.82	−11.25***	0.19	$m1$	-1.43	−15.27*	0.11
		(0.69)	(1.84)			(0.90)	(3.40)			(1.41)	(7.95)	
CCI	$s10$	-0.72	−8.60***	0.13	$bm10$	-0.35	-2.68	0.00	$m10$	-0.58	−5.45**	0.03
		(0.83)	(2.66)			(1.31)	(1.76)			(1.12)	(2.63)	
	$s1-s10$	-0.04	7.00***	0.15	$bm10-bm1$	0.47	8.57***	0.16	$m10-m1$	0.85	9.82	0.06
		(0.69)	(1.85)			(0.84)	(2.63)			(1.09)	(6.77)	
Panel B: Pre-crisis												
	$s1$	-1.00	-1.98	0.02	$bm1$	-1.18	−12.81***	0.31	$m1$	-2.12	−19.96***	0.36
		(0.68)	(1.72)			(0.92)	(2.85)			(1.33)	(6.49)	
CSI	$s10$	-1.06	−10.17***	0.27	$bm10$	-1.08	−3.50***	0.03	$m10$	-0.73	−6.21***	0.06
		(0.84)	(1.86)			(1.33)	(1.14)			(1.15)	(2.38)	
	$s1-s10$	0.06	8.19***	0.22	$bm10-bm1$	0.09	9.31***	0.26	$m10-m1$	-1.39	13.75**	0.27
		(0.71)	(1.56)			(0.88)	(2.56)			(1.04)	(5.92)	
	$s1$	-0.96	−2.07	0.02	$bm1$	-1.05	−13.50***	0.33	$m1$	-2.21	−20.55***	0.37
		(0.68)	(1.77)			(0.92)	(2.65)			(1.35)	(6.52)	
CCI	$s10$	-0.98	−10.68***	0.29	$bm10$	-0.89	−3.93***	0.04	$m10$	-0.67	−6.53***	0.06
		(0.83)	(1.70)			(1.29)	(1.17)			(1.15)	(2.44)	
	$s1-s10$	0.01	8.60***	0.01	$bm10-bm1$	0.16	9.58***	0.20	$m10-m1$	1.54	14.02**	0.27
		(0.70)	(1.53)			(0.86)	(2.52)			(1.06)	(6.07)	
	$s1$	-0.73	-2.37	0.03	$bm1$	-1.00	−13.00***	0.32	$m1$	-1.13	−21.34***	0.42
		(0.63)	(1.65)			(0.88)	(2.79)			(0.95)	(5.99)	
BWI	$s10$	-0.90	−10.36***	0.28	$bm10$	-0.34	−4.61***	0.06	$m10$	-0.74	−6.16***	0.06
		(0.79)	(1.81)			(1.03)	(1.56)			(1.14)	(2.34)	
	$s1-s10$	0.16	7.99***	0.21	$bm10-bm1$	0.66	8.39***	0.21	$m10-m1$	-0.39	15.18***	0.33
		(0.71)	(1.66)			(0.65)	(3.18)			(0.94)	(5.33)	

Table 8: Response of risk factors to FFR shocks during periods of high vs. low sentiment

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors, over FOMC meeting dates of 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 the risk factors and unexpected FFR changes, respectively. SMB (small-minus-big) and HML (value-minus-growth) denote the Fama and French (1993) size and value factors, respectively, while MOM (winner-minus-loser) represents the momentum factor of Carhart (1997). S_t^H is a dummy variable that is equal to 1 if the FOMC meeting occurred during a high sentiment year and 0 otherwise. A year is defined as of high sentiment if the sentiment proxy at the end (December) of the previous year exceeds the full sample median 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 A and B include the full sample (June 1989 - October 2014) and pre-crisis (June 1989 - August 2007) FOMC meetings, respectively, with the exception of the 17 September 2001 meeting, the 22 January 2008 meeting and the unscheduled meetings that were not accompanied by a FOMC statement or other information. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

		Obs	β_1	β_2	$Adj.R^2$
			Panel A: Full sample		
	SMB	227	0.35	2.98***	0.06
			(0.58)	(1.05)	
CSI	HML	227	-0.19	5.70**	0.19
			(0.30)	(2.25)	
	MOM	227	-0.04	6.91*	0.12
			(0.77)	(4.11)	
	SMB	227	0.35	3.09***	0.01
			(0.57)	(1.07)	
CCI	HML	227	-0.15	5.88**	0.07
			(0.30)	(2.27)	
	MOM	227	-0.09	7.36*	0.15
			(0.74)	(4.12)	
			Panel B: Pre-crisis		
	SMB	168	0.41	3.66***	0.11
			(0.58)	(1.13)	
CSI	HML	168	-0.30	6.43**	0.31
			(0.32)	(2.26)	
	MOM	168	0.34	8.87**	0.30
			(0.79)	(3.99)	
	SMB	168	0.39	3.82***	0.11
			(0.58)	(1.17)	
CCI	HML	168	-0.3	6.71***	0.33
			(0.33)	(2.24)	
	MOM	168	0.23	9.39**	0.32
			(0.76)	(3.96)	
	SMB	168	0.60	3.35***	0.09
			(0.59)	(1.17)	
BWI	HML	168	-0.21	6.26**	0.30
			(0.30)	(2.37)	
	MOM	168	-0.18	9.59**	0.36
			(0.71)	(3.69)	

Table 9: Response of size and value double-sorted portfolio returns to FFR shocks during periods of high sentiment

This table presents OLS estimates, with heteroscedasticity and autocorrelation consistent standard errors, of the impact of unexpected FFR changes on portfolio returns during periods of high sentiment, as captured by 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 portfolio returns and unexpected FFR changes, respectively. The criteria used to double-sort stocks in portfolios are size (s), proxied by market capitalization, and value (bm), measured by the book-to-market ratio. The portfolio corresponding to the combination $s1$ and $bm1$ ($s5$ and $bm5$) denote the smallest and growth (largest and value) stocks. All returns are in excess of the 1-month Treasury bill rate. S_t^H is a dummy variable that is equal to 1 if the FOMC meeting occurred during a high sentiment year and 0 otherwise. A year is defined as of high sentiment if the sentiment proxy at the end (December) of the previous year exceeds the full sample median 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 A and B include the full sample (June 1989 - October 2014) and pre-crisis (June 1989 - August 2007) FOMC meetings, respectively, with the exception of the 17 September 2001 meeting, the 22 January 2008 meeting and the unscheduled meetings that were not accompanied by a FOMC statement or other information. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

Panel A: Full sample													
		s1	s2	s3	s4	s5			s1	s2	s3	s4	s5
	$bm1$	−4.97*	−5.93*	−9.33**	−10.63***	−9.38***		$bm1$	−5.29*	−6.24*	−9.77***	−11.13***	−9.91***
		(2.78)	(3.34)	(3.42)	(3.54)	(2.84)			(2.79)	(3.37)	(3.42)	(3.50)	(2.77)
	$bm2$	-3.38	-3.88	−5.20**	−5.25**	−5.53**		$bm2$	-3.43	-4.13	−5.36**	−5.40**	−5.64**
		(2.32)	(2.55)	(2.37)	(1.87)	(2.00)			(2.40)	(2.60)	(2.42)	(1.91)	(2.04)
CSI	$bm3$	-1.99	-2.36	-2.52	−3.11*	−3.84*	CCI	$bm3$	-2.11	-2.50	-2.59	−3.16*	−3.94*
		(1.99)	(2.21)	(2.04)	(1.67)	(2.18)			(2.06)	(2.28)	(2.11)	(1.73)	(2.24)
	$bm4$	-1.30	-2.22	-2.47	-1.19	-1.72		$bm4$	-1.40	-2.38	-2.59	-1.23	-1.83
		(1.77)	(2.12)	(1.91)	(1.69)	(2.29)			(1.83)	(2.18)	(1.96)	(1.76)	(2.38)
	$bm5$	-0.91	-1.14	-2.21	-2.39	-2.56		$bm5$	-1.06	-1.35	-2.32	-2.51	-2.92
		(1.85)	(2.05)	(1.67)	(1.61)	(1.77)			(1.91)	(2.11)	(1.72)	(1.68)	(1.81)
Panel B: Pre-crisis													
	$bm1$	−6.23**	−7.54**	−10.86***	−12.25***	−11.27***		$bm1$	−6.58**	−7.91***	−11.38***	−12.85***	−11.94***
		(2.47)	(2.79)	(2.97)	(3.09)	(2.20)			(2.44)	(2.77)	(2.87)	(2.94)	(1.98)
	$bm2$	−4.19**	−4.84**	−6.46***	−6.11***	−6.76***		$bm2$	−4.21**	−5.12**	−6.65***	−6.27***	−6.89***
		(1.98)	(2.04)	(1.82)	(1.41)	(1.28)			(2.05)	(2.06)	(1.84)	(1.43)	(1.28)
CSI	$bm3$	−2.69*	−3.07*	−3.45**	−3.97***	−5.39***	CCI	$bm3$	−2.80*	−3.19*	−3.53**	−4.00***	−5.51***
		(1.58)	(1.73)	(1.28)	(1.14)	(1.37)			(1.64)	(1.78)	(1.32)	(1.18)	(1.43)
	$bm4$	-1.71	−2.83*	−3.43**	−2.02*	-2.99		$bm4$	-1.77	−2.97*	−3.53**	−2.02*	-3.1
		(1.37)	(1.51)	(1.44)	(1.12)	(2.12)			(1.42)	(1.55)	(1.49)	(1.16)	(2.25)
	$bm5$	-1.38	-2.03	−2.79**	−3.05***	−3.92**		$bm5$	-1.5	-2.23	−2.87**	−3.13***	−4.30**
		(1.47)	(1.34)	(1.09)	(0.94)	(1.51)			(1.52)	(1.38)	(1.10)	(0.98)	(1.59)
	$bm1$	−6.85***	−8.41***	−11.25***	−12.32***	−11.58***							
		(2.30)	(2.56)	(2.81)	(3.06)	(2.09)							
	$bm2$	−4.88**	−5.32**	−6.99***	−6.42***	−6.83***							
		(1.90)	(1.94)	(1.69)	(1.38)	(1.28)							
BWI	$bm3$	−3.01*	−3.54**	−3.86***	−4.56***	−5.37***							
		(1.54)	(1.69)	(1.26)	(1.19)	(1.35)							
	$bm4$	-2.07	−3.40**	−4.18**	−2.81*	-3.51							
		(1.33)	(1.48)	(1.49)	(1.48)	(2.22)							
	$bm5$	-1.97	−2.93*	−3.31***	−3.98***	−4.68**							
		(1.45)	(1.48)	(1.13)	(1.39)	(1.74)							

Table 10: Response of size and momentum double-sorted portfolio returns to FFR shocks during periods of high sentiment

This table presents OLS estimates, with heteroscedasticity and autocorrelation consistent standard errors, of the impact of unexpected FFR changes on portfolio returns during periods of high sentiment, as captured by 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 portfolio returns and unexpected FFR changes, respectively. The criteria used to double-sort stocks in portfolios are size (s), proxied by market capitalization, and momentum (m), captured by past performance based on returns from month $t-12$ to month $t-2$. The portfolio corresponding to the combination $s1$ and $m1$ ($s5$ and $m5$) denote the smallest and loser (largest and winner) stocks. All returns are in excess of the 1-month Treasury bill rate. S_t^H is a dummy variable that is equal to 1 if the FOMC meeting occurred during a high sentiment year and 0 otherwise. A year is defined as of high sentiment if the sentiment proxy at the end (December) of the previous year exceeds the full sample median 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 A and B include the full sample (June 1989 - October 2014) and pre-crisis (June 1989 - August 2007) FOMC meetings, respectively, with the exception of the 17 September 2001 meeting, the 22 January 2008 meeting and the unscheduled meetings that were not accompanied by a FOMC statement or other information. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

Panel A: Full sample													
		s1	s2	s3	s4	s5			s1	s2	s3	s4	s5
	m1	−6.70*	−10.72**	−15.59**	−16.65**	−13.25*		m1	−7.03*	−11.23**	−16.26**	−17.32**	−14.37*
		(3.78)	(4.78)	(5.84)	(6.18)	(7.73)			(3.83)	(4.80)	(5.83)	(6.19)	(7.64)
	m2	-2.34	−5.33*	−7.27**	−7.84**	−7.79*		m2	-2.51	−5.63*	−7.69**	−8.20**	−8.17**
		(1.90)	(2.93)	(2.87)	(2.95)	(3.89)			(1.96)	(2.96)	(2.86)	(2.96)	(3.92)
CSI	m3	-1.57	-3.14	−4.29*	−5.95***	−7.76**	CCI	m3	-1.66	-3.38	−4.46*	−6.17***	−8.10**
		(1.86)	(2.58)	(2.30)	(1.87)	(3.24)			(1.93)	(2.64)	(2.35)	(1.89)	(3.29)
	m4	-1.52	-3.38	−3.90*	−4.64**	-2.92		m4	-1.64	-3.49	−3.99*	−4.87**	-3.05
		(1.63)	(2.53)	(1.95)	(1.80)	(1.96)			(1.68)	(2.60)	(2.01)	(1.83)	(2.04)
	m5	-2.71	-3.71	−4.36*	−3.55*	−4.08**		m5	-2.93	-3.90	−4.53*	−3.65*	−4.22**
		(2.22)	(2.30)	(2.39)	(1.93)	(2.01)			(2.27)	(2.35)	(2.45)	(1.99)	(2.07)
Panel B: Pre-crisis													
	m1	−8.33**	−12.89***	−18.47***	−19.77***	−18.25***		m1	−8.67**	−13.45***	−19.27***	−20.52***	−19.63***
		(3.55)	(4.31)	(5.26)	(5.62)	(6.14)			(3.58)	(4.27)	(5.14)	(5.54)	(5.79)
	m2	−2.85*	−6.34**	−8.66***	−9.41***	−10.55***		m2	−2.99*	−6.65**	−9.14***	−9.81***	−11.02***
		(1.54)	(2.47)	(2.33)	(2.33)	(2.94)			(1.59)	(2.47)	(2.23)	(2.26)	(2.90)
CSI	m3	-2.07	−4.19*	−5.30**	−6.71***	−9.77***	CCI	m3	-2.12	−4.44**	−5.49***	−6.93***	−10.18***
		(1.48)	(2.15)	(1.90)	(1.41)	(2.81)			(1.54)	(2.19)	(1.92)	(1.38)	(2.85)
	m4	-1.71	−4.46**	−4.74***	−5.48***	−3.83*		m4	-1.79	−4.56**	−4.82***	−5.73***	−3.97*
		(1.40)	(2.07)	(1.53)	(1.40)	(1.95)			(1.45)	(2.14)	(1.58)	(1.42)	(2.06)
	m5	−3.47*	−4.76**	−5.46***	−4.38***	−4.83**		m5	−3.71*	−4.98***	−5.66***	−4.49***	−4.98**
		(2.00)	(1.67)	(1.81)	(1.47)	(1.91)			(2.04)	(1.70)	(1.84)	(1.52)	(1.98)
	m1	−9.54***	−14.36***	−19.64***	−20.95***	−18.77***							
		(3.25)	(3.82)	(4.80)	(5.16)	(5.92)							
	m2	−3.44**	−6.97***	−9.11***	−10.00***	−10.96***							
		(1.53)	(2.27)	(2.16)	(2.11)	(2.80)							
BWI	m3	−2.66*	−4.66**	−5.56***	−7.09***	−9.83***							
		(1.45)	(2.06)	(1.82)	(1.30)	(2.79)							
	m4	-2.04	−4.87**	−5.09***	−5.70***	−3.91**							
		(1.34)	(1.99)	(1.49)	(1.37)	(1.93)							
	m5	−3.64*	−5.07***	−5.53***	−4.48***	−4.79**							
		(1.95)	(1.63)	(1.78)	(1.42)	(1.89)							

Table 11: Response of stock market returns to central bank liquidity swaps announcements during periods of decreasing vs. increasing sentiment

This table presents the CRSP value-weighted cumulative average abnormal returns (CAARs) over various event windows. 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 13 announcements related to the initiation or continuation of dollar and foreign currency liquidity swaps between the Fed and other central banks. The sample period is December 2007 - October 2013. 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 (December) of the previous year. The statistical significance of CAARs is evaluated using the Boehmer et al. (1991) test statistic that accounts for event-induced increase in returns volatility. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

Event window	$CAAR$(%)
Panel A: Decreasing sentiment	
(-1, 3)	4.48**
(-1, 1)	4.00***
(0, 0)	1.75**
Panel B: Increasing sentiment	
(-1, 3)	-0.53
(-1, 1)	-0.27
(0, 0)	0.85

Table 12: Response of size, value and momentum sorted portfolio returns to central bank liquidity swaps announcements during periods of decreasing vs. increasing sentiment

This table presents the portfolios cumulative average abnormal returns (CAARs) over various event windows. The criteria used to sort stocks in portfolios are size (s), proxied by market capitalization, value (bm), measured by the book-to-market ratio, and momentum (m), captured by past performance based on returns from month t-12 to month t-2. $s1$, $bm1$ and $m1$ denote the decile 1 portfolios, that is, the smallest, growth and loser portfolio, respectively. $s10$, $bm10$ and $m10$ denote the decile 10 portfolios, that is, the largest, value and winner portfolio, respectively. Decile 1 and 10 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 13 announcements related to the initiation or continuation of dollar and foreign currency liquidity swaps between the Fed and other central banks. The sample period is December 2007 - October 2013. 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 (December) of the previous year. The statistical significance of CAARs is evaluated using the Boehmer et al. (1991) test statistic that accounts for event-induced increase in returns volatility. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

	Event window	$CAAR$(%)		Event window	$CAAR$(%)		Event window	$CAAR$(%)
Panel A: Decreasing sentiment								
	(-1, 3)	4.38**		(-1, 3)	4.20*		(-1, 3)	8.55**
$s1$	(-1, 1)	3.24**	$bm1$	(-1, 1)	3.81***	$m1$	(-1, 1)	7.24**
	(0, 0)	1.71*		(0, 0)	1.73***		(0, 0)	3.23*
	(-1, 3)	3.91**		(-1, 3)	6.48**		(-1, 3)	4.10
$s10$	(-1, 1)	3.68***	$bm10$	(-1, 1)	5.39***	$m10$	(-1, 1)	3.61**
	(0, 0)	1.56***		(0, 0)	3.16***		(0, 0)	1.68**
	(-1, 3)	0.48		(-1, 3)	2.27*		(-1, 3)	-4.45
$s1$-$s10$	(-1, 1)	-0.45	$bm10$-$bm1$	(-1, 1)	1.58**	$m10$-$m1$	(-1, 1)	-3.63
	(0, 0)	0.15		(0, 0)	1.43**		(0, 0)	-1.55
Panel B: Increasing sentiment								
	(-1, 3)	-0.10		(-1, 3)	-0.91		(-1, 3)	-1.59
$s1$	(-1, 1)	-0.38	$bm1$	(-1, 1)	-0.66	$m1$	(-1, 1)	-1.35
	(0, 0)	0.95		(0, 0)	0.60		(0, 0)	0.39
	(-1, 3)	-0.62		(-1, 3)	1.36		(-1, 3)	-0.18
$s10$	(-1, 1)	-0.29	$bm10$	(-1, 1)	0.97	$m10$	(-1, 1)	-0.21
	(0, 0)	0.69		(0, 0)	1.59		(0, 0)	1.55
	(-1, 3)	0.52		(-1, 3)	2.27**		(-1, 3)	1.41
$s1$-$s10$	(-1, 1)	-0.08	$bm10$-$bm1$	(-1, 1)	1.63*	$m10$-$m1$	(-1, 1)	1.14
	(0, 0)	0.26**		(0, 0)	1.00		(0, 0)	1.16

Figure 1: Actual and unexpected FFR changes

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

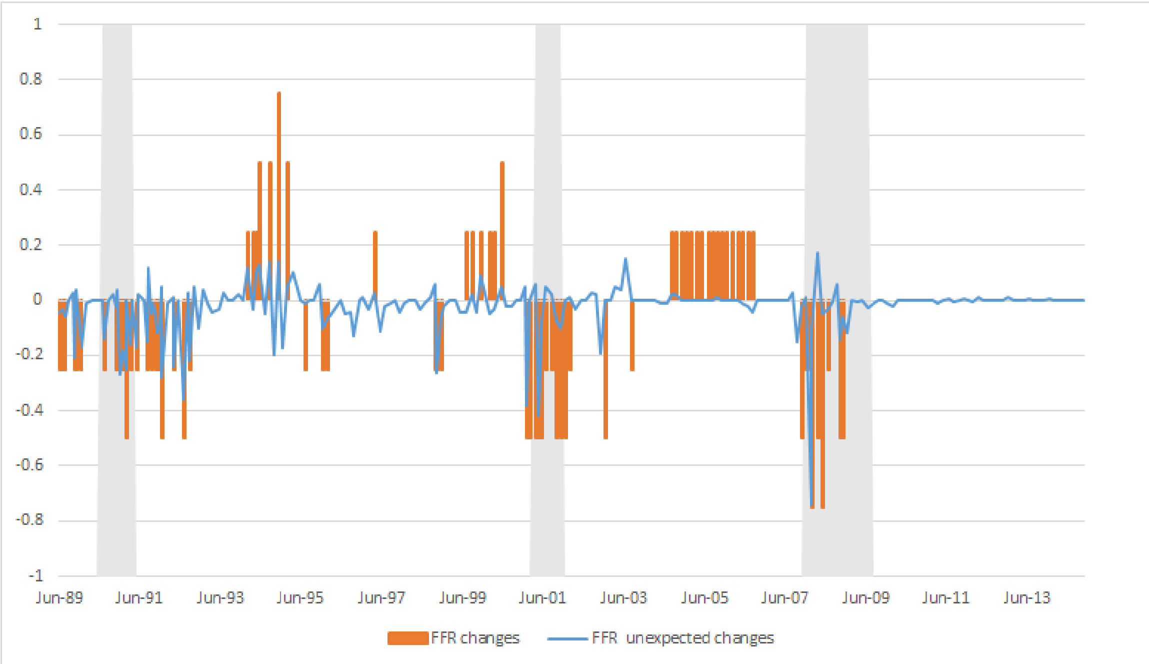


Figure 2: Sentiment indices

This figure plots sentiment indices 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.

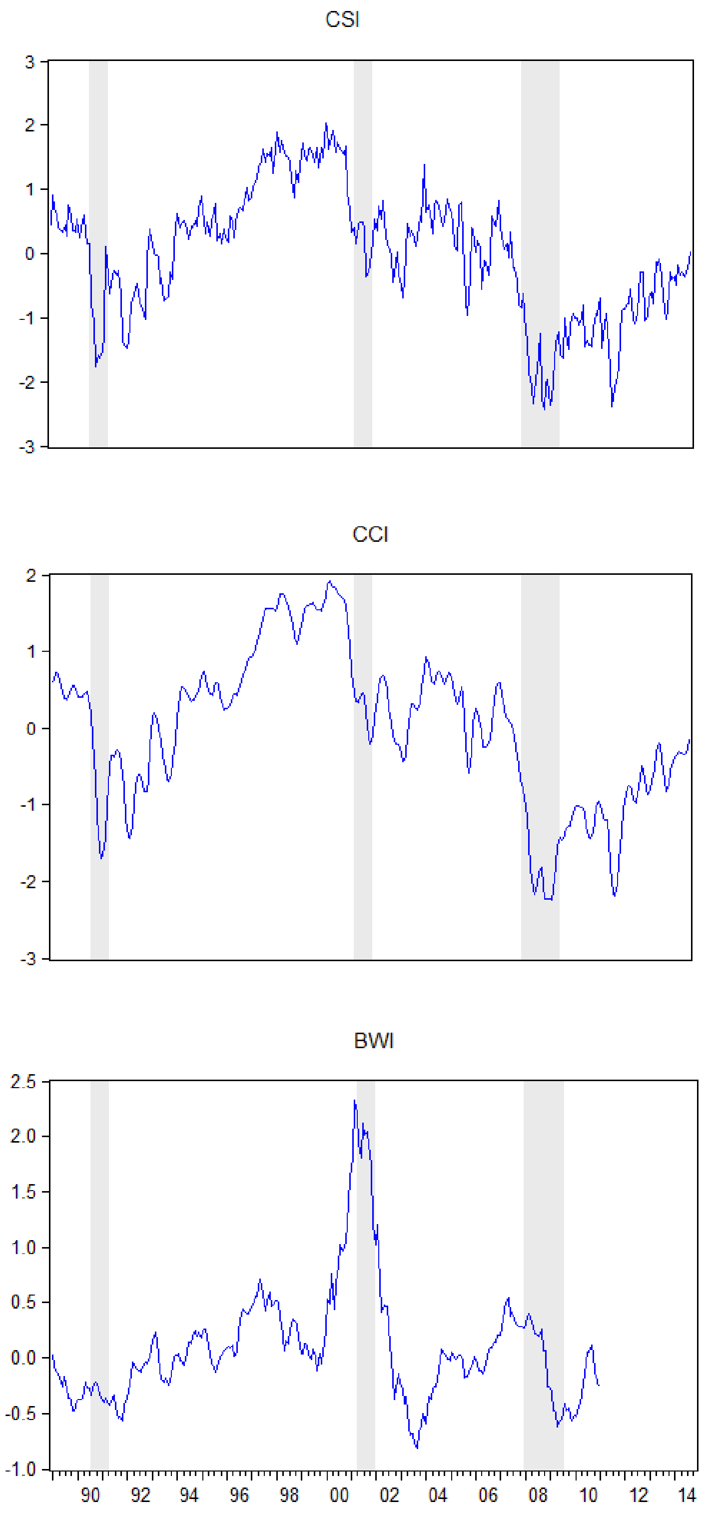
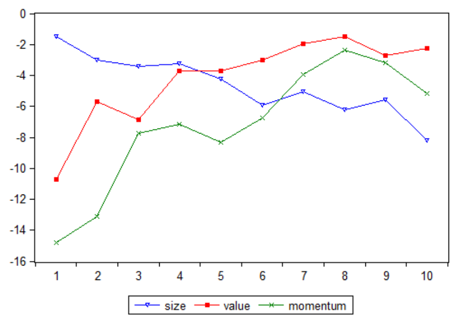


Figure 3: Response of size, value and momentum sorted portfolio returns to monetary policy shocks during periods of high sentiment

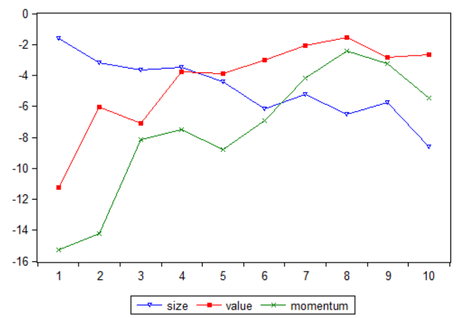
This figure plots OLS estimates of the impact of unexpected FFR changes on portfolio returns during periods of high sentiment, as captured by β_2 in the following model: $R_{it}=\beta_0+\beta_1(1-S_t^H)\Delta i_t^u+\beta_2 S_t^H \Delta i_t^u+\varepsilon_t$, where R_{it} and Δi_t^u denote portfolio returns and unexpected FFR changes, respectively. The criteria used to sort stocks in portfolios are size (s), proxied by market capitalization, value (bm), measured by the book-to-market ratio, and momentum (m), captured by past performance based on returns from month t-12 to month t-2. The corresponding deciles are shown in the X-axis of the plot.$s1$, $bm1$ and $m1$ denote the decile 1 portfolios, that is, the smallest, growth and loser portfolio, respectively. $s10$, $bm10$ and $m10$ denote the decile 10 portfolios, that is, the largest, value and winner portfolio, respectively. The portfolio returns are in excess of the 1-month Treasury bill rate. S_t^H is a dummy variable that is equal to 1 if the FOMC meeting occurred during a high sentiment year and 0 otherwise. A year is defined as of high sentiment if the sentiment proxy at the end (December) of the previous year exceeds the full sample median 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 A and B include the full sample (June 1989 - October 2014) and pre-crisis (June 1989 - August 2007) FOMC meetings, respectively, with the exception of the 17 September 2001 meeting and the unscheduled meetings that were not accompanied by a FOMC statement or other information.

Panel A: Full sample

CSI

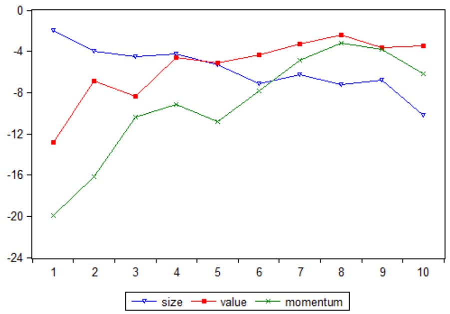


CCI

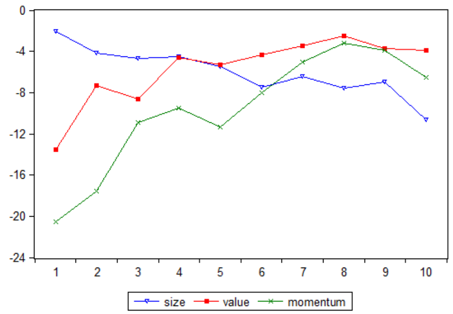


Panel B: Pre-crisis

CSI



CCI



BWI