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

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1 March 2017

Abstract

We investigate whether and how the state of investor sentiment influences the response 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 beginning-of-the-year investor sentiment is high or during periods when investor sentiment is decreasing. This effect is particularly strong for stocks with large size, low book-to-market ratio and low past returns. Moreover, we find that stock prices significantly respond to non-conventional monetary policy announcements.

Keywords: Investor Sentiment, Monetary Policy, Stock Returns, Cross-Section.
JEL classification: G11, G12, G14, E44, E52.

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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, Shleifer, and Thaler, 1991; Kumar and Lee, 2006; Baker and Wurgler, 2006; Stambaugh, Yu, and Yuan, 2012). Baker and Wurgler (2006) find that the cross-section of expected stock returns depend on beginning-of-period sentiment. Yu and Yuan (2011) document that the expected excess return on the stock market shows a positive relation to the conditional variance of the market only in low-sentiment periods. In this paper, we analyze whether the state of investor sentiment influences the responses of the stock market return and the cross-section of stock returns to shocks in monetary policy, both conventional and non-conventional, on the meeting days of the Federal Open Market Committee (FOMC).

Prior studies on the state dependence of monetary policy impacts generally focus on the state of the macroeconomy. To our knowledge, this paper is the first to show that the state of investor sentiment is crucial for the impacts of monetary policy 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.

We discover a crucial role for the state of investor sentiment in the impacts of unanticipated monetary policy shifts on daily returns of the stock market and across the cross-section of stocks. In particular, when sentiment is high at the beginning of the year or during periods when investor sentiment is decreasing, the daily excess stock market return responds positively to expansionary monetary policy shocks in the form of unexpected cuts in the Federal funds rate (FFR). In response to an unexpected cut in the FFR of 25 basis points, the excess stock market return increases by about 2% in a day. In contrast, in months when sentiment is low at the beginning of the year, the impact of monetary policy shocks on the excess stock market return is insignificant. In contrast, when sentiment is low at the beginning of the year or during periods when investor sentiment is increasing, stock returns show little responses to monetary policy shocks.

Moreover, the impact of FFR surprises on portfolio returns tend to be statistically significant only when sentiment is high at the beginning of the year. Importantly, the responses to monetary policy shocks differ 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 beginning of the year. The short-leg portfolios (i.e., large, growth and loser) exhibit stronger response to expansionary surprises, which in turn, reduces the return differentials on the long-short strategies. Our findings are consistent with the notion of overpricing during sentiment build-up period, which is followed by subsequent pricing corrections. Crucially, our evidence suggests that expansionary monetary policy surprises benefit most for stocks that lost value more during the period of pricing correction.

The factor returns on size (SMB), value (HML) and momentum (MOM) portfolios (Fama and French, 1992; Carhart, 1997) are positively related to unexpected FFR changes only when the beginning-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 beginning 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 evidence suggests that the pricing correction of growth and loser stocks are larger relative to value and winner stocks during periods of decreasing sentiment. When an expansionary monetary policy shock occurs, these stocks benefit more with stronger positive price 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.

We measure the excess return on the CRSP value-weighted market index 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. 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 remove the variation due to economic components and obtain sentiment measures that are orthogonalized to a set of macroeconomic variables. We separate the state of investor sentiment in two ways. The first is to classify states into high-sentiment and low-sentiment regimes according to the beginning-of-year value of investor sentiment. We define a year as high sentiment if the sentiment indicator at the end of the previous year exceeds the full sample median value. Our second way of separating the state of investor sentiment is based on changes in investor sentiment. We examine how changes in investor sentiment affect the relationship between FFR shocks and stock market returns. A decreasing sentiment period is defined as years when the value of the sentiment proxy at the end of December is lower than the value at the end of December in the previous year.

We then jointly classify the states according to both the level and changes in sentiment to analyze the effect of monetary policy shocks on stock returns. We find that the effect of policy shifts is stronger during years that sentiment started at high levels but then subsequently declined. We also show that high sentiment levels, typically occurring near business cycle peaks, tend to be followed by negative changes in sentiment throughout economic contractions, consistent with the finding of Chung, Hung, and Yeh (2012) as depicted in their Figure 2.

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

Our findings are robust to the use of alternative sentiment indicators, and are similar during the period before the 2007-2008 financial crisis. 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, using value-weighted and equally-weighted portfolios, and using returns of industry portfolios. All our findings remain strong and consistent, and do not change our conclusions.

Financial economists document that monetary policy shocks have significant impacts on the stock market. Thorbecke (1997), Ehrmann and Fratzscher (2004), Bernanke and Kuttner (2005), and Kontonikas and Kostakis (2013) show that, in line with the present value argument, cuts in unexpected Federal funds rate (FFR) lead to positive stock returns.[1] On the other hand, monetary policy shocks also exert impacts on investor senti-

[1]Theoretically, there are two channels through which monetary policy could affect stock prices. First,

ment. For example, Kurov (2010) finds that expansionary monetary policy shocks increase investor sentiment, especially during bear-market periods. 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 stock prices.

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 affects the way by which investors react to monetary policy news and hence, stock returns. Specifically, we hypothesize that monetary policy shocks have a strong impact on stock returns when sentiment is high at the beginning of the year or during periods when sentiment is decreasing. Our hypothesis is based on the following arguments and empirical evidence.

First, many studies document that the effect of monetary policy shocks on stock returns is state dependent. For example, Chen (2007) finds that monetary policy surprises have much larger effects on stock returns in bear markets than in bull markets. Basistha and Kurov (2008) find that the reaction of stock prices to monetary policy news is much

changes in FFR could change investors' expectation about future cash flows (Bernanke and Kuttner, 2005). Second, it will change the cost of capital, that is, it may affect the real interest rate that is used to discount future cash flows or the risk premium associated with holding stocks (Bernanke and Kuttner, 2005; Maio, 2014).

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, MacDonald, and Saggu (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 economic condition, which indicates that investors are not confident about the market.

Second, asset-pricing research has established strong evidence that investor sentiment affects asset prices (see, e.g., Lemmon and Portniaguina, 2006; 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 predicts the cross-section of stock returns. Such return predictive power, however, is state dependent. Chung, Hung, and Yeh (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 low-sentiment periods, but a weak relation in high-sentiment periods in the U.S. stock market. Stambaugh, Yu, and Yuan (2012) argue that the profitability of 11 anomalies reflects mispricing, and show that the profitability of the long-short arbitrage portfolio 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 portfolio of each of the anomaly strategies.

Intuitively, when beginning-of-period sentiment is high or when sentiment is declining, the correction for overpricing occurs and thus, investors react strongly to shocks in expansionary monetary policy. Further, there is evidence that expansionary monetary policy increases investor sentiment, thereby increasing stock prices (Kurov, 2010; Lutz, 2015). In contrast, when beginning-of-period sentiment is low or when sentiment is increasing, underpricing is unlikely and hence, stock prices do not significantly benefit from expansionary monetary policy shocks.[2] This is also consistent with previous studies that find greater monetary policy impacts during "bad times".[3] Yu and Yuan (2011) argue that there are more sentiment-driven investors when sentiment is high. There is also evidence 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 downturn in the stock market condition, which is also a period of "bad time" and hence, there will be stronger impacts of monetary policy.

3 Data and measurement

Our full sample period is from June 1989 to October 2014, hence including the pre-crisis period, the financial crisis and the period afterward. The financial crisis of 2007-2009 has had a significant impact on the approach to monetary policy implementation by the Federal Reserve. Thus, we cover both conventional and non-conventional policies. We proxy conventional monetary policy shocks by target FFR surprises, while non-conventional policies put particular emphasis on forward guidance, LSAPs and the provision of various liquidity facilities by the Fed. Moreover, we employ several proxies for investor sentiment,

[2]Chung, Hung, and Yeh (2012) provide an excellent discussion on mispricing during different phases of the macroeconomy and sentiment

[3]Bernanke and Kuttner (2005) document that investors react to good monetary news rather than bad news

that encapsulate different dimensions of sentiment.

3.1 Monetary policy measures

3.1.1 Target rate surprises

Up to the recent financial crisis, the conduct of monetary policy in the U.S. is characterised by targeting the 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). The full sample includes 227 FOMC meetings, 23 of which were unscheduled.[4] In line with Bernanke and Kuttner (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 exclude unscheduled meetings that were not accompanied by a FOMC statement or other information.[5] Finally, we remove 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.[6]

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:

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

[4]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 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.

[5]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.

[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.

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

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

Figure 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. 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%. Among the total of 82 FOMC meetings that are associated with FFR changes, 51 of which are of expansionary nature ($\Delta i < 0$), and 31 of them are contractionary ($\Delta i > 0$). On average, target rate surprises are expansionary with the mean of the variable being equal to -0.02%/

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. 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

[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 ($f^1_{m,t}$–$f^1_{m,t-1}$) is used to calculate the FFR surprise. Also, when the FOMC meeting occurs on the first day of the month, $f^1_{m-1,D}$, instead of $f^0_{m,t-1}$, is used to measure the surprise.

financial crisis and the non-conventional policies that the Fed subsequently adopted.[8]

3.1.2 Path surprises

In order to alleviate the constraint to monetary stimulus that the zero lower bound (ZLB) posed, the Fed provides frequent assurances about its intention, the so-called 'forward guidance', to keep the policy rate at near zero in the future (Bernanke, 2013; Doh and Connolly, 2013).[9] 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. Gürkaynak, Sack, and Swanson (2005) develop a methodology that can identify the 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 surprises. 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 learned 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

[8] In line with Kontonikas, MacDonald, and Saggu (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.

[9] 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 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.

the changes in price of the second, third, and fourth eurodollar futures contracts with maturity of up to four quarters. Two principal components are obtained which are then transformed so that fist 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.[10]

Path surprises have not been used as extensively as target rate surprises in the existing literature. Previous studies that examine the stock market response to path surprises using sample periods that end prior to the onset of the recent financial crisis typically report insignificant estimates (Gürkaynak, Sack, and Swanson, 2005; Wongswan, 2009). On the other hand, the findings of Wright (2012) and Swanson (2015) indicate that forward guidance significantly affects the stock market (as measured by the S&P 500) during the ZLB period, with a decrease in expected future short-term rates being associated with higher stock prices. Our analysis of the impact of path surprises focuses on the ZLB era, with the full sample period narrowed to January 2009–October 2014 (47 observations), but unlike the aforementioned studies we account for the role of investor sentiment. The average path surprise in Table 1 is equal to -0.01%, with the variable ranging from -0.62% to 0.46%.

3.1.3 LSAPs and liquidity facilities announcements

Responding to the crisis, in addition to more explicit forward guidance, the Fed resolves to another type of non-conventional policy. Specifically, the Fed's balance sheet size and composition changed significantly through the provision of non-sterilized liquidity facilities and large scale purchases of longer-term assets from the private sector, mainly mortgage

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

backed securities (MBS) and Treasury bonds. Fed's interventions aim to improve financial markets conditions and put downward pressure 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 incorporated: 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 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 overseas markets. In total, there are 46 unique liquidity facilities announcements spanning the period December 2007 to October 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.[11] There are also 22 LSAP 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).[12] 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 LSAP and liquidity facilities announcements, do not overlap with FOMC meetings.

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

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

[12] 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.

liquidity facilities programmes are not available. Hence, we do not attempt to measure "balance sheet shocks", in line with most previous related studies (Gagnon et al., 2011; Ait-Sahalia et al., 2012; Fiordelisi, Galloppo, and Ricci, 2014; Ricci, 2015).[13] Instead, we adopt an event study approach where the behaviour of stock returns will be evaluated in short windows surrounding the LSAPs and liquidity facilities announcements.

3.2 Investor sentiment measures

We use three monthly measures of investor sentiment to ensure that our results are robust to the use of different proxies for sentiment (see, e.g., Lemmon and Portniaguina, 2006; McLean and Zhao, 2014): the University of Michigan's Consumer Sentiment Index (CSI), the U.S. Consumer Confidence Index (CCI) and Baker and Wurgler's (2006) Sentiment Index (BWI).[14] 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 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 with the CSI.

The BWI is another commonly used measure of investor sentiment (see, e.g., Yu and Yuan, 2011; Stambaugh, Yu, and Yuan, 2012), formed as the first principal component of six measures of investor sentiment: the closed-end fund discount, the number and the

[13] A notable exception is Rosa (2012) who 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. Furthermore, Swanson (2015) 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, above and beyond 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)

[14] 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/.

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 the pre-crisis estimations in the next section.

Following Baker and Wurgler (2006), we orthogonalize the BWI, the CSI and the CCI with respect to macroeconomic conditions. Specifically, we obtain the residuals from regressing each of the three sentiment measures on a set of macroeconomic indicators: 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.

Figure 2 plots the three orthogonalized sentiment indices.[15] They all show declines in sentiment around economic contractions. These declines tend to commence prior to the official start of the recessionary episode, as measured by the NBER dates.[16] Hence, even after the removal of variation due to economic components from the sentiment measures, recessions still tend to be associated with declines in sentiment. This finding is in line with previous studies that identify a link between macroeconomic developments and the psychological well-being of individuals (Di Tella, MacCulloch, and Oswald, 2003; Blanchflower et al., 2014). While the CCI and CSI are highly correlated, the BWI exhibits rather different dynamics over time. For instance, the BWI increases significantly in the late 1990s, capturing the episode of the dot-com bubble. This indicates that the BWI and the two survey-based indicators capture different dimensions of sentiment.

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

[16] See also Chung, Hung, and Yeh (2012) for econometric evidence linking developments sentiment with the business cycle.

In order to examine whether the relationship between stock returns and monetary policy shifts is state-dependent, we construct dummy variables that represent two types of sentiment regimes, level-based and changes-based, using the orthogonalized sentiment indices. To capture the level of sentiment, we create a dummy variable, S_t^H, that is equal to 1 if the FOMC meeting occurs 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.[17] We construct the other dummy variable, S_t^D, based on changes in sentiment, which is equal to 1 during decreasing sentiment periods, that is, years when the value of the sentiment proxy in December is lower than the value in December of the previous year.

Figures 3 and 4 plot the level- and changes-based sentiment dummies using the three sentiment indices. The changes-based dummy is more active than the level based-dummy and they both are more active than the NBER recession indicator. For example, over the sample period there are 3 recessions, while, using the CSI index, there are 8 instances of the falling sentiment regime and 4 instances of the high (start of the year) sentiment regime.

Table 3 reports the correlation coefficients between the sentiment dummies. Four stylised facts emerge. First, correlations are stronger amongst the two survey-based measures of sentiment and smaller between them and the BWI proxy. Second, the aforementioned pattern is more pronounced in the case of changes-based sentiment dummies. For example, the CSI-CCI correlation for the level (changes) dummy variable is 0.81 (0.72), while the CSI-BWI correlation is 0.71 (0.47). Third, the correlation between level- and

[17] In the robustness checks we experiment with a monthly classification scheme for the state of sentiment and obtain results similar to those from the baseline annual classification scheme.

changes-based sentiment dummies is positive, ranging from 0.12 in the case of CSI to 0.51 for the BWI. This finding reflects periods when sentiment started at a high level but then subsequently declined. Fourth, there is a positive correlation between changes-based sentiment dummies and the NBER recession indicator, capturing declines in sentiment during recessionary episodes. Nevertheless, the correlation is far from perfect. As we can see in Figure 4, falls in sentiment occur not only during recessions but also during expansions.

3.3 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- and equally-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 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

This section contains event study estimates of the market and portfolio returns responses to monetary policy actions. We consider conventional policy actions, measured by target rate surprises (4.1), as well as non-conventional actions reflected in path surprises (4.2) and announcements of LSAPs and liquidity facilities (4.3).

4.1 The impact of target rate surprises

4.1.1 Market response

We begin our empirical investigation by examining the market-wide response of stocks to target FFR shocks on FOMC meeting days conditional upon the state of the level of sentiment. This is accomplished by interacting FFR surprises with the level-based sentiment dummy, S_t^H, within the following regression model for excess stock returns:

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

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

Table 4 reports the Ordinary Least Squares (OLS) estimates of Equation 3 with Newey and West (1987) standard errors across the full sample (Panel A) and pre-crisis (Panel B) periods, using alternatively value- and equally-weighted excess market returns. Starting with value-weighted returns, the full sample 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 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% 1-day 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.

Using equally-weighted market returns, the magnitude of the impact of FFR shocks, when sentiment is high at the start of the year, declines by about a third as compared to 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.

Asymmetries: Good news vs. bad news

Equation 3 above assumes a symmetric stock market reaction to monetary policy actions, with no distinction between expansionary shocks and contractionary shocks. In other words, good news (unexpected target FFR cuts) and bad news (unexpected target FFR increases) are assumed to affect the stock market in a similar manner. Nevertheless, there is a possibility that the stock market response will depend 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. However, Bernanke and Kuttner (2005) do not account for sentiment regimes in their empirical framework. To do so, we estimate the following regression model that allows for both sentiment dependence and sign asymmetry:

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

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

Table 5 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 reinforce the importance of the state of investor sentiment in the context of the transmission of monetary policy shocks to the stock market. At the same time, however, our results highlight that the stock market response is highly asymmetric, primarily driven by expansionary monetary policy surprises.

Changes in sentiment

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. Moreover, the correlation analysis in Table 3 supports a positive relationship between sentiment regimes identified by level- and changes-based sentiment dummies. 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. Therefore, we replace the sentiment level-based dummy variable of Equation 3 with the changes-based dummy, S_t^D, and estimate Equation 5:

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

The results in Table 6 indicate that during periods of decreasing investor sentiment ($S_t^D = 1$) 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 4, where sentiment level-based states are utilised. Nevertheless, the key message is the similar, that is, the state of investor sentiment significantly influences the way in which the stock market responds to monetary policy surprises.

The correlation between changes in sentiment and recessions that we identified in Table 3 prompts us to consider the hypothesis that the impact of sentiment on the transmission of monetary policy shocks to the stock market is subsumed by the state of the economy. Essentially, since recessions typically overlap with negative changes in sentiment, the strong stock market response to FFR surprises during periods of falling sentiment may simply reflect the effect of these recessionary episodes. In order to examine this conjecture, we interact the changes-based sentiment dummy with the NBER recession indicator and estimate Equation 6:

$$R_t = \beta_0 + \beta_1 S_t^D \Delta i_t^u + \beta_2 S_t^D NBER_t \Delta i_t^u + \varepsilon_t, \quad (6)$$

where $NBER_t$ 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.

As we can see in Table 7, estimates of the interactive term, represented by β_2, are always statistically insignificant. This suggests that state-dependence in the relationship between stock market returns and monetary policy shocks is driven by sentiment. Hence, our findings suggest that the state of investor sentiment plays an important role, distinct from, and not subsumed by, the state of the economy.

Finally, motivated by the positive correlation between level- and changes-based sentiment dummies in Table 3, we use an alternative classification of sentiment regimes. This allows us to account for the joint effect of sentiment level and changes on the reaction of stock market returns to FFR surprises, by estimating Equation 7:

$$R_t = \beta_0 + \beta_1(1 - S_t^{HD})\Delta i_t^u + \beta_2 S_t^{HD} \Delta i_t^u + \varepsilon_t \tag{7}$$

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 8. 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 level but then subsequently declined ($S_t^{HD} = 1$). Estimates of the coefficient of interest (β_2) are similar in statistical significance and very close in magnitude to those reported in Table 4, where the sentiment dummy is based on the level on sentiment solely, across alternative proxies of sentiment and sample periods.[18]

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. Table 9 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 FFR surprises only 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

[18] We also considered a 4-way decomposition where dummies related to periods of "high & increasing", "high & decreasing", "low & increasing", and "low & decreasing" sentiment were utilised. The findings from that exercise (available upon request) are consistent with the findings in Table 8 since they show that the response of stock market returns to FFR shocks is statistically significant only during periods of "high & decreasing" sentiment.

moving from larger, growth and loser towards smaller, value and winner portfolios, the impact of FFR shocks generally decreases in magnitude, albeit not strictly monotonically. Figure 5 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 FFR 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 9, 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 10 and show that, consistently with the extreme deciles portfolio returns differentials results in Table 9, 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 11 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 11 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 FFR shocks to more strongly affect returns 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 12 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 12 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 FFR surprises 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.[19] On the other hand, they are in contrast with Ehrmann and Fratzscher (2004) and Jansen and Tsai (2010) who find that small stocks

[19]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.

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.

4.2 The impact of path surprises

Having established the importance of investor sentiment for the transmission of conventional monetary policy shocks, measured by FFR surprises, we now turn our attention to the unconventional policies of the recent past. 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 separate sentiment regimes since it is equal to zero throughout the ZLB period. On the other hand, as Figure 3 shows, the changes-based sentiment dummy exhibits some variation. Moreover, we do not use sentiment dummies generated from the BWI index since it ends at December 2010 and therefore its incorporation would reduce significantly the number of available observations. Therefore, we only use CSI and CCI changes-based dummies to identify the impact of the state of sentiment on the response of stock market returns to path surprises at the ZLB:

$$R_t = \beta_0 + \beta_1(1 - S_t^D)path_t + \beta_2 S_t^D path_t + \varepsilon_t \quad (8)$$

The findings in Table 13 indicate that the stock market reacts positively to an expansionary path surprise during periods of decreasing sentiment, which is consistent with the results of the previous section. The stock market response is stronger when we use the CSI indicator to generate sentiment regimes, with 1-day excess return of about 1.13% in response to an unexpected 25 basis points decline in the interest rate path. Our results are in agreement with Wright (2012) and Swanson (2015) who also find that forward guidance has a statistically significant effect on the stock market. At the same time, however, we extend the literature on forward guidance by showing that the effect of this non-conventional policy is especially potent during periods of falling sentiment.

We also examine the impact of path surprises on portfolio returns. The results in Table 13 show that, portfolio returns are more affected by path surprises during periods of decreasing sentiment. However, in contrast to the FFR shocks, the small, value portfolios are more affected by path surprises. Past losers, however, are still more affected.

4.3 The impact of LSAPs and liquidity facilities announcements

The other type of non-conventional monetary policy that we examine is related to the interventions of Fed, between December 2007 and October 2013, through LSAPs and the provision of liquidity facilities. We adopt an event study approach where abnormal returns (ARs) are calculated and evaluated 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. 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).

We further classify these events according to the state of investor sentiment at the time that they occurred and conduct the event study across each sentiment regime. Since there is insufficient variation in the level-based sentiment dummy over the period that the non-conventional policy announcements occurred, we just use the CSI changes-based dummy to define sentiment regimes.[20] For example, there are 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, Masumeci, and Poulsen (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):

$$CSAR_i(t_1,t_2) = \sum_{t=t_1}^{t_2} \frac{AR_{i,t}}{S(AR_i)} \tag{10}$$

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:

$$T = \frac{\frac{1}{N}\sum_{i=1}^{N} CSAR_i(t_1,t_2)}{\sqrt{\frac{1}{N(N-1)}[CSAR_i(t_1,t_2) - \frac{1}{N}\sum_{i=1}^{N} CSAR_i(t_1,t_2)]^2}} \tag{11}$$

where N is the number of observations in the sample.

The results in Table 15 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 is statistically insignificant 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

[20] Results using the CCI index to generate sentiment regimes are similar to those from the CSI and are available upon request.

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, Galloppo, and Ricci, 2014; Rogers, Scotti, and Wright, 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 15 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.[21] 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

[21] Results for other type of announcements (available upon request) tend to be insignificant.

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 use data on industry portfolios. Sixth, 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 occurs 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 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, MacDonald, and Saggu, 2013).

5.6 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, unexpected changes and path surprises

Δi_t and Δi_t^u denote FFR target rate changes and unexpected changes, respectively, on FOMC meeting dates over the full sample period (June 1989 - October 2014). $path_t$ denotes path surprises on FOMC meeting dates 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 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 3: Correlation matrix of sentiment regimes

This table presents the correlation coefficients of the sentiment-based dummy variables and the NBER recession dummy. $S_t^{H,i}$ 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. $S_t^{D,i}$ 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. 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. $NBER_t$ 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. The sample period is June 1989 - October 2014 for all cases apart from the correlation coefficients associated with BWI, where the sample is June 1989 - August 2007. *, **, *** indicate statistical significance at the the 10%, 5% and 1% level, respectively.

	$S_t^{H,CSI}$	$S_t^{D,CSI}$	$S_t^{H,CCI}$	$S_t^{D,CCI}$	$S_t^{H,BWI}$	$S_t^{D,BWI}$	$NBER_t$
$S_t^{H,CSI}$	1.00						
$S_t^{D,CSI}$	0.12*	1.00					
$S_t^{H,CCI}$	0.81***	0.21***	1.00				
$S_t^{D,CCI}$	0.26***	0.72***	0.38***	1.00			
$S_t^{H,BWI}$	0.71***	0.11	0.44***	0.05	1.00		
$S_t^{D,BWI}$	0.23***	0.47***	0.30***	0.47***	0.51***	1.00	
$NBER_t$	-0.01	0.37***	0.08	0.34***	−0.17**	0.22***	1

Table 4: 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 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 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.

		Value weighted returns					Equally weighted returns				
	Obs	β_0	β_1	β_2	$\beta_1=\beta_2$	$Adj.R^2$	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	0.19**	-0.85	−4.54*	[0.00]	0.06
		(0.09)	(0.84)	(2.58)			(0.08)	(0.67)	(2.41)		
CCI	227	0.24***	-0.64	−7.58***	[0.00]	0.11	0.20***	-0.80	−4.75*	[0.00]	0.06
		(0.09)	(0.83)	(2.57)			(0.08)	(0.67)	(2.45)		
Panel B: Pre-crisis											
CSI	168	0.16*	-0.92	−8.91***	[0.00]	0.25	0.10*	-1.04	−5.49**	[0.00]	0.17
		(0.07)	(0.95)	(1.17)			(0.06)	(0.67)	(2.29)		
CCI	168	0.16*	-0.88	−9.31***	[0.00]	0.27	0.11**	-1.01	−5.72**	[0.00]	0.18
		(0.09)	(0.81)	(1.68)			(0.09)	(0.66)	(2.31)		
BWI	168	0.13	-0.73	−9.14***	[0.00]	0.28	0.09	-0.72	−5.94***	[0.00]	0.20
		(0.09)	(0.76)	(1.73)			(0.06)	(0.58)	(2.15)		

Table 5: 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_0	β_1	β_2	β_3	β_4	$Adj.R^2$
			Panel A: Full sample				
CSI	227	0.11	-1.02	-1.21	-9.85^{***}	9.47	0.16
		(0.09)	(0.81)	(3.73)	(1.49)	(6.85)	
CCI	227	0.13	-0.95	-1.28	-10.16^{***}	9.14	0.17
		(0.09)	(0.81)	(3.75)	(1.43)	(7.02)	
			Panel B: Pre-crisis				
CSI	168	0.05	-1.23	-0.74	-10.13^{***}	1.29	0.26
		(0.09)	(0.81)	(3.77)	(1.47)	(6.41)	
CCI	168	0.08	-1.14	-0.87	-10.43^{***}	0.33	0.27
		(0.09)	(0.81)	(3.78)	(1.40)	(6.64)	
BWI	168	0.07	-1.06	0.27	-9.68^{***}	-4.06	0.28
		(0.40)	(0.81)	(3.42)	(1.53)	(-10.53)	

Table 6: 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 7: Response of stock market returns to FFR shocks during periods of decreasing sentiment and recessions

This table presents OLS estimates with heteroscedasticity and autocorrelation consistent standard errors, over FOMC meeting dates of the following model: $R_t=\beta_0+\beta_1 S_t^D \Delta i_t^u+\beta_2 S_t^D NBER_t \Delta i_t^u+\varepsilon_t$, 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^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. $NBER_t$ 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. 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***	−6.82***	4.55	[0.00]	0.07
		(0.09)	(2.58)	(3.49)		
CCI	227	0.24***	−7.19***	4.84	[0.00]	0.09
		(0.09)	(2.46)	(3.48)		
			Panel B: Pre-crisis			
CSI	168	0.13	−7.20***	3.09	[0.00]	0.17
		(0.09)	(2.59)	(3.26)		
CCI	168	0.14	−7.08***	2.98	[0.00]	0.17
		(0.09)	(2.59)	(3.26)		
BWI	168	0.13	−10.29***	4.21	[0.00]	0.25
		(0.08)	(2.08)	(2.96)		

Table 8: 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 9: 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.

	Portfolios	β_1	β_2	$Adj.R^2$	Portfolios	β_1	β_2	$Adj.R^2$	Portfolios	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 10: 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			
CSI	SMB	227	0.35	2.98***	0.06
			(0.58)	(1.05)	
	HML	227	-0.19	5.70**	0.19
			(0.30)	(2.25)	
	MOM	227	-0.04	6.91*	0.12
			(0.77)	(4.11)	
CCI	SMB	227	0.35	3.09***	0.01
			(0.57)	(1.07)	
	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			
CSI	SMB	168	0.41	3.66***	0.11
			(0.58)	(1.13)	
	HML	168	-0.30	6.43**	0.31
			(0.32)	(2.26)	
	MOM	168	0.34	8.87**	0.30
			(0.79)	(3.99)	
CCI	SMB	168	0.39	3.82***	0.11
			(0.58)	(1.17)	
	HML	168	-0.3	6.71***	0.33
			(0.33)	(2.24)	
	MOM	168	0.23	9.39**	0.32
			(0.76)	(3.96)	
BWI	SMB	168	0.60	3.35***	0.09
			(0.59)	(1.17)	
	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 11: 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 12: 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 13: Response of stock market returns to path surprises at the zero lower bound 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: $R_t = \beta_0 + \beta_1(1 - S_t^D)path_t + \beta_2 S_t^D path_t + \varepsilon_t$, 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 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 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. 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	$\beta_1 = \beta_2$	$Adj.R^2$
CSI	47	0.25*	0.45	−4.51***	[0.00]	0.11
		(0.15)	(0.64)	(1.74)		
CCI	47	0.31	-2.17	−2.75***	[0.83]	0.04
		(0.17)	(2.50)	(0.79)		

Table 14: Response of size, value and momentum sorted portfolio returns to path surprises at the zero lower bound 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: $R_{it}=\beta_0+\beta_1(1-S_t^D)path_t+\beta_2 S_t^D path_t+\varepsilon_t$, where R_{it} and $path_t$ denote portfolio returns and path surprises, 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^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 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 the 10%, 5% and 1% level, respectively.

	Portfolios	β_1	β_2	$Adj.R^2$	Portfolios	β_1	β_2	$Adj.R^2$	Portfolios	β_1	β_2	$Adj.R^2$
	$s1$	1.11	-5.93^{***}	0.16	$bm1$	-0.43	-3.02	0.03	$m1$	0.02	-19.59^{***}	0.50
		(2.17)	(1.83)			(0.81)	(2.16)			(0.97)	(4.76)	
CSI	$s10$	0.26	-3.84^{**}	0.09	$bm10$	0.50	-9.02^{***}	0.20	$m10$	0.29	-2.75	0.00
		(0.55)	(1.71)			(1.17)	(2.52)			(1.81)	(2.66)	
	$s1-s10$	0.85	-2.09^{***}	0.09	$bm10-bm1$	0.94	-6.00^{***}	0.26	$m10-m1$	0.26	16.84^{***}	0.48
		(0.54)	(0.41)			(1.16)	(1.53)			(1.22)	(6.04)	
	$s1$	-2.14	-3.94^{***}	0.05	$bm1$	-2.71	-1.12	0.02	$m1$	-2.87	-20.74^{***}	0.46
		(2.83)	(0.73)			(2.39)	(0.69)			(3.06)	(4.52)	
CCI	$s10$	-2.18	-2.08^{**}	0.03	$bm10$	-3.70	-6.54^{***}	0.10	$m10$	-3.03	0.18	0.00
		(2.29)	(0.67)			(3.80)	(2.08)			(3.60)	(0.77)	
	$s1-s10$	0.04	-1.86^{**}	0.03	$bm10-bm1$	-0.99	-5.43^{***}	0.16	$m10-m1$	-0.16	20.92^{***}	0.60
		(0.60)	(0.39)			(1.60)	(1.78)			(0.94)	(4.10)	

Table 15: 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 (%)) 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 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, including 13 announcements about central bank (CB) liquidity swaps, 13 announcements about the term auction facility (TAF) and 21 announcements about other liquidity facilities. 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 (December) 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 the 10%, 5% and 1% level, respectively.

Event window	Liquidity facilities (All)	CB liquidity swaps	TAF	Others	LSAPs
Panel A: Decreasing sentiment					
(-1, 3)	-0.03	4.48**	-1.91	-0.79	1.53
(-1, 1)	0.60	4.00***	-0.73	0.09	2.04
(0, 0)	0.13	1.75**	-0.42	-0.06	0.14
Panel B: Increasing sentiment					
(-1, 3)	-0.15	-0.53	-	-	-0.68
(-1, 1)	0.29	-0.27	-	-	-0.43
(0, 0)	0.99	0.85	-	-	-0.04

Table 16: 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 central bank liquidity swaps over the period 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, Masumeci, and Poulsen (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.

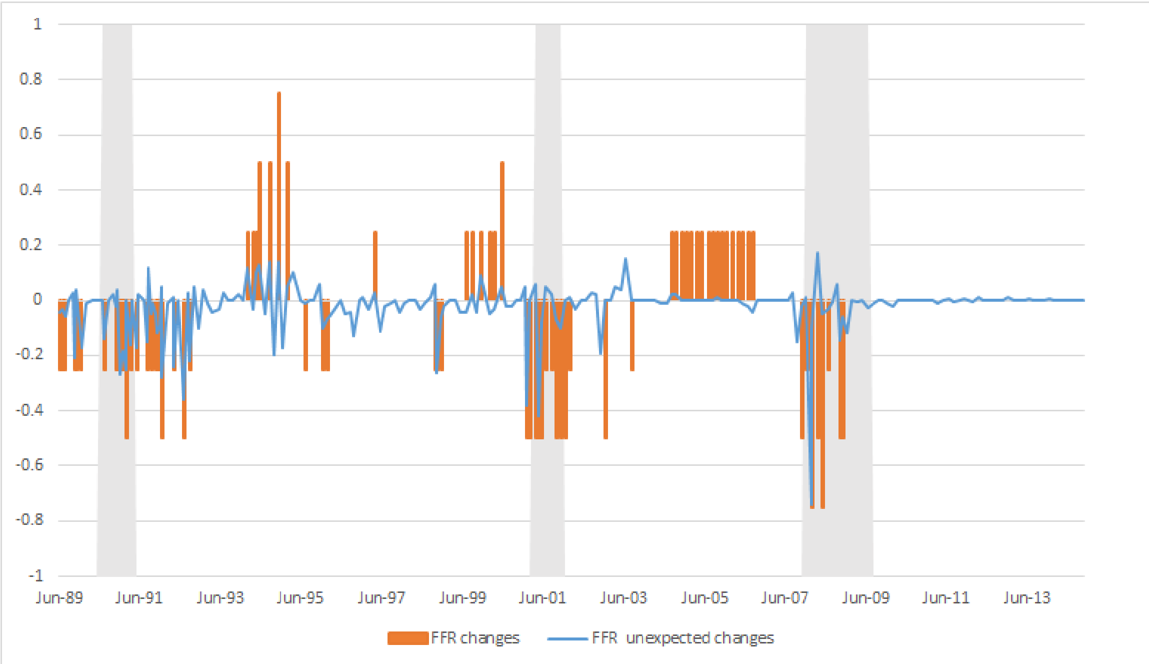


Figure 2: Sentiment indices

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.

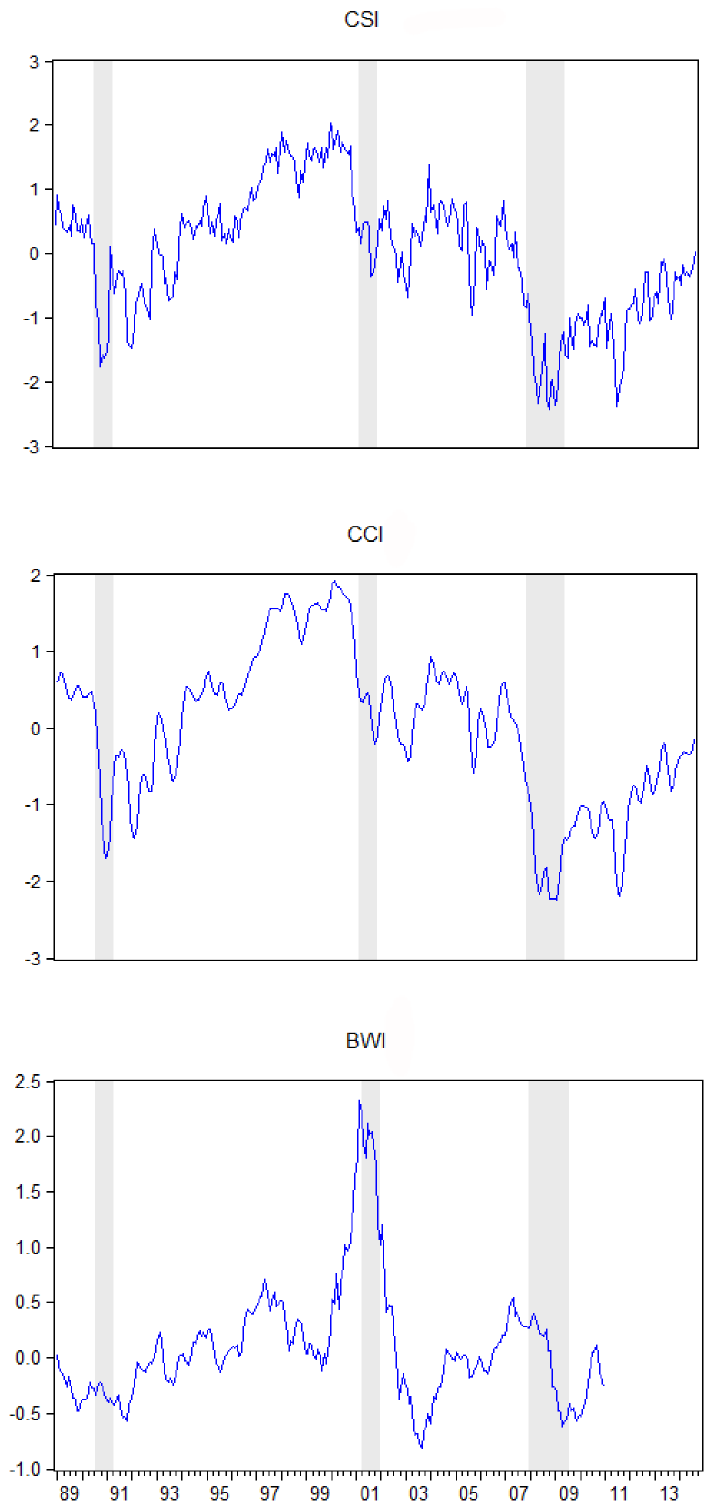


Figure 3: Sentiment level-based regimes

This figure plots level-based sentiment dummy variables, $S_t^{H,i}$, over the period December 1988 - October 2014. The dummy variable 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. 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.

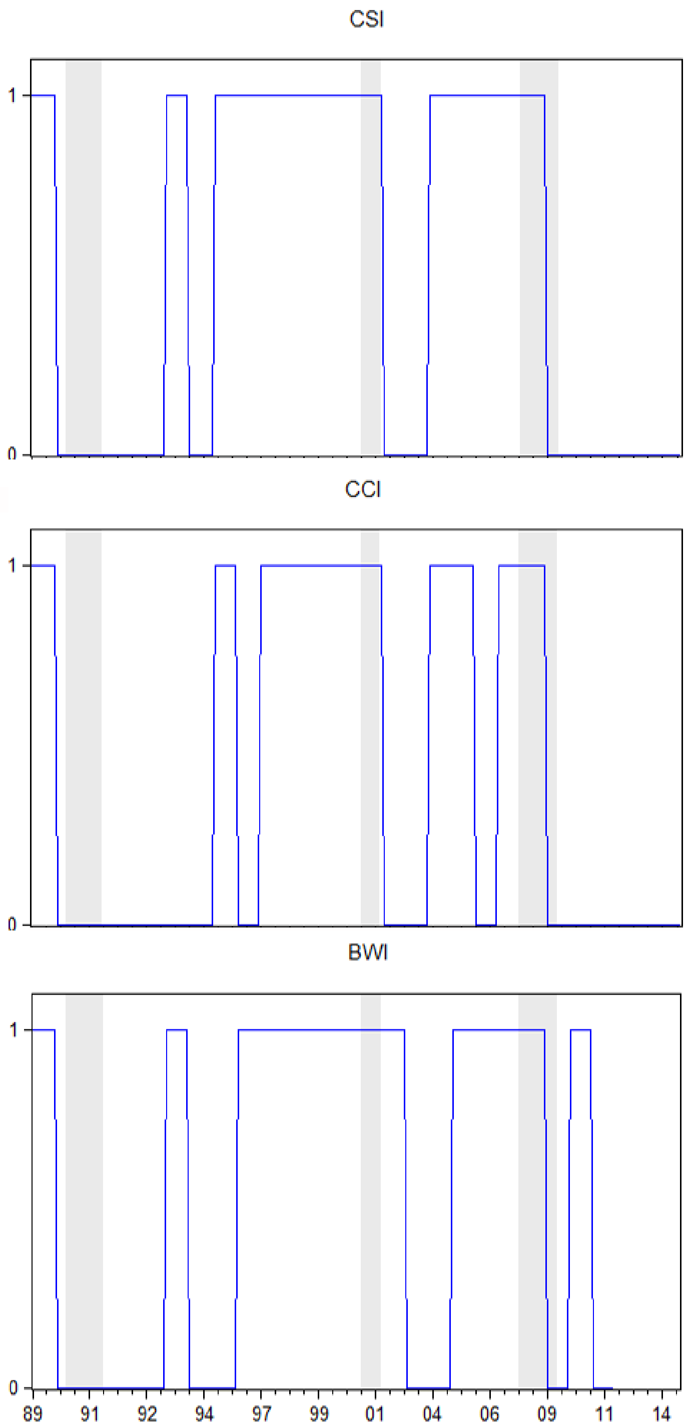


Figure 4: Sentiment changes-based regimes

This figure plots changes-based sentiment dummy variables, $S_t^{D,i}$, over the period January 1989 - October 2014. The dummy variable 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. 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.

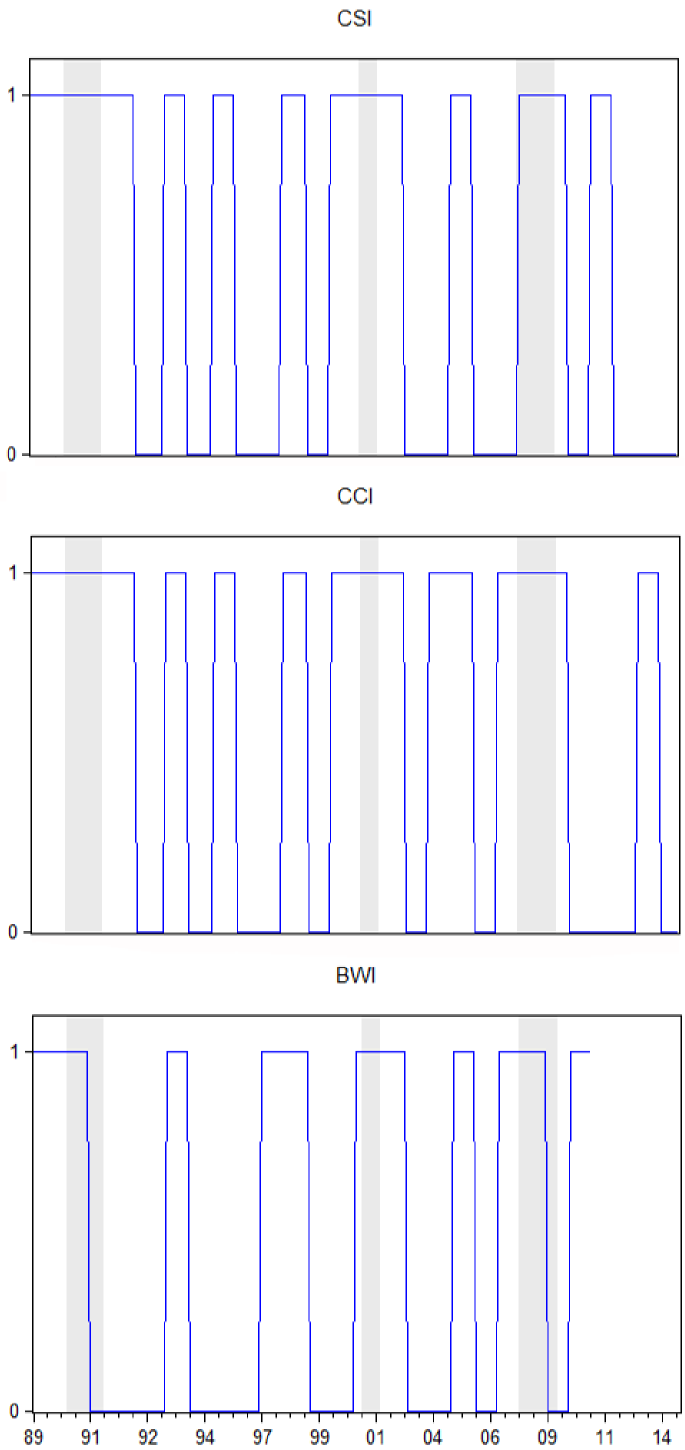
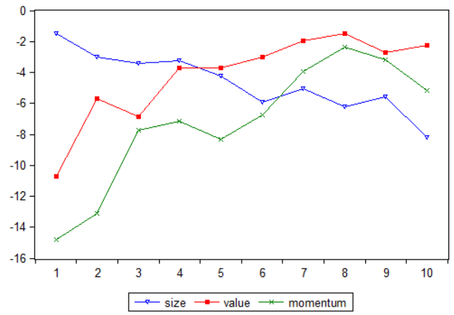


Figure 5: Response of size, value and momentum sorted portfolio returns to monetary policy shocks during periods of high sentiment

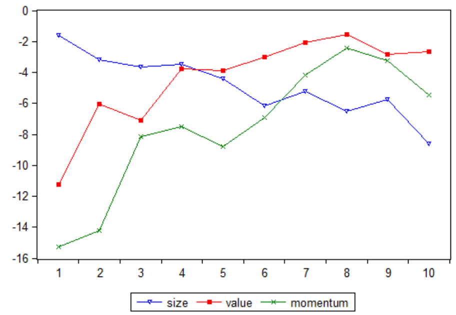
This figure plots OLS estimates of the impact of unexpected FFR changes on portfolio returns during periods of high sentiment, as captured by β_2 in the following model: $R_{it}=\beta_0+\beta_1(1-S_t^H)\Delta i_t^u+\beta_2 S_t^H \Delta i_t^u+\varepsilon_t$, where R_{it} and Δi_t^u denote portfolio returns 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

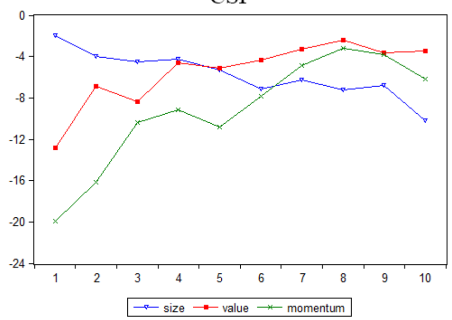


CCI



Panel B: Pre-crisis

CSI



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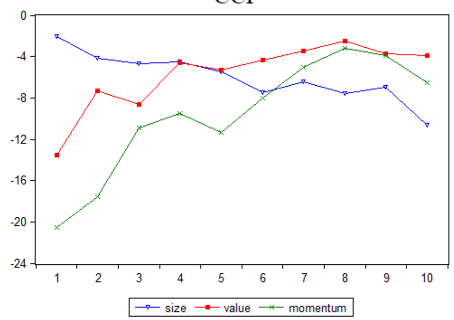

BWI