The FOMC Risk Shift*

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Abstract

We identify a component of monetary policy news that is extracted from high-frequency changes in *risky* asset prices. These surprises, which we call "risk shifts", are uncorrelated, and therefore complementary, to risk-free rate surprises. We show that (i) risk shifts capture the lion's share of stock price movements around FOMC announcements; (ii) that they are accompanied by significant investor fund flows, suggesting that investors react heterogeneously to monetary policy news; and (iii) that price pressure amplifies the stock market response to monetary policy news. Our results imply that central bank information effects are overshadowed by short-term dynamics stemming from investor rebalancing activities and are likely to be more difficult to identify than previously thought.

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1. Introduction

US monetary policy announcements are one of the most anticipated news events and are well known for frequently triggering large movements in stock prices. However, previous studies focusing on the response of equity returns to surprises in risk-free interest rates around FOMC announcements typically account only for a small share of these large stock price movements. For example, the seminal work by Bernanke and Kuttner (2005) concludes that "only a small portion of the overall variability of stock prices" around FOMC announcements of less than 20% is explained by surprises in risk-free rates. Studies using more recent samples and high frequency data confirm this finding (e.g., Gorodnichenko and Weber (2016)).

The fact that more than 80% of the FOMC stock market response remains unexplained means that a sizeable component of the information provided by FOMC announcements must be *unrelated* to risk-free rate surprises. It is this "dark matter" of the impact of FOMC news that is the subject of this paper.

Previous work has already shown that monetary policy surprises have several facets, and it has decomposed "risk-free rate surprises" around monetary policy events into (i) news about economic fundamentals (e.g., the information channel studied by, e.g., Campbell, Evans, Fisher, and Justiniano (2012), Nakamura and Steinsson (2018), or dividend growth (Bernanke and Kuttner, 2005)), and (ii) risk premium changes (e.g., again Bernanke and Kuttner (2005)). However, from an asset pricing perspective, it is unlikely that risk-free rate surprises *fully* encode all new information about economic fundamentals and risk premia in particular. Hence, monetary policy surprises extracted from changes in risk-free interest rates alone will necessarily lack an important part of the information contained in monetary policy announcements.

Against this backdrop, we make three contributions to the literature. Our first contribution is to propose a parsimonious way of identifying a component of monetary policy news that is extracted from *risky* asset prices and goes beyond the information reflected in risk-free rate surprises. We refer to this component of monetary policy news as "risk shifts" in the following. Our approach follows a high frequency event-study design (as in, e.g., Cochrane and Piazzesi, 2002; Gürkaynak, Sack, and Swanson, 2005; Gorodnichenko and Weber, 2016). Under the usual assumption that only monetary policy news is released to the market in a short-window around FOMC announcements, we can measure monetary policy news from the price reaction of a cross-section of risk-free assets (short-term and long-term government bond futures) and risky assets (the VIX, CDS premia and the US dollar).

To extract "risk-free rate surprises" and "risk shifts", we rely on a standard factor analysis (e.g., Gürkaynak, Sack, and Swanson, 2005; Swanson, 2020). The first two surprise components we extract capture short- and long-term interest rate surprises as in the earlier literature (Bernanke and Kuttner, 2005; Gürkaynak, Sack, and Swanson, 2005; Hanson and Stein, 2015; Swanson, 2020). The third surprise component is novel and captures changes in how investors evaluate and price risks—hence, our label "risk shifts". Understanding risk shifts is crucial for shedding light on the large stock return response to FOMC news that has remained unexplained by risk-free rate surprises. Risk shifts are *by construction* orthogonal to risk-free rate surprises and thus reflect monetary policy news released around FOMC announcements that goes beyond what is captured by risk-free assets.

Our second contribution is to provide a better understanding of how financial markets absorb FOMC news. The two risk-free rate surprises together account for less than 20% of the variation in equity returns in our sample, which is in line with the most recent estimates in the literature (e.g., Gorodnichenko and Weber, 2016).[1] By contrast, we find that risk shifts emerge as a more powerful driver of stock returns on FOMC announcement days. For example, a one-standard deviation FOMC risk shift corresponds to an initial equity excess return of 0.70% and accounts for about 70% of the event window variation in equity returns.

When looking at the persistence of the impact of risk shifts, however, we find a large part of the price response to FOMC risk shifts to be reversed after about four weeks. This result in

[1] There is a large and growing literature on the link between risk-free rate surprises and stock returns. A non-exhaustive set of contributions includes Shiller, Campbell, and Schoenholtz (1983), Adrian and Shin (2010), Borio and Zhu (2012), Bekaert, Hoerova, and Duca (2013), Morris and Shin (2016), Gertler and Karadi (2015), Hattori, Schrimpf, and Sushko (2016), Gorodnichenko and Weber (2016), Schmeling and Wagner (2019), Leombroni, Vedolin, Venter, and Whelan (2020), Adrian and Liang (2018), Neuhierl and Weber (2019), Ozdagli and Weber (2016), Swanson (2020)), Boyarchenko, Haddad, and Plosser (2017), or Drechsler, Savov, and Schnabl (2017), Nakamura and Steinsson (2018), Bauer, Lakdawala, and Mueller (2019) among others.

turn suggests that the reaction of asset prices driven by FOMC risk shifts is mostly transitory in nature and unlikely to be *fully* driven by changes in (expected) fundamentals and/or longer horizon risk premia. Our empirical finding of mean-reverting stock prices in response to risk shifts is particularly surprising, as the contemporaneous study by Neuhierl and Weber (2020) reports that conventional risk-free rate surprises generate a drift in stock prices. Put differently, risk-free rate surprises and risk shifts, which are uncorrelated by construction, tend to generate opposite empirical stock price responses. At the same time, both empirical findings show that a large part of the response of prices to monetary policy news is not confined to short event windows that are typical in the literature.[2]

A novelty of our work is that we look at both prices and *quantities*. Bernanke and Kuttner (2005) already conjectured that "the large movement in excess returns associated with monetary policy" might also reflect, at least in part, "excess sensitivity or overreaction of stock prices to policy actions". Our analysis addresses this conjecture by studying fund flows and trading volumes triggered by exchange traded fund (ETF) investors around FOMC announcements.[3]

Large fund flows and trading volumes around FOMC announcements indicate that one group of investors must buy (or sell) from another group of investors. Our finding that risk shifts trigger a sizeable response of ETF flows and trading volumes implies that investors *must* react heterogeneously to monetary policy news. Thus, a natural explanation is that the impact of news about fundamentals on stock prices is amplified by price pressure due to rebalancing demands from a subset of investors (e.g., Scholes (1972); Stoll (1978); Grossman and Miller (1988)).

Our third contribution is to provide a deeper understanding of *why* risk shifts occur and why they are associated with the bulk of the stock market response to FOMC announcements. As a first step, we quantify the importance of fluctuations in risk premia versus price pressures as drivers of the stock market reaction to FOMC news. We use two complementary approaches. In

[2] See also Hanson, Lucca, and Wright (2018), who provide evidence that long-term rates show "excess sensitivity" at high-frequencies.

[3] Ben-David, Franzoni, and Moussawi (2018) show that ETFs are popular among active institutional investors and account for a large share of the trading volume of the underlying individual shares. Other recent papers that stress the importance of using investment quantities to gauge investors' expectations and preferences include, e.g., Jotikasthira, Lundblad, and Ramadorai (2012), Greenwood and Shleifer (2014), Ben-Rephael, Kandel, and Wohl (2012), Berk and van Binsbergen (2016), Gabaix and Koijen (2020), Koijen, Richmond, and Yogo (2020).

the first (vector autoregressions), we estimate the role of risk premia and measure price pressure indirectly as the unexplained part of returns (cf. Campbell and Shiller, 1988; Bernanke and Kuttner, 2005). In the second, we identify price pressure directly by using fund flows.[4] We conclude that our results put a lower bound of 50% (directly estimated) and an upper bound of 54% (indirectly estimated) on the role of price pressures. Thus, the asset price dynamics stemming from trading among investors turn out to be of roughly equal importance as the fundamental news content of FOMC announcements.

A central question remains, however: *why* do investors react so strongly to the monetary policy surprises captured by FOMC risk shifts, such that we observe a large trading volume and a rebalancing of risky assets? To answer this question, we first rely on textual analysis of news article sentiment and market commentary to shed light on investors' risk rebalancing decisions. If "risk shifts" reflect that certain groups of (presumably more active) investors seek greater exposure to risk, we should expect news sentiment around such FOMC days to turn more positive. We find that positive FOMC risk shifts correlate with more positive news articles as measured via sentiment scores. Second, we provide a qualitative analysis and collect commentary from market participants (e.g., traders, analysts, economists) on the outcome of the meeting shortly after an FOMC announcement. Although this type of analysis is not intended to establish causality, the results are in line with the idea that when the Fed delivers a policy action confirming the prior views of market participants, we observe a positive risk shift and higher stock prices.

A plausible interpretation of these results is that the short term dynamics around FOMC announcements are shaped by the interactions of heterogeneous investors. Market participants naturally differ in their rebalancing frequencies and investment horizons. Some players rebalance their portfolios frequently and may adjust their positioning based on monetary policy news. Others, by contrast, play a more passive role by just absorbing such flows, e.g., market makers and long-term passive investors such as insurance or pension funds. Our results suggest that monetary policy news that does not conform with the priors of active traders leads to a drop in

[4]Earlier studies that find evidence for fund-flow induced price pressure effects include, e.g., Jotikasthira, Lundblad, and Ramadorai (2012), Coval and Stafford (2007), and Mitchell, Pulvino, and Stafford (2004).

their willingness to take risks and a rebalancing away from risky assets. Such negative risk shifts go hand in hand with a surge in trading volume and price pressure to induce passive investors to absorb these flows, which is subsequently reverted.[5] Opposite patterns are observed in the case of the central bank's action conforming with active traders' priors.

What these patterns suggest is that heterogeneous demands for risky assets add a layer of short-term transitory movements to risky asset prices following FOMC announcements. Such an effect can be seen as complementary to the traditional drivers of asset prices in macro-finance. For example, Campbell (2017) shows that heterogeneous investor beliefs can amplify traditional stochastic discount factors (SDFs) and therefore lead to "excess volatility". So even if traditional SDFs are usually slow-moving, heterogeneous demands for risky assets can allow for volatile short-term dynamics of the SDF and thus asset prices.

An alternative explanation is that "the market" agrees on the revealed news. The transitory component then reflects changes in expected returns (or dividends) that happen at a much higher frequency than assumed in traditional equilibrium models. This explanation would require, however, that such changes in expectations are not captured in our return decomposition (or changes in expectations about dividends happen faster than dividends are realized). But such an explanation, in fact, cannot explain the large ETF flows that we document.

Another alternative explanation could be that "the market" overreacts in the aggregate. In this case, the average investor has overly optimistic/pessimistic expectations after certain FOMC announcements and subsequently adjusts to more realistic expectations. We do not test such a hypothesis, as it would require high-frequency (daily) survey expectations of investors. However, we notice again that such an aggregate overreaction effect cannot explain at the same time the large ETF flows that we observe, which requires differential demands between investors.

Our results have a number of implications for the literature on how monetary policy affects financial markets. First, several recent papers study stock market returns around FOMC announcements. The sizeable mean-reverting component that we document suggests that the

[5]Recently, Bollerslev, Li, and Xue (2018) study the relationship between trading volume and return volatility for various macroeconomic announcements. They argue that the observed relationship is in line with models that allow for disagreement between investors, which squares with our findings.

announcement response of stock prices overstates the fundamental news content of these events. Second, our fund flow results are direct evidence that investors react heterogeneously to the announcement of monetary policy. Thus, theory that tries to understand how market expectations are shaped by monetary policy may want to consider the possibility that investors "disagree" in their assessment of monetary policy and react differently. Third, we find that surprises unrelated to risk-free rates capture the lion's share of stock returns around FOMC announcements but that their impact on prices is largely transitory. This finding challenges the view that asset prices immediately and fully reflect fundamental information about the real economy after FOMC announcements. Instead, the mean-reverting stock market response indicates that the impact of news about fundamentals on stock prices is amplified by price pressure, due to rebalancing demands from a subset of investors, which can overshadow central bank information effects. In other words, financial market participants require time to digest monetary policy announcements via the trading process.

2. Monetary policy surprises

2.1. Conceptual framework and connection to the literature

We are interested in the channels through which news about monetary policy affects stock prices. One way to think about different channels is the standard present-value relation, which states that stock return surprises

$$r_{t+1} - E_t r_{t+1} \cong (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \triangle d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \left(rf_{t+1+j} + rp_{t+1+j} \right), \qquad (1)$$

must come from (i) news about future dividends ($\triangle d_{t+1+j}$), (ii) changes in the risk-free component of discount rates (rf_{t+1+j}), and (iii) changes in the risk premium component of discount rates (rp_{t+1+j}), e.g., Campbell (1991). Hence, if stock prices respond to monetary policy news, the effect *must* be operating through one (or a combination) of these three channels.

It is straightforward to see that risk-free rate surprises could affect stock returns directly, via their effect on current discount rates (rf_{t+1+1}), or the term structure of expected discount rates (rf_{t+1+j}). The three channels (rf_{t+1+j}, $\triangle d_{t+1+j}$, rp_{t+1+j}) are likely to overlap to some degree. That is, risk-free rate surprises might also reveal information regarding future expected (dividend) growth ($\triangle d_{t+1+j}$), in line with an information channel (see, e.g., Campbell, Evans, Fisher, and Justiniano, 2012). Similarly, risk-free rate surprises might contain information regarding risk premia (rp_{t+1+j}) as well (see, e.g., Bernanke and Kuttner, 2005).

Crucially, though, risk-free rates are unlikely to *fully* span all relevant information about dividend growth and particularly risk premia—by now a well-accepted view in the asset pricing literature (see, e.g., Cochrane, 2017, for a survey).[6] We therefore go beyond risk-free rates and extract monetary policy surprises from a set of variables known to strongly covary with changes in risk premia to capture this missing piece of information.

Based on this argument, Figure 1 provides a taxonomy of monetary policy news and distinguishes between news about (current and future) risk-free rates (*), e.g. Kuttner (2001); Gürkaynak, Sack, and Swanson (2005), as well as news embodied in risk-free rates that reflect expectations about economic growth and risk premia (**), e.g., Bernanke and Kuttner (2005); Campbell, Evans, Fisher, and Justiniano (2012); Nakamura and Steinsson (2018). The upper and lower left quadrants indicate the main focus of the prior literature in this field. The lower right quadrant indicates news that this paper explores but which has received much less attention in the literature so far.

The novelty of our approach is that it seeks to capture the part of growth news and changes in risk premia relevant for stock prices, which is not captured by risk-free rates. This is what we refer to as "risk shifts" in this paper. We argue that this complementary component of monetary policy news is crucial for explaining the financial market reaction to monetary policy

[6] To give some examples, in the habit model as proposed Campbell and Cochrane (1999), the parameters that drive the risk-free rate are chosen such that the equity risk premium is perfectly uncorrelated. In the long-run risk model of Bansal and Yaron (2004), the risk-free rate and the risk premium load differently on the state variables (long-run (growth) risk and time-varying volatility risk) making the two weakly connected. In the time-varying rare disaster risk model of Wachter (2013), there is a single state variable (the rare disaster risk probability) making the risk-free rate and the risk premium rather strongly correlated. She argues that this correlation is counterfactual and discusses how adding a second (catastrophe) state variable to the model would weaken the correlation. See Seo and Wachter (2018) for such an extended version of the model.

announcements.[7]

Figure 1: A simple taxonomy of monetary policy news

	news captured by risk-free rates	news captured by risky asset prices but not captured by risk-free rates
news about current and future short-term rates	**"risk-free rate surprises"** direct effect of risk-free rates	-
news about economic growth and risk premia	**"risk-free rate surprises"** information channel	**"risk shifts"** extended information channel

The empirical analysis in this paper can be understood against the backdrop of this taxonomy. Our goal is to quantitatively measure the return component which moves the stock market upon the revelation of monetary policy news and is unrelated to risk-free rate surprises.

2.2. Measurement

Following the argument above, our goal is to extract monetary policy surprises that are *orthogonal* to risk-free interest rate surprises from a cross-section of asset price changes. We do so by means of a factor analysis on FOMC announcement days following the methodology put forth in Gürkaynak, Sack, and Swanson (2005) and Swanson (2020). In contrast to the previous literature, we expand the cross-section of assets beyond risk-free interest rates and also extract information about risky asset prices. More specifically, we employ a broad cross-section of changes in 3-month rates, as well as 2-, 5- and 10-year Treasury yields implied by futures prices. In addition, we augment this set of risk-free assets with a cross-section of risky asset prices, namely changes in CDS spreads (CDX corporate investment grade index), changes in

[7] A few papers study how FOMC announcements affect market uncertainty, e.g. Fernandez-Perez, Frijns, and Tourani-Rad (2017) and Boguth, Gregoire, and Martineau (2019), which can be viewed as a subset of the risk premium channel. These studies do not link to the stock market response to FOMC announcements. See also the contemporaneous study by Bauer, Lakdawala, and Mueller (2019), which investigates how monetary policy uncertainty affects financial markets.

the value of a broad US dollar index (for which a higher reading means a dollar appreciation), as well as changes in S&P500 option implied volatility (VIX) (see, e.g., Boguth, Gregoire, and Martineau, 2019; Fernandez-Perez, Frijns, and Tourani-Rad, 2017; Mueller, Tahbaz-Salehi, and Vedolin, 2017, for related papers).[8]

The three risk proxies are directly derived from market prices, i.e., they are able to quickly respond to news, and we can measure them at high frequencies. Moreover, it is well understood that these asset prices are very sensitive to changes in investors' perceptions and risk compensations. Bollerslev, Tauchen, and Zhou (2009) and Martin (2017) show that changes in option-implied volatility are linked to changes in the equity premium under rather general conditions. Merton (1974) and recently Seo and Wachter (2018) show that the credit risk premium is theoretically affected by factors common to the equity premium. Recent papers have argued that movements in the dollar are related to policy uncertainty (Mueller, Tahbaz-Salehi, and Vedolin, 2017) and are a key barometer of risk (Avdijev, Du, Koch, and Shin, 2017).

We take a comprehensive view and collect intraday data on days with scheduled (# 112) and unscheduled (# 2) FOMC announcements between 2006 and 2019, for which detailed data on prices (and fund flows) are available.[9] We then measure the change of the seven variables within an event window of 90 minutes (-15m:+75m) around FOMC announcements. Since 2011, the Fed frequently holds a press conference about one up to two hours after the actual announcement. Recent evidence suggests that press conferences carry important information for investors (e.g., Boguth, Gregoire, and Martineau (2019) and Cieslak and Schrimpf (2019)). In these cases (36), we extend the event window to the closing price (16:15) of the announcement day.[10] We use log changes of the three risky asset prices to reduce the impact of heteroscedasticity and standardize all seven variables based on their FOMC day standard deviation.

>>> TABLE 1 ABOUT HERE <<<

[8]Over large parts of our sample, the ultra-short end of the yield curve was constrained by the effective lower bound on interest rates. Thus, we do not include overnight interest rates or futures on Fed funds rates in this exercise to extract monetary policy surprises. The robustness section compares our results to monetary policy surprises based on Fed funds futures for the period prior to the effective lower bound.

[9]We provide robustness based on a longer sample periods going back to 1994 (with less detailed data) later in the paper. Our event list is available in the Internet Appendix, Table IA.4.

[10]The robustness section provides results for (i) tighter and wider event windows, (ii) ignoring press conferences, (iii) removing the financial crisis, or (iv) the period where rates are close to the ELB from the sample.

To extract monetary policy surprises, we then run a principal component analysis (PCA) of the asset price changes at high frequency. The left hand side of Table 1 shows that the first three principal components explain more than 90% of the variances of the seven variables. However, the three factors are purely determined by how much variance they explain. Thus, to obtain monetary policy surprises that are easier to interpret economically, we apply an orthogonal factor rotation on the first three principal components (e.g., Gürkaynak, Sack, and Swanson (2005)).[11] Table 1 shows that the first rotated factor targets the front-end of the yield curve. The second targets the remaining long-term bond yields. The third factor targets the market-based risk proxies (VIX, CDS prices and the US dollar). This factor is orthogonal to the two others *by construction*. It hence captures monetary policy news that is not spanned by risk-free rate surprises.

2.3. Characterisation of rotated factors

The loadings on the rotated factors are reported on the right hand side of Table 1. Based on these loadings, we characterise the three monetary policy surprises as follows:

(1) "*Short Rate Surprises*": The first factor primarily loads on 3-month and 2-year yields and has low loadings on all other variables. It is mildly exposed to the market-based risk proxies. This surprise measure thus mostly captures changes in the central bank's policy target as well as expectations of its evolution over the nearer term.

(2) "*Long Rate Surprises*": The second factor loads particularly on 5- and 10-year yields. Thus it captures news about asset purchases that affect the yields on long term bonds through signalling and/or portfolio rebalancing channels. While it has basically no exposure to short-term yields, it has some exposure to the risk proxies. However, these exposures are small in magnitude and also have opposing signs (negative for VIX, but positive for the US dollar) so that there is no clear link to risky asset prices.

(3) "*Risk Shifts*": The third factor loads consistently negatively on all three market-based risk proxies, but does not load strongly on yields. A rise in this surprise measure goes along

[11] Technical details on the factor rotation are provided in the Internet Appendix, Section IA.B.

with a drop in the VIX, a weakening of the Dollar, and a compression in CDS premia. We thus label this policy surprise a "risk shift" in the following.

To be clear, the labels we assign to the monetary policy surprises are purely descriptive and simply indicate on which asset prices they predominantly load. We investigate the economic mechanisms driving these surprises more closely in Section 4 below.

Illustration: We plot the realizations of *risk shifts* (standardized to a unit standard deviation) in event time in Figure 2. Plots for the more familiar short-rate and the long-rate surprises can be found in the Internet Appendix (Figure IA.2 and IA.3).

>>> FIGURE 2 ABOUT HERE <<<

Interestingly, we observe large risk shifts on several days with important monetary news, even though risk shifts are by construction uncorrelated with movements in risk-free short and long rate surprises. For example, we find that risk shifts are positive on key announcements related to the introduction of QE2 and QE3. While interest rates barely moved on these announcements, a positive risk shift suggests that financial markets moved into "risk-on" mode. By contrast, we observe a negative risk shift realization on the announcement of an unscheduled cut of interest rates by 75 bp in January 2008. Likewise, we find a large negative risk shift in mid-2013 when the FOMC alluded to the possibility that it might slow down its asset purchases (an episode known as the "taper tantrum"). These examples serve to show that risk shifts are strongly affected by monetary policy news, but that they capture a dimension not spanned by risk-free rate surprises.[12]

[12]Since our approach of extracting (rotated) factors is crucial for the remainder of our paper, we provide several checks to document that our risk shift measure is robust and meaningful. We show that (i) the third (rotated) factor is not simply identical to the VIX by conducting a "leave-one-out"-analysis where we sequentially exclude one of the three risky asset prices when constructing our factors (see Figure IA.5). (ii) We test the reliability of the factor analysis by conducting a simulation experiment such that we can compare the empirically extracted surprises with "true" monetary policy surprises from a reduced-form model. Our results indicate that the factor analysis is indeed able to filter the "true" factors with high accuracy (Section IA.C). (iii) We show that a simple regression-based orthogonalization leads to similar results as the PCA-based factor analysis (Figure IA.6).

2.4. Fund flows and additional data

Fund flows: A novel angle in this paper is to study how quantities respond to monetary policy news alongside prices. To this end, we collect daily ETF data from Bloomberg. We aggregate individual funds to asset classes. Our measure for US equity is based on funds that belong to Bloomberg's category "Blend". We construct flows for other asset classes in the same way. Fund flows at the asset class level are measured as:

$$F_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}\,(1 + R_{i,t})}{TNA_{i,t-1}}, \tag{2}$$

where $TNA_{i,t}$ are total net assets of asset class i (e.g., equities) at time t, and $R_{i,t}$ is the fund return of asset class i. Because fund flows do not have an economically meaningful long-run mean or standard deviation, we apply a normalization of flows (see, e.g., Berk and van Binsbergen (2016), Menkhoff, Sarno, Schmeling, and Schrimpf (2016)). We rescale all flows to a zero mean and 1% standard deviation using a backward 250-days rolling window. The standardized flows are stationary according to the Augmented Dickey-Fuller test (p-values: 0.00; Internet Appendix, Table IA.2.)

Our baseline sample starts in January 2006 and ends in December 2019. The starting year 2006 ensures that we observe an equity flow at every single day (Internet Appendix, Table IA.2). Further details on the fund flow data and their coverage over time is provided in the Internet Appendix.

Additional data: Results for intraday asset price movements are based on the S&P500 index provided by Tickdata (symbol SP). For results on prices and quantities at the daily or longer horizons, we simply rely on the fund return $R_{i,t}$ for asset class i. Using fund returns ensures that the fund flow identity implied by Equation (2) is exactly satisfied and we capture the total change of investors' exposure to asset class i. We refer to the Internet Appendix for further details.

3. Returns and fund flows on FOMC days

In this section, we first study how US equity prices and quantities (flows) respond to the revelation of news on FOMC days. Subsequently, we study for how long these effects persist.

3.1. Initial response

Method: We run regressions of equity returns and flows on our monetary policy surprises on FOMC announcement days:

$$X_{t|FOMC} = a + b \times Monetary\ Policy\ Surprise_{j,t|FOMC} + \xi_{t|FOMC}. \tag{3}$$

Monetary policy surprises are measured intraday as outlined above. The baseline event window is 90 minutes and ranges from -15 to +75 minutes for announcements without a press conference, and -15 minutes to the closing price (16:15) for announcements with a press conference. Equity returns are measured (i) intraday using the S&P 500 index and covering the identical event window as for the monetary policy surprises, or (ii) daily (close to close) using equity ETFs.[13] Equity fund flows are measured daily using the same ETFs as for the daily returns. Standard errors are based on a bootstrap that accounts for the fact that the regressors are estimated.[14] Table 2, Panel A, shows our baseline results.

Equity prices: We find that stock prices react negatively to short and long interest rate surprises, in line with intuition. The t-statistics, however, indicate a relative low precision of the estimates and the regression R^2s are fairly low (below 10%). Risk-free rate surprises thus do not account for a large amount of variation in stock returns on FOMC days. Hence, judging from risk-free rate surprises alone, the stock market response largely represents "dark matter". This in turn implies that the well-documented strong response of the equity market to FOMC news must to a large extent be driven by economic forces not spanned by risk-free rate surprises.

[13] We use all equity ETFs that belong to the Bloomberg category Blend; see the Internet Appendix for details.

[14] We implement a pairwise bootstrap where the monetary policy factors are re-calculated from the re-sampled underlying financial assets such that the bootstrap standard errors account for the fact that the explanatory variables are estimated. Further details can be found in the Internet Appendix, Section IA.D.

>>> TABLE 2 ABOUT HERE <<<

Our results in Table 2 show that risk shifts emerge as a much more powerful factor to explain the stock market response on FOMC days than risk-free rate surprises. We find that a one standard deviation rise in our risk shift measure goes hand in hand with an intraday equity return of 0.69%, which is highly significant (t: 9.6). The large R^2 of 72% shows that risk shifts capture the bulk of the stock market response to the revelation of monetary policy news. Put differently, the same economic forces that move the financial instruments underlying our FOMC risk shift variable also lead to a strong equity price reaction. Point estimates for daily returns match with the intraday response (0.64%). The R^2 and t-statistics are lower, reflecting the fact that daily returns measure the response to monetary policy news with more noise (as also information unrelated to the monetary policy event gets impounded into prices when moving beyond a tight intraday event window). The effect of FOMC risk shifts is economically large. The annualized effect of a one-standard deviation surprise raises equity returns by 5.5% p.a. (=0.69%×8)—a similar order of magnitude as estimates of the unconditional equity premium.

Comparison to non-FOMC days: It is instructive to compare what happens on FOMC days with non-FOMC days, especially to see if we see similar effects induced by risk shifts. We hence present results for a control group experiment in Panel B of Table 2 where we first construct "pseudo" factors using all other days in our sample based on an event window that ranges from 11:00 to 12:30. These factors use the same weights as in Table 1. The difference is that there is no systematic link to monetary policy news.[15]

Our results based on the control group indicate that the asset price response on FOMC days is markedly different compared to days without any monetary policy news. For example, bond yields and equity returns are positively related on normal days, while equity returns covary much more with changes in long-term as opposed to short-term rate surprises (also see Cieslak and Schrimpf, 2019, on the comovement of stock returns and bond yields in response to risk premium fluctuations.). As expected, we find that equity returns respond positively to risk

[15]We simply use all other days and not days based on certain criteria (e.g., "no news days") to not influence the outcome by setting the selection criteria. This convention should provide conservative and robust results.

shifts in the control group as well. But, the reaction is much more muted, as indicated by a substantially smaller initial impact (point estimates of 0.25 vs 0.69) and a smaller R^2 (48% vs 72%). The market reaction on FOMC days hence seems special and not purely mechanical.

Equity fund flows: Turning to the reaction of quantities, we find that investors' portfolio reallocation decisions closely follow the price response of equities. A positive one unit standard deviation FOMC risk shift is associated with significant daily flows to equities of 0.42% (t: 4.0) on FOMC announcement days. The comparison to the control group shows that the equity fund flow reaction is much stronger on FOMC days (point estimates of 0.09 vs 0.42). Finally, we find that a pick-up in short-term rates typically goes hand in hand with outflows from equities, in line with the reasoning that monetary policy tightening signals lower stock returns going forward. These initial reallocations are economically sizeable (about -0.20%) and confirm that monetary policy surprises lead to some significant position adjustments by investors.

Discussion: We find that risk shifts are more successful in explaining the stock market response on FOMC days than conventional risk-free rate surprises are. Risk shifts thus are the primary candidate to explain the strong stock market response unexplained by changes in risk-free rates. We provide extensive robustness checks on this novel result later in the paper. Among other things, we show that (i) the weak result for risk-free rate surprises is also present in an extended sample from 1994 to 2019.[16] (ii) our results are mainly unaffected by sensible variations in the event window (Table IA.11). (iii) we find that other macroeconomic news (e.g. nonfarm payrolls) also share the elevated sensitivity of stock returns to our measure of risk shifts, but do not trigger nearly as large fund flows. At the same time, their impact on stock prices is also more persistent, in line with a fundamental news component being impounded in prices (Figure IA.10).

[16] We also find that removing the effective lower bound (ELB) period (12/2008 to 12/2015) has little effect on the results for all three surprise measures and that risk shifts have been significant drivers of the stock market response already prior to the effective lower bound period (see Figure 7 and Tables IA.7, IA.8, IA.9) our results are robust to using surprises measured from Fed funds futures instead of short and long-term bond yields (Table IA.10)

3.2. Persistence of the response

The main goal of this subsection is to study the persistence of the effects documented above. All left-hand side variables, flows and returns, are sampled daily (close-close) and are based on ETF data for consistency. The policy surprises are measured intraday using a 90-minutes window as before.

Method: To estimate the long-horizon reaction of asset prices and fund flows, we run local linear projections (Jorda, 2005) of fund returns and flows on monetary policy surprises:

$$X_{t \to t+h} = a_h + b_h \times Monetary\ Policy\ Surprise_{j,t} \times D_{FOMC,t} + \xi_{t+h}, \tag{4}$$

where $X_{t \to t+h}$ denotes the cumulative fund return, or flow, h denotes the horizon over which we cumulate the dependent variable (from $h = -1$ to $h = 20$ business days), $MonetaryPolicySurprise_{j,t}$ is one of the three orthogonal monetary policy surprises (see Table 1 for details), and $D_{FOMC,t}$ is a dummy variable taking the value of one at FOMC announcement days between 2006 to 2019. As above, standard errors are based on a bootstrap that accounts for the fact that the regressors are estimated (see Table 2 for details).

Since our goal is to estimate the *longer-term* response of asset prices and flows to monetary policy surprises here, we have to guard against potentially confounding information due to other monetary policy news released by the Fed (up to the horizon h). For this reason, we employ the database of monetary policy events by Cieslak and Schrimpf (2019) to screen for other events that take place in the window from $h = +1$ to h=+20 business days after a particular announcement. As a result, we remove 18 confounding events from the event list and the last announcement, as we do not observe sufficient observations afterwards.[17] This leaves us with 95 monetary policy decision events that allow us to estimate the longer-term effects of our

[17] These are 13 FOMC events followed by unscheduled announcements of unconventional monetary policy, one unscheduled rate decision that was followed by a scheduled announcement shortly thereafter, and four events that were followed by influential speeches. See Table IA.4 in the Internet Appendix for details.

monetary policy surprises.[18]

Risk shifts: Figure 3 summarizes the reaction of equity prices and flows to a unit standard deviation increase of the FOMC risk shift variable. Reproducing our finding from above, an increase in risk shifts goes hand in hand with significantly higher daily returns of 0.65% (bootstrap t-statistic of 7.3) on FOMC days (close-close). However, as is also evident from Figure 3, we find the impact to be largely transitory. After about one week, the initial increase in equity prices begins to melt away and is substantially reversed after about four weeks.

>>> FIGURE 3 ABOUT HERE <<<

Turning to the reaction of quantities (lower panel of Figure 3), we find that portfolio reallocations quite closely follow the price response. More precisely, a positive one unit standard deviation FOMC risk shift leads to significant initial increase of 0.62% in standardized flows on FOMC days. In the following couple of days, the shift to equities continues and cumulates to about 0.72% after five days. Afterwards, these reallocations are starting to reverse with ETF investors pulling out from equities, mirroring the pattern for prices.

Risk-free rate surprises: Table IA.5 and Figure IA.4 in the Internet Appendix present results on the longer-horizon effects for all three monetary policy surprises. In addition, the table shows results for bonds as well as the difference between equities and bonds, i.e., a measure of the equity premium. We find that a one standard deviation surprise in short rates decreases equity prices by -0.49% (bootstrap t-statistic of -4.4). Point estimates indicate a more persistent response over horizons of up to four weeks. Turning to the fund flows, we find that the initially sizeable reallocations are also transitory at a four-week horizon. One would have also expected surprises to long-term rates to have become more prominent as drivers of stock prices during the period of the effective lower bound (ELB) and unconventional policies since 2009. Yet, this is not borne out in the data as we detect no statistically significant effects on stock returns.

[18]Note that as a result we look at a slightly different set of FOMC announcements compared to the previous section (Table 2). For that reason, we do not expect to find the exactly identical results for daily returns and daily fund flows. The 18 confounding events cluster around the financial crisis; 17 confounding events fall into the period 12/2007 - 08/2011. As discussed in the robustness section, the Internet Appendix provides results when we ignore confounding events or when we remove the period of the financial crisis altogether.

4. Understanding FOMC risk shifts

We now turn to the crucial question of *why* we observe such strong price and flow movements in relation to FOMC risk shifts. More specifically, we evaluate three main hypotheses: (i) monetary policy may lead investors to change their required risk premium (expected future excess return); (ii) monetary policy might affect investors' expected future dividend growth; (iii) the strong but transitory movement in stock prices documented above could arise, at least in part, from price pressure driven by differential demands for risky assets due to investor heterogeneity.

4.1. VAR decomposition: Setup

We use the standard VAR procedure put forth by Campbell and Shiller (1988) to decompose daily market excess returns (S&P 500 index returns minus the short-term risk-free rate) into risk premium changes and a residual. To capture the former, we rely on recently proposed short-horizon equity premium predictors and consider specifications that include the lower bound on the equity premium (i.e., the SVIX-based measure of the equity premium Martin (2017) and the variance risk premium (Bollerslev, Tauchen, and Zhou (2009)).[19] Our VAR also includes the dividend-price ratio for completeness, even though it is known to capture more slow-moving variation in expected returns which is highly persistent (with half-lives of several quarters). That said, including the dividend-price ratio is important for the VAR to produce meaningful decompositions (Engsted, Pedersen, and Tanggaard (2012)).[20] We refer to the Internet Appendix, Section IA.E, for details on the implementation.

4.2. VAR decomposition: Risk premia

Figure 4 illustrates which return components respond the most to the revelation of FOMC news. The black line depicts the reaction of the total return (as before), and the blue line represents

[19] Bollerslev, Tauchen, and Zhou (2009) show that the difference between option implied volatility and expected realized variance predicts future returns at the monthly and quarterly horizon, but not at the annual horizon. Martin (2017) derives an option-implied lower bound on the equity premium and shows that this proxy of the expected equity premium forecasts returns over the short run (also see Martin and Wagner (2019)).

[20] We only have Ian Martin's SVIX data up to 08/2014. For the period 09/2014-12/2019 we thank Karamfil Todorov who provided us with an updated version.

the component that can be attributed to changes in risk premia as measured via the VAR. Thus, the difference between the black and the colored line can be interpreted as the residual return component.

>>> FIGURE 4 ABOUT HERE <<<

We find that (short-term) fluctuations in risk premia play a prominent role on FOMC days, explaining about 46% of the immediate market reaction. Hence, an important part of the price action can be attributed to risk premium changes induced by monetary policy news.[21] That said, the reaction of stock returns is stronger than what can be justified by changes in risk premia alone. The largest part of the price reaction (54%) is transitory, and (as indicated by the difference between the black line and the blue line) almost vanishes after about one week. This finding speaks against the idea that the residual can be explained by dividend growth news as suggested by the present value decomposition, given that one would expect expectations about fundamentals to exhibit a more persistent impact. Yet, this result squares well with the notion that "price pressure" effects amplify the stock return response on FOMC days. We turn to the role of price pressures next.

4.3. Price pressure

Intraday ETF prices and volume. A natural explanation for the large, but transitory, price changes around FOMC days is price pressure due to investor rebalancing, which acts as an amplifier in the short run. To evaluate this possibility, we first document the intraday pattern of ETF prices and volumes around FOMC risk shifts in Figure 5.

>>> FIGURE 5 ABOUT HERE <<<

Figure 5 (left panel) shows the intraday response of the largest US equity ETF, the SPDR S&P 500 ETF. Note that this exercise is based on an extended sample period, which is discussed

[21] Since the VAR relies on a particular set of short-term return predictors, we also consider an (almost) model free specification by just looking at the change in Martin (2017)'s SVIX-based measure of the equity premium at the one year horizon in Figure 4. It provides a conservative estimate because it ignores changes in expectations beyond one year. However, this proxy cannot suffer from overfitting or sample selection issues, as the relationship with expected returns does not need to be estimated. Using the SVIX corroborates the VAR-based conclusion that FOMC risk shifts relate—at least in part—to changes in risk premia.

in detail in Section 5. In this figure, we distinguish depending on the sign of risk shifts but also show the response when pooling over all events. These results confirm that FOMC risk shifts lead to a large response in equity prices following the release of FOMC statements.

Figure 5 (right panel) also reports ETF volume, expressed in relative terms to the average volume in the first two trading hours of the respective day. Trading volume increases substantially with the release of the FOMC statement, on average by a factor of 4.3. The increase is substantially higher for events when large FOMC risk shifts occur (by a factor of 6.1), compared to those with small risk shifts (3.7). Put differently, trading volume is 65% (6.1/3.7-1) higher for FOMC events for which we observe a large risk shift.

This finding confirms that the elevated investor flows measured at the daily horizon can be directly traced to FOMC announcements.[22] This result suggests that there must be a subset of (active) investors, which is particularly sensitive to FOMC news, and expressing its views on monetary policy and the stock market via ETFs. These seemingly more active investors react with economically large reallocations to equities as well as other risky assets.

Fund flow-induced price pressure: We now estimate the amount of price pressure that is *directly* driven by flows to better understand the strong stock market response to FOMC news. To do so, we employ an empirical strategy that is comparable to the earlier literature that distinguishes between the potential information content and price pressure effects stemming from fund flows (e.g., Jotikasthira, Lundblad, and Ramadorai, 2012; Coval and Stafford, 2007; Mitchell, Pulvino, and Stafford, 2004).

There are two theoretical possibilities as to why we observe large flows linked to FOMC risk shifts. First, if flows reflect superior information available to fund investors, we should observe that an initial price reaction is permanent in nature. Second, if flows reflect heterogenous demands of investors without containing superior information such reallocations absorb liquidity and, thus, ultimately give rise to transitory "price pressures" that amplify the stock market

[22] This volume reaction suggests a role for investor heterogeneity in driving the stock market response. For example, Bogousslavsky (2017) shows that infrequent rebalancing by some investors can generate substantial seasonality in asset returns. Such a channel has not yet been considered to theoretically explain the stock market around FOMC events and provides an interesting avenue for future research.

response.[23]

We first decompose stock returns into a component explained by ETF flows and a residual:

$$\begin{aligned} R_t^e = & \; constant + 0.29F_t - 0.08F_{t-1} - 0.02F_{t-5:t-2} - 0.01F_{t-20:t-6} \\ & + (0.20F_t + 0.07F_{t-1} + 0.04F_{t-5:t-2} - 0.05F_{t-20:t-6}) \times D_{FOMC,t} + \iota_t. \end{aligned} \tag{5}$$

This approach is inspired by popular long-memory models of expected volatility, e.g., Corsi (2009). We then compare which of these two components is more permanent and which is transitory. For that purpose, we regress (i) the total return (R_t^e, black), (ii) the return component unexplained by fund flows ($R_{M,t}^e = constant + \iota_t$, blue), and (iii) the return component explained by fund flows ($R_{S,t}^e = R_t^e - constant - \iota_t$, red) on FOMC risk shifts.

Figure 6 summarizes the results. We find that it is indeed the component explained by fund flows that captures most of the transitory reaction. Fund flows thus do not seem to capture information (that is not yet already included in prices), but give rise to substantial price pressures. We find that these "flow-induced price pressures" play a significant part in explaining the FOMC "dark matter", accounting for about 50% (0.33/0.65) of the initial stock return reaction.

>>> FIGURE 6 ABOUT HERE <<<

4.4. Changes in beliefs and risk sentiment

We now turn to an analysis of changes in investor beliefs to better understand the origin of risk shifts. We do so by examining the sentiment in news articles around FOMC days. The rationale for this approach is as follows: if positive risk shifts indeed reflect that more active investors seek greater exposure to risk, by entering into a "risk on" mode, we should observe that news sentiment around such FOMC days becomes more positive. Moreover, the large trading volume around FOMC days suggests sizeable heterogeneity in beliefs between different groups

[23] We provide a detailed explanation of this argument in the Appendix IA.F. We notice that our approach uses the same identification strategy as in the previous literature (e.g., Jotikasthira, Lundblad, and Ramadorai (2012), Coval and Stafford (2007), and Mitchell, Pulvino, and Stafford (2004)).

of investors, which leads to a strong portfolio rebalancing once the more active traders trade towards their desired portfolio allocations (e.g., Scholes (1972); Glosten and Milgrom (1985); Grossman and Miller (1988); or most recently Hendershott and Menkveld (2014)).

News-based sentiment: To test whether risk shifts are indeed related to a change in beliefs of (at least some) market participants, we measure sentiment as the average event sentiment score (ESS) of all articles in the Ravenpack News Analytics database related to "United States Federal Reserve" and "Board of Governors of the Federal Reserve System" in the x days before an FOMC meeting and separately for the x days after an FOMC meeting (we let x vary from 3,5,7,10,...14 days). The change in sentiment is measured as the change in the average of relevance-weighted sentiment scores across the pre- and post-FOMC windows.[24] We then regress these sentiment changes on the three types of monetary policy surprises in univariate and multivariate specifications.

The results are reported in Table 3.[25] We find that news sentiment improves following positive FOMC risk shifts. Results for the yield-based surprise measures are mixed. Long rate surprises that lead to a policy tightening tend to depress sentiment—in line with the idea that monetary policy surprises inferred from long rates are potential proxies for market confidence (Boyarchenko, Haddad, and Plosser (2017)). By contrast, we do not find that short rate surprises have a meaningful relation to the tone of news articles.

>>> TABLE 3 ABOUT HERE <<<

Overall, we find that positive risk shifts, which essentially capture the greater desire by more active market participants to take on risk (akin to a "risk on" mode), are accompanied by a more positive news flow around FOMC meetings. While investor beliefs are not directly observable, this positive correlation of news sentiment and our measure of market-based risk shifts lends some credence to the view that we are indeed capturing a shift in active investors' risk perceptions triggered by FOMC news. Interestingly, we find that long-rate surprises, which

[24]Ravenpack ESS scores are a standard way of proxying for news sentiment. See, e.g., Asness, Liew, Pedersen, and Thapar (2019) for another paper that also relies on these sentiment scores (in a different context).

[25]The sample period is limited to 2006-2017 because of the data available to us.

are orthogonal to risk shifts by construction, also affect news sentiment which underscores our result that there are different, but complementary, components in monetary policy surprises.

Textual analysis of market commentary: To examine the news content *on* FOMC days in more depth, we turn to an analysis of market participants' own interpretation of monetary policy events. We collect market commentaries on the FOMC meeting from *Thomson Reuters Instant View* (TRIV). TRIV collects and publishes views and commentary from market experts (e.g., traders, analysts, economists) on the outcome of the meeting shortly after an FOMC announcement (same day in the late afternoon). We always pick the complete TRIV column for each scheduled FOMC event and do not select particular analysts or firms. We then count the frequency of words relating to economic and financial conditions or the surprise content of the news, divided by the total number of words.

Equipped with these measures, we regress the absolute FOMC risk shift on the relative frequency of these words for the 96 scheduled FOMC meetings from 2006-2017. It is noteworthy that economic conditions (inflation, employment, growth) do not explain a large share of the size of FOMC risk shifts (Table IA.13 in the Internet Appendix). Instead, we find that the phrases capturing changes in investors' risk sentiment or beliefs more generally such as "surprise", "confidence", and "disagreement" are much more closely related. Together, they explain up to 31% of absolute FOMC risk shifts.[26] These results confirm that risk shifts are associated with changes in market participants' risk perceptions. This finding squares with the one above that risk shifts are accompanied by large trading volume and ETF fund flows and suggests that disagreement between different groups of investors plays a pivotal role in generating large price reactions to FOMC news.

Market narratives: Finally, we complement the above results on news sentiment with a *qualitative* approach. In this context, we closely read through the market commentary around FOMC days with large risk shifts and look for common narratives. Our source of information

[26]The Internet Appendix also provides the corresponding results for short rate surprises (Table IA.14 and Table IA.15). We find that both yield-based factors relate to market commentary about "employment". Long rate surprises, in addition, correlate with commentary about"growth" and "confidence".

is again TRIV. We document examples of the type of commentary in Tables IA.16 and IA.17 in the Internet Appendix and only summarize some key take-aways from this exercise here.

A prime example of a risk shift event is the announcement of the Fed's third large-scale asset purchase program (QE3). It comes with one of the largest positive FOMC risk shifts in our sample. A representative quote taken from the markets commentary characterizes the policy action as "exactly what Wall Street and, quite frankly, Main Street wanted from the Fed" (Tables IA.16). Another instructive example is the "taper tantrum" in 2013, which is associated with one of the most negative FOMC risk shifts in our sample. Analysts were taken by surprise by the announcement and summarized that "investors always freak out at what looks like a sea change in policy" (Tables IA.16). A final example comes from the two meetings in early 2015, when the Fed decided to keep the policy rate low for the moment but left the possibility of later hikes open (Table IA.17). At the January FOMC, this was a surprise to markets, as "everybody [had] baked into the cake at least one interest rate hike". In the following meeting in March, the statement removed ambiguity from the statement, and Wall street "applaud[ed] the Fed's action today".

Overall, the qualitative analysis of market commentary suggests that whenever the Fed deviates from expectations by (active) market participants, we tend to observe negative risk shifts akin to a "risk off" mode. Such adverse risk shifts in turn are associated with a drop in stock returns, a higher VIX, higher CDS spreads and a stronger dollar. By contrast, when the Fed delivers a policy action confirming the prior views held by investors, we observe a positive risk shift and active market participants enter into a "risk on" mode.

5. Robustness and further results

Extended sample period, 1994-2019: How does the impact of our three policy surprise measures, in particular that of risk shifts, evolve over time? To address this question, we first re-run our monetary policy factor analysis using an extend sample of 213 FOMC announcements from 1994 to 2019. We rely on the same set of risk-free interest rates as in the baseline results.

However, due to data limitations, we include the VIX as the only risk asset.[27] Table IA.7 in the Internet Appendix provides the results of the extended factor analysis. Furthermore, we conduct a sub-sample analysis by joining the extended sample period data with that from our baseline specification. These results are summarized in Figure 7. Tabulated results can be found in the Internet Appendix, Table IA.8.

>>> FIGURE 7 ABOUT HERE <<<

The upper left figure shows the R^2 of a regression of intraday equity returns on our three policy surprises for 213 FOMC announcements from 1994 to 2019, as well as for 156 announcements that exclude the period where the effective lower bound (ELB) might affect our results (12/2008 to 12/2015). The extended sample results are qualitatively similar to our baseline results (2006 - 2019). Risk shifts explain the bulk of the stock market response around FOMC announcements (44%), followed by short and long rate surprises (at 13% and 0% respectively). Removing the ELB period (12/2008 to 12/2015) has little effect on the R^2s of the three surprise measures.

The remaining sub-figures show results from rolling regressions using the past 40 FOMC announcements (i.e. effectively a 5-year rolling window). Vertical lines indicate the full sample results and the results when we exclude the ELB period for the ease of comparison. We find that short rate surprises played a more important role before the end of 2005, as indicated by R^2s as large as 40%. After 2005, i.e. well before conventional monetary policy was constrained by the ELB, short rates tend to lose in importance as indicated by a fall in R^2s. Regarding long-rate surprises, the subsample analysis confirms that long rate surprises are no important driver of the stock market in any subperiod that we study. This is surprising as one would have suspected a larger role of long-term rates that could at least partly compensate for the declining effect of short rate surprises in the ELB period.[28]

[27]The source and construction of the 1994-2005 data is explained in the Internet Appendix. For the period 1994-1997, we rely on the open and close for the VIX to construct intraday surprises.

[28]First, Swanson and Williams (2014) show that long rates remained responsive to macro news and hence were not constrained by the ELB. Second, certain monetary policies during the ELB, such as quantitative easing and forward guidance, were designed to operate via long rates.

Our weak results for short rate surprises are also not driven by our measure of (short-rate) rate surprises. The sub-figure for short rate surprises adds results based on changes in Fed funds futures as reported in Gorodnichenko and Weber (2016), drawing on the replication data for their paper. We find that the latter only explain marginally more variation of stock returns (FFR:16% vs SR:11%) in the sample period before the effective lower bound. Detailed results can be found in Table IA.9 and Table IA.10. Interestingly enough, we find that changes in Fed funds futures only have a meaningful explanatory power until the end of 2005. The regression R^2s then collapses to 1% in the sample 2006-2009 (in line with Gorodnichenko and Weber (2016), Table 3). In comparison, the three-month rates (or our short-rate surprises) produce more stable results across subsamples.

Finally, the sub-sample analysis provides several interesting insights regarding the role of risk shifts. We find that before 2005, risk shifts explain between 20% up to 40% of the variation of stock returns on FOMC announcement days. This is similar to the fraction of the FOMC stock market response explained by short rate surprises during this period. However, the explanatory power of risk shifts increases gradually starting in 2005 and reaches up to 80% in the subsamples just *before* short rates hit the effective lower bound. Post 12/2008, we find that R^2s actually drop a bit and only come back to 80% towards the end of the sample.

To sum up, we find that risk shifts played a prominent role even in the earliest possible sub-sample that we can study. We find that post-2005 the importance of risk shifts picks up, well before the financial crisis and the period when rates hit the ELB.[29]

Risk shifts in other asset classes: Our fund dataset allows us to study the impact of FOMC risk shifts on a broader set of asset classes, as shown in Table IA.6 in the Internet Appendix. The other risky asset classes are proxied by long-short strategies based on Bloomberg categories and are long in the risky asset (e.g., corporate bonds) and short in the safe counterpart (e.g., broad US bonds).

We find that FOMC risk shifts are accompanied by significantly higher returns in corporate

[29]The long horizon response of equity prices and flows for the extended sample period from 1994-2019 as well as the sub sample 1994-2005 is discussed in the Internet Appendix (Section IA.G and Figure IA.11). These results are qualitatively similar.

bonds (+0.10%, t: 4.8) and emerging market bonds (+0.21%, t: 3.3) compared to US government and investment grade bonds ("broad" market bonds). Similarly, emerging market equities outperform US equities by 0.49% (t: 5.2).

Fund flows generally mirror the patterns in returns. Flows into the relatively riskier assets react positively to monetary policy induced risk shifts. Moreover, positive risk shifts go hand in hand with significant fund flows from safe to riskier assets at a weekly horizon. Overall, the results for other risky assets strongly corroborate the key findings in the previous section: FOMC risk shifts do not just affect US equities, but have a sizeable effect on risky asset classes more generally and on an international scale.

Leave one out *"risk shifts"*: We study the robustness of our risk shift measure via a "leave out" analysis. To see whether one specific risky asset (VIX, CDX, or DOL) is crucial for the construction of the risk shift factor, we drop one after another of three variables, re-run the factor analysis, and then re-estimate the effect of risk shifts on asset markets. Figure IA.5 in the Internet Appendix shows that the results are virtually unchanged to the baseline results. In essence, this analysis shows that two of the risky asset prices span the information content of all three variables.[30]

Tighter or wider event windows: In event studies of the style we conduct in this paper it is of interest to investigate the sensitivity of the results to sensible variations in the event window. Table IA.11, in the Internet Appendix, reports how results change for a tighter or wider event window. The wide event window (Panel A) starts 15 minutes before each announcement but always ends at the close. The tight event window (Panel B) starts 15 minutes before each announcement but always ends 45 minutes afterwards, also on days that include a press conference. We generally find that estimates are quite similar to the baseline specification. The R^2s of daily returns and flows tend to increase in case of the longer window, which makes sense

[30] To see how our factor analysis to extract monetary policy surprises might affect the main results, we consider an alternative, more simple, risk shift measure in Figure IA.6 of the Internet Appendix. The alternative risk shift factor is the simple average of the three (standardized) risky asset price changes, orthogonalized with respect to the four yield changes using linear regressions. We find very similar results: large initial price and flow reactions that show a large transitory component.

as the event window in this case has a larger overlap with the daily returns. The R^2s of daily returns and flows tend to decrease as we use a tighter window, which makes sense as the event window has now a smaller overlap with the daily returns.

Does the financial crisis drive our results? Our baseline results already exclude events that might be confounded by additional announcements of monetary policy news within the event window. In the Internet Appendix (Figure IA.8), we show results when the financial crisis period is removed from the event list, i.e., all FOMC announcements that fall into the period from 08/2007 - 12/2009 are excluded. We find that the main conclusions from our baseline results are unchanged.[31]

Evidence from macroeconomic news announcements: Are FOMC announcements special? In the Internet Appendix (Figure IA.10), we analyse the response of equity prices and flows to risk shifts on days when important macroeconomic news (i.e. nonfarm payrolls, the producer price index, or the consumer survey report) are released. To avoid events that overlap with FOMC announcements, we exclude macro announcement in the vicinity of FOMC events, i.e. observations 5 days prior and up to 10 days after FOMC days.

We find some notable difference between macroeconomic data releases and FOMC events. The equity price response to a risk shift generated by macro news even tends to be somewhat stronger in the short-term (+0.73%). The overall effect on prices (after 20 trading days) has a large persistent component—indicative of fundamental news being embedded in prices. That said, we find the reaction of flows to macro news to be relatively weak, in stark contrast to how fund flows respond to FOMC news.

In sum, macro news generate a permanent impact on stock prices, and they do not impact flows as much as FOMC announcements do. One possible interpretation is that macro news leads investors to update their (dividend) growth expectations (which causes a permanent change in prices). By contrast, FOMC announcements trigger abnormal fund flows and lead to a largely

[31] Moreover, as discussed above, we carefully account for the effects of potentially confounding events when gauging the longer-horizon effects of our monetary policy surprises. In the Internet Appendix, we provide results for the full sample and when *including* the confounding events (Figure IA.7). We find similar point estimates, but confidence bands are wider compared to the baseline results, or when we simply exclude the financial crisis.

transitory change in stock prices driven by price pressure effects.[32]

NYSE order flow: In the Internet Appendix (Figure IA.12), we investigate the impact of a broader measure of order flow on stock returns around FOMC risk shifts. We collect total trading volume for the NYSE and de-trend this time-series by dividing it by its past 20 days moving average. We use the sign of returns multiplied by trading volume to approximate order flow, as proposed by Pastor and Stambaugh (2003). The advantage of this measure is that it goes beyond the order flow originating from ETFs. The disadvantage is that it is only a proxy and is less precisely measured than ETF flows. We find that high absolute FOMC risk shifts come with unusually large order flow and a return reversal. Low absolute FOMC risk shifts, by contrast, come with flat order flow and no return reversal. These results corroborate our core findings based on ETF flows.

6. Conclusion

FOMC decisions are arguably one of the most anticipated news events watched by market participants and frequently generate large movements in stock prices. Yet, surprise movements in risk-free rates, the focus of most of the earlier literature, are able to explain only a modest fraction of less than 20% of these stock price movements. The remainder is unexplained "dark matter" and constitutes the main object of interest in this paper.

Our main starting point is that it is unlikely that risk-free rates fully capture information about risk premia. Instead, it is vital to go beyond risk-free rate surprises to capture the various dimensions of monetary policy surprises. As our first contribution, we therefore propose a parsimonious extension of standard methods to construct "risk shifts", which capture the response of risky asset prices that is orthogonal to risk-free rate surprises.

Second, we find that risk shifts emerge as a powerful driver of stock returns around FOMC

[32]Ernst, Gilbert, and Hrdlicka (2019) find that a large fraction of average macroeconomic announcement returns, as reported in Savor and Wilson (2013), can be explained by the turn and mid of the month effects. They also conclude that average FOMC announcement day returns "stand out from other macroeconomic announcements" and are robust to calendar effects. In unreported results, we find that FOMC risk shifts are also not affected by dropping the first, mid, and last three days of a month.

days. They robustly account for about 70% of the variation in stock returns, measured intraday over a tight event window around FOMC announcements. That said, we detect a strong mean-reversion in stock prices in response to risk shifts, accompanied by large ETF investor flows. These results, together with our finding of large spikes in volume around FOMC meetings, show that investors must react heterogeneously to monetary policy news. They also indicate that price pressures play a hitherto unappreciated role to explain the short-horizon price dynamics around monetary policy announcements.

Third, we analyze *why* monetary policy news induce changes in risk perceptions and lead to portfolio rebalancing, altering investors' exposures to risky assets. Our results based on textual analysis and news sentiment suggest that, in particular, monetary policy news that does not conform with the priors of active market participants leads to a drop in fund investors' willingness to take risks, a reduction in sentiment and a rebalancing away from risky assets. Such negative risk shifts go hand in hand with a surge in trading volume and contemporaneous price pressure to induce the passive investors to absorb these flows, which is subsequently reverted.

Our results have important implications for policy and academic research on the transmission of monetary policy. It is common in both the literature and policy discussions to presume that prices of financial assets immediately jump to their new fundamental value after the announcement of monetary policy news. Our results cast doubt on this view. Different demands for risky assets mean that investors "disagree" in their assessment of monetary policy. The mean-reverting stock market response, together with our evidence on fund flows and trading volume, suggests that the impact of fundamental news on stock prices is amplified by price pressures. What this means is that information effects (Campbell, Evans, Fisher, and Justiniano (2012), Nakamura and Steinsson (2018)) measured from stock prices are likely to be, at least to some degree, overshadowed by transitory short-term price dynamics. Our results thus complement findings in Neuhierl and Weber (2020) who show that stock prices drift around FOMC meetings in response to risk-free rate surprises, which is not captured by short-event windows around monetary policy announcements.

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Table 1: Monetary Policy Surprises

We collect the following seven variables around scheduled (112 events) and unscheduled (2) FOMC announcements from 01/2006 to 12/2019: simple changes of three month interest rates as proxied by Eurodollar futures, simple changes of the two, five, and ten year treasury yields as proxied by treasury futures (ED, TU, FV, TY, provided by Tickdata), the log change of the squared CBOE Volatility Index (VIX^2, provided by Tickdata), log changes of the Credit Default Spread Index of investment grade corporate bonds with a maturity of five years (CDX, provided by CMA Datavision), the log change of an equally weighted portfolio of foreign exchange futures (DOL, denomination is in FCUs for one USD; the FCs are: AUD, CAD, CHF, EUR, GBP, JPY, NZD, provided by Thomson Reuters Tick History). We normalize all seven variables by their event standard deviation. The event window is 90 minutes (-15m:+75m) if the announcement is not followed by a press conference (78) and is extended to the market close (-15m:close) if the announcement is followed by a press conference 36). In a first step, we run a principal component analysis on FOMC announcement days (114 observations) to extract statistical factors (results below "PCA on FOMC Days"). Following Swanson (2020), in a second step, we apply a standard (orthogonal) factor rotation on the first three principal components to extract economic monetary policy surprises (results below "Orthogonal Rotation"); {*} indicate our target matrix. The obtained monetary policy surprises are: "Short Rate" surprises, as these surprises load on short maturity yields; "Long Rate" surprises, as these surprises load on long maturity yields; and "Risk Shifts", as these surprises load negatively on risky assets (VIX^2, CDX, DOL).

	Monetary Policy Surprises					
	PCA on FOMC Days (#114)			**Orthogonal Rotation**		
	(1)	**(2)**	**(3)**	**"Short Rate"**	**"Long Rate"**	**"Risk Shift"**
$\triangle ED(3M)$	0.42	-0.18	-0.49	0.67*	0.00	0.00
$\triangle TU(2Y)$	0.44	-0.21	-0.23	0.50	0.20	0.05
$\triangle FV(5Y)$	0.47	-0.11	0.21	0.17	0.50	-0.01
$\triangle TY(10Y)$	0.44	-0.09	0.40	0.01	0.61*	0.00
$\triangle log\left(VIX^2\right)$	0.14	0.64	-0.57	0.34	-0.38	-0.70*
$\triangle log(CDX)$	0.12	0.67	0.39	-0.38	0.25	-0.64*
$\triangle log(DOL)$	0.42	0.21	0.15	0.09	0.37	-0.31
Var. expl., %	60.05	24.06	7.82			

Table 2: Response of Equity Returns & Flows to Monetary Policy Surprises

Panel A reports the response (b) of equity returns and equity flows ($X_{t|FOMC}$) to a unit standard deviation monetary policy surprise on FOMC days:

$$X_{t|FOMC} = a + b \times Monetary\ Policy\ Surprise_{j,t|FOMC} + \xi_{t|FOMC},$$

as well as average returns/flows conditional on observing a positive ($mu_{MP\ Surprise>0}$) or negative ($mu_{MP\ Surprise<0}$) monetary policy surprise. Event window equity returns are measured intraday by the S&P 500 index. The event window is 90 minutes (-15m:+75m) if the announcement is not followed by a press conference (78) and is extended to the market close (-15m:close) if the announcement is followed by a press conference (36). Daily equity returns are measured by daily (close:close) equity ETF returns, and daily equity flows are measured by daily (close:close) equity ETF flows. The monetary policy surprises include short rate surprises (SR), long rate surprises (LR), and risk shifts (RS) and are described in Table 1. The sample includes 114 FOMC announcements from 01/2006 to 12/2019. T-statistics are based on bootstrap standard errors that account for the fact that the regressors are estimated. Panel B reports the response of equity returns and equity flows from a control group experiment. We compute pseudo factor surprises on days without monetary policy news using a 90 minutes event window (11:00:12:30). T-statistics are based on bootstrap standard errors without regressor resampling.

Panel A. Baseline (event window: -15m:+75m/close if followed by press conference)

	Equity Returns						**Equity Flows**		
	Event Window Returns			Daily Returns			Daily Flows		
	SR	LR	RS	SR	LR	RS	SR	LR	RS
b	-0.19	-0.06	0.69	-0.37	-0.06	0.64	-0.20	-0.07	0.42
$t(b)$	-2.07	-0.79	9.55	-2.26	-0.46	6.51	-2.00	-0.51	3.99
R^2	5.72	0.53	72.40	8.99	0.27	26.97	3.31	0.43	14.46
$mu_{MP\ Surprise>0}$	-0.08	0.19	0.52	0.01	0.35	0.60	0.29	0.43	0.51
$s.e.$	0.11	0.08	0.07	0.15	0.16	0.14	0.14	0.15	0.12
$mu_{MP\ Surprise<0}$	0.21	-0.01	-0.60	0.40	0.13	-0.34	0.29	0.09	-0.08
$s.e.$	0.09	0.11	0.12	0.16	0.16	0.18	0.14	0.14	0.17

Panel B. Control group, reaction to pseudo surprises (all days using the event window 11:00 - 12:30)

	Equity Returns						**Equity Flows**		
	Event Window Returns			Daily Returns			Daily Flows		
	SR	LR	RS	SR	LR	RS	SR	LR	RS
b	0.09	0.17	0.25	0.07	0.16	0.27	0.01	0.03	0.09
$t(b)$	8.67	19.63	26.56	2.76	6.08	11.25	0.45	1.78	5.37
R^2	5.59	23.34	47.58	0.42	2.12	5.71	0.01	0.10	1.00

Table 3: Regression of Changes in Textual Sentiment on Monetary Policy Surprises

Regressions of changes in textual sentiment (ΔS_t) on monetary policy surprises separately and jointly. Sentiment is measured as the average sentiment score of all articles in Ravenpack News Analytics (www.ravenpack.com) related to *"United States Federal Reserve"* and *"Board of Governors of the Federal Reserve System"* in the x days before an FOMC meeting and separately for the x days after an FOMC meeting and we let x vary from $3, 5, 7, 10, ...14$ days. All articles entering the average sentiment score are weighted by their relevance score (ranging from $0, ..., 100$) so that articles with higher relevance receive a higher weight. We then compute the change in sentiment as the difference between the average, relevance-weighted sentiment scores in the post-FOMC window and then average, relevance-weighted sentiment scores in the pre-FOMC window. We do this for each of our 96 scheduled FOMC meetings to obtain a time-series of sentiment changes. To avoid timing issues we do not include the day before the FOMC decision and the day after the FOMC meeting in the computation of sentiment scores. For example, if the FOMC meetings ends on July 27th, 2016, the $x = 3$ day pre-FOMC window runs from July 22nd to 25th whereas the 3-day post-FOMC window runs from July 29th to 31st. t-statistics in squared brackets are based on White standard errors. The sample period is from 2006 to 2017; 96 scheduled FOMC announcements.

	Days Around FOMC Meeting				
	3	**5**	**7**	**10**	**14**
	Univariate Regression				
Short Rate Surprises	-1.30	-1.35	-0.69	0.94	2.45
t	[-1.25]	[-1.28]	[-0.69]	[0.91]	[1.43]
R^2	0.01	0.01	0.00	0.01	0.05
Long Rate Surprises	-3.33	-3.69	-2.76	-2.23	-2.12
t	[-2.93]	[-3.80]	[-3.16]	[-2.58]	[-2.36]
R^2	0.07	0.11	0.06	0.04	0.04
Risk Shifts	2.68	2.45	2.44	2.47	1.61
t	[2.06]	[2.18]	[2.29]	[2.06]	[1.04]
R^2	0.04	0.05	0.05	0.05	0.02
	Multivariate Regression				
Short Rate Surprises	-1.31	-1.36	-0.69	0.94	2.45
t	[-1.47]	[-1.58]	[-0.80]	[1.03]	[1.48]
Long Rate Surprises	-3.33	-3.69	-2.76	-2.23	-2.12
t	[-3.15]	[-4.03]	[-3.35]	[-2.64]	[-2.30]
Risk Shifts	2.68	2.44	2.44	2.47	1.61
t	[2.24]	[2.38]	[2.34]	[2.10]	[1.07]
adj. R^2	0.09	0.15	0.08	0.07	0.07

Figure 2: Risk Shifts on FOMC Announcement Days

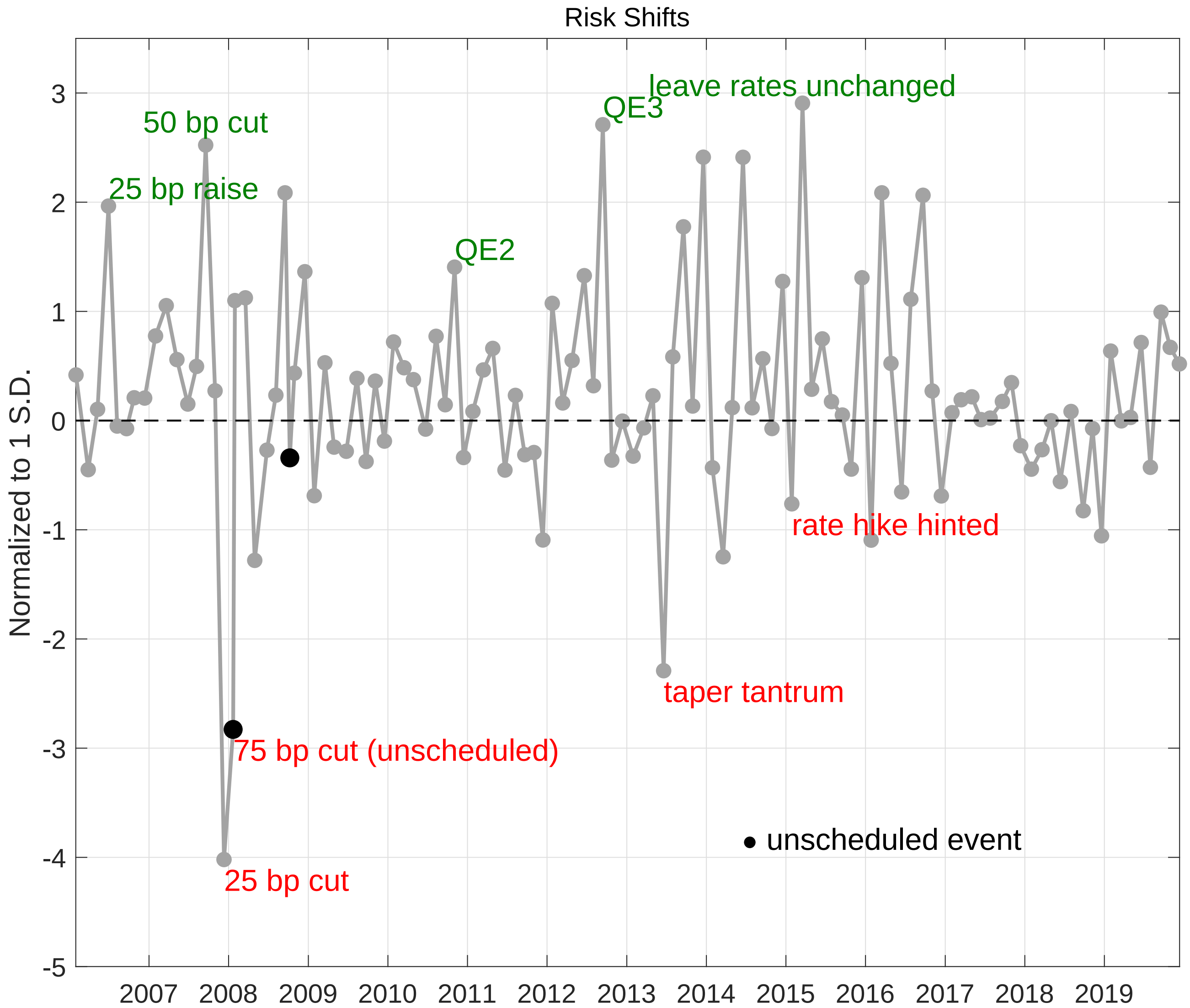


Figure 3: The FOMC Risk Shift

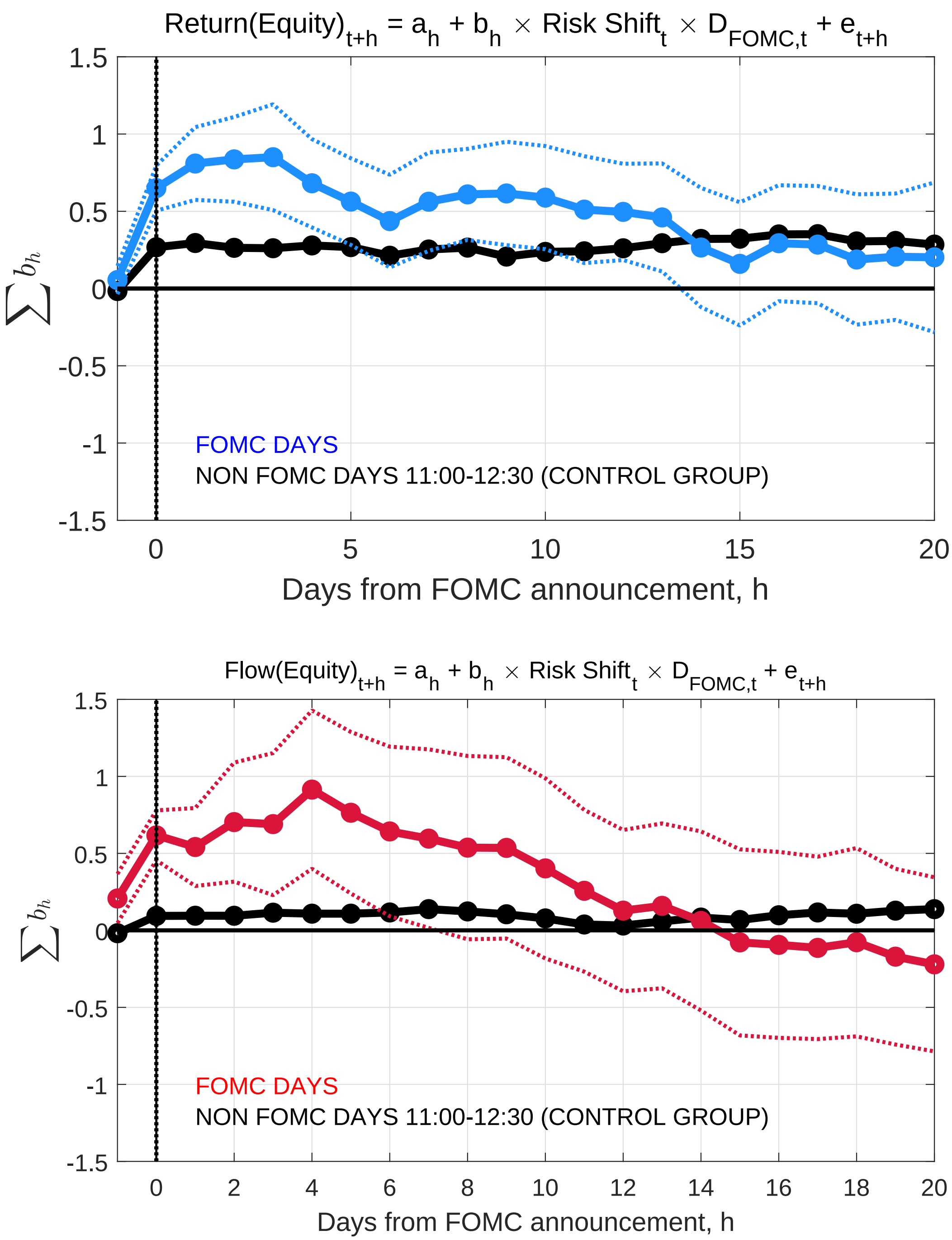


Figure 4: Return Decomposition: Discount Rate News

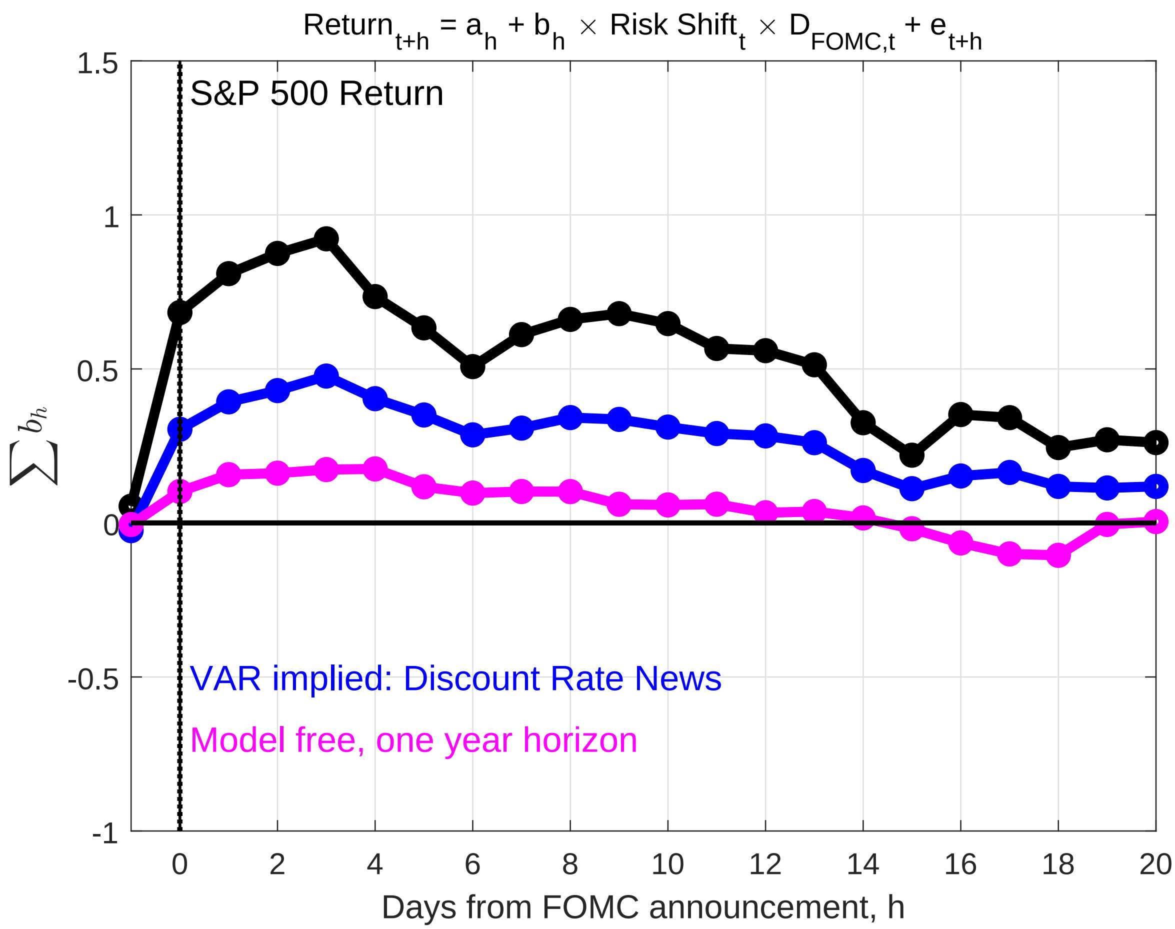


Figure 5: The SPDR S&P 500 ETF: Returns and Trading Volume on FOMC days

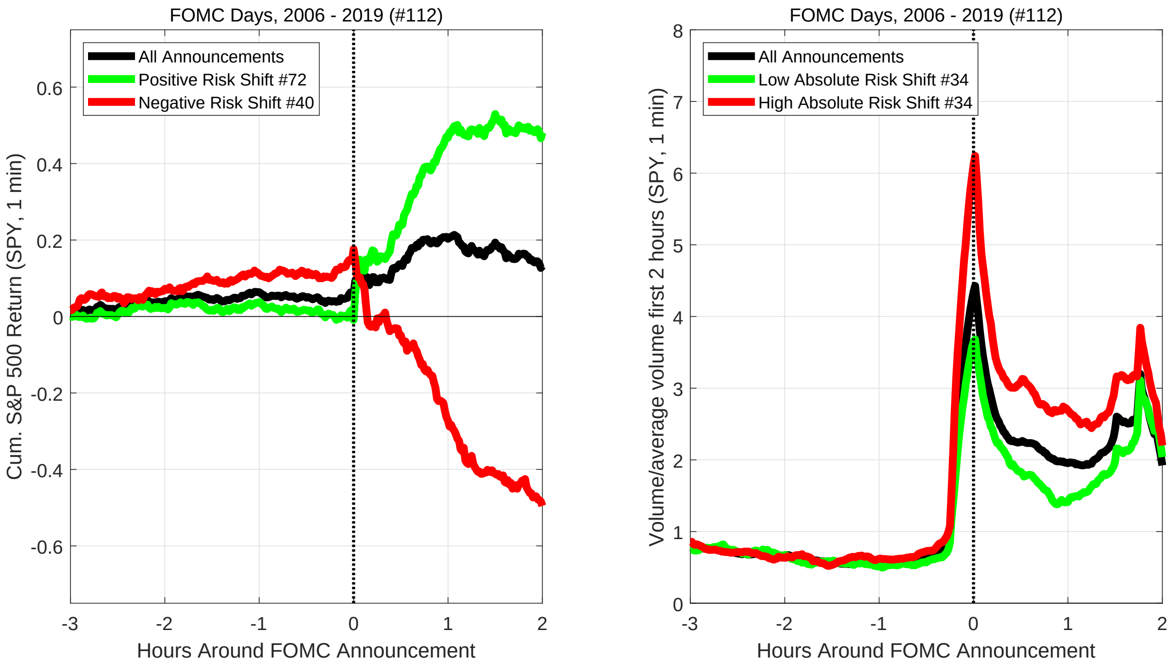


Figure 6: Fund Flow-Induced Price Pressures

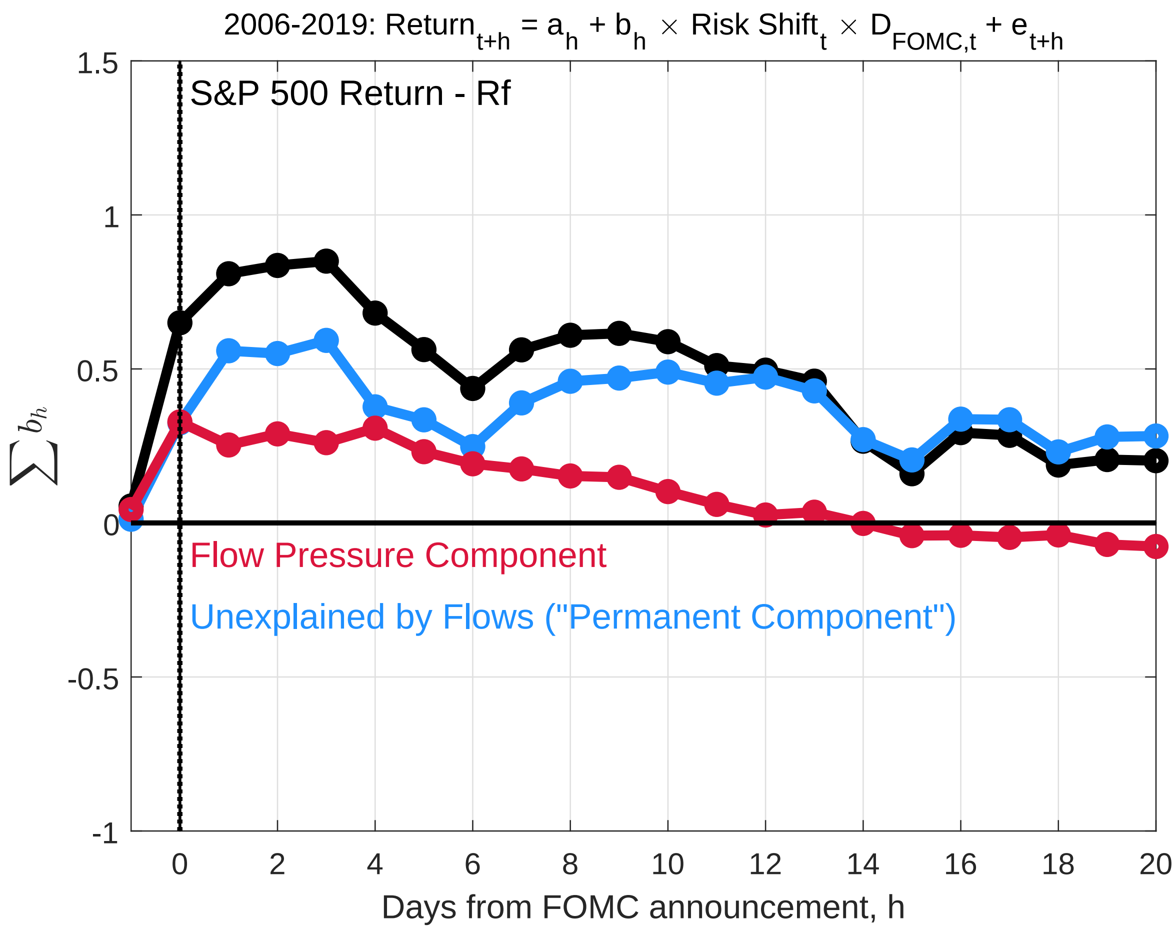
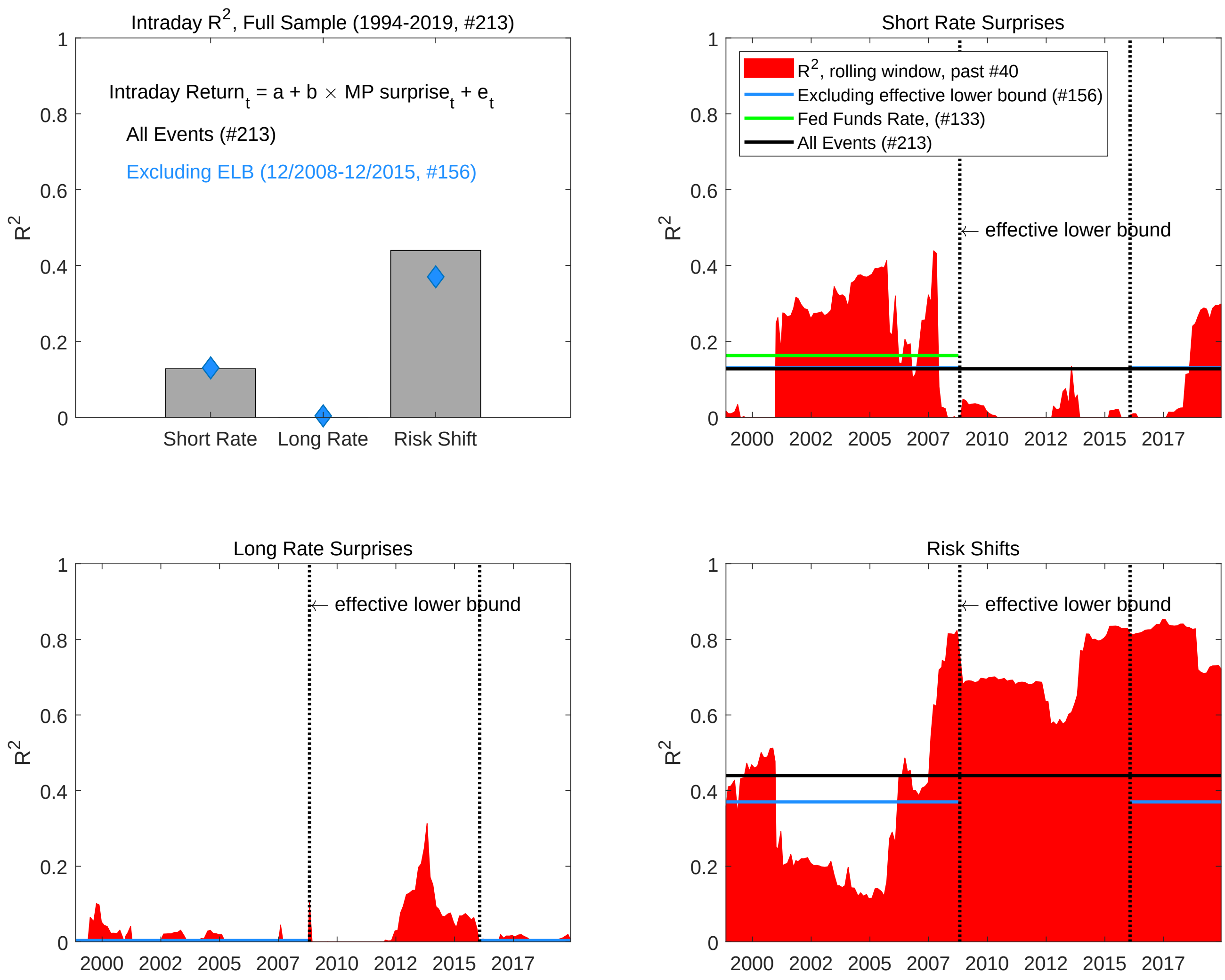


Figure 7: Intraday Returns: Extended Sample & Subsamples



Internet Appendix for

The FOMC Risk Shift

Supplementary material

(not for publication)

Outline:

IA.A. Details on data and variables construction

High frequency data: The sources of the high-frequency data are Tickdata.com, Thomson Reuters TickHistory, Kibot.com, and CMA (Credit Market Analysis Ltd.) Datavision. Treasury bond futures of a given maturity refer to a hypothetical bond with a coupon of 6%. We back out the future implied yield and assume that the maturity of the cheapest to deliver bond matches with the face maturity of the future. There are no CDX futures available. Intraday data on the CDX index is sourced from CMA Datavision who collects information on executable and indicative CDS quotes directly from dealers in credit markets. We use intraday VIX data from Tickdata.com for the period 2006 to 2019, and from Kibot.com for the period 1998 to 2005. To the best of our knowledge, for the period 1994 to 1997, no granular intraday data for the VIX are available. For this period, we use the open-close change available from www.cboe.com. We scale the open-close changes to changes of comparable size as observed during the event window based on regressions of open-close changes on the event window changes.

Fund flows: We collect daily ETF data from Bloomberg. The dataset covers (almost) all ETFs traded in the US. We aggregate individual funds to asset classes. Our measure for US equity is based on all funds that belong to the Bloomberg category "Blend".[33]

[33] More specifically, Bloomberg categorizes all US funds into a strategy and the fund objective within a strategy. We select funds with the strategy "Blend" and the objectives "Blend Large-Cap", "Blend Mid-Cap", "Blend Small-Cap" ,"Large-Cap", "Mid-Cap", "Small-Cap".

Our measure for broad US bonds is based on all funds that belong to the Bloomberg category "Aggregate", or "Government".[34]

Fund flows at the asset class level are measured as:

$$F_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}\left(1 + R_{i,t}\right)}{TNA_{i,t-1}},$$

where $TNA_{i,t}$ are total net assets of asset class i (equity or bond) at time t, and $R_{i,t}$ is the fund return of asset class i. Because fund flows do not have an economically meaningful long-run mean or standard deviation, we follow the recent literature (e.g., Berk and van Binsbergen (2016), Menkhoff, Sarno, Schmeling, and Schrimpf (2016)) and use a normalization. In particular, we normalize flows by their moving average and standard deviation:

$$\tilde{F}_{i,t} = \frac{F_{i,t} - \mu_{i,t}\left(F_{i,t-250;t-1}\right)}{\sigma_{i,t}\left(F_{i,t-250;t-1}\right)},$$

where $\mu_{i,t}\left(F_{i,t-250;t-1}\right)$ and $\sigma_{i,t}\left(F_{i,t-250;t-1}\right)$ are computed over lagged 250-day rolling days. If there is a zero flow, we ignore this observation when computing the rolling mean or standard deviation and we also do not adjust any zero flow observation in the sample. This means that we remove any local trends in the data, i.e. comparable to a year/fund category fixed effect.

We use the Bloomberg data as reported. We notice that other data providers (e.g., Datastream) often report shares outstanding with a lag of one day compared to Bloomberg.[35]

Figure IA.1 provides an overview of total net assets of ETFs over time. The cut-off year 2006 for our baseline results (from 01/02/2006 to 12/13/2019, 3,512 daily observations; 114 FOMC announcements) ensures that we almost always observe non-zero flows for "Blend" equity and "Broad" bond funds, see Table IA.2. Before the year 2006, equity flows come with a large fraction of days with a zero fund flow, which would make our analysis of fund flows unreliable.

In our empirical analysis, we mainly focus on ETF fund flows as these flows are more likely to represent "fast money". Transaction costs are low for ETFs (there are no front-end loads). They allow investors to quickly build up, or reduce, positions in one asset class or another. This point is also made in Ben-David, Franzoni, and Moussawi (2017) and Lettau and Madhavan (2018), among others. Indeed, ETFs are frequently used by institutional investors to obtain tactical exposure to certain asset classes, in particular at short horizons.[36]

In the Internet Appendix, we also compare results from ETFs with mutual funds. We refer to mutual funds as "slow money", because of their fairly high transaction costs (front-end fees, but also buying/selling restrictions for large block investors). Mutual fund flows are thus likely

[34] We select funds with the strategy "Aggregate", or "Government", and the objective "Aggregate", or "Government".

[35] As pointed out by Staer (2017), shares outstanding are a book value and not a market value. This can lead to a reporting lag of one day in certain databases and motivates the t+1 timing convention (matching flows reported for day t+1 with returns on day t). For further details about the creation and redemption process, see the excellent reviews by Ben-David, Franzoni, and Moussawi (2017) and Lettau and Madhavan (2018), or for even more details on the timing, "Understanding Exchange-Traded Funds: How ETFs Work", by the Investment Company Institute available at https://www.ici.org.

[36] Balchunas (2016) and Madhavan (2016) argue that ETFs are popular among institutional investors for (short-term) tactical asset allocation decisions. Madhavan (2016) reports that ETFs have high institutional ownership (about 65%) and a much higher annual turnover (more than 20 times assets under management) compared to comparable passive mutual funds (less than 20%). Based on 13-F institutional holdings data, Ben-David, Franzoni, and Moussawi (2018) provide direct empirical evidence for institutional investors using ETFs for tactical asset allocation decisions.

to be less responsive to news (e.g., Barber, Odean, and Zheng, 2005; Frazzini and Lamont, 2008).

Mutual fund data are collected from Trimtabs for the sample period 01/2006 to 12/2017.[37] Trimtabs conduct their own survey to obtain fund flows and returns for approximately 15% of the market.[38]

IA.B. Details on the factor construction

In a first step, we de-mean and re-scale all asset price responses X $(T \times N)$ to mean zero and a variance of 1%. We then compute the first three principal components and apply a standard orthogonal factor rotation using the target matrix indicated in the main paper.[39] Table 1 in the main paper shows the original PCA weights w $(N \times 3)$ as well as the rotated weights $w_{rot} = wT$ $(N \times 3)$, where T (3×3) is the rotation matrix. The orthogonal rotated factors with a unit standard deviation F $(T \times 3)$ are obtained by $F = X\hat{w}T$, where $\hat{w}$ is each row of w scaled by the (1×3) vector $std(Xw)$.

Our identifying assumption is that risk shifts are orthogonal to risk-free rate surprises, in line with our goal to capture news beyond to what is already reflected by risk-free assets (see our taxonomy in Figure 1). In the following, we illustrate the factor analysis using a numerical example. We also provide an indication on the expected performance of the factor analysis for empirical data.

IA.C. Illustration of the spanning argument

A simulation experiment illustrates that the described factor construction is accurate and recovers between 80% and 90% of the true underlying factors. We first define how observed asset prices relate to the three orthogonal monetary policy surprises in a stylized reduced form model.

Risk-free assets: Changes in the risk-free rates (with maturity of 3 months, or 2, 5, and 10 years) are driven by the following dynamics:

$$\triangle y_t(3M) = l_{3M}\triangle Level_t + s_{3M}\triangle Slope_t,$$

$$\triangle y_t(2Y) = l_{2Y}\triangle Level_t + s_{2Y}\triangle Slope_t,$$

$$\triangle y_t(5Y) = l_{5Y}\triangle Level_t + s_{5Y}\triangle Slope_t,$$

$$\triangle y_t(10Y) = l_{10Y}\triangle Level_t + s_{10Y}\triangle Slope_t,$$

i.e., they are completely spanned by a "Level" and a "Slope" factor. These two factors are, in turn, determined by news about short-rates, NSR_t, and news about long-rates (e.g., driven

[37]http://trimtabs.com.

[38]The Investment Company Institute estimates the mutual fund market - all equity and bond funds - to about 12 trillion USD at the end of 2015, see http://www.ici.org/research/stats/trends.

[39]More specifically, we use the Matlab functions pca(.) and rotatefactors(.), with the options 'method','pattern','target', TGT, 'Type', 'orthogonal' where TGT is the target matrix.

by forward guidance), NLR_t , and a bond market specific component (news un-spanned by monetary policy):

$$\triangle Level_t = m_l NSR_t + f_l NLR_t + \vartheta_{l,t},$$

$$\triangle Slope_t = m_s NSR_t + f_s NLR_t + \vartheta_{s,t}.$$

Without loss of generality, and to facilitate the interpretation of the underlying factors, NSR_t and NLR_t can always be re-defined such that they are uncorrelated with each other.

In economic terms, the the two yield-based factors could capture news about expected short-term interest rates, expected economic growth, and expected inflation. Measured around a short window around FOMC announcements, these terms capture news about short and long rates revealed by monetary policy news.

Risky assets: Following present-value logic (Campbell (1991); Campbell and Shiller (1988)), an unanticipated change in the stock market price must come from changes in the required rate of return (discount rate news: $NDR_{Mt} = (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+j}$) or cash flow news ($NCF_{Mt} = (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j \triangle d_{t+j}$):

$$r_{Mt} - E_{t-1}(r_{Mt}) \approx NDR_{Mt} + NCF_{Mt}$$

Cash flow news are modelled as a function of the news that also drive the bond markets (NSR_t, NLR_t) plus a stock market specific component ($\vartheta_{CF,t}$):

$$NCF_{Mt} = m_{CF} NSR_t + f_{CF} NLR_t + \vartheta_{CF,t}.$$

Similarly, discount rate news are driven by economy wide factors (that can effect many asset classes) as well as a stock market specific component ($\vartheta_{DR,t}$). The economy wide components are driven by the same factors as the bond market (NSR_t,NLR_t) and in addition by changes in investors perception of risk, or a "risk shift" (NRS_t), that is specific to risky assets and absent in risk-free assets (i.e., uncorrelated with NSR_t,NLR_t, $\vartheta_{l,t}$, and $\vartheta_{s,t}$):

$$NDR_{Mt} = m_{DR} NSR_t + f_{DR} NLR_t + \gamma_{DR} NRS_t + \vartheta_{DR,t}.$$

In economic terms, "risk shifts" (NRS_t) could reflect the effects from a time-varying price of risk that are not reflected in risk-free yields, or changes in time-varying amount of risk that are also not reflected in risk-free yields. Measured around a short window around FOMC announcements, this component captures news about the perception of risk triggered by the revelation of monetary policy news.

According to equilibrium asset pricing models, changes in the price/amount of risk potentially also affect risk-free rates. However, they must do so differently compared to equities. Otherwise, if risk-free assets are driven by the identical factors as risky assets, the equity premium would be completely spanned by risk-free rates which would be counterfactual to the empirically observed large equity premium as well as a large theoretical literature.

Following similar arguments, changes of other risky asset prices also load on the the structural factors defined above:

$$\Delta log(VIX^2) \approx m_{VIX} NSR_t + f_{VIX} NLR_t + \gamma_{VIX} NRS_t + \vartheta_{VIX,t}$$

$$\Delta log(CDX) \approx m_{CDX} NSR_t + f_{CDX} NLR_t + \gamma_{CDX} NRS_t + \vartheta_{CDX,t}$$

$$\Delta log(DOL) \approx m_{DOL} NSR_t + f_{DOL} NLR_t + \gamma_{DOL} NRS_t + \vartheta_{DOL,t}$$

plus asset market specific components, $\vartheta_{VIX,t}, \vartheta_{CDX,t}, \vartheta_{DOL,t}$.

Importantly, we allow all risky assets to be subject to asset class specific drivers of "re-pricing", $\vartheta_{CF,t}, \vartheta_{DR,t}, \vartheta_{VIX,t}, \vartheta_{CDX,t}, \vartheta_{DOL,t}$. In this sense, NRS_t represents economy wide re-pricing of "all" risky assets, not just equities. Finally, notice that we do not need to take a strong view on how much (or if any) a particular risky asset load on the three structural factors. The only identifying assumption we require is that risky assets load on NRS_t and that the risk-free assets do not load on NRS_t. Put differently, we assume that the risky assets market premium is unspanned by the factors driving risk-free rates.

Factor Analysis: To filter the structural factors (NSR_t, NLR_t, NRS_t) from a cross-section of asset prices we follow the two-step procedure put forth by Gürkaynak, Sack, and Swanson (2005) and Swanson (2020). In this paper, we will mainly study the re-pricing of the equity market. To avoid that our filtered risk shift factor ($\triangle RS_t = \widehat{NRS_t}$) mechanically explains equity returns (because of the two equity market specific components, $\vartheta_{CF,t}, \vartheta_{DR,t}$) we do not include equities in the principal component analysis. Instead, we include a diversified pool of *other* risky assets - the VIX, the CDX, and the DOL - that should allow us to identify NRS_t.

Of course, ideally, we would like to further expand the cross-section of risky assets. Due to (intraday) data availability, however, this is not possible. We argue that this issue does not drive our results. First, the asset market specific components ($\vartheta_{VIX,t}, \vartheta_{CDX,t}, \vartheta_{DOL,t}$) add, if anything, asset market specific "noise" to our risk shift factor. This should work against identifying the relationship between risk shifts and the equity market. Second, in the robustness section, we exclude one of the three "other" risky asset markets before running the factor analysis (i.e. one of the three components $\vartheta_{VIX,t}, \vartheta_{CDX,t}, \vartheta_{DOL,t}$ at the time is removed from our risk shift factor). We find that our results are almost unaffected, which indicates that the asset market specific components are indeed relatively well diversified. In line with this finding, we find that the three factors that we extract in our factor analysis explain 80%+ of the variance in the cross-section of assets; which suggests that asset market specific news are relatively small.

Simulation: We run a simulation experiment to illustrate that the described setup is in line with the empirical factor structure that we document.

We simulate 1,000 artificial data with the following properties: All economy wide news (NSR_t, NLR_t, NRS_t) are Gaussian and normalized to a unit standard deviation. All asset market specific news ($\vartheta_{CF,t}, \vartheta_{DR,t}, \vartheta_{VIX,t}, \vartheta_{CDX,t}, \vartheta_{DOL,t}$) are Gaussian with a standard deviation of 0.30. The loadings for the level and slope factors are: $m_l = 0.50$, $f_l = 0.50$, $m_s = -0.50$, $f_s = 1.00$, and the yield coefficients are: $l_{3M} = 1.0$, $s_{3M} = 0.0$, $l_{2Y} = 1.0$, $s_{2Y} = 0.50$, $l_{5Y} = 1.0$, $s_{5Y} = 0.75$, $l_{10Y} = 1.0$, $s_{10Y} = 1.00$.

For the risky assets, we set the loadings on the news terms to: $m_{VIX} = 0.20$, $f_{VIX} = -0.20$ $\gamma_{VIX} = 0.80$; $m_{CDX} = 0.20$, $f_{CDX} = 0.00$, $\gamma_{CDX} = 0.80$; $m_{DOL} = 0.20$, $f_{DOL} = 0.40$, $\gamma_{DOL} = 0.40$. We then standardize all seven innovations in asset prices and run the factor analysis as in the main paper.

The result is reported in Table IA.1. The first PCA reflects that all assets load on short-rate news. The second PCA captures that there is variation in risky asset prices that is not present in the risk-free assets. Finally, the third PCA reflects that long-term yields load on an additional long rate factors. The factor rotation then facilitates the interpretation of the factors. The lower right of the table shows the R^2 of a regression of the filtered news, e.g. $\triangle RS_t = \widehat{NRS_t}$, on the true news NRS_t. We find that the filtered factors recover between 80% and 90% of the true factors.

Table IA.1: Simulated Monetary Policy Surprises

	Simulated Monetary Policy Surprises					
	PCA			**Orthogonal Rotation**		
	(1)	**(2)**	**(3)**	**"Short Rate"**	**"Long Rate"**	**"Risk Shift"**
$\triangle Y(3M)$	0.43	-0.02	-0.85	0.96	0.00	0.00
$\triangle Y(2Y)$	0.48	-0.13	-0.01	0.23	0.44	0.00
$\triangle Y(5Y)$	0.47	-0.16	0.23	0.01	0.54	0.00
$\triangle Y(10Y)$	0.46	-0.17	0.39	-0.13	0.61	0.00
$\triangle log\left(VIX^2\right)$	0.03	0.64	-0.11	0.10	-0.21	-0.61
$\triangle log(CDX)$	0.12	0.63	0.13	-0.08	-0.02	-0.64
$\triangle log(DOL)$	0.37	0.35	0.21	-0.02	0.30	-0.46
Var. expl., % / Recovered, %	59.74	31.76	4.08	80.31	87.23	90.00

IA.D. Details on the bootstrap procedure

We implement a pairwise bootstrap where we jointly draw returns, flows, the event dummy, and the high frequency changes of the financial asset prices underlying the monetary policy factors (the four risk-free rates, the VIX, the CDX, and the DOL portfolio). In each bootstrap sample, we re-run the factor analysis on the drawn FOMC announcement days in the same way as in the empirical sample to get re-sampled monetary policy factors. As a result, our bootstrap standard errors account for the fact that the monetary policy factors are estimated. For event day regressions, we draw 10,000 bootstrap samples. For long-horizon regressions, we draw at each horizon 1,000 bootstrap samples in blocks of 45 days, which corresponds to the average FOMC cycle.

The pairwise bootstrap has the advantage that bootstrap standard errors are robust against heteroscedasticity. This is particularly important if all data are measured at high frequency and the variables are subject to an event-induced increase in volatility. Because we also draw the FOMC announcement days, the composition of FOMC days varies between samples and does not condition on specific announcements (e.g., QE1). This is reasonable, as we also do not condition our analysis on specific events and consider FOMC announcements in general (see also the analysis on subsamples, Section 5).

In unreported results, we find that asymptotic heteroscedasticity robust inference leads to similar inference for risk shifts and that the statistical significance of our results does not depend on using either the pairwise bootstrap or the residual bootstrap.

IA.E. Details on the return decomposition

Campbell and Shiller (1988) and Campbell (1991) show that unexpected realized returns are equal to revisions in future expected dividends minus revisions in future expected returns:

$$r_{t+1} - E_t\left[r_{t+1}\right] = \eta_{d,t+1} - \eta_{r,t+1},$$

where $\eta_{d,t+1} = E_{t+1}\left[\sum_{j=0}^{\infty} \rho^j d_{t+1+j}\right] - E_t\left[\sum_{j=0}^{\infty} \rho^j d_{t+1+j}\right]$ summarizes "cash-flow news", and $\eta_{r,t+1} = E_{t+1}\left[\sum_{j=1}^{\infty} \rho^j r_{t+1+j}\right] - E_t\left[\sum_{j=1}^{\infty} \rho^j r_{t+1+j}\right]$ summarizes "discount rate news".

To decompose stock returns, we follow a large literature (including Campbell and Shiller (1988)) and use a VAR of the form $\boldsymbol{z}_{t+1} = \boldsymbol{A}\boldsymbol{z}_t + \boldsymbol{\varepsilon}_{t+1}$, with $\boldsymbol{z}_t = [Ret_t - Rf_t,\, \boldsymbol{x}_t]'$. The first element of $\boldsymbol{z}_t$ is the excess return of the S&P 500 index $(Ret_t - Rf_t)$ and the following elements contain the up to three return predictors $(\boldsymbol{x}_t)$. The VAR coefficient estimates for the model with three predictors can be inspected in Table IA.12.

Defining a vector where the first element is one and all other elements are zero (e.g., $\mathbf{e1}' = [1,\, 0,\, 0,\, 0]'$) we can measure discount rate news as:

$$\eta_{r,t+1} = \mathbf{e1}' \sum_{j=1}^{\infty} \rho^j \boldsymbol{A}^j \boldsymbol{\varepsilon}_{t+1} = \mathbf{e1}' \rho \boldsymbol{A} \left(I - \rho \boldsymbol{A}\right)^{-1} \boldsymbol{\varepsilon}_{t+1}.$$

According to the VAR, the unexpected excess return is equal to $\mathbf{e1}'\boldsymbol{\varepsilon}_{t+1}$. Because unexpected excess returns are the difference between revisions in expected future dividends $(\eta_{d,t+1})$ and discount rate news $(\eta_{r,t+1})$, it is possible to back out cash-flow news as $\eta_{d,t+1} = \mathbf{e1}'\boldsymbol{\varepsilon}_{t+1} + \eta_{r,t+1}$. This definition assumes that the predictor variables in the VAR indeed capture all available information about future returns, i.e. any missing information will go into the residual.

The return component that can be attributed to discount rate news is $-\eta_{r,t+1}$, and hence we run the linear projections:

$$-\eta_{r,t+1} = a + b_h \times MP\ Surprise_{j,t} \times D_{FOMC,t} + \xi_{t+h},$$

and plot these in Figure 4. We compare results to linear projections of $Ret_{t+1} - Rf_{t+1}$. Thus, the difference between the two projections show (approximately) how the residual return component reacts to monetary policy surprises.

IA.F. Details on flow-induced price pressures

We follow the exposition of Hendershott and Menkveld (2014) and think of the observed (log) price of the stock market (p_t) to be the sum of an information component (or efficient price component, m_t; capturing expected future cash flows and discount rates) and an error component $(s_t$; capturing everything else):

$$p_t = m_t + s_t.$$

There are at least two possible reasons for why we observe flows upon the realisation of news. First, fund flows might reflect superior information of some investors and thus help to determine the efficient price (m_t), which should be permanent in nature. Second, fund flows might reflect heterogenous demands for risky assets without containing superior information such that they lead to transitory price pressure effects, reflected in a mean-reverting component (s_t).[40]

Under the assumption that fund flows have no information component, we expect that the information component (Δm_t) is uncorrelated with fund flows. In this case, the return component explained by fund flows will reveal the price pressure component (Δs_t) and should be transitory. The unexplained part plus the constant of this regression can be interpreted as the information component (Δm_t) and should be more permanent.

In Figure 6, we find that the return component explained by fund flows is indeed highly transitory. Following an earlier literature that documents fund flow-induced price pressure effects, we conclude that fund flows do not contain superior information and thus help to reveal fund flow-induced price pressure (e.g., Jotikasthira, Lundblad, and Ramadorai (2012), Coval and Stafford (2007), and Mitchell, Pulvino, and Stafford (2004)).

In the Internet Appendix (Table IA.18), we provide detailed statistics on the return decomposition. It shows that the fund flow-induced price pressures component is usually strong around FOMC days and in particular for FOMC days that come with a large absolute risk shifts.

IA.G. Further results

Descriptive statistics and details on returns, flows, and events: Table IA.2 reports descriptive statistics for equity and bond fund returns, as well as flows. Remarkable is the modest degree of equity (bond) fund flow persistence, as indicated by variance ratios close to one (well below 2) at the 20-day horizon. Low persistence indicates that ETF flows, particularly in the case of equities, quickly respond to new information.

Table IA.3 provides the average announcement returns for the intraday event window as well as the three monetary policy surprises.

Our event list is provided in Table IA.4. This event list is obtained from the comprehensive database collected by Cieslak and Schrimpf (2019).

Figure IA.1 gives an overview on the ETF flow data that are available. The figure shows total assets under management for the equity and bond category that we employ in this paper. As discussed in Section 3 of the main paper, we observe fund flows almost every day when we start the sample in 2006.

Figures IA.2 and IA.3 visualize the short rate and long rate monetary policy surprises.

Extended Sample Period: Table IA.7 shows the results from the factor analysis (as in Table 1) using the extended (but less detailed) sample from 1994 - 2005. We then splice these monetary policy surprises from 1994 - 2005 with those from the more detailed dataset reported in Table 1 from 2006 - 2019.

Table IA.8 compares the effect of the three monetary policy surprises on event window S&P 500 returns across several sub-samples. These results are (in part) shown in Figure 7 of the main paper.

[40]See, e.g., Scholes (1972), Glosten and Milgrom (1985), Grossman and Miller (1988).

Table IA.9 compares our monetary policy surprises (short rate, long rate and risk shifts) to fed fund rate futures (from Gorodnichenko and Weber (2016)) and the rate surprises extracted from Eurodollar futures. These results are (in part) also shown in Figure 7 of the main paper.

Table IA.10 considers mulitvariate regressions where we also control for changes in the VIX. We find that the sub-sample where univariate regressions of stock returns on short rate proxies lead to the largest R^2 is also the sub-sample where short rate proxies tend to have the highest correlation to changes in the VIX. The full sample correlation is basically zero, however.

Variations in the event window: In Table IA.11 we re-consider the effect of the three monetary policy surprises on the stock market (as in Table 2 of the main paper) using a wider (Panel A) or a tighter (Panel B) event window. Panel B also ignores the information content of press conferences. We find that the tight event window results are qualitative similar to the baseline, but more muted during the event window for all three monetary policy surprises in our sample period. Interestingly, at the daily horizon, the results are very similar to the baseline. We find that the wide event window results are very similar to the baseline results, at the event window horizon and the daily horizon.

Are events with a press conference different? The recent literature has shown that press conferences carry important information for financial markets (e.g., Boguth, Gregoire, and Martineau (2019)). Thus, it is interesting to ask whether results are different for FOMC announcements that are not followed by a press conference. To level the playing field between events with and without a press conference, in this exercise, we extend the event window for events without a press conference to the closing price of the announcement day, i.e., the event windows are the same for both types of events.

In the Internet Appendix (Figure IA.9), we show that restricting the sample to the 61 events without a subsequent press conference leads to point estimates for return and flow responses similar to those for the baseline. However, we find that long-horizon confidence intervals tend to be larger when press conferences are excluded. Using the narrow -15m:+75m event window for events without a press conference leads also to similar point estimates but even wider confidence bands. On the other hand, restricting the sample to the 34 FOMC announcements with a subsequent press conference leads to tighter confidence intervals. Overall, our results seem to depend very little on the in- or exclusion of press conferences.

Mutual funds vs ETFs: It is interesting to compare the reactions of ETF investors to those in mutual funds. Mutual fund flows can be thought of as "slow money" since these investment vehicles are typically subject to front-end fees and thus are not well suited for gaining short-term exposure to an asset class. Furthermore, retail clients account for a sizeable share of mutual fund volume, and retail investors are typically less responsive to news (Frazzini and Lamont, 2008). Based on this reasoning, we expect that mutual fund flows are not subject to (large) FOMC risk shifts. Consistent with this prior, we find that mutual fund flows do not respond in a meaningful way to FOMC risk shifts. Figure IA.13 in the Internet Appendix provides the results based on data provided by Trimtabs for the sample period 01/2006-12/2017. In fact, flows remain flat within the event window. However, mutual fund returns follow the overall market, as one might expect.

Robustness and further results: Figure IA.4 shows the longer-horizon response of equity prices and flows to short rate and long rate surprises. Table IA.5 provides numerical results for Figure 3, results for bonds, short-rate and long-rate surprises.

Section 5 discusses several robustness checks. In this Internet Appendix, we provide the according results not reported in the main paper. We find that our baseline results are mainly robust to: excluding the financial crises, Figure IA.8; including potentially confounding events, Figure IA.7

We also discuss that an alternative construction of risk shifts (that is based on a regression-based orthogonalization of a portfolio of risky assets) leads to similar results (Figure IA.6).

In contrast, macro economic news tend to generate a more persistent response (Figure IA.10).

Figure IA.11 provides the long horizon response of equity prices and flows for the extended sample period from 1994-2019 as well as the sub sample 1994-2005. The downside of the longer sample is that we need to rely on less detailed and less reliable data for this exercise.[41] Yet, the reaction of stock returns is overall very similar to the results documented above for the more recent sample period. Prices revert back to a large extent within four weeks. The point estimates of the response of fund flows is more muted in the early sample period (1994-2005).

Figure IA.12 uses the signed trading volume at the NYSE as a rough measure of order flow (Pastor and Stambaugh (2003), p.644). We find that high absolute risk shifts come with higher than usual order flow and return reversal. By contrast, low absolute risk shifts come with a flat order flow and no return reversal.

Figure IA.13 shows fund flows of mutual fund instead of ETFs. As discussed in the main paper, we find that mutual fund flows do not respond in a meaningful way to FOMC risk shifts.

Influential observations can affect the results in a material way in event studies of the type we run in this paper. Figure IA.14 provide the results of an outlier analysis. We re-estimate the initial response of intraday returns, as well as daily fund returns and flows but with leaving one observation out. We find that FOMC risk shifts are unaffected. Results on the short rate and long rate surprises are more dependent on specific observations. This result squares well with the subsample analysis presented in Figure 7.

VAR parameter estimates: In Section 4 of the main paper, we utilize the discount rates news estimated by a Campbell and Shiller (1988)/Campbell (1991)-VAR. The procedure is explained in Appendix IA.E. Table IA.12 provides the parameter estimates.

Textual analysis of market commentary: In Section 4 of the main paper, we discuss the results of an analysis of market commentary *on* FOMC days.

As mentioned in the main text, for his purpose, we collect market commentaries on the FOMC meeting from *Thomson Reuters Instant View*. *Thomson Reuters Instant View* collects and publishes views and commentary from market experts (e.g., traders, analysts, economists) on the outcome of the meeting shortly after an FOMC announcement (i.e., on the same day in the late afternoon). We always pick the complete *Thomson Reuters Instant View* column for each of our 96 scheduled FOMC announcements and do not select particular analysts or firms.

[41] We extend the sample period back to 1994 by focusing on returns and flows of the SPDR S&P 500 ETF (ticker: SPY) from State Street Global Advisors. The SPY was the first ETF introduced in 1993 and is until today the largest US equity ETF. We count almost no zero flows after 2006 for the SPY (less than 5%). However, around one half of the flow observations are zero in the earlier sample from 1994 to 2005, which indicates less frequent ETF trading in this sub-sample. There are no bond ETF funds available for the complete 1994 - 2005 sample period and for that reason we focus on equity markets only.

We then count the frequency of words that relates to economic and financial conditions or the surprise content of the news divided by the total number of words. Finally, we regress the absolute FOMC risk shift on the relative frequency of these words for the 96 scheduled FOMC meetings in our sample.

Tables IA.13, IA.14, and IA.15 show the results from regressions of the absolute of the three monetary policy surprises on the frequency of words that relates to economic and financial conditions or the surprise content of the news divided by the total number of words.

In Section 4 of the main paper, we discuss the results from a qualitative approach based on market commentary. In this context, we closely read through the market commentary around FOMC days with large risk shifts.

Tables IA.16 and IA.17 provide some illustrative commentaries on well known monetary policy events to illustrate our take-away from this exercise.

Internet Appendix: Tables

Table IA.2: Descriptive Statistics: Daily Fund Returns and Flows

This table reports descriptive statistics for daily ETF fund returns and ETF fund flows (as studied in Table 2 of the main paper). The reported statistics are the mean (mu, % p.d.) and standard deviation ($s.d.$, % p.d.), the variance ratio (vr_h) computed for horizons from $h = 2$ up to $h = 20$ days, the p-value of an ADF test ($pv(ADF)$) with the null hypothesis of a unit root, the number of zero observations ($\#zeros$), and the number of total observations ($\#obs$); 01/02/2006 to 12/13/2019.

	Returns, %			**Flows, %**		
	"Equity Premium" Equity-Bond	**Equity**	**Bond**	**"Equity Premium" Equity-Bond**	**Equity**	**Bond**
	All Observations					
mu	0.03	0.03	0.00	0.00	0.00	0.00
$s.d.$	1.16	1.13	0.17	1.39	0.95	0.98
vr_2	0.92	0.93	0.96	1.18	1.13	1.19
vr_5	0.81	0.83	0.91	1.47	1.21	1.65
vr_{10}	0.71	0.75	0.89	1.68	1.10	2.11
vr_{20}	0.67	0.70	0.94	1.97	0.99	2.63
$pv(ADF)$	0.00	0.00	0.00	0.00	0.00	0.00
$\#zeros$	0	0	0	0	0	7
$\#obs$	3512	3512	3512	3512	3512	3512
	FOMC Announcement Days (t=0)					
mu	0.22	0.26	0.04	0.21	0.29	0.08
$s.d.$	1.21	1.24	0.25	1.52	1.09	1.01
$\#obs$	114	114	114	114	114	114

Table IA.3: Average FOMC Returns and Monetary Policy Surprises

This table reports average means (% p.d.) with standard errors (s.e.) for the intraday S&P 500 returns and the three monetary policy surprises (as studied in Tables 1 and 2 of the main paper).

	Intraday Event Window Around FOMC Announcements			
	Returns	**Monetary Policy Surprises**		
	S&P 500, %	**Short Rate**	**Long Rate**	**Risk Shift**
mu	0.11	-0.34	0.10	0.24
s.e.	0.08	0.09	0.09	0.09
$\#pos : \#neg$	68:46	41:73	67:47	72:42

Table IA.4: Event List of FOMC Announcements: 1994-2019

No.	Date and Time	Scheduled	Unsched.	With PC	Confounding and Date		Distance	Description
1	04.02.1994 11:05	1	0	0	0			
2	22.03.1994 14:20	1	0	0	0			
3	17.05.1994 14:26	1	0	0	0			
4	06.07.1994 14:18	1	0	0	0			
5	16.08.1994 13:17	1	0	0	0			
6	27.09.1994 14:18	1	0	0	0			
7	15.11.1994 14:20	1	0	0	0			
8	20.12.1994 14:17	1	0	0	0			
9	01.02.1995 14:14	1	0	0	0			
10	28.03.1995 14:13	1	0	0	0			
11	23.05.1995 14:13	1	0	0	0			
12	06.07.1995 14:15	1	0	0	0			
13	22.08.1995 14:15	1	0	0	0			
14	26.09.1995 14:14	1	0	0	0			
15	15.11.1995 14:16	1	0	0	0			
16	19.12.1995 14:15	1	0	0	0			
17	31.01.1996 14:16	1	0	0	0			
18	26.03.1996 11:39	1	0	0	0			
19	21.05.1996 14:16	1	0	0	0			
20	03.07.1996 14:14	1	0	0	0			
21	20.08.1996 14:17	1	0	0	0			
22	24.09.1996 14:14	1	0	0	0			
23	13.11.1996 14:17	1	0	0	0			
24	17.12.1996 14:16	1	0	0	0			
25	05.02.1997 14:13	1	0	0	0			
26	25.03.1997 14:14	1	0	0	0			
27	20.05.1997 14:15	1	0	0	0			
28	02.07.1997 14:15	1	0	0	0			
29	19.08.1997 14:15	1	0	0	0			
30	30.09.1997 14:13	1	0	0	0			
31	12.11.1997 14:12	1	0	0	0			
32	16.12.1997 14:15	1	0	0	0			
33	04.02.1998 14:12	1	0	0	0			
34	31.03.1998 14:12	1	0	0	0			
35	19.05.1998 14:15	1	0	0	0			
36	01.07.1998 14:15	1	0	0	0			
37	18.08.1998 14:12	1	0	0	0			
38	29.09.1998 14:15	1	0	0	1	15.10.1998 15:15	16	Unscheduled FOMC Rate Decision
39	15.10.1998 15:15	0	1	0	0			
40	17.11.1998 14:15	1	0	0	0			
41	22.12.1998 14:15	1	0	0	0			
42	03.02.1999 14:15	1	0	0	0			
43	30.03.1999 14:15	1	0	0	0			
44	18.05.1999 14:15	1	0	0	0			
45	30.06.1999 14:15	1	0	0	0			
46	24.08.1999 14:15	1	0	0	0			
47	05.10.1999 14:15	1	0	0	0			
48	16.11.1999 14:15	1	0	0	0			
49	21.12.1999 14:15	1	0	0	0			
50	02.02.2000 14:15	1	0	0	0			
51	21.03.2000 14:15	1	0	0	0			
52	16.05.2000 14:15	1	0	0	0			
53	28.06.2000 14:15	1	0	0	0			
54	22.08.2000 14:15	1	0	0	0			
55	03.10.2000 14:15	1	0	0	0			
56	15.11.2000 14:15	1	0	0	0			
57	19.12.2000 14:15	1	0	0	1	03.01.2001 13:15	15	Unscheduled FOMC Rate Decision
58	03.01.2001 13:15	0	1	0	0			
59	31.01.2001 14:15	1	0	0	0			
60	20.03.2001 14:15	1	0	0	0			
61	18.04.2001 10:55	0	1	0	1	15.05.2001 14:15	27	Scheduled FOMC Rate Decision
62	15.05.2001 14:15	1	0	0	0			
63	27.06.2001 14:12	1	0	0	0			
64	21.08.2001 14:15	1	0	0	1	17.09.2001 08:20	27	Unscheduled FOMC Rate Decision
65	02.10.2001 14:15	1	0	0	0			
66	06.11.2001 14:20	1	0	0	0			
67	11.12.2001 14:14	1	0	0	0			
68	30.01.2002 14:15	1	0	0	0			
69	19.03.2002 14:15	1	0	0	0			
70	07.05.2002 14:15	1	0	0	0			
71	26.06.2002 14:15	1	0	0	0			
72	13.08.2002 14:15	1	0	0	0			
73	24.09.2002 14:15	1	0	0	0			
74	06.11.2002 14:14	1	0	0	0			
75	10.12.2002 14:15	1	0	0	0			
76	29.01.2003 14:16	1	0	0	0			
77	18.03.2003 14:15	1	0	0	0			
78	06.05.2003 14:13	1	0	0	0			
79	25.06.2003 14:15	1	0	0	0			
80	12.08.2003 14:15	1	0	0	0			
81	16.09.2003 14:19	1	0	0	0			
82	28.10.2003 14:15	1	0	0	0			
83	09.12.2003 14:15	1	0	0	0			
84	28.01.2004 14:15	1	0	0	0			
85	16.03.2004 14:15	1	0	0	0			
86	04.05.2004 14:15	1	0	0	0			
87	30.06.2004 14:15	1	0	0	0			
88	10.08.2004 14:15	1	0	0	0			
89	21.09.2004 14:15	1	0	0	0			
90	10.11.2004 14:15	1	0	0	0			
91	14.12.2004 14:15	1	0	0	0			
92	02.02.2005 14:15	1	0	0	0			
93	22.03.2005 14:15	1	0	0	0			
94	03.05.2005 14:15	1	0	0	0			
95	30.06.2005 14:15	1	0	0	0			
96	09.08.2005 14:15	1	0	0	0			
97	20.09.2005 14:15	1	0	0	0			
98	01.11.2005 14:15	1	0	0	0			
99	13.12.2005 14:15	1	0	0	0			

Table IA.4 continued...

No.	Date and Time	Scheduled	Unsched.	With PC	Confounding and Date		Distance	Description
100	31.01.2006 14:14	1	0	0	0			
101	28.03.2006 14:15	1	0	0	0			
102	10.05.2006 14:15	1	0	0	0			
103	29.06.2006 14:15	1	0	0	0			
104	08.08.2006 14:15	1	0	0	0			
105	20.09.2006 14:15	1	0	0	0			
106	25.10.2006 14:15	1	0	0	0			
107	12.12.2006 14:15	1	0	0	0			
108	31.01.2007 14:15	1	0	0	0			
109	21.03.2007 14:15	1	0	0	0			
110	09.05.2007 14:15	1	0	0	0			
111	28.06.2007 14:15	1	0	0	0			
112	07.08.2007 14:15	1	0	0	0			
113	18.09.2007 14:15	1	0	0	0			
114	31.10.2007 14:15	1	0	0	0			
115	11.12.2007 14:15	1	0	0	1	12.12.2007 05:03	1	Announcement of Unconventional MP
116	22.01.2008 08:20	0	1	0	1	30.01.2008 14:15	8	Scheduled FOMC Rate Decision
117	30.01.2008 14:15	1	0	0	0			
118	18.03.2008 14:15	1	0	0	0			
119	30.04.2008 14:15	1	0	0	1	02.05.2008 04:11	2	Announcement of Unconventional MP
120	25.06.2008 14:15	1	0	0	0			
121	05.08.2008 14:15	1	0	0	0			
122	16.09.2008 14:15	1	0	0	1	18.09.2008 02:55	2	Announcement of Unconventional MP
123	08.10.2008 07:00	0	1	0	1	13.10.2008 02:00	5	Announcement of Unconventional MP
124	29.10.2008 14:17	1	0	0	1	25.11.2008 08:15	27	Announcement of Unconventional MP
125	16.12.2008 14:15	1	0	0	1	19.12.2008 08:02	3	Announcement of Unconventional MP
126	28.01.2009 14:15	1	0	0	1	03.02.2009 08:00	6	Announcement of Unconventional MP
127	18.03.2009 14:15	1	0	0	1	19.03.2009 04:25	1	Announcement of Unconventional MP
128	29.04.2009 14:15	1	0	0	0			
129	24.06.2009 14:15	1	0	0	1	25.06.2009 12:00	1	Announcement of Unconventional MP
130	12.08.2009 14:15	1	0	0	0			
131	23.09.2009 14:15	1	0	0	1	24.09.2009 10:00	1	Announcement of Unconventional MP
132	04.11.2009 14:15	1	0	0	0			
133	16.12.2009 14:15	1	0	0	0			
134	27.01.2010 14:15	1	0	0	0			
135	16.03.2010 14:15	1	0	0	0			
136	28.04.2010 14:15	1	0	0	1	10.05.2010 21:18	12	Announcement of Unconventional MP
137	23.06.2010 14:15	1	0	0	0			
138	10.08.2010 14:15	1	0	0	1	27.08.2010 10:00	17	Bernanke speech, Jackson Hole
139	21.09.2010 14:15	1	0	0	1	15.10.2010 08:15	24	Bernanke speech, Boston Fed
140	03.11.2010 14:15	1	0	0	0			
141	14.12.2010 14:15	1	0	0	1	21.12.2010 09:00	7	Announcement of Unconventional MP
142	26.01.2011 14:15	1	0	0	0			
143	15.03.2011 14:15	1	0	0	0			
144	27.04.2011 12:30	1	0	1	0			
145	22.06.2011 12:30	1	0	1	1	22.06.2011 14:15	7	Announcement of Unconventional MP
146	09.08.2011 14:15	1	0	0	1	26.08.2011 10:00	17	Bernanke speech, Jackson Hole
147	21.09.2011 14:15	1	0	0	0			
148	02.11.2011 12:30	1	0	1	0			
149	13.12.2011 14:15	1	0	0	0			
150	25.01.2012 12:30	1	0	1	0			
151	13.03.2012 14:15	1	0	0	0			
152	25.04.2012 12:30	1	0	1	0			
153	20.06.2012 12:30	1	0	1	0			
154	01.08.2012 14:15	1	0	0	0			
155	13.09.2012 12:30	1	0	1	0			
156	24.10.2012 14:15	1	0	0	0			
157	12.12.2012 12:30	1	0	1	0			
158	30.01.2013 14:15	1	0	0	0			
159	20.03.2013 14:00	1	0	1	0			
160	01.05.2013 14:00	1	0	0	1	22.05.2013 10:00	21	Bernanke Testimony
161	19.06.2013 14:00	1	0	1	0			
162	31.07.2013 14:00	1	0	0	0			
163	18.09.2013 14:00	1	0	1	0			
164	30.10.2013 14:00	1	0	0	0			
165	18.12.2013 14:00	1	0	1	0			
166	29.01.2014 14:00	1	0	0	0			
167	19.03.2014 14:00	1	0	1	0			
168	30.04.2014 14:00	1	0	0	0			
169	18.06.2014 14:00	1	0	1	0			
170	30.07.2014 14:00	1	0	0	0			
171	17.09.2014 14:00	1	0	1	0			
172	29.10.2014 14:00	1	0	0	0			
173	17.12.2014 14:00	1	0	1	0			
174	28.01.2015 14:00	1	0	0	0			
175	18.03.2015 14:00	1	0	1	0			
176	29.04.2015 14:00	1	0	0	0			
177	17.06.2015 14:00	1	0	1	0			
178	29.07.2015 14:00	1	0	0	0			
179	17.09.2015 14:00	1	0	1	0			
180	28.10.2015 14:00	1	0	0	0			
181	16.12.2015 14:00	1	0	1	0			
182	27.01.2016 14:00	1	0	0	0			
183	16.03.2016 14:00	1	0	1	0			
184	27.04.2016 14:00	1	0	0	0			
185	15.06.2016 14:00	1	0	1	0			
186	27.07.2016 14:00	1	0	0	0			
187	21.09.2016 14:00	1	0	1	0			
188	02.11.2016 14:00	1	0	0	0			
189	14.12.2016 14:00	1	0	1	0			
190	01.02.2017 14:00	1	0	0	0			
191	15.03.2017 14:00	1	0	1	0			
192	03.05.2017 14:00	1	0	0	0			
193	14.06.2017 14:00	1	0	1	0			
194	26.07.2017 14:00	1	0	0	0			
195	20.09.2017 14:00	1	0	1	0			
196	01.11.2017 14:00	1	0	0	0			
197	13.12.2017 14:00	1	0	1	0			
198	31.01.2018 14:00	1	0	0	0			
199	21.03.2018 14:00	1	0	1	0			
200	02.05.2018 14:00	1	0	0	0			
201	13.06.2018 14:00	1	0	1	0			
202	01.08.2018 14:00	1	0	0	0			
203	26.09.2018 14:00	1	0	1	0			
204	08.11.2018 14:00	1	0	0	0			
205	19.12.2018 14:00	1	0	1	0			
206	30.01.2019 14:00	1	0	0	0			
207	20.03.2019 14:00	1	0	1	0			
208	01.05.2019 14:00	1	0	0	0			
209	19.06.2019 14:00	1	0	1	0			
210	31.07.2019 14:00	1	0	0	0			
211	18.09.2019 14:00	1	0	1	0			
212	30.10.2019 14:00	1	0	0	0			
213	11.12.2019 14:00	1	0	1	1			13.12.2019 is the end of our sample

Table IA.5: Long-Horizon Effects of Monetary Policy Surprises

This table reports the effect of a unit standard deviation monetary policy surprises on daily fund returns (close-close) and daily fund flows on FOMC announcement days ($h = 0$), the cumulated impact over the next 5 days ($h = 5$), and the next 20 days ($h = 20$). Results are obtained from linear projections of the form:

$$X_{t\to t+h} = a_h + b_h \times Monetary\ Policy\ Surprise_{j,t} \times D_{FOMC,t} + \xi_{t+h},$$

where $X_{t\to t+h}$ is the cumulative fund return, or flow, from time t up to time $t + h$, $Monetary\,Policy\,Surprise_{j,t}$ is one of the three orthogonal monetary policy surprises measured intraday around FOMC announcements (see Table 1 for details), and $D_{FOMC,t}$ is a dummy variable which is one on FOMC announcement days. If another monetary policy announcement falls into the event window (-1d:+20d), we remove this event from the sample (19 cases, as listed in the Internet Appendix). The sample period is from 2006 to 2019 with 95 non-confounding FOMC announcements. T-statistics are based on bootstrap standard errors that account for the fact that the regressors are estimated.

	Returns, %			**Flows, %**		
	Equity-Bond	**Equity**	**Bond**	**Equity-Bond**	**Equity**	**Bond**
	Short Rate Surprises on FOMC Days					
b_0	-0.42	-0.49	-0.07	-0.29	-0.45	-0.17
$\sum_{h=0}^{5} b_h$	-0.32	-0.36	-0.03	-0.52	-0.28	0.24
$\sum_{h=0}^{20} b_h$	-0.91	-0.96	-0.04	-0.63	-0.05	0.58
t_0	-3.47	-4.36	-2.39	-1.76	-3.56	-1.82
$t_{\sum 5}$	-1.27	-1.61	-0.57	-1.15	-0.89	0.90
$t_{\sum 20}$	-2.68	-3.20	-0.53	-0.98	-0.15	1.16
	Long Rate Surprises on FOMC Days					
b_0	0.33	0.19	-0.14	0.22	0.19	-0.03
$\sum_{h=0}^{5} b_h$	0.55	0.33	-0.22	1.27	0.66	-0.61
$\sum_{h=0}^{20} b_h$	0.12	-0.04	-0.15	0.44	0.54	0.11
t_0	2.27	1.53	-2.87	1.42	1.40	-0.36
$t_{\sum 5}$	2.09	1.43	-2.83	2.21	1.92	-1.57
$t_{\sum 20}$	0.37	-0.12	-1.94	0.46	1.25	0.14
	Risk Shifts on FOMC Days					
b_0	0.56	0.65	0.09	0.67	0.62	-0.05
$\sum_{h=0}^{5} b_h$	0.46	0.56	0.10	1.65	0.76	-0.89
$\sum_{h=0}^{20} b_h$	0.10	0.20	0.10	1.71	-0.22	-1.93
t_0	6.11	7.25	5.46	5.20	6.20	-0.50
$t_{\sum 5}$	2.53	3.30	2.84	3.87	2.39	-2.98
$t_{\sum 20}$	0.33	0.68	1.69	2.50	-0.64	-3.66

Table IA.6: Other Risky Asset Classes and Risk Shifts

This table reports for an extended set of risky asset classes the effect of a unit standard deviation risk shift on daily fund returns (close-close) and daily fund flows on FOMC announcement days ($h = 0$), the cumulated impact over the next 5 business days ($h = 5$), and the next business 20 days ($h = 20$). The risky asset classes are proxied by long-short strategies based on Bloomberg fund categories: "Corp.-Broad" is corporate minus all broad bond funds, "EM-Broad Bonds" is emerging market bond minus all broad bond funds, and "EM-US Equities" is emerging market equity minus all U.S. blend equity funds. The max. sample period is from 2006 to 2019 and is shorter for the EM bond category. #FOMC reports the number of non-confounding FOMC announcement days available.

	Other Risky Asset Classes & Risk Shifts		
	Bonds		**Equities**
	Corp.-Broad	**EM-Broad**	**EM-US**
#FOMC	**95**	**79**	**95**
		Returns, %	
b_0	0.10	0.21	0.49
$\sum_{h=0}^{5} b_h$	0.14	0.39	0.27
$\sum_{h=0}^{20} b_h$	0.11	0.22	0.79
t_0	4.82	3.33	5.21
$t_{\sum 5}$	2.91	2.72	1.39
$t_{\sum 20}$	1.41	1.10	1.85
		Flows, %	
b_0	0.16	0.33	-0.25
$\sum_{h=0}^{5} b_h$	1.75	2.16	1.23
$\sum_{h=0}^{20} b_h$	1.54	3.86	1.77
t_0	1.31	2.10	-1.88
$t_{\sum 5}$	3.98	3.38	2.69
$t_{\sum 20}$	1.80	3.23	1.97

Table IA.7: Monetary Policy Surprises: Extended Sample (1994 - 2005)

Monetary policy factor extraction is as described in Table 1 of the main paper, but for an extended sample starting in 1994. The VIX is the only risky asset in the extended sample; VIX intraday data from 01/1998 to 12/2005 come from kibot.com. For the period 01/1994 to 12/1997, we use the open and close price available from www.cboe.com. For this sub-period, we scale the open-close change of the VIX according to regressions of the open-close changes on event window changes.

	Monetary Policy Surprises					
	PCA on FOMC Days (#99)			**Orthogonal Rotation**		
	(1)	**(2)**	**(3)**	**"Short Rate"**	**"Long Rate"**	**"Risk Shift"**
$\triangle ED(3M)$	0.45	-0.09	-0.86	0.98*	0.00	0.00
$\triangle TU(2Y)$	0.50	-0.14	0.18	0.09	0.54	0.00
$\triangle FV(5Y)$	0.49	-0.11	0.44	-0.15	0.64	-0.03
$\triangle TY(10Y)$	0.50	-0.13	0.18	0.09	0.54*	0.00
$\triangle log\left(VIX^2\right)$	0.24	0.97	0.01	0.00	-0.02	-1.00*
Var. expl.,%	76.9	16.7	5.3			

Table IA.8: Extended Sample Period Results, 1994 - 2019

This table considers an extended sample period going back to 1994. For the period 1994-2005, monetary policy surprises are recalculated using the four interest rates (3 months, 2 years, 5 years, 10 years) plus the VIX (see Table IA.7). The extended (full) sample covers 213 FOMC announcements from 1994 to 2019. Results provided for subsample refer to the period before rates hit the effective lower bound (1998-11/2008) and when we exclude the effective lower bound period (12/2008-12/2015). T-statistics are based on bootstrap standard errors.

Extended sample period results (-15m:+75m/close if followed by press conference)

	Full sample (1994-2019, #213)			Before ELB (1994-11/2008, #124)			Exclude ELB (ex.12/2008-12/2015, #156)		
	SR	LR	RS	SR	LR	RS	SR	LR	RS
b	-0.31	-0.04	0.58	-0.31	-0.05	0.53	-0.30	0.10	0.53
$t(b)$	-3.22	-0.40	10.83	-2.73	-0.34	7.60	-2.79	0.72	8.44
R^2	13.19	0.21	44.25	14.45	0.25	34.30	13.57	1.00	37.43
$mu_{MP\ Shock>0}$	-0.06	0.13	0.37	-0.01	0.12	0.33	-0.14	0.15	0.29
$s.e.$	0.09	0.07	0.06	0.11	0.11	0.09	0.10	0.09	0.07
$mu_{MP\ Shock<0}$	0.17	-0.01	-0.47	0.15	0.00	-0.43	0.16	-0.15	-0.47
$s.e.$	0.08	0.10	0.10	0.13	0.14	0.15	0.10	0.11	0.14

Table IA.9: Monetary Policy Factor Comparisons

This table compares different rate surprises extracted from fed fund futures and Eurodollar futures to our three monetary policy surprises. The data based on fed fund futures are taken from Gorodnichenko and Weber (2016).

	Intraday Returns and Monetary Policy Surprises														
	1994 - 11/2008 (#124)					1994 - 2005 (#99)					2006 - 11/2008 (#25)				
	FFR	*ED*	*SR*	*LR*	*RS*	*FFR*	*ED*	*SR*	*LR*	*RS*	*FFR*	*ED*	*SR*	*LR*	*RS*
b	-4.65	-4.69	-0.31	-0.05	0.53	-6.31	-5.58	-0.45	-0.02	0.45	-0.82	-3.09	-0.12	-0.11	0.69
$t(b)$	-2.73	-3.89	-2.71	-0.34	7.65	-5.02	-4.17	-3.86	-0.13	5.12	-0.22	-1.18	-0.61	-0.32	6.30
R^2	19.49	18.13	14.45	0.25	34.30	34.02	22.00	23.23	0.05	23.76	0.68	10.44	2.91	1.86	70.54

Table IA.10: Short Rate Surprises and Risk Shifts

This table compares results from our monetary policy surprises to changes in Fed funds rates (FFR) and simple changes in three month rates (Eurodollar, ED). The Fed funds rate data come from Gorodnichenko and Weber (2016). Data sources of the other data are described in Table 1. In Panel A, we control for change in the VIX, while Panel B provides the results from univariate regressions. Panel C shows the correlation coefficient between changes in rates and changes in the VIX. T-statistics are based on bootstrap standard errors.

Panel A. Fed funds rate (FFR) / three-month rate (ED) surprises with controlling for VIX

Intraday Returns and Monetary Policy Surprises (-15m:+75m)

	1994 - 11/2008 (#124)		1994 - 2005 (#99)		2006 - 11/2008 (#25)	
	FFR	*ED*	*FFR*	*ED*	*FFR*	*ED*
$\triangle RATES_{t\vert FOMC}$	-3.94	-3.14	-5.18	-3.88	-1.96	-2.28
t	-3.03	-2.80	-3.42	-2.41	-0.99	-1.33
$\triangle log(VIX^2_{t\vert FOMC})$	-0.06	-0.06	-0.05	-0.05	-0.07	-0.07
t	-6.22	-6.31	-3.58	-3.58	-5.97	-6.17
R^2	53.89	47.68	50.55	38.48	71.31	73.14

Panel B. Fed funds rate (FFR) / three-month rate (ED) surprises without controlling for VIX

Intraday Returns and Monetary Policy Surprises (-15m:+75m)

	1994 - 11/2008 (#124)		1994 - 2005 (#99)		2006 - 11/2008 (#25)	
	FFR	*ED*	*FFR*	*ED*	*FFR*	*ED*
$\triangle RATES_{t\vert FOMC}$	-4.65	-4.69	-6.31	-5.58	-0.82	-3.09
t	-2.77	-3.96	-4.99	-4.18	-0.22	-1.18
R^2	19.49	18.13	34.02	22.00	0.68	10.44

Panel C. Correlation coefficients with changes in the VIX

	FFR	*ED*	*FFR*	*ED*	*FFR*	*ED*
corr	0.11	0.25	0.25	0.33	-0.13	0.11

Table IA.11: Response of Equity Returns & Flows to Monetary Policy Surprises: Variations

This table considers different event windows to estimate the response of equity returns and equity flows to monetary policy surprises (Table 2). Panel A provides results when we extend the event window from -15 minutes to the close on all days. Panel B reports results when we constrain the event window from -15 minutes to +45 minutes on all days (and ignore the information content of press conferences). T-statistics are based on bootstrap standard errors. Panel B and C account for the fact that the regressors are estimated.

Panel A. Wide event window (-15:close)

	Equity Returns						**Equity Flows**		
	Event Window Returns			Daily Returns			Daily Flows		
	SR	LR	RS	SR	LR	RS	SR	LR	RS
b	-0.19	-0.09	0.83	-0.30	-0.03	0.83	-0.12	-0.11	0.45
$t(b)$	-1.61	-0.90	9.90	-1.83	-0.23	7.67	-1.13	-0.82	4.25
R^2	3.62	0.78	70.61	5.77	0.06	45.05	1.29	1.00	16.58

Panel B. Tight event window (-15m:+45m), ignore press conferences

	Equity Returns						**Equity Flows**		
	Event Window Returns			Daily Returns			Daily Flows		
	SR	LR	RS	SR	LR	RS	SR	LR	RS
b	-0.03	-0.11	0.62	-0.26	-0.17	0.42	-0.15	-0.15	0.36
$t(b)$	-0.32	-0.79	7.17	-1.32	-1.09	3.20	-1.37	-1.05	3.51
R^2	0.16	2.35	75.67	4.48	1.87	11.51	1.78	1.87	10.94

Table IA.12: Discount Rate News: VAR Parameter Estimates

This table shows VAR parameter estimates (b) for a first-order VAR model including a constant, the daily S&P500 excess return ($Ret_t - Rf_t$), the option implied lower bound on the expected equity premium for a horizon of one month (EP_t), as in Martin (2017)), the variance risk premium (the difference between option implied variance and the expected realized variance, $VIX_t^2 - RV_t^2$, as in Bollerslev, Tauchen, and Zhou (2009); where we estimate the expected realized variance as in Corsi (2009)), and the dividend price ratio (provided by Datastream, "DSDY"). EP_t and $VIX_t^2 - RV_t^2$ are scaled such that they correspond to a daily frequency. We then apply the classic formulas (e.g., Campbell (1991)) to compute "discount rate news" and the "cash-flow news" (="residual news"). This proxy of "discount rate news" is then used in Figure 3 as a dependent variable. The data are daily (close-close) and the sample period is from 2006 to August 2014.

	VAR Parameter Estimates			
	$Ret_{t+1} - Rf_{t+1}$	EP_{t+1}	$VIX_{t+1}^2 - RV_{t+1}^2$	DP_{t+1}
$b(Ret_t - Rf_t)$	-0.07	0.00	0.02	0.00
$b(EP_t)$	15.30	0.91	-4.83	-0.41
$b(VIX_t^2 - RV_t^2)$	0.65	0.00	0.73	-0.02
$b(DP_t)$	-0.24	0.00	0.07	1.00
$t(Ret_t - Rf_t)$	-2.62	0.82	4.95	2.25
$t(EP_t)$	2.58	31.79	-5.93	-2.41
$t(VIX_t^2 - RV_t^2)$	3.22	-3.06	25.60	-3.15
$t(DP_t)$	-0.84	2.13	2.44	128.88
F, pv	0.00	0.00	0.00	0.00
R^2, %	2.61	94.47	80.52	98.69
$Var(CF)$	23.87			
$Var(DR)$	36.65			
$Cov(DR, CF)$	-19.74			

Table IA.13: Absolute Risk Shifts and Market Commentary

We collect market commentary on scheduled FOMC announcement days from *Thomson Reuters Instant View.* We then count the frequency of words that relates to economic and financial conditions or the surprise content of the news divided by the total number of words, $F_{i,FOMC}$, and run the following regressions: $|Risk\ Shift_{t|FOMC}| = a + bF_{i,FOMC} + e_{t|FOMC}$, where $|Risk\ Shift_{t|FOMC}|$ is the absolute Risk Shift on a FOMC announcement day (see Table 1 for details). The sample period is from 2006 to 2017; 96 scheduled FOMC announcements.

	$\|Risk\ Shift_{t\|FOMC}\| = a + bF_{i,t\|FOMC} + e_{t\|FOMC}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inflation	-0.08								
t	[-1.58]								
Employment		-0.11							
t		[-1.68]							
Growth			-0.06						
t			[-0.96]						
Fin. Market				0.21					0.09
t				[1.86]					[1.28]
Risk					0.20				0.18
t					[2.48]				[2.71]
Surprise						0.15			0.05
t						[2.00]			[0.88]
Confidence							0.18		0.23
t							[2.13]		[2.84]
Disagreement								0.30	0.27
t								[2.55]	[2.84]
Constant	0.77	0.78	0.75	0.43	0.46	0.51	0.56	0.63	0.10
t	[8.03]	[7.72]	[7.02]	[3.37]	[5.55]	[5.91]	[6.62]	[9.77]	[0.72]
Observations	96	96	96	96	96	96	96	96	96
Adj. R^2	0.00	0.01	0.00	0.07	0.07	0.03	0.05	0.16	0.31

Table IA.14: Absolute Short Rate Surprises and Market Commentary

We collect market commentary on scheduled FOMC announcement days from *Thomson Reuters Instant View.* We then count the frequency of words that relates to economic and financial conditions or the surprise content of the news divided by the total number of words, $F_{i,FOMC}$, and run the following regressions:$|Short\ Rate_{t|FOMC}| = a + bF_{i,\ \mathrm{t|FOMC}} + e_{t|FOMC}$, where $|Short\ Rate_{t|FOMC}|$ is the absolute Short Rate Surprise on a FOMC announcement day (see Table 1 for details). The sample period is from 2006 to 2017; 96 scheduled FOMC announcements.

	$\lvert Short\ Rate_{t\lvert FOMC}\rvert = a + bF_{i,t\lvert FOMC} + e_{t\lvert FOMC}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inflation	0.04								
t	[0.65]								
Employment		-0.18							
t		[-3.18]							
Growth			0.01						
t			[0.17]						
Fin. Market				0.18					0.17
t				[1.93]					[1.67]
Risk					0.03				0.01
t					[0.37]				[0.09]
Surprise						0.04			-0.02
t						[0.54]			[-0.23]
Confidence							0.07		0.07
t							[0.93]		[0.99]
Disagreement								0.08	0.04
t								[0.84]	[0.59]
Constant	0.43	0.61	0.46	0.24	0.43	0.41	0.42	0.45	0.20
t	[4.43]	[5.35]	[5.05]	[2.69]	[3.77]	[3.17]	[6.19]	[5.93]	[1.55]
Observations	96	96	96	96	96	96	96	96	96
Adj. R^2	0.00	0.05	0.00	0.05	0.00	0.00	0.00	0.00	0.02

Table IA.15: Absolute Long Rate Surprises and Market Commentary

We collect market commentary on scheduled FOMC announcement days from *Thomson Reuters Instant View.* We then count the frequency of words that relates to economic and financial conditions or the surprise content of the news divided by the total number of words, $F_{i,FOMC}$, and run the following regressions: $|LongRate_{t|FOMC}| = a+bF_{i,\ \mathrm{t|FOMC}}+e_{t|FOMC}$, where $|LongRate_{t|FOMC}|$ is the absolute Long Rate Surprise on a FOMC announcement day (see Table 1 for details). The sample period is from 2006 to 2017; 96 scheduled FOMC announcements.

	$\|Long\ Rate_{t\|FOMC}\| = a + bF_{i,t\|FOMC} + e_{t\|FOMC}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inflation	-0.03								
t	[-0.56]								
Employment		-0.15							
t		[-2.57]							
Growth			-0.09						
t			[-1.99]						
Fin. Market				0.13					0.12
t				[1.42]					[1.38]
Risk					-0.02				-0.03
t					[-0.27]				[-0.44]
Surprise						0.07			0.02
t						[1.12]			[0.39]
Confidence							0.13		0.13
t							[2.13]		[2.03]
Disagreement								0.06	0.04
t								[0.58]	[0.49]
Constant	0.73	0.82	0.80	0.53	0.72	0.62	0.60	0.69	0.45
t	[6.17]	[7.69]	[7.52]	[4.87]	[6.08]	[6.98]	[8.30]	[9.53]	[3.08]
Observations	96	96	96	96	96	96	96	96	96
Adj. R^2	0.00	0.03	0.01	0.02	0.00	0.00	0.02	0.00	0.02

Table IA.16: Market Commentary Example: Confirmation and Surprise About Quantitative Easing

	13.09.2012 (QE3); Risk Shift: +2.4
Action:	Announcement of QE3
Market Comments:	JEFF SAVAGE, REGIONAL CHIEF INVESTMENT OFFICER FOR WELLS FARGO PRIVATE BANK IN PORTLAND, OREGON: ”The markets are at a very different place at the start of QE3 versus QE2 and QE1 and it will just get harder to continue to push higher using this same tool again. So there is no question the markets are not disappointed but they are certainly not going to get propelled off of these numbers. A lot of folks were expecting even less (from the Fed). A number of people were looking at statistics beyond the jobs report that would have made it hard for the Fed to do anything here.” BRAD BECHTEL, MANAGING DIRECTOR, FAROS TRADING, STAMFORD, CONNECTICUT: ”We got QE3, though I think it’s a little less than what the market was hoping for. I think markets will read this as a positive sign, so risk should rally. But I don’t necessarily think we’ll have raging euphoria for it. It’s positive, but not extremely positive.” TODD SCHOENBERGER, MANAGING PRINCIPAL AT THE BLACKBAY GROUP IN NEW YORK: ”This is exactly what Wall Street and, quite frankly, Main Street wanted from the Fed today.”
	19.06.2013 (taper tantrum); Risk Shift: -2.3
Action:	First meeting after taper tantrum (May 2013); Fed confirms the course
Market Comments:	COMMENTS: BRIAN LEVITT, SENIOR ECONOMIST AT OPPENHEIMERFUNDS IN NEW YORK, NY: ”The Fed is obviously more optimistic than they had otherwise been about the US economy and I think it confirms a lot of the better economic conditions that we had been seeing too. ”Certainly the Treasury market is telling us something. The Fed does not appear to be as worried about things as they had suggested in prior statements and that signals to the market that they are taking somewhat of a more hawkish tone. . . . “ ”Investors always freak out at what looks like a sea change in policy, but typically policy normalization and or tightening is coincident with improving macro conditions and a generally healthy environment for stocks.” STEPHEN MASSOCCA, MANAGING DIRECTOR, WEDBUSH EQUITY MANAGEMENT LLC IN SAN FRANCISCO: ”You would think everything he would be saying would be good for bonds, not bad for bonds. This started well before he started speaking. It’s beyond me. I could see if the taper had begun. The only thing I could think of is that people were positioned to short the dollar and they used the proceeds from being short the dollar to be long bonds and somehow they see this is as being positive for the dollar. But none of this makes any sense - it’s almost the opposite of what is expected.“ AXEL MERK, PRESIDENT AND CHIEF INVESTMENT OFFICER, MERK INVESTMENTS, PALO ALTO, CALIFORNIA: ”The main news is that they do indeed plan to taper purchases later this year and hope to be done by next summer. Bernanke wants to communicate that this is not necessarily tightening, but the market may not see it that way. “

Table IA.17: Market Commentary Example: Confirmation and Surprise About the Exit

	28.01.2015 (rate hike hinted); Risk Shift: -1.1
Action:	Fed hints a rate hike later the year (keep low at the moment)
Market Comments:	BARRY HoAire, FIXED INCOME PORTFOLIO MANAGER AT LOS ANGELES BASED BEL AIR INVESTMENT ADVISORS: "The Federal Reserve kind of... maintained the pledge that they're going to be patient. That was big, because everybody has baked into the cake at least one interest rate hike this year. Some people thought maybe even two. Now they're still telling you they expect to give you an interest rate hike. It may not be as early as some people expect. They're still telling you they expect to give you a 25 basis point increase this year. There's probably a good chance that happens." BRUCE MCCAIN, CHIEF INVESTMENT STRATEGIST AT KEY PRIVATE BANK IN CLEVELAND, OHIO: "Given some recent economic statistics, the Fed feels there's a need to hold off on raising rates until mid-year or even later. No earlier than mid-year. Being "patient" means the Fed is in no hurry with respect to inflation or any other factor in the economy that it is watching. This isn't surprising at all; the Fed was always more patient than other observers. "I don't think markets will move too much on this. The bigger issue is where the economy goes from here, and investors have been sobering up on that, as it becomes clear that we're growing, but below historical levels."
	18.03.2015 (leave rates unchanged); Risk Shift: +2.7
Action:	Fed announces to keep rates low this year
Market Comments:	DAVID JOY, CHIEF MARKET STRATEGIST, AMERIPRISE FINANCIAL, BOSTON: "I applaud the Fed's actions today. By eliminating 'patient' from its guidance it removed an artificial stricture on its flexibility, creating room for the data to dictate its future actions. At the same time, by lowering its expectations for the pace at which rates will rise, it sent a clear signal that it is in no hurry to push rates higher as it views the economy as growing only moderately. Today's decision should be constructive for risk assets, and relieve some upward pressure on the dollar." DAN MORRIS, GLOBAL INVESTMENT STRATEGIST, TIAA-CREF, NEW YORK: "You're looking for something that isn't going to scare the horses, they've been clearly trying to signal as much as they can ahead of time what they're going to do, and tell you what they're going to do and then do what they said they were going to do. So the fact that they dropped 'patient' is what everyone expected. So that's a good thing. "Kudos in terms of the message you're getting out of the Fed, I think they've been doing that well, and that's important. Now what does it mean? This is where the market can play the schizophrenia thing. "The path that's going to play out slightly longer term is 'Yes, the economy is OK.' The biggest challenge for equities isn't per se the fact that rates are going up, I don't see that as a real barrier, the bottom line is valuations are high right now and that's a bigger concern." GARY THAYER, HEAD OF MACRO STRATEGY AT WELLS FARGO INVESTMENT INSTITUTE IN ST. LOUIS: "It's positive in the sense the Fed is not going to step on the brakes too hard here, that they are going to be cautious in their rate movements and I think that is appropriate."

Table IA.18: Measuring Flow-Induced Price Pressure

This table reports properties of the "flow-induced price pressure" and the "information" component of S&P 500 excess returns. The return decomposition is based on a regression of daily S&P 500 excess returns on daily contemporaneous and lagged equity (ETF) flows:

$$R_t^e = constant + 0.29F_t - 0.08F_{t-1} - 0.02F_{t-5:t-2} - 0.01F_{t-20:t-6} + ...$$

$$... (0.20F_t + 0.07F_{t-1} + 0.04F_{t-5:t-2} - 0.05F_{t-20:t-6}) \times D_{FOMC,t} + \iota_t$$

The "information component" of S&P 500 excess returns is measured as the constant and the unexplained part: $R_{M,t}^e = constant + \iota_t$. The "flow-induced price pressure component" is the part explained by fund flows: $R_{S,t}^e = R_t^e - R_{M,t}^e$. The table reports the mean, standard deviation and the the R^2(in %) of a regression of the total excess return on the information or the flow-induced price pressure component. Results are reported for days that do not include FOMC announcements (ex FOMC), for FOMC announcement days (FOMC days), and for the 50% FOMC announcement days with the largest absolute risk shift (FOMC days, high absolute RS). The sample includes 114 FOMC announcements from 01/2006 to 12/2019.

	Total Excess Return	**Unexplained (Information Component)**	**Price Pressure Component**
	R_t^e	$R_{M,t}^e$	$R_{S,t}^e$
mean, ex FOMC days, %	0.02	0.02	0.00
mean, FOMC days, %	0.26	0.11	0.15
mean, FOMC days, high abs. RS, %	0.47	0.14	0.33
std, ex FOMC days, %	1.12	1.09	0.28
std, FOMC days, %	1.24	1.10	0.59
std, FOMC days, high abs. RS, %	1.35	1.15	0.61
	Total Excess Return (R_t^e) Explained by:		
	R_t^e	$R_{M,t}^e$	$R_{S,t}^e$
R^2, ex FOMC days	100 %	94 %	6 %
R^2, FOMC days	100 %	77 %	21%
R^2, FOMC days, high abs. RS	100 %	80 %	29 %

Figure IA.1: Coverage of ETF Flow Data

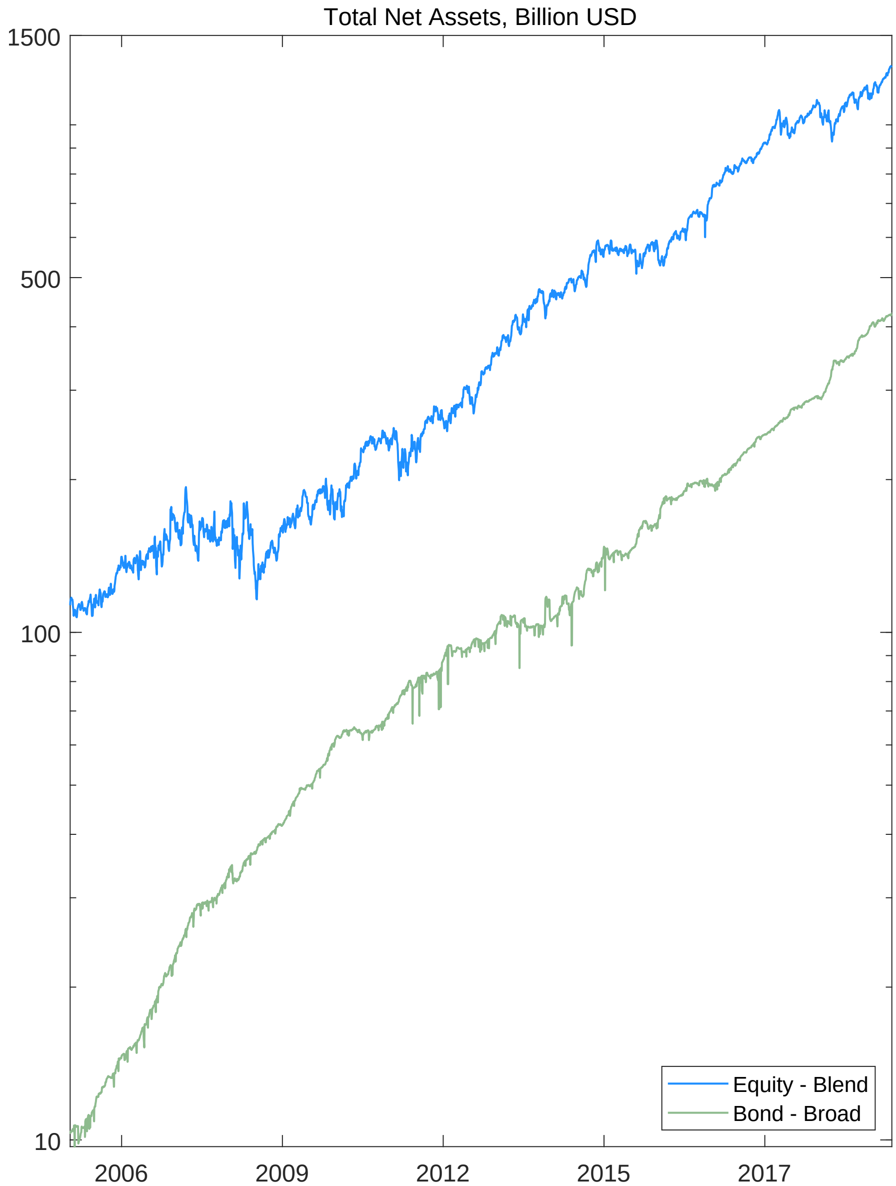


Figure IA.2: Short Rate Surprises on FOMC Announcement Days

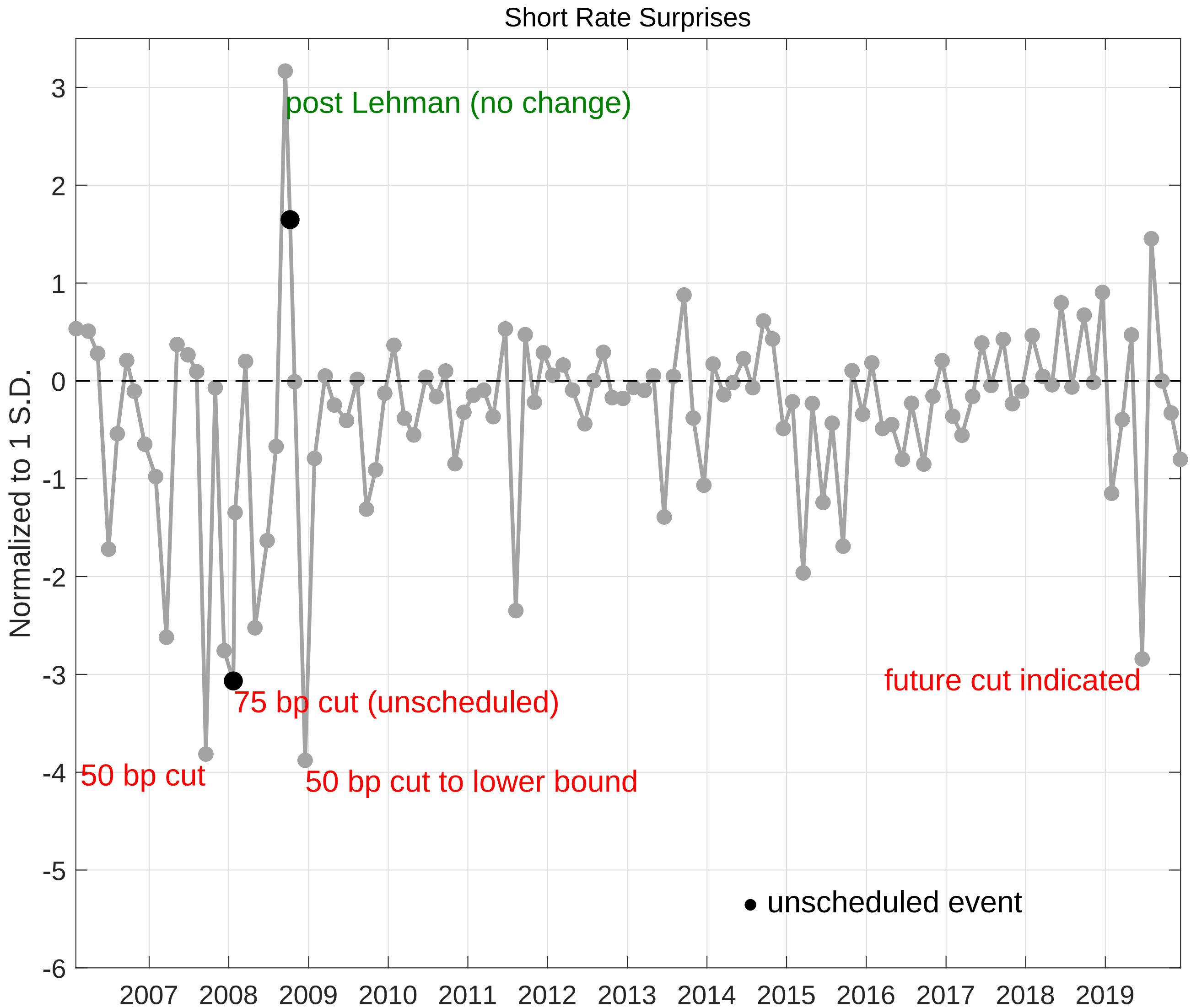


Figure IA.3: Long Rate Surprises on FOMC Announcement Days

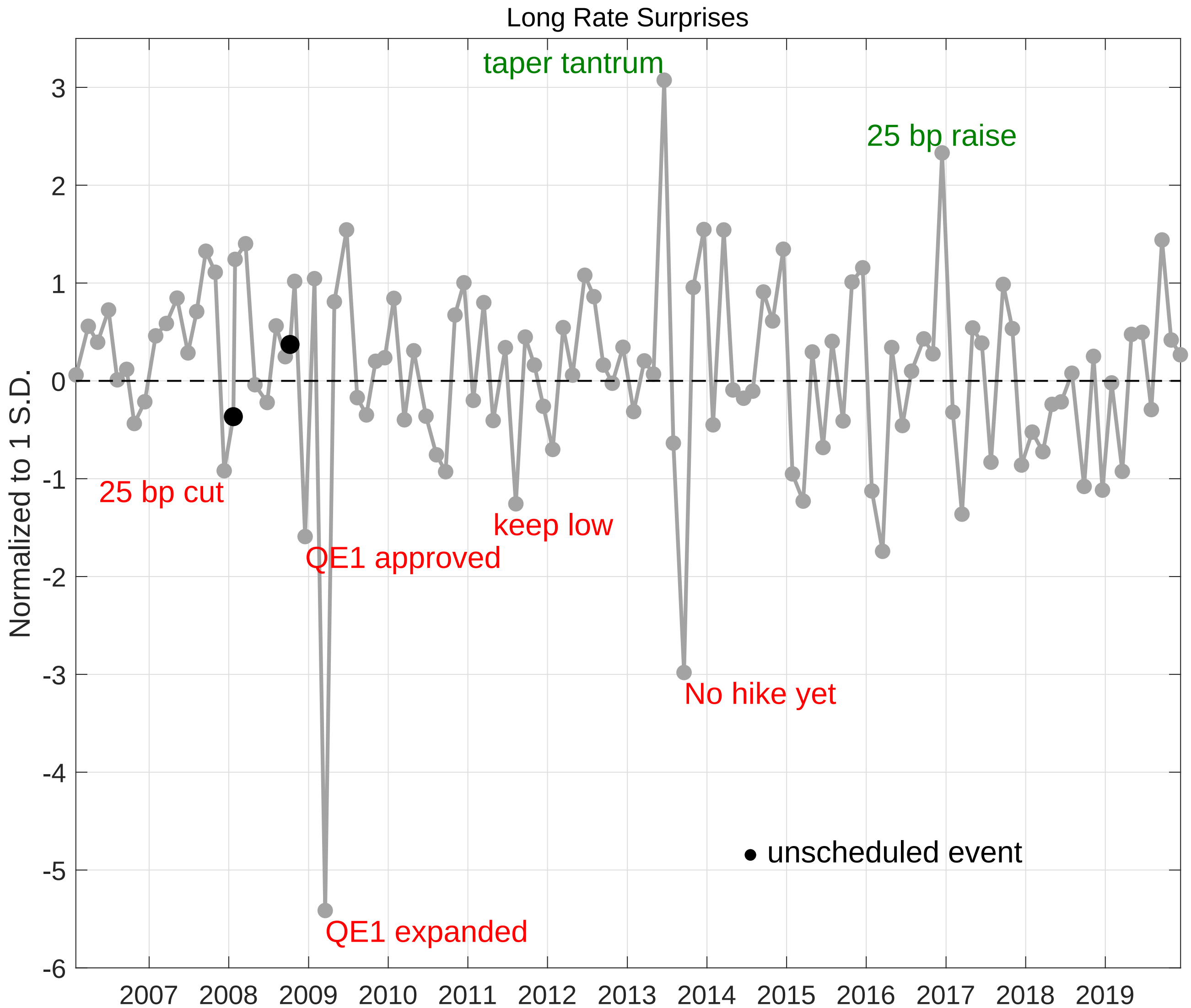


Figure IA.4: Stock Market Response to Short and Long Rate Surprises on FOMC Days

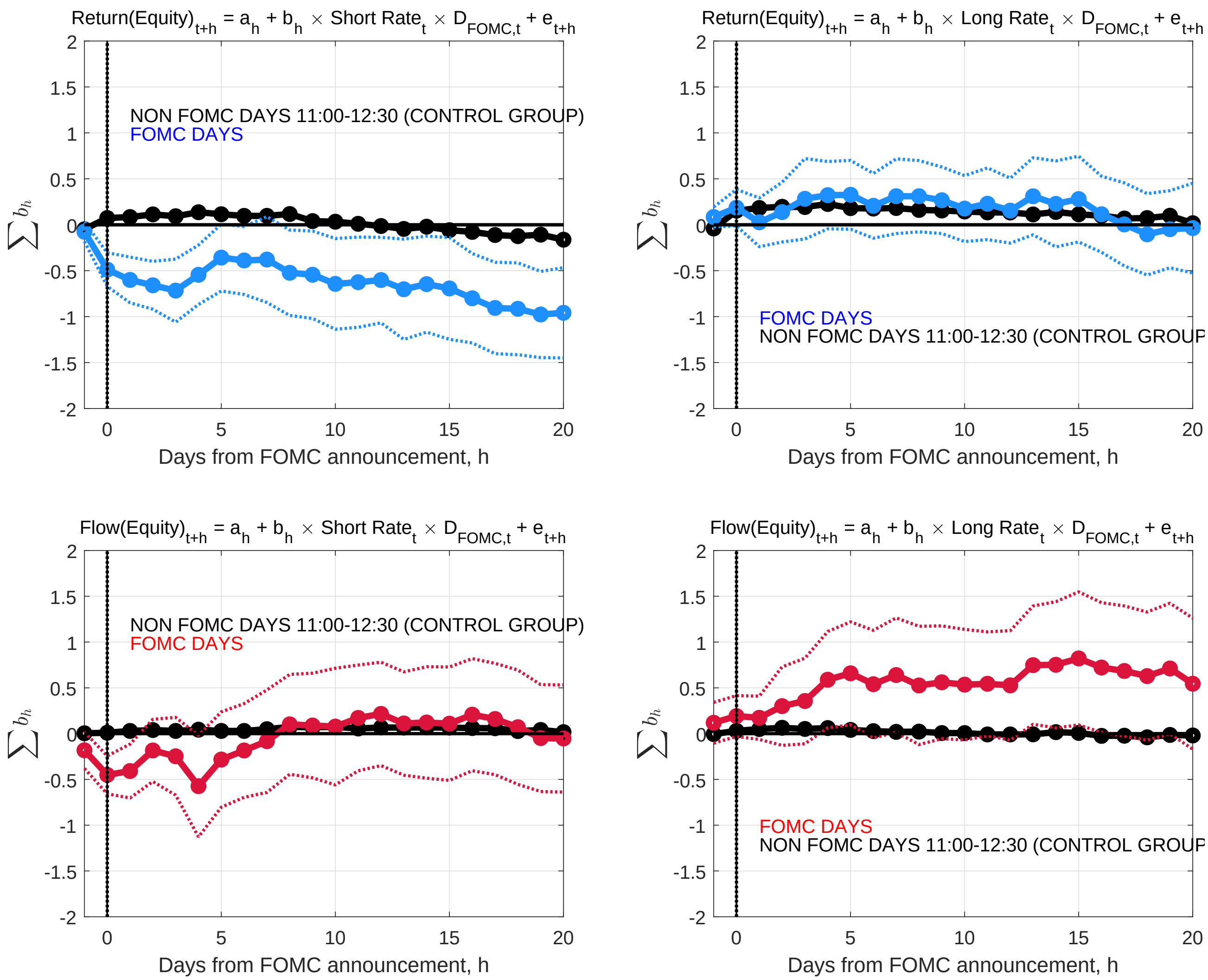


Figure IA.5: Alternative Risk Shift Factor: Dropping the VIX, CDX, or FX

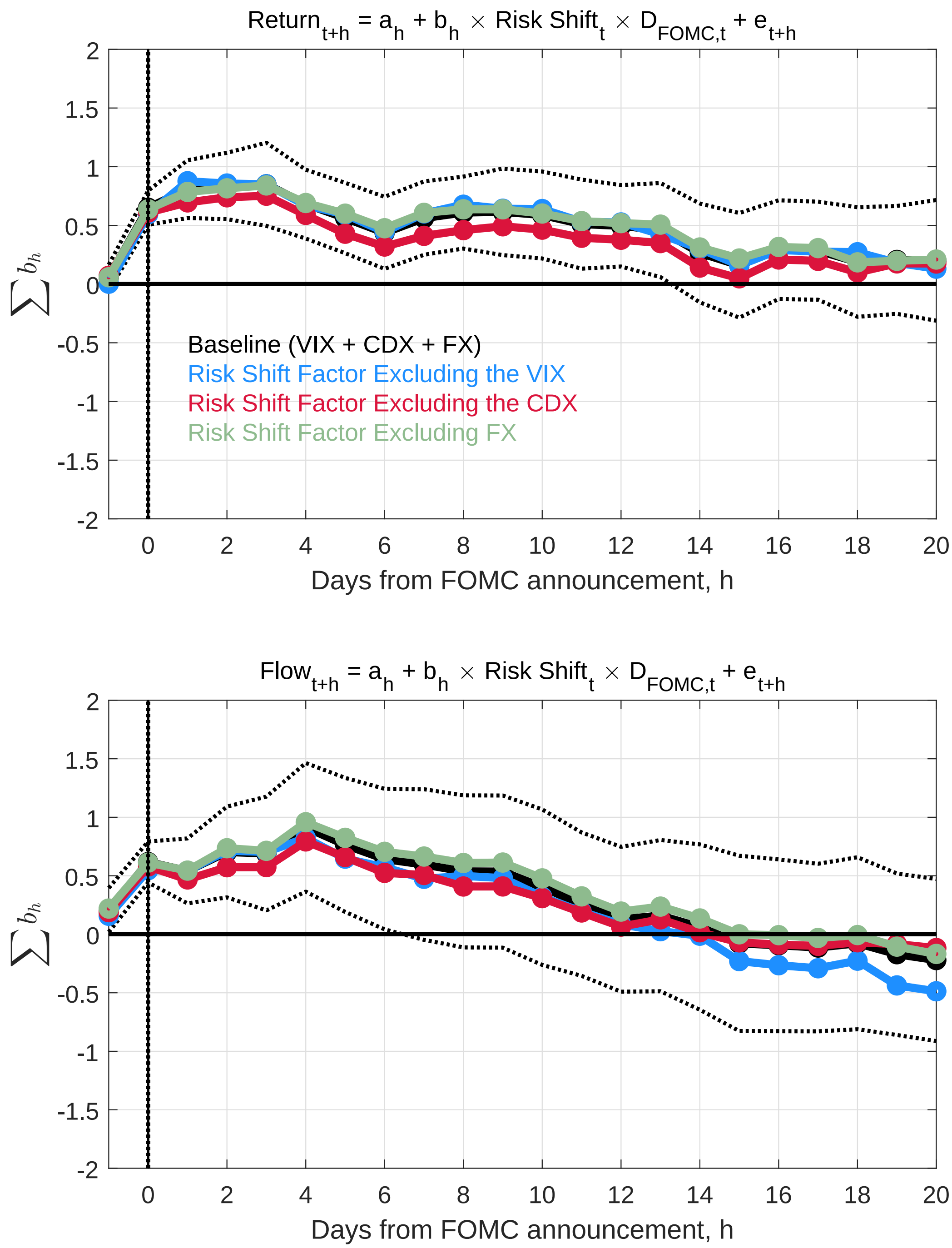
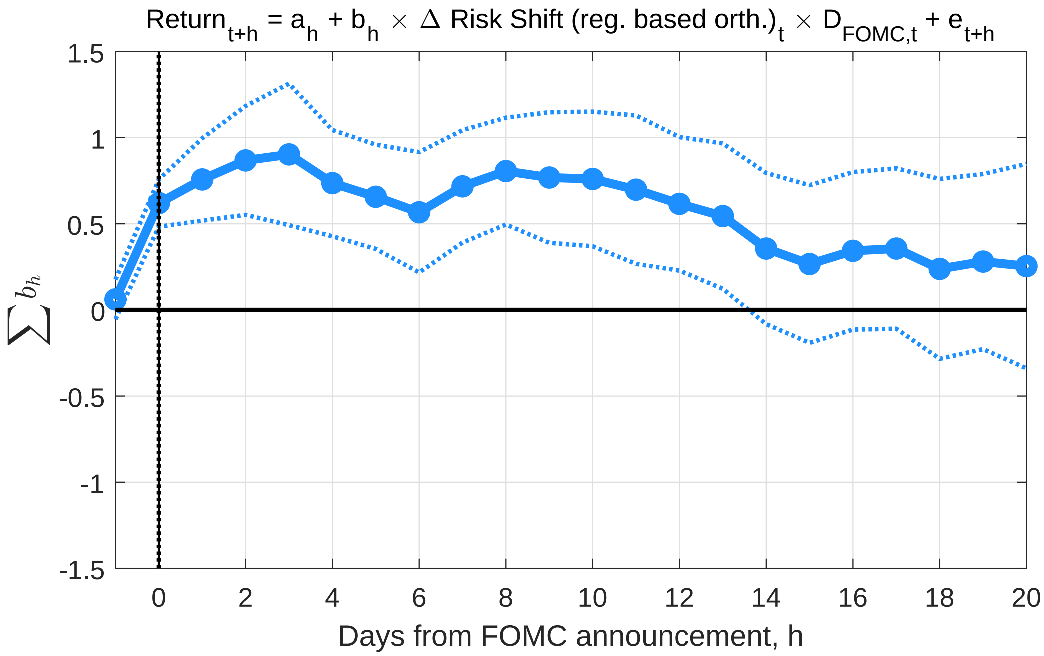


Figure IA.6: Alternative Risk Shift Factor: Regression-based Orthogonalisation of Risky Asset Prices



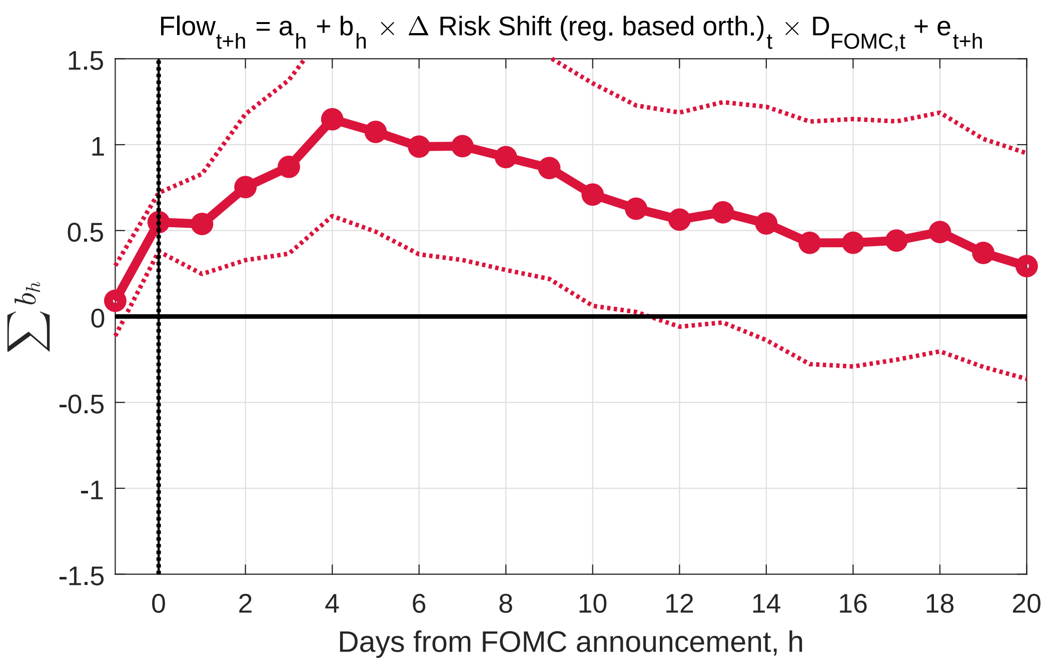


Figure IA.7: Include Confounding Events

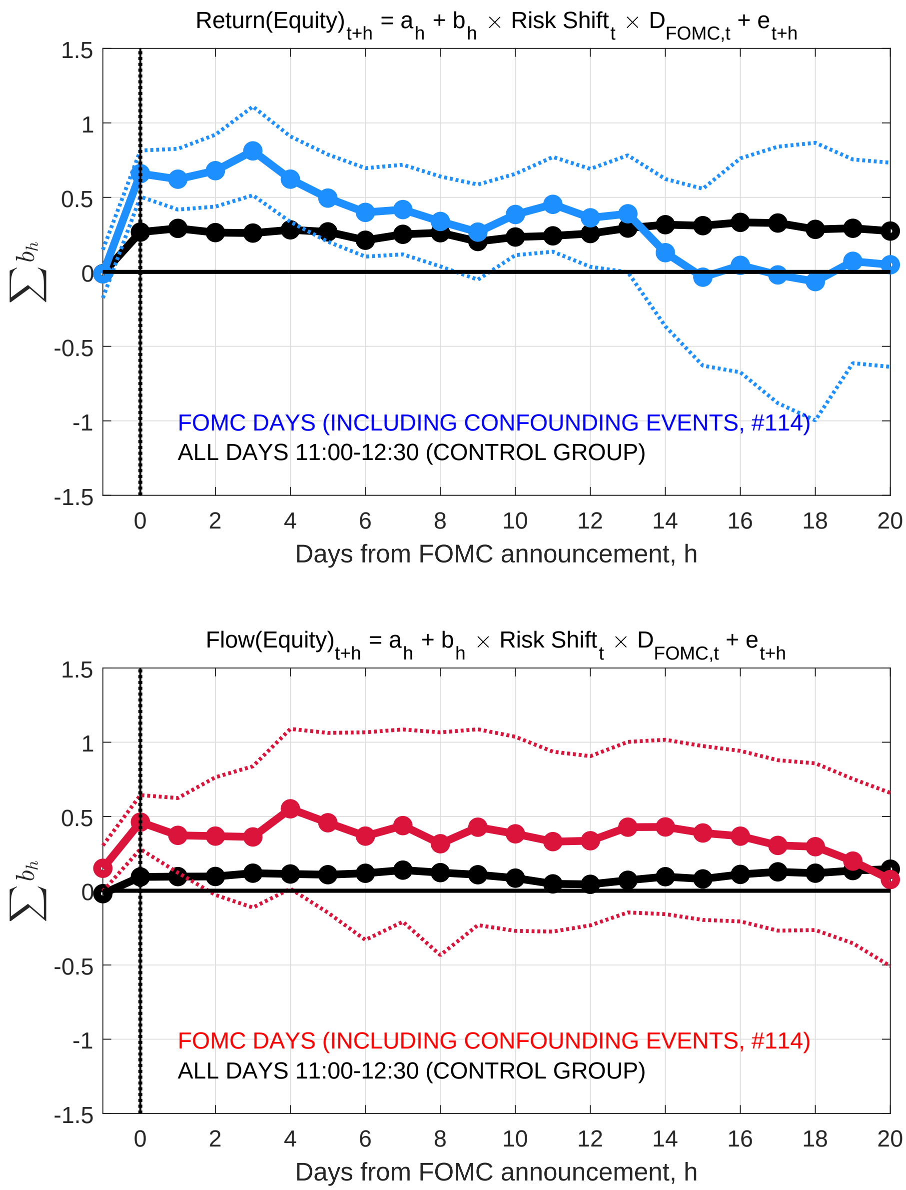
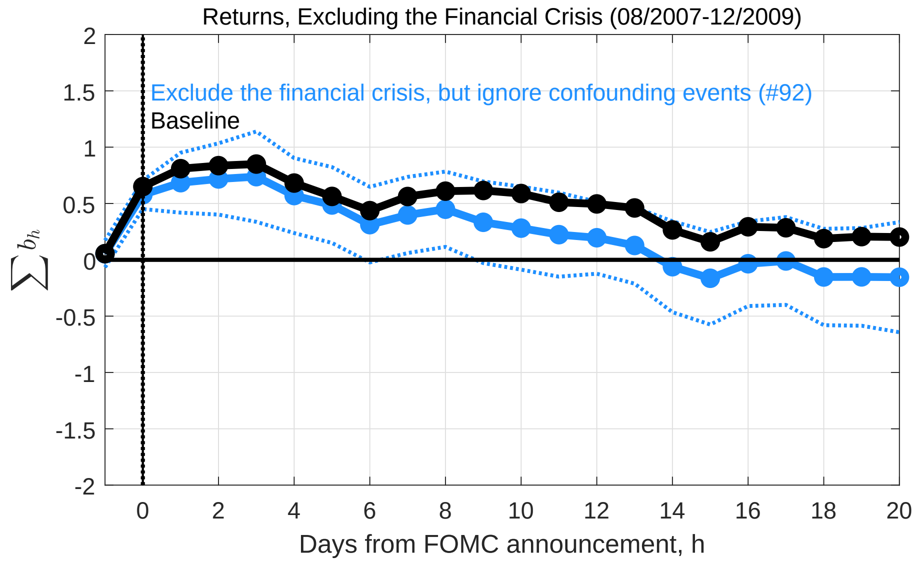


Figure IA.8: Excluding the Financial Crisis



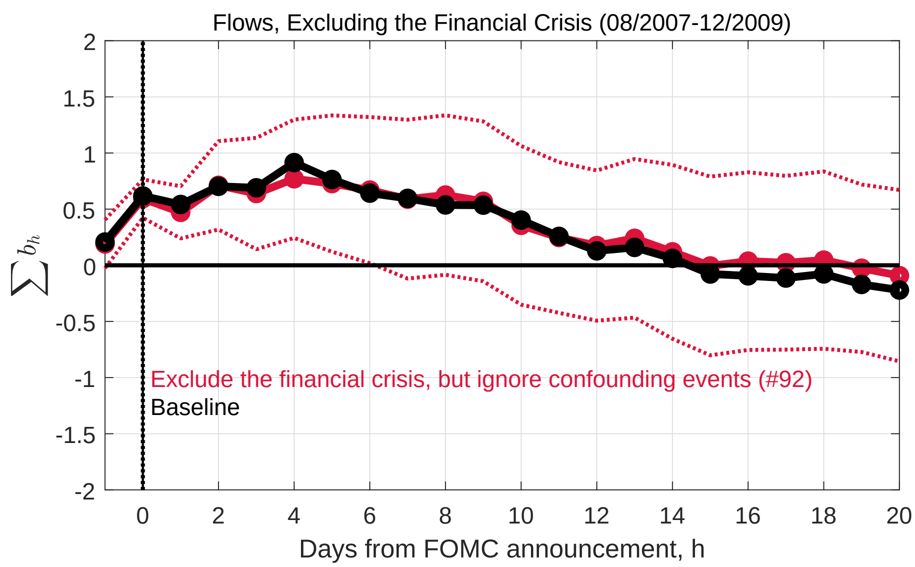


Figure IA.9: Exclude or Focus on Press Conferences

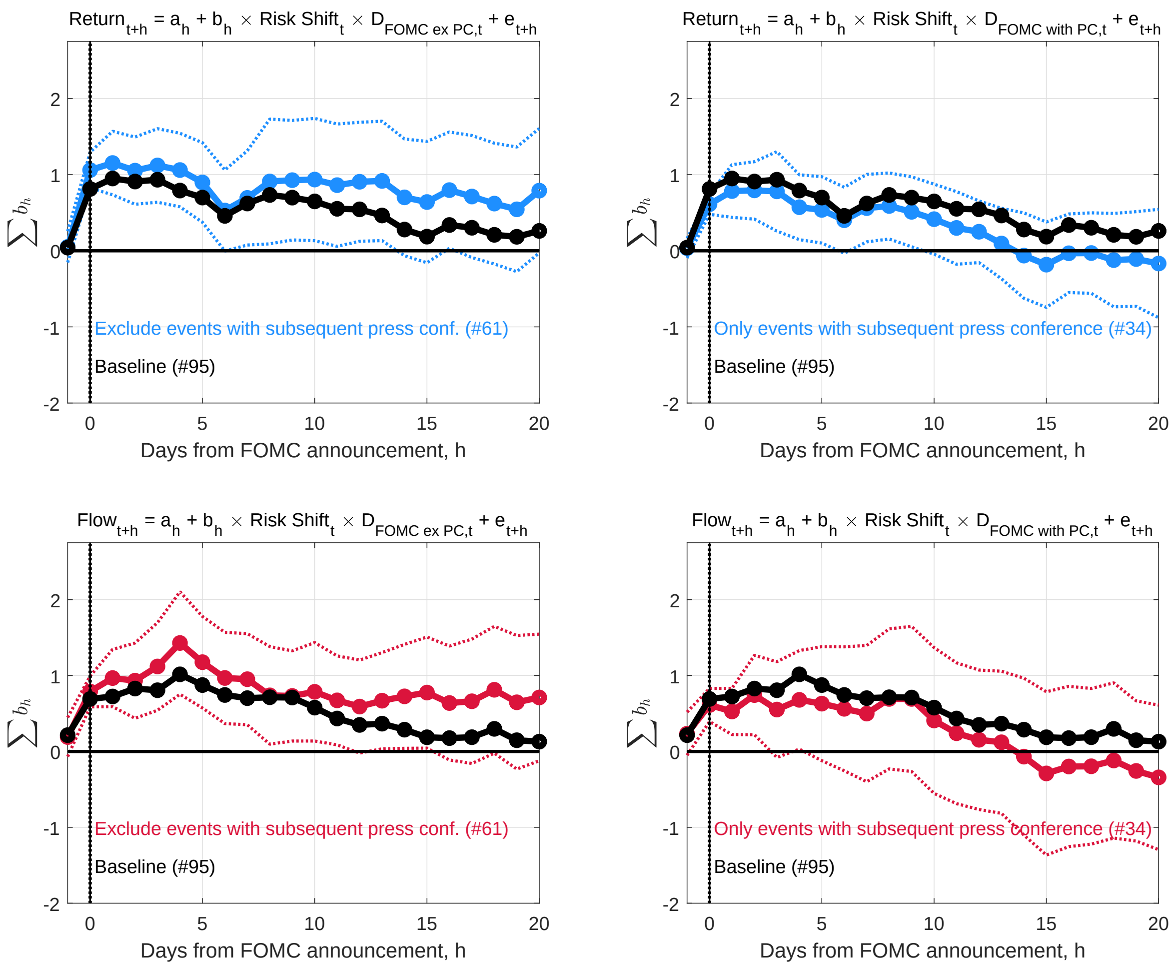
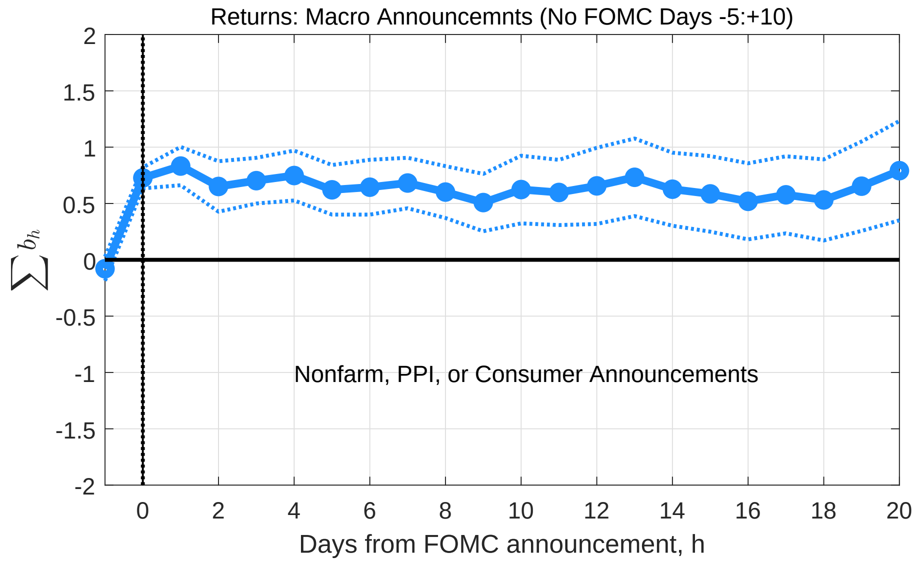


Figure IA.10: Macro Announcements



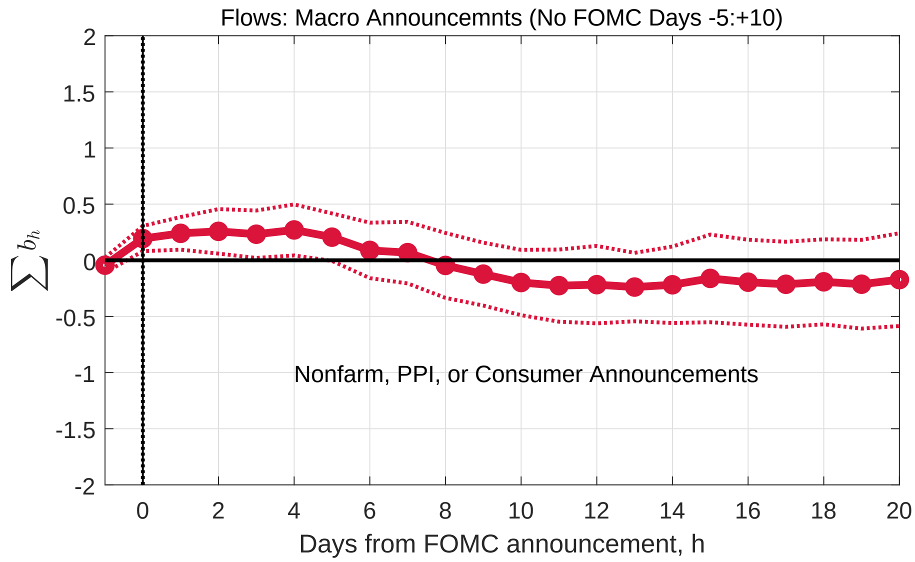


Figure IA.11: Long Sample Results

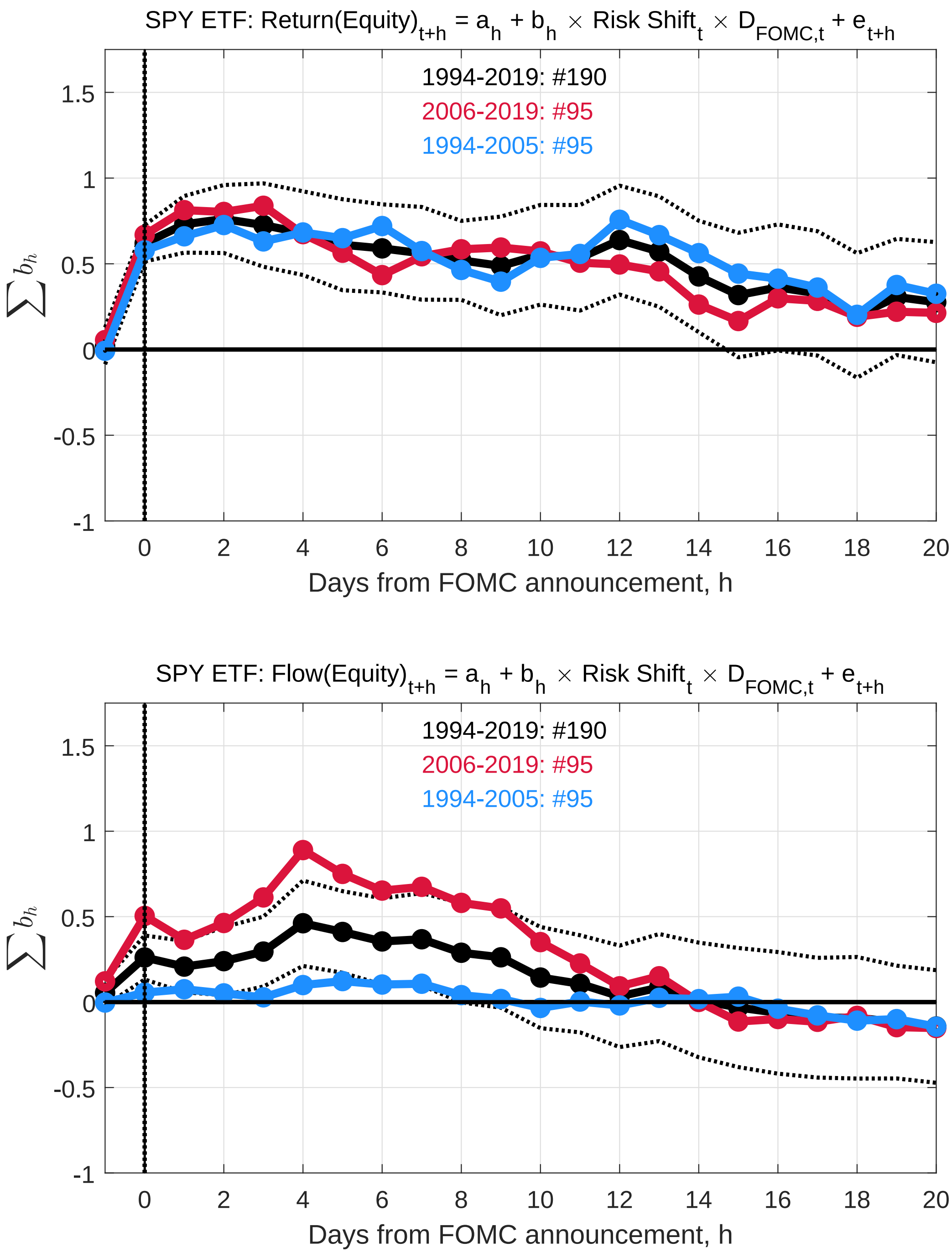


Figure IA.12: NYSE Order Flow

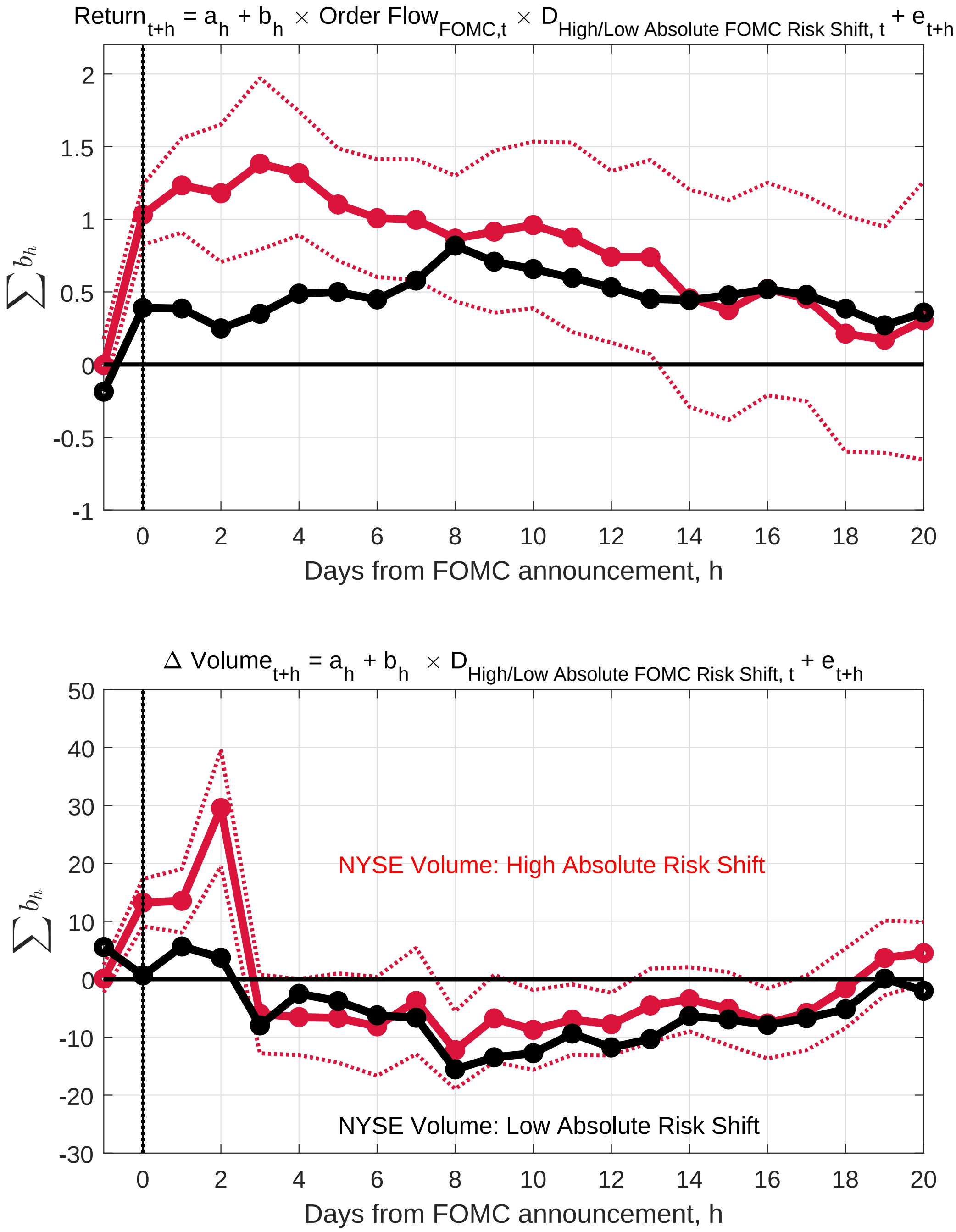


Figure IA.13: Mutual Funds

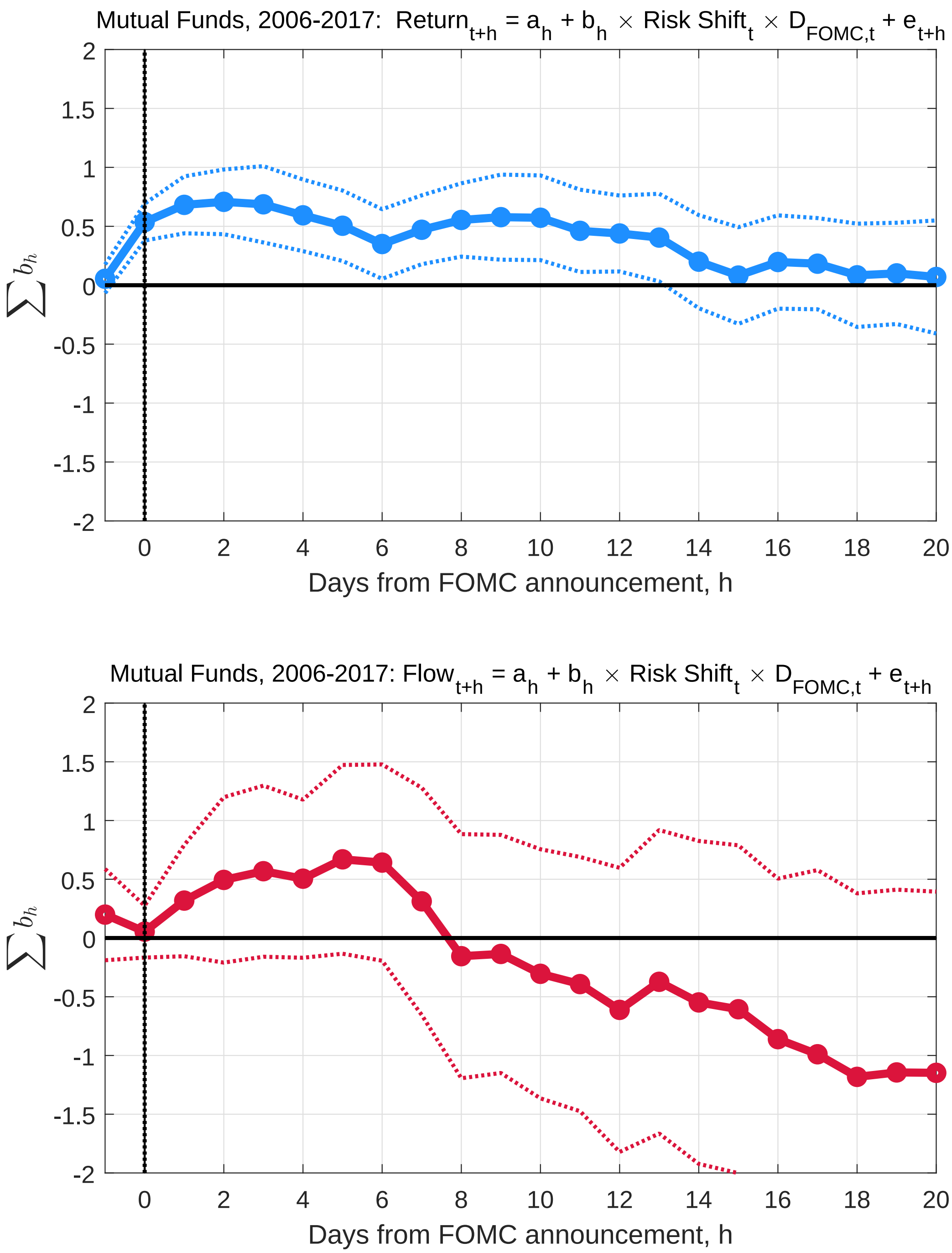


Figure IA.14: Outlier Analysis: S&P 500 Intraday Returns