Three Essays in Monetary and Financial Economics

by

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Abstract

This dissertation consists of three essays in the field of monetary and financial economics. Specifically, we use high-frequency financial data to study monetary policies with a focus on the information effect, namely, that some of the interest rate movements around central bank announcements are not policy-driven, but are results of the market becoming aware of the central bank's view about future economic prospects. Understanding the role played by the information effect will help us apprehend monetary policy implications in both normal times and extraordinary situations.

Chapter 1 evaluates the impact of unconventional monetary policy in the newly developed instrumental variable structural Vector Autoregression (VAR) framework. In the current low interest rate environment, central banks must resort to using unconventional monetary policies, such as forward guidance and quantitative easing, to flight recessions. To empirically evaluate the effectiveness of these unconventional policies, we need to rely on the clean policy shock. A prominent concern is that the often used high-frequency interest rate surprises not only reflect unexpected policy changes, but also contain the information effect. We contribute to the literature by using a heteroskedasticity identification approach, taking advantage of changes in the relative dominance of economic shocks around different macroeconomic announcements. Analysis based on clean policy shocks suggests that the unconventional policies successfully aided the recovery in the U.S. More importantly, we show that the information effect, while it may introduce bias, is rather modest when it comes to estimating the real impact of unconventional monetary policies.

Chapter 2 studies the stock return pattern after the U.S. Federal Open Market Committee (FOMC) announcement. This research is motivated by recent literature that documents stock returns drifts, both before and after FOMC announcements, according to policy rate surprises. Indeed, research has shown that the information contained in the central bank announcement is multifaceted: its current monetary policy stances (monetary policy news) and news about future economic prospects (non-monetary policy news). Our contribution is to combine these two strands of literature. To the best of our knowledge, no study has looked at stock market reactions to the non-monetary news stemming from policy announcements. We identify both good and bad news events using a combination of sign restriction with high-frequency financial prices. The novel finding is that following bad FOMC announcements, that is the market interpreted the Fed announcements as revealing negative information about the economy, we observe significant positive stock returns in a 20-day period. We call this the "post-FOMC drift." Further analysis suggests that the drift is likely caused by relatively heightened risks associated with bad announcements, although the drift is consistent with market overreactions as well. Moreover, the post FOMC drift is a market-wide phenomenon and can be exploited in an easy-to-implement trading strategy with a historical record of earning 40% of the annual equity premium.

In Chapter 3, we explore the channels through which the FOMC announcements affect the financial market. While much of the existing literature measures the surprise components with only changes in policy rates (surrounding the announcement), we contribute to the existing literature by taking a broader view through examining unexpected changes in longer-term yields, corporate credit spreads, and inflation expectations (a proxy for growth prospects), using high-frequency financial data. Through a regression analysis, our findings show that these additional surprises provide orthogonal information and sharply increase the goodness of fit in explaining stock returns around FOMC announcements, with the inclusion of inflation expectations having the biggest contribution. The important role of inflation expectation suggests that the current literature, which uses stock prices together with nominal rates to disentangle the information contents of central bank announcements, may be too limited in the scope of information it uses.

Preface

Chapter 2 “Post-FOMC Drift” is coauthored with Ms. Xiaowen Zhang (Ph.D. Candidate) in the Department of Finance at the Alberta Business School. Both authors contributed equally to the paper.

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Chapter 1

Using Stock Prices to Help Identify Unconventional Monetary Policy Shocks for External Instrument SVAR

Abstract

In times when short-term policy rates are at or near the zero lower bound, central banks use unconventional policies, such as forward guidance and quantitative easing, to influence the slope of the yield curve. In this paper, we analyze the dynamic responses of key U.S. macroeconomic variables to the Fed's slope policy in the newly developed instrumental variable structural VAR framework. We contribute to the literature by using stock price movements to help identify policy surprises that are free of the Fed information effect; namely, that some of the interest rate movements are not policy-driven but are results of the financial market becoming aware of the Fed's view about economic fundamentals. We use a heteroskedasticity identification approach, taking advantage of changes in the relative dominance of economic shocks around different types of macroeconomic announcements. Analysis based on the cleaned policy shocks suggests that the slope policies successfully aided economic recovery by lowering unemployment and overall credit costs. More importantly, we show that the Fed information effect, while a valid concern, is not strong enough to bias the estimated policy effect substantially. This finding supports the approach commonly seen in the literature that ignores the Fed information effect and treats high-frequency changes around FOMC announcements as pure policy surprises.

1.1 Introduction

During the Great Recession, with the policy rate stuck at the zero lower bound (ZLB), the Federal Reserve (the Fed) used unconventional monetary policies such as forward guidance and quantitative easing (QE), to stimulate the economy. These unconventional policies are widely believed to have improved financial conditions during and after the financial crisis (Bernanke, 2020). Since these policies affect the slope of the yield curve, they are referred to as "slope policies" in the literature (Eberly, Stock, & Wright, 2019). The 2020 COVID-19 pandemic again forced the Fed to lower the federal funds rate to near zero, and resort to slope policies.[1]

While the slope policies' impacts on financial asset prices are well studied (see Kuttner, 2018, for a review), their impacts on the real economy have yet to be fully understood and are the focus of a growing literature. Much of this literature adopts the newly-developed external instrument variable structural vector autoregression (IV-SVAR) approach (e.g., Gertler & Karadi, 2015; Kim, 2017; Eberly et al., 2019; Lakdawala, 2019). Rather than the standard timing restrictions used to identify the impact of short-term policy rates (e.g., Cholesky restrictions), this approach uses rate changes around the Federal Open Market Committee (FOMC) announcements as external instruments to achieve the identification. With the IV-SVAR approach, surprise movements in the near-term federal funds futures are used as an instrument for conventional monetary policy (i.e., policy changes concerning the federal fund rate), while unexpected variations in the slope of the Treasury yield curve are adopted as an instrument for the slope policy (Eberly et al., 2019).

A prominent concern is the existence of the Fed's private information (i.e., "Delphic forward guidance" as addressed in Campbell et al., 2012; "Fed information effect" as addressed in Nakamura & Steinsson, 2018a) could potentially confound the estimation. In particular, these studies find that a positive surprise (unanticipated change) to the interest rate leads to an increase rather than decrease in the expected output growth, which contradicts the predictions of the classical New Keynesian model. The intuition is that following the FOMC announcements, mar-

[1] The Fed released a statement on March 15, 2020, that "the Committee decided to lower the target range for the federal funds rate to 0 to 1/4 percent. The Committee expects to maintain this target range until it is confident that the economy has weathered recent events and is on track to achieve its maximum employment and price stability goals. *[...]* the Committee will increase its holdings of Treasury securities by at least $500 billion and its holdings of agency mortgage-backed securities by at least $200 billion." Further actions, including "purchase Treasury securities and agency mortgage-backed securities in the amounts needed to support smooth market functioning" were announced later.

ket participants learn not only the current and the future path of monetary policy stances, but also the Fed's private information about future economic fundamentals. In other words, if a monetary tightening (an increase in the slope of the yield curve) is interpreted as the Fed's endogenous reaction to a better economic outlook, market participants will update their beliefs and anticipate that output might indeed go up. From a market point of view, if investors learn from the Fed announcements that the central bank is optimistic about future economic growth, they may reduce their holding of defensive assets, such as longer-term Treasury bonds, thus leading to a sell-off, a fall in prices, a rise in longer-term yields, and a steeper yield curve.

Crucially, existing literature has not formed a consensus regarding how important the Fed information is to the IV-SVAR approach. Eberly et al. (2019) choose to ignore it by arguing that the information concerning future growth is likely unimportant and that its existence serves only to downwardly bias any estimated effects of the slope policy. Lakdawala (2019), on the other hand, cleanses the instrument for the slope policy by purging it of the information difference between the Fed and the private sector using Greenbook data, the economic projections by research staff at the Board of Governors that are released with a 5-Year lag. Contrary to the conjecture in Eberly et al. (2019), Lakdawala (2019) findings indicate substantial importance of the Fed information effect in the IV-SVAR approach; if the instrument for the slope policy is not cleansed of the Fed's private information, it will produce counterintuitive results, showing expansionary effects from a contractionary policy action.

Further complicating the picture is the fact that the two papers measure slope policy differently. Lakdawala (2019) focuses on the relatively shorter end of the yield curve, measuring the slope policy using 1-Year rate as the indicator for the forward guidance. Eberly et al. (2019) measure the slope policy with the difference between the 10-Year rate and the Fed's policy rate. To the best of our knowledge, there has been no effort in the existing literature that cleanses the slope policy measure used in VAR.

In this paper, we take the view that there is a large amount of information available in the financial market, especially the price of stocks, which could allow us to isolate policy shocks from surprise news about economic fundamentals (or the Fed information effect). Furthermore, financial data are usually available in real-time rather than with a delay as in the case of the Greenbook projections. For instance, without changes in investors' views about economic prospects, a pure policy tightening will reduce both bond prices and stock prices. If, on the other hand, a certain FOMC announcement triggers rising optimism among investors, we would expect the bond price to fall (since the Fed is more likely to tighten in the future), while the movements in stock prices can be ambiguous, with positive effect arising from investor optimism, and negative effects arising from the fear of the Fed's tightening.

Consistent with the intuition, our approach to dealing with the Fed information effect involves using movements in both stock prices and Treasury yields to identify the "pure" slope policy shock. The stock market reacts instantaneously to actual Fed policies and perceived Fed intentions. It also responds to the economic outlook and investor sentiments (Ehrmann & Fratzscher, 2005; Beaudry & Portier, 2006). Therefore, bringing stock prices increases the information we have, compared to approaches that rely solely on bond yields.

We now need a way to identify monetary policy shocks from the movements of stock and bond prices. For that purpose, we adopt the well-established heteroskedasticity identification method introduced by Rigobon (2003) and Rigobon and Sack (2004). The intuition behind the approach resembles the use of instrumental variable but in a probabilistic manner. In a classic demand-supply system, one way to consistently estimate the demand curve is to have external instruments for exogenous changes in supply. Plotting the price against "instrumented" supply changes reveals the slope of the demand curve. External instruments for demand changes, on the other hand, help reveal the slope of the supply curve. Suppose under certain circumstances, supply shocks are more likely to occur than demand shocks (i.e., the volatility of supply shocks is relatively greater), the cloud of realized price and quantity will tilt towards the demand curve. If, in some other situations, demand shocks dominate supply shocks, the realized cloud of data should tilt toward the supply curve. This shift in relative shock importance helps solve the identification problem.

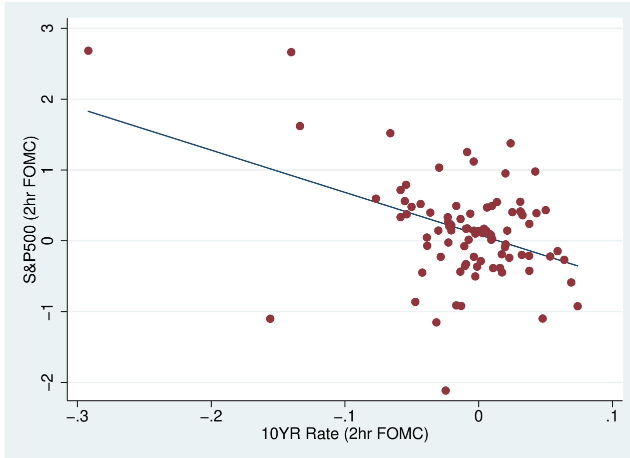
We rely on different types of macroeconomic announcements to find circumstances of changes in the relative dominance of underlying shocks, similar to the approach taken in Rigobon and Sack (2004), who assumed an increase in the variance of monetary policy shocks on days of FOMC meetings and the Fed Chairman's policy testimonies, relative to days immediately preceding those policy dates. Here, we assume that, in relative terms, monetary policy shocks play a more significant role around monetary-policy announcements, while news about economic fundamentals is more important around releases of major economic statistics. Indeed, the scatter plots in Figures 1.1 and 1.2 confirm this intuition by depicting stock and Treasury price movements in a two-hour window bracketing FOMC announcements and the Fed's G.17-Industrial Production and Capacity Utilization releases.[2]

Figure 1.1 supports the conjecture that around FOMC announcements, monetary policy shocks are more likely to occur (i.e., high volatility in monetary policy shock) as its cloud of realized data points follows a negative relationship with an increase in longer-term interest rates accompanied by a decline in the stock price. Theoretically, the negative relationship arises because, all else the same, higher rates lead to lower stock prices (e.g., through lowering the present value of expected future payoffs from stocks).[3] Figure 1.2, on the other hand, shows a cloud of data points that tilt towards a positive direction around the Industrial Production releases. This suggests that news about economic fundamentals likely plays a dominant role because brighter economic prospects push both Treasury yields and stock prices. By exploiting changes in relative shock volatility, we can then back out of the underlying structural parameters governing the co-movements of stock and bond prices and use them to identify monetary policy shocks, assuming that those structural parameters are invariant when relative volatility of underlying shocks changes.

[2]See Section 1.4.1 for details about data construction.

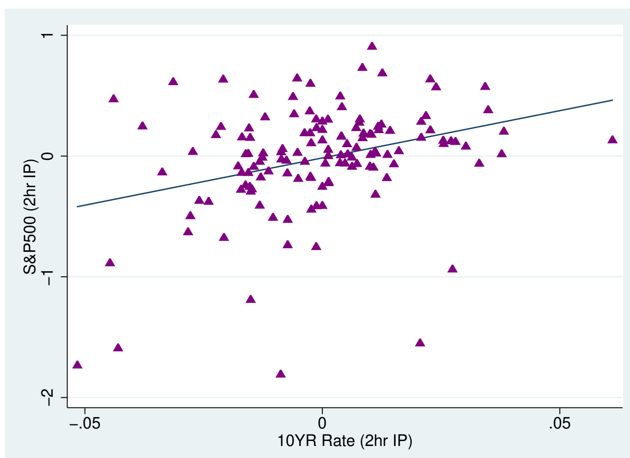
[3]There seem to be some "outliers" in this scatter plot. However, as shown in Figures 1.6 and 1.7 in the Appendix, dropping the "outliers" will not change the negative relations. The "outliers" are associated with some of the extreme actions the Fed took as labeled in Figure 1.6.

Figure 1.1: Changes in stock price and 10-Year yield around FOMC announcements



Note: 10-Year interest rate changes and price changes of S&P 500 are calculated in a 2-hour window around the FOMC announcements and expressed in %. Variance(10YR Rate)=0.003; Variance(S&P500)=0.51; Covariance=-0.015.

Figure 1.2: Changes in stock price and 10-Year yield around G.17 releases



Note: 10-Year interest rate changes and price changes of S&P 500 are calculated in a 2-hour window around the Industrial Production announcements and expressed in %. Variance(10YR Rate)=0.0003; Variance(S&P500)=0.20, Covariance=0.003.

Under the two different regimes (i.e., FOMC/Industrial Production), we have two realized clouds of data and, thus, six observations. Specifically, the FOMC regime gives us two variances (of the observed data) and one negative covariance; the Industrial Production regime gives us another two variances and one positive covariance. With the six observations, we can back out of six structural parameters:

two variances of the structural shocks under FOMC, two variances of the structural shocks under Industrial Production, one parameter capturing the relative impact of the policy shock on stock prices and bond yields, and one capturing the relative impact of economic news on the two financial variables. A more detailed discussion can be found in section 1.3.2. Notably, the heteroskedasticity identification method hinges upon the shift in the shock's relative importance. Without changes in relative variances, we would have only three observations (two variances and one covariance) but four unknown structural parameters.

The proposed method also has a similar spirit as in Jarociński and Karadi (2020), who use sign restrictions to identify monetary policy and information shocks from the stock price dynamics. A sign restriction on co-movements of interest rates and stock prices typically assumes that with a pure contractionary policy shock ("monetary policy shock" in Jarociński & Karadi, 2020), bond yield will rise, and stock prices will fall. With a good news shock ("central bank information shock" in Jarociński & Karadi, 2020), on the other hand, the bond yield rises, but stock price may rise as well. This suggests that if around a particular event, there is a movement in the bond yield, and the stock price moves in the opposite direction (thus creating a large divergence), the dominant force is likely a monetary policy shock. If there is a movement in the bond yield but the stock price moves in the same direction (thus a small divergence), it is likely to be influenced by a news shock. The "divergence" measure can be reflected from changes in relative variances of underlying shocks. Our proposed method is, to some extent, a quantified version of this intuition, with shocks identified from analyzing high-frequency movements of Treasury bond yields and stock prices around two distinct macroeconomic announcements.

Using the heteroskedasticity identification method, we derive a pure slope policy shock and use it as an external instrument in a Structural VAR. Our impulse responses suggest that slope policies successfully aided economic recovery by lowering unemployment and overall credit costs. It is also worth noting that our findings are at odds with Lakdawala (2019), but in line with Eberly et al. (2019), which implies that the tightening slope policy is actually contractionary, even though our estimated effects are slightly stronger if purging the information effect. Therefore, the concern that the slope policy contains a significant amount of information about economic fundamentals is qualitatively plausible but quantitatively negligible. To our knowledge, our paper is the first in the literature to quantify the importance of the Fed information effect when it comes to estimating the impact of the slope policy in an IV-SVAR framework. Moreover, our findings are also consistent with a recent study by Hoesch, Rossi, and Sekhposyan (2020) that provides empirical evidence of the disappeared Fed information channel in early 2000, which could be attributed to the Fed's improving communication strategies.

The remainder of the paper is organized as follows: Section 1.2 reviews the relevant literature, Section 1.3 explains the empirical methodology in the study, Section 1.4 presents and discusses the results, and Section 1.5 concludes.

1.2 Related Literature

Setting the target (or the range) of the federal funds rate has been the primary monetary policy tool for the Fed to achieve goals of "maximum employment, stable prices, and moderate long-term interest rates."[4] As a direct response to the global financial crisis, the Fed cut the policy rate to a range of 0-0.25% in December 2008, which left the Fed with no room to further lower the policy rate. Given that the economy still needed to be stimulated, the Fed adopted unconventional policy tools, including forward guidance and large-scale asset purchases (LSAP or QE). Thus, the effectiveness of monetary accommodation depends almost entirely on these unconventional policies (Eberly et al., 2019).

Unlike conventional monetary policy, which aims to control long-term real rates mainly through policy rates (Gertler & Karadi, 2015), unconventional policies are transmitted via a range of channels. In brief, forward guidance works through explicitly conveying information about the future trajectory of interest rate or economic condition (Campbell et al., 2012); QE works through controlling the supply of long-term bonds and providing liquidity for the loan market (Stroebel & Taylor, 2012; Hanson, Lucca, & Wright, 2018).

In a broader context, our paper is related to a growing literature that studies the efficacy of unconventional monetary policies. As pointed out by Nakamura and

[4]See the U.S. Federal Reserve Act amended in 1977.

Steinsson (2018b), isolating the exogenous policy changes (shocks) that could be used to infer causal effects remains a key challenge. Given the heterogeneity of the unconventional policy tools, the traditional approaches (e.g., the classical monetary SVAR in Christiano, Eichenbaum, & Evans, 1996; the Narrative/Greenbook approach in Romer & Romer, 2004), which derives monetary shocks as innovations of the Fed's policy responses to macroeconomic conditions, could not be justified. Therefore, many papers adopt the event study approach using high-frequency identification to assess announcement effects on various long-term rates. The underlying assumption is that in a narrow window around an FOMC announcement, interest rate changes are purely due to the monetary policy revealed by the statement.[5]

Using various methods, Gagnon, Raskin, Remache, and Sack (2011) and Bauer and Neely (2014), among others, find that the QE policies effectively lower the 10-Year Treasury yield. Gilchrist, López-Salido, and Zakrajšek (2015) separately identify monetary shocks with a two-dimension structure, namely changes in the 2-Year Treasury yield around policy announcements, and changes in the 10-Year Treasury yield that are orthogonal to the 2-Year rate. Their analysis suggests that the effectiveness of the unconventional policy on lowering real borrowing costs is comparable to the conventional policy. Swanson (2017) extends the factor model adopted by Gürkaynak, Sack, and Swanson (2005) to identify the effects of forward guidance and asset purchase, concluding that both policies significantly affect asset prices. The event study approach mainly focuses on the policy's short-run impacts on financial prices. There are debates in the literature that these short-term financial market effects can either be over or under estimated for various reasons (Rigobon & Sack, 2004; Hanson & Stein, 2015; Hanson et al., 2018; Neuhierl & Weber, 2021).

In any case, the short-run focus means the event study literature is largely silent on the impacts of the policy actions on the economy over the medium and long run. For that purpose, there has been extensive effort to combine the high-frequency approach with the structural vector autoregression (VAR) approach, which is the standard tool for time series analysis of monetary policy's impacts on economic activity, inflation, and interest rates over time. The high-frequency approach identifies

[5]The idea of using high-frequency identification can be traced back to Kuttner (2001), see Nakamura and Steinsson (2018b) for a detailed review.

surprise movements of key interest rates around FOMC announcements, which is then used as an instrument for policy shocks in the VAR to achieve the identification. This hybrid approach is called IV-SVAR or external instrument SVAR in the literature.

An important example of the IV-SVAR approach is Gertler and Karadi (2015), which builds on the framework of Stock and Watson (2012) and Mertens and Ravn (2013). Gertler and Karadi (2015) focus on traditional interest rate policy. Other papers that use the IV-SVAR approach to study conventional monetary policy include, for instance, Kamber and Mohanty (2018).

More closely related to our paper is Eberly et al. (2019) and Lakdawala (2019), which study the unconventional slope policies. They both use two policy tools in the monthly VAR (i.e., federal funds rate and spread between 10-Year Treasury in Eberly et al., 2019; federal funds rate and 1-Year Treasury yield in Lakdawala, 2019) and two corresponding high-frequency measures to separately identify effects of conventional and slope policies. However, their findings differ markedly. Eberly et al. (2019) found that the accommodative slope policy is quite effective in lowering future unemployment gap (though with a wide confidence interval); while Lakdawala (2019) showed that the contractionary slope policy has an expansion effect on output, which is in line with the explanation of "Delphic forward guidance" or the "Fed information effect" (Campbell et al., 2012; Nakamura & Steinsson, 2018a).

Indeed, several studies provide evidence that the information contained in the FOMC announcements is multifaceted, not restricted to changes in monetary stances (e.g., Jarociński & Karadi, 2020; Cieslak & Schrimpf, 2019). News about future economic fundamentals or market risk-on risk-off could be associated with interest rate changes. Therefore, the raw measure of instruments, even with high-frequency identification, is still not a pure slope policy shock. While this point is well accepted in the literature, the quantitative importance of the Fed information effect in the IV-SVAR approach is largely unknown, with the contrasting findings between Eberly et al. (2019) and Lakdawala (2019) being the case in point. This is where our paper will contribute to the literature.

As for how to extract the clean policy shock, the most straightforward of these is the regression approach, as used by Bernanke and Kuttner (2005), Miranda-

Agrippino and Ricco (2018), and Lakdawala (2019). By regressing observed interest rate surprises onto a set of the Fed's private information (i.e., GDP, CPI, unemployment forecasts in the Greenbook), the residuals are purged from the contamination. The main shortcoming of such an approach is that the Greenbook forecast is publicly available with a 5-Year lag.

In this paper, we instead follow a well-established heteroskedasticity identification method introduced by Rigobon (2003) and Rigobon and Sack (2004). The idea is that underlying shocks are heteroskedastic under different regimes. Those shifts in relative volatility affect the shape of realized data clouds and provide necessary variations to identify the underlying structural parameters. More details will be discussed in the next section.

1.3 Empirical Framework

1.3.1 A stylized model

Rigobon (2003) and Rigobon and Sack (2004) proposed a method for identifying simultaneous equations based on the shifts in the variance of underlying structural shocks. To explain how we use this identification method, we begin with a stylized model of two financial price movements: changes in stock prices and changes in 10-Year Treasury bond yields around the Fed's FOMC announcements and another major economic statistical releases. This stylized model will eventually become a more agnostic econometric model that allows us to describe the identification scheme.

Specifically, we use x_{1t} to indicate percentage movements in stock price and x_{2t} to indicate percent changes in the longer-term yields. We assume that short-term policy rates are bounded at zero, so that changes in the 10-Year yield are also changes in the slope of the yield curve in the relevant segment.[6]

Stock price change is a function of both the changes in the benchmark yield x_{2t} as well as the two orthogonal shocks: ϵ_{1t}, which indicates changes in investors' sentiment about the economic prospect and ϵ_{2t}, which indicates changes in mone-

[6] In our actual empirical work, we will relax this assumption and allow the possibility of variable short-term policy rates when deriving our instruments for slope policy shocks.

tary policy, as in equation (1.1). A positive ϵ_{1t} indicates investors becoming more optimistic or less concerned about financial and economic risks.[7] Meanwhile, shifts in ϵ_{2t} (originating from central bank policy announcements) can also affect stock prices; for instance, through changes in equity premium as suggested in Bernanke and Kuttner (2005), or "reaching for yield" investors.

$$x_{1t} = \beta x_{2t} + \epsilon_{1t} + \delta\epsilon_{2t} \tag{1.1}$$

Shifting investor sentiment also affects bond yields. A brighter economic prospect and greater confidence reduce investor demand for safe-haven assets, including longer-term Treasury bonds, which pushes down bond prices and increases yields. Moreover, the long-term bond yield is also used or perceived to be used as a policy tool by central banks. Therefore, it will also be influenced by actual unconventional policies such as forward guidance and QE, as well as investors' expectations about those policies and monetary policy stance in general in both the medium and longer term. We will use ϵ_{2t} to indicate changes in the interest rate that are due to monetary policy. Equation (1.2) decomposes bond yield movements into the two fundamental forces, with ϵ_{1t} for changes in investor sentiment about the economy and ϵ_{2t} for actual or expected changes in monetary policy.

$$x_{2t} = \gamma\epsilon_{1t} + \epsilon_{2t} \tag{1.2}$$

We note that ϵ_{2t} eventually will be identified based on movements in financial prices instead of using policy rates or reading of Fed documents. As a result, a positive or negative ϵ_{2t} can stem from surprises in the actual Fed's policy announcement or from sudden shifts in investors' expectations about the Fed's policy that in turn affect bond prices.[8] For example, consider a scenario in which the financial market

[7]If a more formal model is needed, one can use the Gordon Growth model of stock prices, which expresses stock price as a function of current dividends, benchmark bond yields, equity premium and the expected rate of dividend growth that is pinned down by the expected economic growth rate at the aggregate level. In that model, ϵ_{1t} will just be changes in the term that is the expected growth rate minus the equity premium, so a positive ϵ_{1t} can arise from an increase in the expected growth rate, or from a reduction in risk premium.

[8]Specific events behind ϵ_{2t} can be surprise decisions by the Fed, unexpected changes of tone in the Fed's announcements/speeches, or sudden changes in investors' view about the Fed's policy priority or sensitivity prompted by new information about the Fed's thinking or economic conditions.

believes that the Fed is particularly sensitive to a potential uptick in the economy, perhaps to guide against future inflation. As a result, the Fed would respond to the uptick, if it happens, with a powerful tightening relative to what it would typically do in the past. Under such a belief, an optimistic view about the economy means higher yield. When this expectation shifts downward, perhaps the Industrial Production statistics are not as strong as expected, then the yield will fall by an amount that is more than what can be justified by the relatively weak economic statistics. This sudden turn in the interest rate, albeit prompted by information about the economy's performance, is actually a combination of the two forces: information about the economic situations and changing narrative surrounding future monetary policy. The former is captured by ϵ_{1t}, the latter by ϵ_{2t}. Changes in the interest rate that are beyond the contribution from a weaker economy will be counted as changes in investors' expectations about future monetary policy stances. The idea captured by the equation above, can be rearranged into equation (1.3), where $\gamma\epsilon_{1t}$ is the contribution from the weaker economy. After taking out that contribution, what is left in the yield movement can then be attributed to changes in expected monetary policy.

$$\epsilon_{2t} = x_{2t} - \gamma\epsilon_{1t} \tag{1.3}$$

Rearranging the two-equation model above into equation (1.4) tells us how to back out of the ϵs, if we know the underlying parameters from the observed price movements.

$$\begin{bmatrix} 1 & -(\beta+\delta) \\ -\frac{\gamma}{1+\beta\gamma} & 1 \end{bmatrix} \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} (1-\delta\gamma)\epsilon_{1t} \\ \frac{1-\delta\gamma}{1+\beta\gamma}\epsilon_{2t} \end{bmatrix} \tag{1.4}$$

We can now discuss how shifting volatility can affect the slope of the realized data clouds if we plot x_{1t} and x_{2t} together, as we have done in Figures 1.1 and 1.2. We start from the position, based on standard asset pricing theories, that $\beta + \delta < 0$ and $\gamma > 0$, which says, all else the same, a higher interest rates lowers stock prices through a higher longer-term rate (i.e., $\beta < 0$) and/or higher equity premium (i.e., $\delta < 0$), while brighter economic prospects (or a greater investor confidence) increase interest rates. In turn, this implies that the realized data cloud of stock and Treasury yield movements would have a negative slope if we set $\epsilon_{1t} = 0$ at all times and let ϵ_{2t} be the only driving force behind the price movements. In the opposite case, when $\epsilon_{2t} = 0$ at all times, we can have either a positive or negative slope depending on whether the term $1 + \beta\gamma$ is positive or negative. The uncertainty arises from the double edges of better economics news: on the one hand, they could raise stock prices by raising expected dividends growth and reducing risk premium. On the other, they negatively affect stock prices by raising the benchmark interest rates (through the parameter γ) that in turn lowers stock prices (through the parameter β). If the product of the two parameters has a modest magnitude (i.e., $1+\beta\gamma > 0$), then better economic news raises stock prices as well as bond yields, and thus drives a positive relationship between the two.

As a result, when we move from the regime when the monetary policy shocks are dominant (such as around FOMC announcements) to a regime where news about economic conditions are prevalent (such as around Industrial Production releases), the scatter plot will shift from a negative slope to a positive slope. That is precisely what is shown in Figures 1.1 and 1.2.

1.3.2 Identification based on heteroskedasticity

More generally, consider the case of two endogenous variables X two structural shocks ε) as in equation (1.5).

$$\begin{bmatrix} 1 & a_{12} \\ a_{21} & 1 \end{bmatrix} \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{1.5}$$

This model is identical to what we have earlier, once we allow $a_{12} = -(\beta + \delta)$, $a_{21} = -\frac{\gamma}{1+\beta\gamma}$, $\varepsilon_{1t} = (1 - \delta\gamma)\epsilon_{1t}$, and $\varepsilon_{2t} = \frac{1-\delta\gamma}{1+\beta\gamma}\epsilon_{2t}$, with the last two equations indicating rescaling of the structural shocks. Now we are facing a more agnostic econometric model in which we can easily discuss our identification approach.

In the model, all the shocks are assumed to have zero correlations: $E[\varepsilon_{it}, \varepsilon_{jt}] = 0$ $\forall i \neq j$, and $i, j \in \{1, 2\}$. There is no serial correlation either. The structural shock i has variance $\sigma^2_{\varepsilon_i}$ in regime s. In a more compact form, equation (1.5) can be rewritten as

$$\mathbf{A}\mathbf{x} = \varepsilon \tag{1.6}$$

We further assume that the parameters in $\mathbf{A}$ are stable across all regimes, as in Rigobon (2003). This is a key assumption behind the heteroskedasticity identification approach. Fundamentally, what we are insisting here is that the structural relationships among financial prices are more stable than shifts in relative volatility caused by different kinds of policy announcements and statistic releases.

Taking variance of equation (1.6) yields:

$$\mathbf{A\Omega_s A'} = \mathbf{\Omega_{\varepsilon s}} \tag{1.7}$$

where Ω_s and $\Omega_\varepsilon s$ denote the variance-covariance matrix of the observed variables and underlying structural shocks in regime s, respectively. We observe X in different regimes, so that the variance-covariance matrix Ω_s is known in each regime s as in equation (1.8).

$$\Omega_s = \begin{bmatrix} w_{11,s} & w_{12,s} \\ . & w_{22,s} \end{bmatrix} \tag{1.8}$$

Our goal is to fully identify this system of two endogenous variable equations, thus back up the structural shock ε. In each regime s, we have 3 observations (2 variances $w_{11,s}$, $w_{22,s}$ and 1 covariance $w_{12,s}$) but 4 unknowns: a_{12}, a_{21}, $\sigma^2_{\varepsilon 1s}$, $\sigma^2_{\varepsilon 2s}$ (note that $\Omega_{\varepsilon s}$ is a diagonal matrix because the two structural shocks are assumed to be orthogonal). With two regimes, the system can be just identified (i.e., with 3 observations under each regime, entailing 6 observations in total, and 6 unknowns).[9,10] As suggested in Rigobon (2003), the whole system can be estimated using generalized method of moments (GMM) with equation (1.7) as moment conditions.

Finally, we know that the heteroskedasticity approach identifies parameters a_{12} and a_{21}, but not deeper parameters. Since $a_{12} = -(\beta + \delta)$, $a_{21} = -\frac{\gamma}{1+\beta\gamma}$, knowing a_{12} and a_{21} does not allow us to identify β, γ, and δ. As a result, we cannot use equation (1.3) to identify monetary shocks ϵ_{2t}. Instead, we use equation (1.5) to

[9] In a more general case, Rigobon (2003) proved that the total number of regimes S should satisfy $S \geq 2\frac{(N+K)(N-1)}{N^2-N-2K}$, where N is the number of endogenous variables and K is the number of common unobservable shocks. Therefore, in the absence of common unobservable shocks, only two regimes are required to fully identify the system.

[10] As shown by Rigobon (2003), the rank condition, in this two endogenous variable case, can be written as $w_{11,1}w_{12,2} - w_{11,2}w_{12,1} \neq 0$, which means that the observed variance-covariance matrix Ω_s cannot be proportional to each other. In other words, the heteroskedasticity identification hinges on the shift of shock's *relative* variances across different regimes.

identify ε_{2t}. But for the IV-SVAR approach in the next step, ε_{2t} is sufficient because it is uncorrelated with the economic fundamental shocks.[11]

1.3.3 Tracking dynamic responses using IV-SVAR

Following the notations in Gertler and Karadi (2015), let $\mathbf{Y}_t$ be a vector of economic and financial variables, $\mathbf{A}$ and $\mathbf{C}_j$ $\forall\ j \geq 1$ be the conformable coefficient matrices; ε_t be a vector of structural white noise shocks with $E[\varepsilon_t] = 0$, $E[\varepsilon_t \varepsilon_t'] = I$, and $E[\varepsilon_t \varepsilon_s'] = 0$ for $t \neq s$; p be the number of lagged periods. The general structural VAR model we are considering could be written as equation (1.9).

$$\mathbf{A}\mathbf{Y}_t = \sum_{j=1}^{p} \mathbf{C}_j \mathbf{Y}_{t-j} + \varepsilon_t \tag{1.9}$$

Multiplying both sides of the equation by $\mathbf{A}^{-1}$ and getting the reduced form representation as in equation (1.10), we can then recover the structural form (with imposed constraints)

$$\mathbf{Y}_t = \sum_{j=1}^{p} \mathbf{B}_j \mathbf{Y}_{t-j} + \mathbf{u}_t \tag{1.10}$$

where $\mathbf{u}_t$ is the reduced form shock,

$$\mathbf{u}_t = \mathbf{S}\varepsilon_t \tag{1.11}$$

with $\mathbf{B}_j = \mathbf{A}^{-1}\mathbf{C}_j$ and $\mathbf{S} = \mathbf{A}^{-1}$. The variance-covariance matrix of the reduced form residual is equal to Σ as in equation (1.12).

$$E[\mathbf{u}_t \mathbf{u}_t^{'}] = E[\mathbf{S}\mathbf{S}^{'}] = \Sigma \tag{1.12}$$

Let $Y_t^{policy} \in \mathbf{Y_t}$ be the monetary policy indicator, $\mathbf{s}$ denotes a column in matrix $\mathbf{S}$ corresponding to the vector of the reduced form residual $\mathbf{u}_t$ of the structural policy shock ε_t^{policy}. Thus, to compute the impulse response function (IRF) of a monetary policy shock, we only need to estimate equation (1.13).

$$\mathbf{Y}_t = \sum_{j=1}^{p} \mathbf{B}_j \mathbf{Y}_{t-j} + \mathbf{s}\varepsilon_t^{policy} \tag{1.13}$$

[11]An alternative model set up, which expresses both event window stock returns and yield changes in terms of the two shocks, can be found in the Appendix.

With no further restrictions of matrix $\mathbf{S}$, our goal is to identify the vector $\mathbf{s}$, which is related to monetary policy shocks. Notice that the reduced form residual of policy indicator u_t^{policy} can be estimated from the reduced form OLS regression (by partitioning the estimated reduced form VAR residual $\mathbf{u}_t$ as the residual from policy indicator u_t^{policy} and the other part). However, we need to properly isolate the variations in u_t^{policy} that are purely driven by monetary policy shocks, not other economic shocks. The IV-SVAR achieves this by introducing proper instrument variables as the exogenous component of monetary policy. Let $\mathbf{Z}_t$ be a vector of instrument variables. As usual, $\mathbf{Z}_t$ must be correlated with the structural monetary policy shock ε_t^{policy} (relevance condition) but orthogonal to other structural shocks ε_t^{other} (exogeneity condition), that is

$$Cov[\mathbf{Z}_t \varepsilon_t^{policy\prime}] \neq \mathbf{0} \tag{1.14}$$

$$Cov[\mathbf{Z}_t \varepsilon_t^{other\prime}] = \mathbf{0} \tag{1.15}$$

The elements of $\mathbf{s}$ are obtained as follows:

(1) estimating of $\mathbf{s}^{other}/s^{policy}$: Let $s^{policy} \in \mathbf{s}$ be the response of u_t^{policy} to a unit increase of the monetary shock ε_t^{policy} and $\mathbf{s}^{other} \in \mathbf{s}$ be the response of u_t^{other} to a unit increase of the monetary shock ε_t^{policy}. Then, we can get the the estimate of $\mathbf{s}^{other}/s^{policy}$ from the two stage least squares regression of $\mathbf{u}_t^{other}$ on u_t^{policy}, using $\mathbf{Z}_t$ as the instrument;[12]

(2) deriving s^{policy} from the estimated variance-covariance matrix Σ;[13]

(3) recovering $\mathbf{s}$.

Our ultimate interest is the IRF associated with the monetary shock. The column corresponding to the monetary policy indicator $\mathbf{s}$ will be the starting point

[12] The first stage regresses u_t^{policy} on $\mathbf{Z}_t$ in order to get $u_t^{\hat{policy}}$, which isolates the variation of u_t due solely to the structural monetary policy shock ε_t^{policy}; the second stage regression of $\mathbf{u}^{other}$ on $u_t^{\hat{policy}}$ will yield consistent estimates of $\mathbf{s}^{other}/s^{policy}$ since $\frac{cov(u_t^{\hat{policy}}, \mathbf{u}_t^{other})}{var(u_t^{\hat{policy}})} = \frac{cov(s^{policy}\varepsilon_t^{policy}, \mathbf{s}^{other}\varepsilon_t^{policy} + \mathbf{s}^{*}\varepsilon^{other})}{var(s^{policy}\varepsilon_t^{policy})} = \frac{\mathbf{s}^{other}}{s^{policy}}$, where $\mathbf{s}^{*} \in \mathbf{S}$, which is different from $\mathbf{s}$.

[13] Following the proof in Mertens and Ravn (2013) and Gertler and Karadi (2015), $\mathbf{u}_t = [u_t^{policy}, \mathbf{u}_t^{other}]' = [u_{1t}, \mathbf{u}_{2t}]'$, $\mathbf{S} = [\mathbf{s}, \mathbf{s}^*] = \begin{bmatrix} s^{policy} & \mathbf{s}_{12} \\ \mathbf{s^{other}} & \mathbf{s}_{22} \end{bmatrix}$, and $\Sigma = \begin{bmatrix} \Sigma_{11} & \mathbf{\Sigma}_{12} \\ \mathbf{\Sigma}_{21} & \mathbf{\Sigma}_{22} \end{bmatrix}$, then $(s^{policy})^2 = \Sigma_{11} - \mathbf{s}_{12}\mathbf{s}_{12}' = \Sigma_{11} - (\mathbf{\Sigma}_{21} - \frac{\mathbf{s}^{other}}{s^{policy}}\Sigma_{11})'\mathbf{Q}^{-1}(\mathbf{\Sigma}_{21} - \frac{\mathbf{s}^{other}}{s^{policy}}\Sigma_{11})$ with $\mathbf{Q} = \frac{\mathbf{s}^{other}}{s^{policy}}\Sigma_{11}\frac{\mathbf{s}^{other\prime}}{s^{policy}} - (\mathbf{\Sigma}_{21}\frac{\mathbf{s}^{other\prime}}{s^{policy}} + \frac{\mathbf{s}^{other}}{s^{policy}}\mathbf{\Sigma}_{21}') + \mathbf{\Sigma_{22}}$.

(contemporaneous responses). One way to think about this is to assume that all the elements of $\mathbf{Y}_t$ are zeros for $t \leq p$, $\mathbf{Y}_{p+1} = \sum_{j=1}^{p} \mathbf{B}_j \mathbf{Y}_{p+1-j} + \mathbf{u}_t = \mathbf{S}\varepsilon_{p+1}$, where S is the partially identified matrix and $\varepsilon_{p+1} = [0, ..., 1, 0]^{'}$ with 1 corresponds to the monetary policy indicator. The following effects on $\mathbf{Y}_{p+2}$, $\mathbf{Y}_{p+3}$, ..., $\mathbf{Y}_{p+horizon}$ can then be calculated by using the estimated $\mathbf{B}_j$ s. Finally, we graph the IRFs simply by plotting $\mathbf{Y}_t$ over t.

1.4 Empirical Results

1.4.1 Identify the slope policy shock

Following the heteroskedasticity identification method proposed by Rigobon (2003) and Rigobon and Sack (2004), we use movements in stock prices, together with Treasury bond prices, to back out of monetary policy shocks. We need at least two different regimes (i.e., macroeconomic announcements) to achieve the identification. In addition to the FOMC announcements that are widely exploited in the literature, we include another key data release also made by the Fed: the G.17-Industrial Production and Capacity Utilization. Intuitively, the G.17 releases provide a broad measure of the economic activity in the U.S., and hence are closely related to economic fundamentals. In addition, we assume that there are two orthogonal structural shocks, namely the monetary policy shock and the economic fundamental shock, that govern responses of the stock and the Treasury bond.[14] In a narrow window around the FOMC announcements, the co-movements between the two are more likely driven by the monetary policy shock, whereas around the Fed G.17 releases, the economic fundamental shock would play the dominant role. This shift of relative importance (i.e., changes in the variance of the shock) makes it possible to identify the monetary policy shocks.

As explained earlier, we adopt the heteroskedasticity approach to identify slope policy shocks based on changes in interest rates instead of readings of the Fed's documents. As a result, anything that affects the interest rates can be interpreted as policy shocks, including not only actual surprise decisions by the Fed, but also

[14]Our assumption is similar to the one in Jarociński and Karadi (2020). Based on their findings, the two structural shocks (monetary policy and economic fundamental shocks) around macroeconomic announcements are reasonable.

changes in the Fed's tones or market perceptions of the Fed's policy. Those changes may happen around the release of Industrial Production statistics. New information about the economy can affect interest rates through non-policy channels, but it can also do so through the policy channel by forcing investors to re-examine their previously held views about the Fed's priority or sensitivity. The part of interest rate changes that cannot be explained by economic forces alone in our identified system will be considered as a result of monetary policy or perceived policy changes.

Finally, our slope policy shock (i.e., a shock that changes the slope of the yield curve without necessarily affecting the level of short rates, and is free of the Fed information) is derived by taking residuals from heteroskedasticity identified monetary shocks regressed on innovations in the federal funds rates.

To be comparable to the existing study, we estimate the slope policy shock from January 2008 to February 2019, the same period as in Eberly et al. (2019), "during which the instruments of the slope policy were refined and implemented" as they argue.[15] Moreover, we also follow Eberly et al. (2019) to construct the same two-hour announcement window changes in stock returns and 10-Year Treasury bond yields. Although the FOMC announcements occurred during normal trading hours (mostly around 2:00 pm EST), the monthly G.17 releases are issued at 9:15 am EST.[16] Therefore, we obtain the corresponding futures: the E-mini S&P 500 future and the 10-Year T-Note future, tick-by-tick trading data from Tick data.

Table 1.1: Variances of high-frequency changes in 10-Year rates and stock returns

	FOMC announcements	IP announcements
Variance (10YR rate)	0.03	0.0003
Variance (S&P500)	0.51	0.20
Covariance	-0.015	0.003

[15]As acknowledged in Eberly et al. (2019), the first use of slope policy in the modern era was the appearance of forward guidance in 2003, but other policy tools such as QE were not developed until the recent financial crisis. Therefore, before 2007, the Fed has almost no reliance on the slope policy. Moreover, their empirical analysis confirms that before 2007 no slope policies are detected.

[16]Before 2011, FOMC statements were regularly released at 2:15 pm EST, however, since the meeting on April 27, 2011, the Fed started to alternate the statement release time between 12:30 pm and 2:15 pm (depending on whether the meeting was followed by a press conference). From the meeting on March 20, 2013, the FOMC statements are published at 2:00 pm EST.

Figures 1.1 and 1.2 depict the relationship between 10-Year rate and stock return around FOMC announcements and Fed G.17 Industrial Production releases, respectively. The scatter plots reassure us that our assumption is reasonable. The negative relationship around FOMC announcements is mainly driven by the traditional monetary policy transmission channel (e.g., a higher interest rate will increase the cost of capital or risk premium, see Bernanke & Kuttner, 2005), while the positive relationship around Industrial Production releases is predominantly affected by the information channel (i.e., a higher interest rate signals the better economic fundamental). In addition, Table 1.1 presents realized variances around FOMC and Industrial Production announcements. It is also evident that monetary policy shocks are relatively more important around FOMC announcements, whereas fundamental shocks are relatively more important on Industrial Production releases.

Using the moment condition as in equation (1.7), we identify the structural parameters and back out of the monetary policy shock for each of the FOMC announcement and Industrial Production release. Those estimated parameters imply the adjustments formula that calculates the policy shock as the "raw" percentage-point changes in the 10-Year Treasury yield minus 0.0254 multiplied by the percent changes in the stock price. The minus sign is consistent with the perception that an increase in the Treasury yield that is accompanied by a decrease in the stock price is a likely signal of a Fed tightening. The adjustment magnitude is substantial in terms of standard deviations. In times when both the 10-Year yield and the stock price increase by one standard deviation, only about 0.6 standard deviation of the yield change is regarded as the true policy shock, while the remaining 0.4 standard deviation is regarded as the Fed information effect.[17]

We then convert the event-level shock into monthly shock using the same method as in Romer and Romer (2004).[18] Although employing totally different identification strategies, our policy shock is highly correlated with the slope shock in Eberly et al. (2019), with correlation coefficient 82.01%.

[17] A time series plot of the heteroskedasticity identified monetary policy shock and the high-frequency 10-Year rate changes can be found in the Appendix Figure 1.8. The full sample standard deviations for 10-Year yield changes and stock returns are 0.0354 and 0.5740, respectively.

[18] In months with no event, the value of the monetary policy shock is zero; in months with multiple events, the policy shock is the summation of the shocks in that month. Otherwise, the policy shock is the single shock in that month.

1.4.2 Literature replication

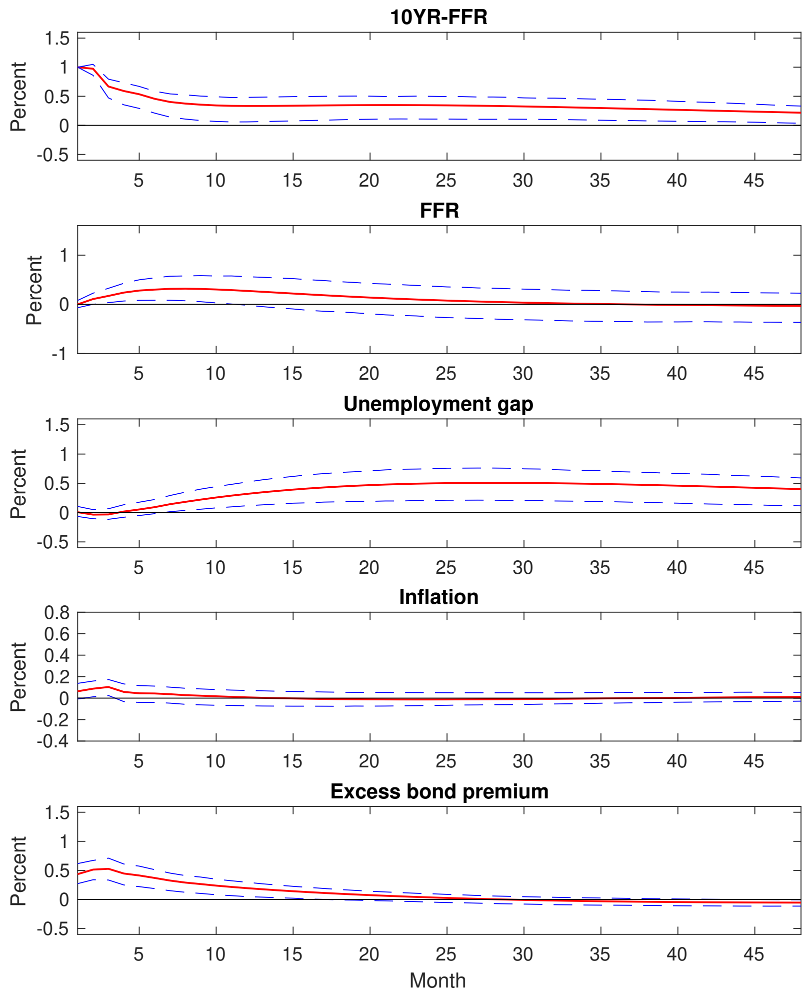
To stand on the common ground with existing studies, we first replicate the findings in leading studies that use the IV-SVAR technique. Figure 1.3 represents our benchmark study of the slope policy by Eberly et al. (2019). Their VAR consists of the Federal Funds Rate (FFR), the interest rate slope (i.e., the spread between the 10-Year Treasury yield and the federal funds rate, 10YR-FFR), the unemployment gap, the core PCE inflation rate, and the Gilchrist and Zakrajšek (2012) excess bond premium.[19]

The reduced-form monthly VAR is estimated with 4 lags over the period of January 1990 to February 2019. The instrument for the slope policy shock is the residual from regressing the high-frequency announcement-window changes in the 10-Year rate on changes in the Federal funds rate implied by the current month federal funds future FF1 (both in monthly frequency). Its sample period is from January 2010 to February 2019, which is two years shorter than the original paper due to the federal funds future data availability.[20]

[19] The federal funds rate, 10-Year Treasury yield, unemployment rate, natural rate of unemployment, and PCE inflation rate are from FRED. Gilchrist and Zakrajšek (2012) excess bond premium is the spread between corporate bonds and a similar maturity government bond after default risk is removed. The excess bond premium is extracted from https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv, accessed in September, 2019.

[20] Tick data only provides federal funds futures beginning January 2010.

Figure 1.3: Eberly et al. (2019) IV-SVAR ignore Fed information effect



Note: The solid red lines are dynamic responses associated with 1% shock in interest rate slope (10YR-FFR), the blue dash lines are 68% confidence bands computed using bootstrapping.

A distinctive feature is the inclusion of both the Fed's conventional policy tool - the federal funds rate, and the unconventional policy tool - the interest rate slope in the VAR. Although the Fed does not explicitly set a target for any long-term rates, the unconventional monetary policy tools (e.g., direct purchases of longer-term Treasuries and mortgage-backed securities) applied extensively during the ZLB period are intended to depress longer-term interest rates. Nevertheless, previous studies view the slope (especially the exclusion of longer-term rates) as a knot-in-the-chain between monetary policy and economic activity, which limits our understanding of the slope policy. Thus, it is crucial to shed direct light on how the slope policy could affect the real economy.

From the impulse responses, we can see that a 1 percentage point slope shock (i.e., a shock that increases the spread between 10-Year Treasury yield and federal funds rate by 1 percentage point) increases the unemployment rate by a peak of about 0.5 percentage points. The excess bond premium goes up by more than 50 basis points in a few months, while the PCE inflation shows a puzzling up-tick in the first year, leading to a so-called "price puzzle."[21] However, the price puzzle mutes within a few months, and commonly occurs in various monetary VARs (e.g., Ramey, 2016 and Lakdawala, 2019).

Notice that in our replication exercise, the federal funds rate does not respond to the slope policy shock contemporaneously. This is consistent with the idea that a pure slope shock should affect only the slope of the yield curve. Technically, this happens because we have removed the slope instrument's contemporaneous correlation with the federal fund rate using a regressions approach. However, this extra step may not be necessary. If we do not remove the contemporaneous correlation, federal funds rate would respond positively and slightly, but other results change little.[22] Overall, the replicated impulse responses are very similar to the results in Eberly et al. (2019).[23]

As discussed earlier, a concern in the literature is that the high-frequency identified monetary shock may contain news about the economic fundamentals other than reactions to monetary policy actions. By looking at signs of responses in the unemployment gap and the excess bond premium, Eberly et al. (2019) argue that

[21]A tightening of monetary policy generally is expected to reduce the price level (in the short run), if it appears to be contrary to the theory, it is called the "price puzzle" in literature.

[22]Alternatively, we can remove the correlation between the slope instrument and the short-term policy rate around the event windows instead of the monthly time series, by regressing the time series of event-window 10-Year rate changes on event-window federal funds rate changes. Again, the results are similar though the federal rate fund still responds positively to the slope policy shock in the same month. This suggests that some minor degree of correlation exists in the monthly time series after aggregating the event-window time series to the monthly series.

[23]Eberly et al. (2019) found that 1 percentage point slope shock increases the unemployment rate by a peak of about 0.7 percentage points, increases the excess bond premium by a peak of about 0.6 percentage points. The authors did not present the impulse responses of inflation and the federal funds rate in their paper.

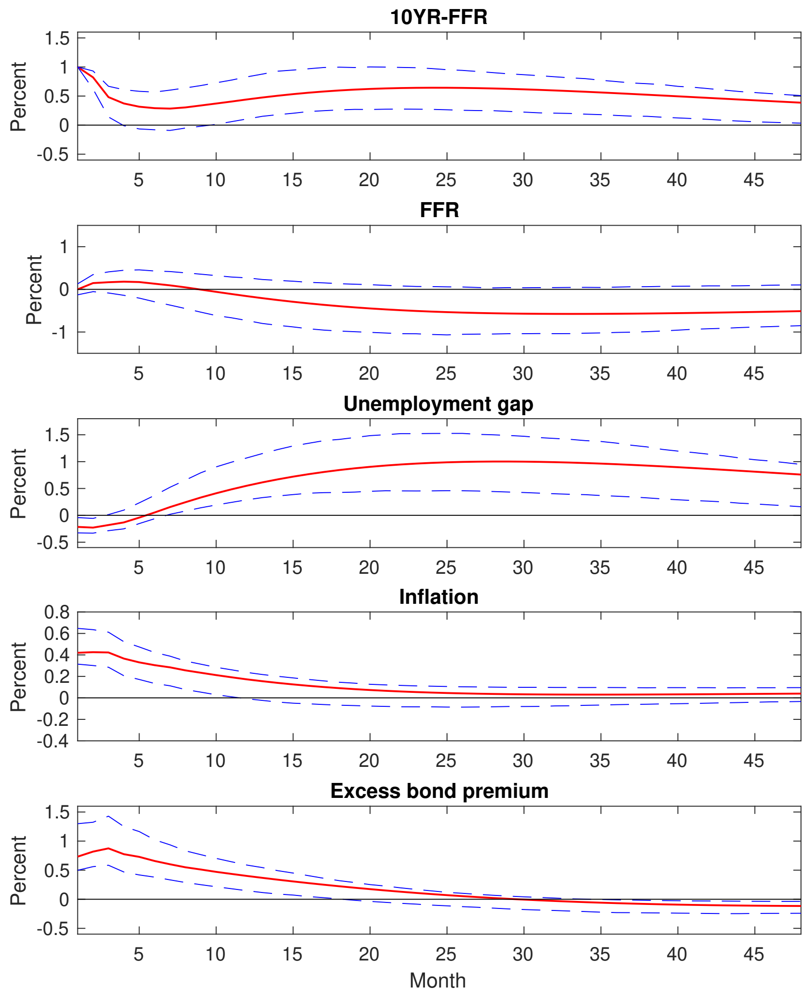
the impulse responses are in line with the slope policy channel – the accommodative slope policy could lower unemployment and overall credit costs.[24] However, as they acknowledged, these qualitative observations cannot rule out bias from announcements having information about economic fundamentals. It is therefore important to use an alternative identification strategy to back up the slope policy shock that is robust to the information bias (i.e., orthogonal to the economic fundamental shock). For this reason, we adopt the well-established heteroskedasticity identification in the literature and use the identified slope policy shock as an external instrument in the structural VAR analysis.

1.4.3 Empirical results

Following the insights of Eberly et al. (2019), our VAR consists of two monetary policy indicators: the federal funds rate, which is used to capture conventional monetary policies; and the spread between 10-Year Treasury yield and federal funds rate, which is a direct measure of the slope policy. Additionally, we include the unemployment gap, core PCE inflation rate, and the Gilchrist and Zakrajšek (2012) excess bond premium. The reduced form VAR is estimated using monthly data from January 1990 to February 2019 with 4 lags and the slope policy instruments are used from January 2008 to February 2019. We keep our reduced form VAR specification the same as Eberly et al. (2019). The critical difference is that we will use our heteroskedasticity identified instrument for the slope shocks that are free of the Fed information effect.

[24] Another qualitative observation that Eberly et al. (2019) provided is that the announcement-window change in the S&P 500 is negatively correlated with their slope policy instrument, which is consistent with the traditional monetary policy transmission mechanism.

Figure 1.4: IV-SVAR remove Fed information effect using heteroskedasticity identification



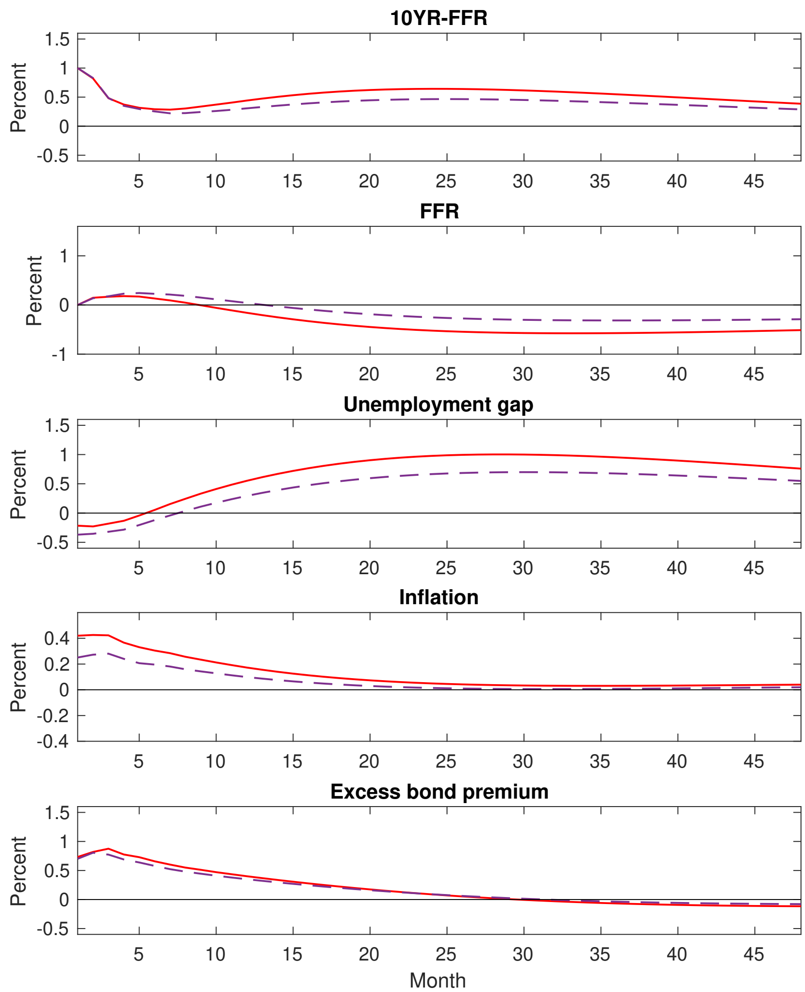
Note: The solid red lines are dynamic responses associated with a 1% shock in interest rate slope (10YR-FFR), the blue dash lines are 68% confidence bands computed using bootstrapping.

Figure 1.4 presents the estimated effects of the slope policy using our heteroskedasticity identified shocks as an external instrument. Again, we first remove the identified shocks' contemporaneous correlation with the federal funds rate by regressing it on the latter's innovations in the monthly time series, and then use the residuals as the actual instrument. This ensures that the same-month response of the federal funds rate to the slope shock is zero. But similar to what we found earlier when replicating results from Eberly et al. (2019), this extra step may not be unnecessary; if we use the heteroskedasticity identified monetary shock as the slope shock instrument (i.e., without the extra regression step), federal funds rate would respond slightly to the slope shock, but all other results would be very similar.

In response to a 1 percentage point slope shock, the unemployment rate rises by roughly 1 percentage point in about 2 years. Moreover, under a tightening slope shock, the credit market immediately feels the tense, and excess bond premium hikes up for almost 90 basis points in a few months. The elevated credit costs remain statistically significant for another 2 years. Not surprisingly, we also find that a contractionary slope shock raises the price level slightly, i.e., the price puzzle that, as described earlier, commonly occurs in the VAR literature.

Using the slope policy shock that is orthogonal to economic fundamentals as the instrument, our estimated effects are, as expected, stronger than what Eberly et al. (2019) had documented. This finding, the information purged monetary shock has more pronounced real impacts, is also in line with Jarociński and Karadi (2020).

Figure 1.5: Comparing models with and without the Fed information effect



Note: The solid red lines are dynamic responses as in our main result (Figure 1.4); the purple dash lines are dynamic responses with potential Fed information effect.

Figure 1.5 compares the findings from models both with and without removing the Fed information effect via the heteroskedasticity approach. The dynamic responses of the real economic variables are very similar. In this respect, our analysis provides supportive evidence that the raw event-window changes in long-term rates primarily reflect the slope (monetary) policy channel, as argued by Bauer and Swanson (2020).[25] Therefore, concerns about the Fed information channel in the slope

[25] Using a stylized model, Bauer and Swanson (2020) demonstrate that "high-frequency monetary policy surprises can be used, without adjustments, to help estimate and identify the effects of

policy instrument appear to be qualitatively valid but quantitatively misplaced.

To ensure the robustness of our results, we test the case which excludes the Industrial Production dates when constructing monthly slope policy shocks (i.e., all else the same as our main results in Figure 1.4, but only use FOMC announcement days to construct monthly slope shock). This is consistent with the literature that uses only FOMC days derived shocks and can also partiality alleviate the concern about the monetary policy shock we identified from non-monetary events. Impulse responses are plotted in the Appendix Figure 1.9. The results are very close to our baseline case. In addition, we also test the alternative assumption that there is no slope shock around the Industrial Production release (see Appendix for details). Figure 1.10 in the Appendix summarizes the impulse responses. The results are also consistent with our main results. Moreover, we also use instruments based on alternative slope measures in the heteroskedasticity identification scheme. Figures 1.11 and 1.12 in the Appendix summarized the impulse responses with announcement window slope change measured as the spread between the 10-Year rate and the FF1 and regression residual of the 10-Year rate and the FF1, respectively.[26] Clearly, our baseline results are robust to these alternative measures.

A caveat worth noting is the potential problem of the weak instrument (i.e., equation 1.14, the relevance condition). A rule of thumb proposed by Stock and Yogo (2005) requires the F-statistic in first-stage instrument variable regression to be greater than 10. Our F-statistic is 6.1, it is slightly better than the F-statistic 5.8 in Eberly et al. (2019). One possible way to improve the relevancy is using the moving-average method as in Gertler and Karadi (2015) to convert event-level slope shock into monthly shock. However, as suggested by Ramey (2016), it could

monetary policy."

[26]In our baseline specification, the heteroskedasticity based identification of the slope policy shock is applied using changes in 10-Year rate and S&P500 around different events. In other words, we use 10-Year rate changes as the high-frequency measure for slope policy. In the robustness test, however, we test alternative slope policy measure, namely, 10-Year rate - FF1 and the residual of regressing 10-Year rate on FF1. The latter is the exact same measure used in Eberly et al. (2019). As we documented earlier, our federal funds future data start from 2010. For the events in 2008 and 2009, instead of FF1, we use daily changes in the effective federal funds rate (available at https://apps.newyorkfed.org/markets/autorates/fed-funds-search-page) encompassing the event. Because the daily changes in the federal funds rate are in general bigger than the announcement window changes in the FF1, we adjust the scale of the daily changes using estimated relationship from overlapping years (i.e., 2010.1-2019.2). The impulse responses are also very similar.

deteriorate the shock's exogeneity by the added serial correlation.

Another common concern in the use of IV-SVAR is the invertibility.[27] As documented in Stock and Watson (2018) and Lakdawala (2019), this issue may become particularly relevant if the external instrument is out of scope of SVAR's information set. However, similar to the existing studies like Gertler and Karadi (2015), our heteroskedasticity based slope shock is identified using contemporaneous movements of the 10-Year rate, which is (partially) included of the SVAR. In addition, in the Appendix, we follow Stock and Watson (2018) to formally test the null that the SVAR is invertible. Result suggests that invertibility cannot be rejected in our model.

1.5 Conclusion

Since the recent global financial crisis, much of the developed world has experienced a low interest rate environment. Given this situation, central banks' power to respond to the economic downturn is quite limited. Slope policies, like forward guidance and QE, are becoming new tools of monetary policy. While most of the studies focus on slope policies' impact on financial prices, its impact on the real economy has yet to be fully understood.

In this paper, we study the real economic impact of the slope policy using a newly developed external instrument SVAR framework, which relies on high-frequency movements of Treasury yields around FOMC meetings as instruments for surprise changes in the stance of monetary policies. But a growing body of literature has provided evidence that those interest rate movements can represent more than just changes or expected changes in monetary stances; they can also reflect expectations about future economic fundamentals. This multifaceted feature poses a challenge to the proper identification of the slope policy because the instrument for slope policy often involves changes in longer-term Treasury yields, which are particularly sensitive to market optimism or pessimism about the future economy. While this concern of "Fed information effect" is widely known in the literature, it is largely

[27] SVAR is invertible if the structural shocks can be recovered from current and lagged values of the observed data.

unknown how much bias it actually introduces to the IV-SVAR approach. The existing literature presents contrasting findings.

This paper contributes to the literature by adding the well-established heteroskedasticity identification approach to the IV-SVAR framework, bringing in movements in stock prices to help identify the underlying structural shocks. A main advantage of this approach is the benefit of not having to rely on Greenbook, which reveals the actual Fed information in the form of the Fed staff forecasts, that has a 5-Year publication lag. In addition to this methodological contribution, another of our contributions is to show that the bias introduced by the Fed information effect, even though it is in the expected directions predicted by the hypothesis, is rather modest. The estimated effects of the slope policy from the heteroskedasticity identified external instrument trend in the same directions, and are only marginally stronger than those based on the "raw" yield changes. This finding supports the commonly adopted approach in the literature that ignores the Fed information effect and treats high-frequency yield changes around FOMC announcements as pure policy surprises. To our knowledge, our paper is the first in the literature to quantify the bias using heteroskedasticity identified interments in a SVAR framework.

1.6 Appendix

(1) Additional Tables and Figures

Figure 1.6: Changes in stock price and 10-Year yield around FOMC announcements

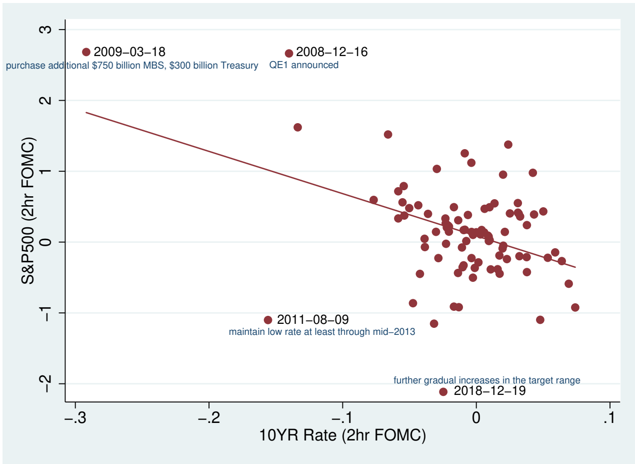
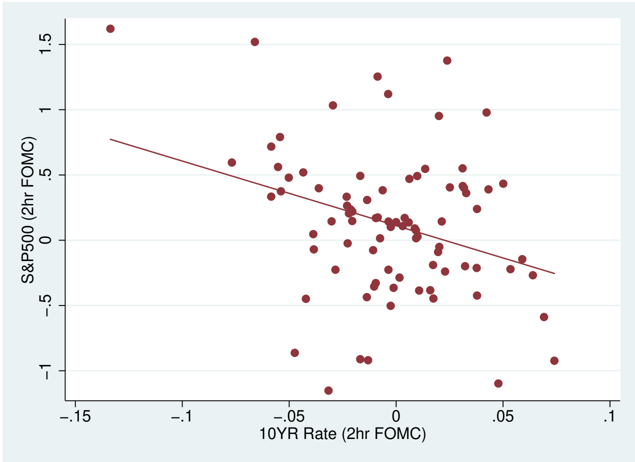


Figure 1.7: Changes in stock price and 10-Year yield around FOMC announcements without outliers



Note: 10-Year interest rate changes and returns of S&P 500 are calculated in a 2-hour window around the FOMC announcements and expressed in %. Variance(10YR Rate)=0.001; Variance(S&P500)=0.30.

Figure 1.8: Heteroskedasticity identified monetary shock and high-frequency 10-Year rate changes

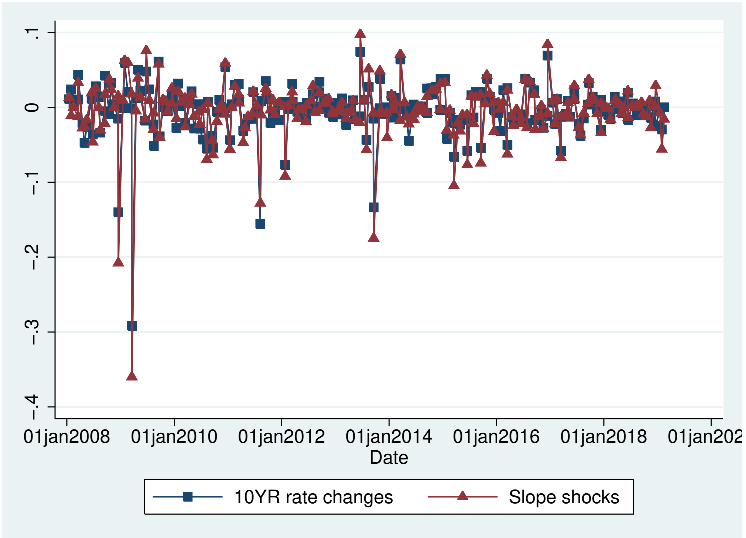
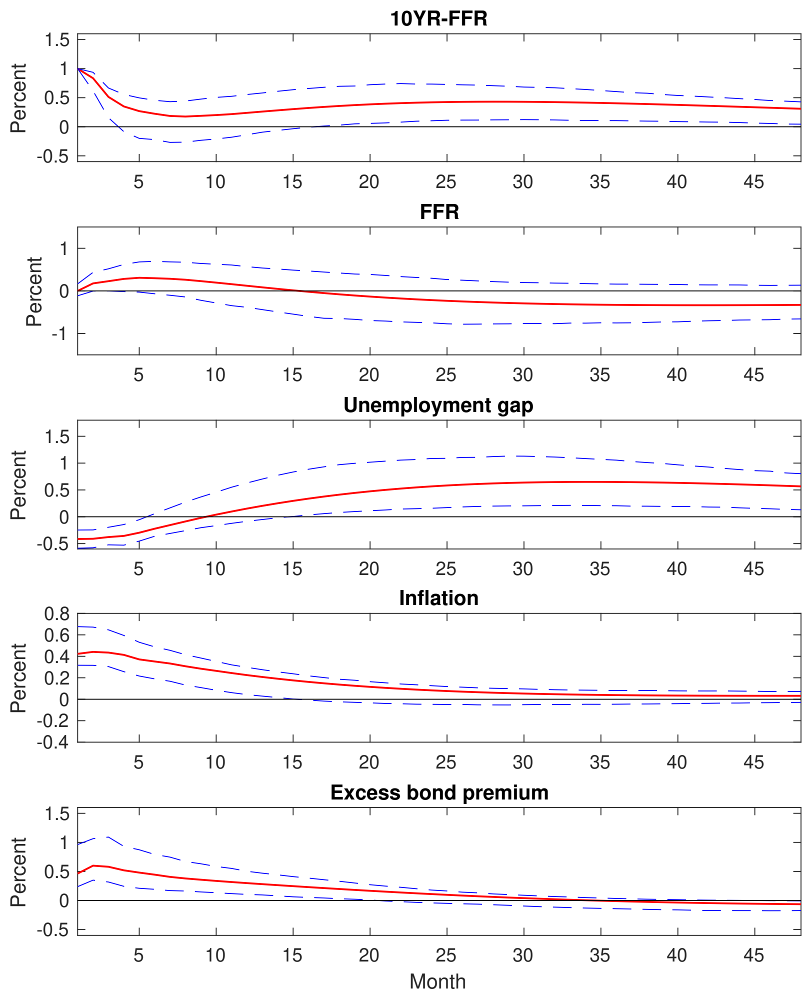
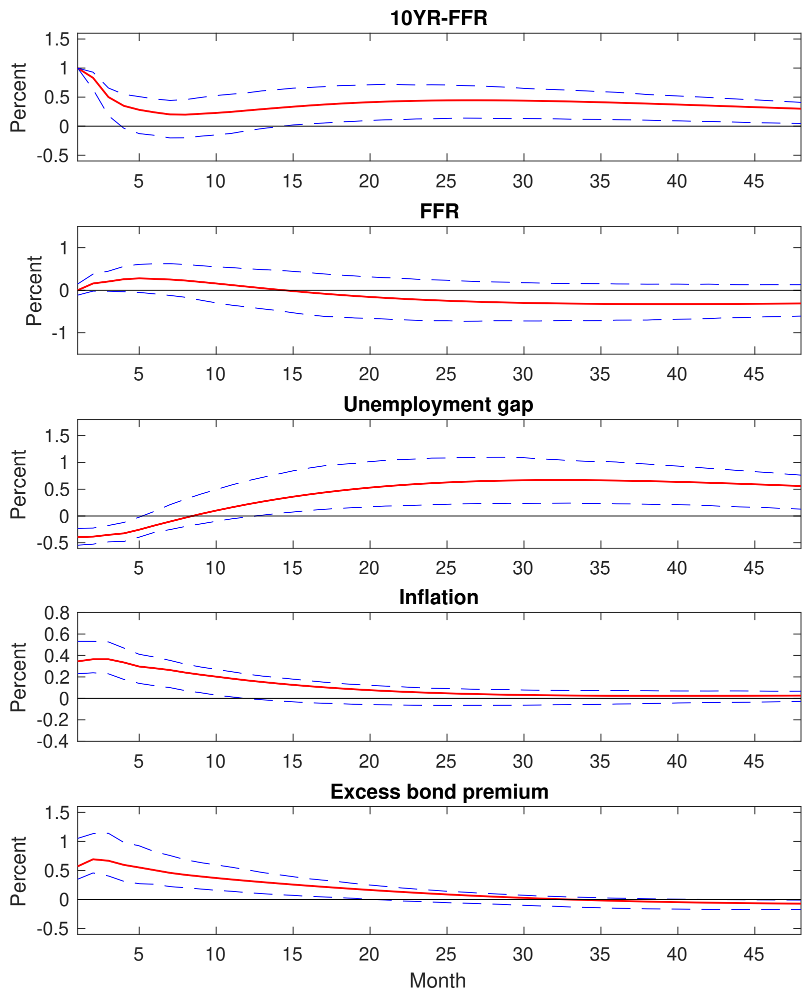


Figure 1.9: Robustness: construct heteroskedasticity identified shock using FOMC only



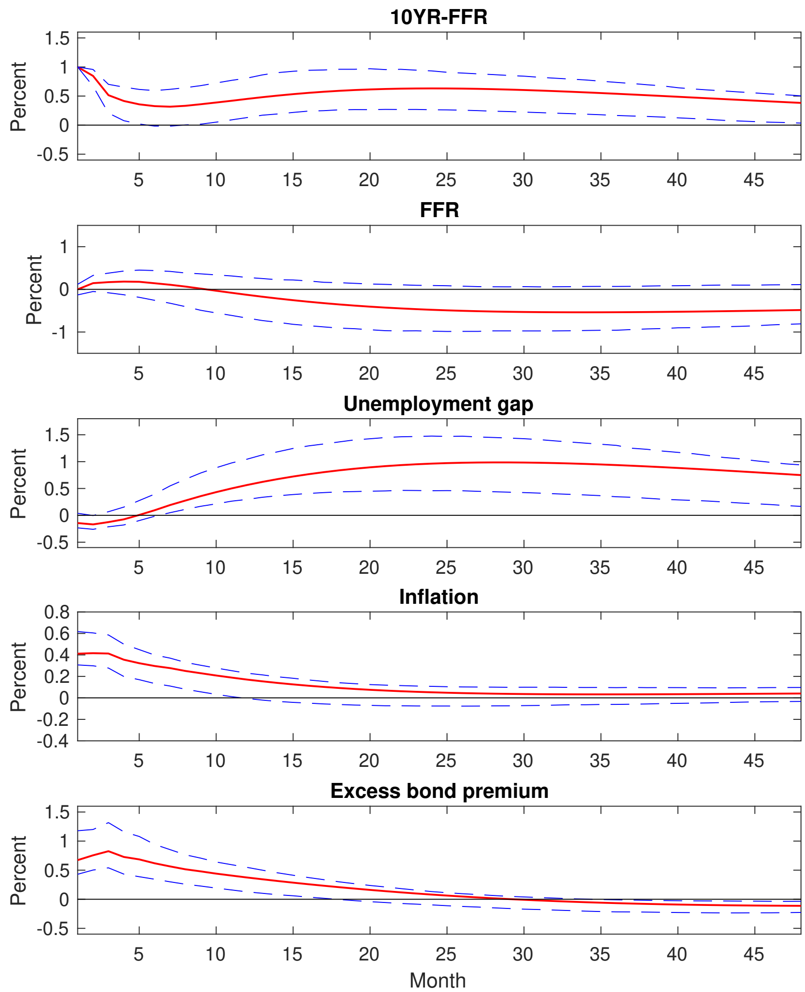
Note: The solid red lines are dynamic responses associated a 1% shock in interest rate slope (10YR-FFR), the blue dash lines are 68% confidence bands computed using bootstrapping.

Figure 1.10: Robustness: no slope shock around Industrial Production release



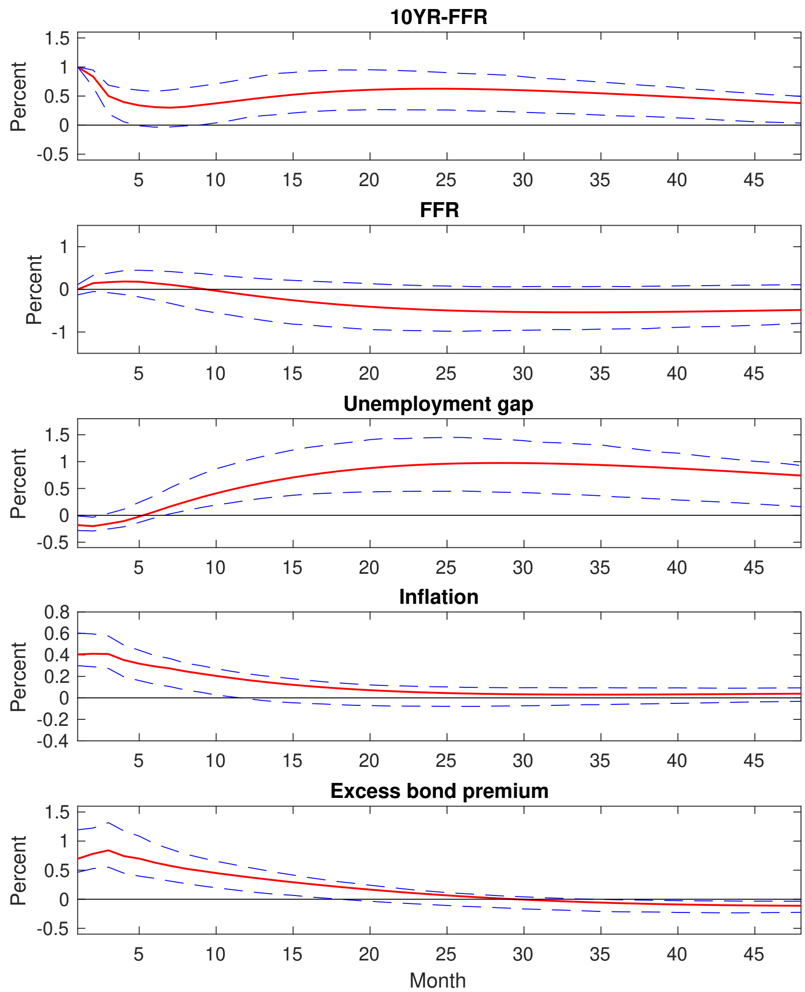
Note: The solid red lines are dynamic responses associated a 1% shock in interest rate slope (10YR-FFR), the blue dash lines are 68% confidence bands are computed using bootstrapping.

Figure 1.11: Robustness: construct heteroskedasticity identified shock using 10-Year rate minus FF1



Note: The solid red lines are dynamic responses associated with a 1% shock in interest rate slope (10YR-FFR), the blue dash lines are 68% confidence bands computed using bootstrapping. Some data are extrapolated before 2010.

Figure 1.12: Robustness: construct heteroskedasticity identified shock using residual of 10-Year rate on FF1



Note: The solid red lines are dynamic responses associated with a 1% shock in interest rate slope (10YR-FFR), the blue dash lines are 68% confidence bands are computed using bootstrapping.

(2) Robustness: No slope shock around Industrial Production

In our heteroskedasticity-based identification of the slope policy shock, we essentially assume that around both the Fed's FOMC and Industrial Production announcements, there are two underlying structural shocks, the monetary slope shock and the economic fundamental shock, as in equation (1.5). While it is widely believed that information contained in FOMC announcements is multifaceted (i.e., contain the Fed information effect or our fundamental shock), around the Industrial Production announcements, the slope policy shock may not occur due to the fact that the monthly output update is only one of the many factors that affect the Fed's decision making.[28]

$$\begin{bmatrix} 1 & a_{12} \\ a_{21} & 1 \end{bmatrix} \begin{bmatrix} Treasury_{t,s} \\ Stock_{t,s} \end{bmatrix} = \begin{bmatrix} \varepsilon_{slope,t,s} \\ \varepsilon_{fundamental,t,s} \end{bmatrix} \quad s \in \{FOMC, IP\} \tag{1.16}$$

With no monetary slope shock around Industrial Production releases, co-movements between stock returns and bond yields can be written as

$$\begin{bmatrix} 1 & \widetilde{a}_{12} \\ \tilde{a}_{21} & 1 \end{bmatrix} \begin{bmatrix} Treasury_{t,IP} \\ Stock_{t,IP} \end{bmatrix} = \begin{bmatrix} 0 \\ \varepsilon_{fundamental,t,IP} \end{bmatrix} \tag{1.17}$$

where $\widetilde{a}_{12}$ reflects how Treasury yields (10-Year rate) respond to stock returns when there is no slope policy shock (i.e., only economic fundamental shock) at present. Remember that around FOMC announcements, there are two underlying structural shocks,

$$\begin{bmatrix} 1 & \breve{a}_{12} \\ \breve{a}_{21} & 1 \end{bmatrix} \begin{bmatrix} Treasury_{t,FOMC} \\ Stock_{t,FOMC} \end{bmatrix} = \begin{bmatrix} \varepsilon_{slope,t,FOMC} \\ \varepsilon_{fundamental,t,FOMC} \end{bmatrix} \tag{1.18}$$

$\breve{a}_{12}$ measures how Treasury yields (10-Year rate) respond to stock returns when both shocks are in place. To back out of the slope policy shock, we can simply apply the estimated relationship $\widetilde{a}_{12}$ (around Industrial Production) to co-movements around FOMC announcements and the residuals will be clean slope policy shocks. Using the slope shocks as IV, impulse responses are plotted in Figure 1.10.

(3) SVAR Invertibility

Following Stock and Watson (2018), we test SVAR invertibility by hypothesizing our external instrument, the heteroskedasticity identified slope shock, does not Granger

[28]On the other hand, as remarked by Powell (2019), the current Fed Chair, "monetary policy is data dependent." Particularly with regard to the monthly Industrial Production releases, he said that "the Fed's efforts were among the earliest in creating timely measures of aggregate production. Over the century of its existence, our industrial production team has remained at the frontier of economic measurement, using the most advanced techniques to monitor U.S. industry and nimbly track changes in production."

cause the endogenous variables in the SVAR. Table 1.2 reports the result for F-statistics of 4 lags of the instrument the coefficients are jointly zero in each of the equations. As we can see, the invertibility cannot be rejected at 5% level of significance.

Table 1.2: VAR invertibility test

Slope	FFR	Unemployment	Inflation	EBP
0.1869	0.5933	0.0535	0.9381	0.8732

Note: P-values for F-test the null that the coefficients on 4 lags of the instrument (heteroskedasticity identified slope shock) are jointly zero in each of the SVAR equations.

(4) Literature Replication

Figure 1.13 shows the baseline instrument SVAR impulse responses in Gertler and Karadi (2015). Their VAR consists of monthly data of log industrial production, log consumer price index, 1-Year government bond rate, and the Gilchrist and Zakrajšek (2012) excess bond premium (a measure of overall credit cost which can be viewed as the sum of the risk and the term premium) over the period of July 1979 to June 2012. Specifically, they choose the 1-Year rate as the monetary policy indicator and high-frequency identified 3-month ahead futures rate (notationally FF4 as in Gürkaynak et al., 2005) as external instruments.[29] Notice that the instruments are only available from January 1991 through June 2012, accordingly, they use the full sample to estimate reduced form residuals (innovations), and then select the corresponding period to identify the contemporaneous impact of monetary policy surprises. As they argued, the response from the excess bond premium indicates that small movements in short rates can potentially lead to large movements in credit costs, which is important but absent from traditional monetary policy transmission.

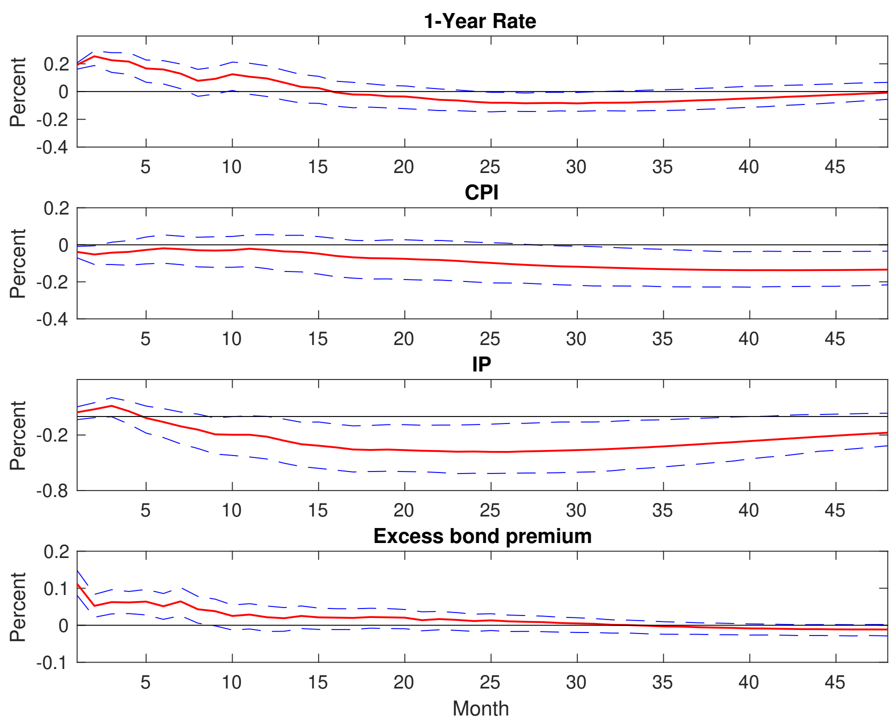
Figure 1.14 replicates the finding in Lakdawala (2019).[30] His VAR specification

[29]As documented in Gertler and Karadi (2015), "the data of course includes the recent crisis, a period where the short-term interest rate reached the zero lower bound. However, until 2011, our baseline policy indicator, the 1-Year government bond rate, remained positive, indicating some degree of central bank leverage over this instrument", see their paper for a detailed discussion for policy indicator and instrument choice. The reduced form VAR is estimated with 12 lags and the IRF focuses on future 48 months.

[30]Left column VAR includes the federal funds rate (IV: current month federal funds future

in the right column is similar to Gertler and Karadi (2015) but excludes the excess bond premium. Focusing on the part of slope policy (i.e., forward guidance which corresponds to the right column with 1-Year rate as policy indicator), his finding suggests that a positive shock to the long-term interest rates has an expansionary effect on output, which he attributed to the superior information that the Fed has than the public.

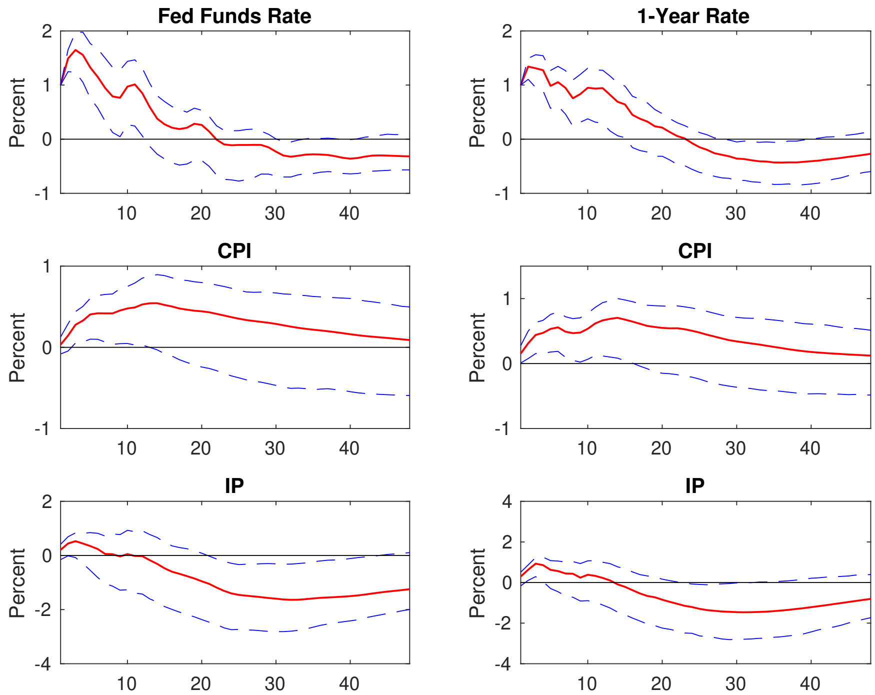
Figure 1.13: IRF in Gertler and Karadi (2015) IV-SVAR baseline



Note: The solid red lines are dynamic responses associated with a 1 standard deviation surprise monetary tightening, the blue dash lines are 95% confidence bands are computed using bootstrapping.

available from January 1991 to December 2011), log industrial production, and log consumer price index from July 1979 to December 2011. Right column VAR includes the 1-Year Treasury yield (IV: 3-month ahead federal funds future available from January 1991 to December 2011), log industrial production, and log consumer price index from July 1979 to December 2011. The red lines are impulse responses to 1 unit of monetary policy shock. The confidence intervals are generated using bootstrapping, not the Jentsch and Lunsford (2016) method used in the paper.

Figure 1.14: IRF in Lakdawala (2019) Figure 3



Note: The solid red lines are dynamic responses associated with a 1% surprise monetary tightening (i.e., 1% shock to FFR in the left panel; 1% shock to 1-Year rate in the right panel), the blue dash lines are 68% confidence bands computed using bootstrapping.

(4) Alternative Model Set-up

Stock price change in the tight event window is a function of both ϵ_{1t}, which indicates changes in investors' sentiment about the economic prospects and ϵ_{2t}, which indicates changes in the interest rate that are due to monetary (slope) policy, as in equation (1.19). A positive ϵ_{1t} suggests investors becoming more optimistic or less concerned about financial and economic risks. Meanwhile, shifts in ϵ_{2t} (originating from central bank policy announcements) can also affect stock prices through, for instance changes in equity premium as suggest in Bernanke and Kuttner (2005) or "reaching for yield" investors.

$$x_{1t} = \epsilon_{1t} + \beta\epsilon_{2t} \tag{1.19}$$

Shifting investor sentiment also affects bond yields. A brighter economic prospect and greater confidence reduce investor demand for safe-haven assets, including longer-term Treasury bonds, which pushes down bond prices and increases yields. Moreover, the long-term bond yield is also used or perceived to be used as a policy tool by central banks. Therefore, it will also be influenced by actual unconventional policies such as forward guidance and QE, as well as investors' expectations about those policies and monetary policy stance in general in the medium and longer run. Equation (1.20) decomposes bond yield movements into the two fundamental forces, with ϵ_{1t} for changes in investor sentiment about the economy and ϵ_{2t} for actual or expected changes in monetary policy.

$$x_{2t} = \gamma\epsilon_{1t} + \epsilon_{2t} \tag{1.20}$$

Rearranging the two-equation model above into equation (1.21), which tells us how to back out of the ϵs, if we know the underlying parameters from the observed price movements.

$$\begin{bmatrix} 1 & -\beta \\ -\gamma & 1 \end{bmatrix} \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = (1-\beta\gamma) \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \tag{1.21}$$

This is an identical model as what we have earlier, once we allow $a_{12} = -\beta$, $a_{21} = -\gamma$, $\varepsilon_{1t} = (1-\beta\gamma)\epsilon_{1t}$, and $\varepsilon_{2t} = (1-\beta\gamma)\epsilon_{2t}$, with the last two equations indicating a simple rescaling of the structural shocks.

Chapter 2

Post-FOMC Drift

Abstract

We study the patterns of stock returns around the Federal Reserve monetary policy announcements. Much of the existing literature interprets changes in short rates around the announcement windows as policy surprises. In contrast, we follow the "Fed information effect" literature that posits that financial markets react to central bank announcements not just for unexpected changes in monetary policy stances (monetary policy news), but also for central banks' previously unknown private information about economic conditions (non-monetary policy news) that are revealed to the public through announcements or policy decisions. In addition to studying stock market's responses to policy news, we also study its reaction to non-policy news contained in those policy announcements. We identify the good/bad news using a combination of sign restrictions with high-frequency financial data. "Bad news" events are times when the market interpreted the Fed decisions/announcements as revealing negative Fed information about the economy, and vice versa for "good news" events. A novel finding is that following bad news events, we observe significant positive stock returns in a 20-day period. The observation is consistent with a story of market overreactions to both good and bad news, though alternative explanation based on good and bad news' asymmetric impacts on the level of uncertainty are possible as well. Further analysis shows that the post-FOMC drift to economic news in Fed announcements is a market-wide phenomenon and can be exploited in an easy-to-implement trading strategy.

2.1 Introduction

How does the financial market react to monetary policy announcements? Understanding this question can help us uncover the transmission of monetary policy to the asset market and the real economy. There has been a long-established strand of literature that focuses on stock market reactions to the Federal Open Market Committee (FOMC) decisions. Bernanke and Kuttner (2005) find that on the announcement day, an unexpected interest-rate cut of 25 basis points leads to an increase in the Center for Research in Security Prices (CRSP) value weighted market index of about 1 percentage point. The market does not only respond to policy decisions contemporaneously (i.e., on the FOMC announcement day), in an influential paper, Lucca and Moench (2015) document the striking pre-FOMC announcement drift: 24-hour before the announcement, returns drift upwards (about 0.5% in terms of the average daily excess return) independent of the direction of the monetary policy surprise (i.e., regardless of whether it is an unexpected contractionary or an expansionary).

Our paper is more closely related to Neuhierl and Weber (2021), who examine a longer window around FOMC meetings, and document a prolonged drift before and after the announcements: 25 days before expansionary monetary policy surprises, stock returns tend to go up, and returns continue to drift in the same direction for another 15 days after the announcement, while for contractionary surprises, stock return drifts down before and after the announcement.

In this paper, we focus on stock return drifts after FOMC announcements, similar to Neuhierl and Weber (2021). Our contribution is to combine it with the Fed information effect. Much of the literature in the area interprets changes in short rates around the announcement windows as policy surprises. In contrast, we follow a growing literature on the Fed information effect showing that information contained in the FOMC announcement is multifaceted. It reflects not only the Fed's current (and future path) monetary policy stances, but also the central bank's private information about economic fundamentals that is previously unknown to the financial markets (Gürkaynak et al., 2005; Nakamura & Steinsson, 2018a; Cieslak & Schrimpf, 2019). Such views can be expressed explicitly through official Fed communications, or can be inferred implicitly as what might have motivated a policy decision.

A series of questions arise naturally once we interpret interest rate changes around FOMC windows to be more than just policy surprises. First, the stock drift patterns reported in Neuhierl and Weber (2021) may be more than just a response to changes in monetary policy; it can also be response to the Fed information, since what is interpreted as policy surprise by Neuhierl and Weber (2021) can now be considered a combination of policy surprises and new information about the Fed's view on economic conditions. Perhaps the upward drift after a rate decline (previously interpreted as policy easing) is a result of the market processing the unexpected pessimism that led to the Fed's decision to ease.[1] Answering these questions will help deepen our understanding on the stock drifts reported in Neuhierl and Weber (2021), and a clearer picture of how markets react to policy surprises.

Secondly, an entirely new front of research now opens up: how does the financial market process the Fed's private information? There has been no empirical report, to our best knowledge. Theoretically, ambiguity abounds. With announcements of policy decisions, the uncertainty of policy directions likely declines. But if the market infers from those decisions (some surprise news about the Fed's view on economic conditions), the level of uncertainty can increase instead. Changes in the level of uncertainty, in turn, can affect returns from the stock market. Another interesting question is whether good news and bad news affect markets in the same way. At the level of individual stocks, there is evidence that bad news travels more slowly than good news, resulting in downward return drifts after bad news (Hong, Lim, & Stein, 2000; Frank & Sanati, 2018). But it is also possible that bad news in the Fed's announcement raises uncertainty relative to good news. In that case we would expect a upward drift in stock prices after bad news. There is yet another possibility, perhaps financial markets have a tendency to overreact to news, becoming euphoric in the case of good news and panicky in the case of bad news. If so, we would expect upward drifts after bad news and downward drifts after good news. There are cases to be made for all these conjectures. Only a careful examination of data can help clear the picture.

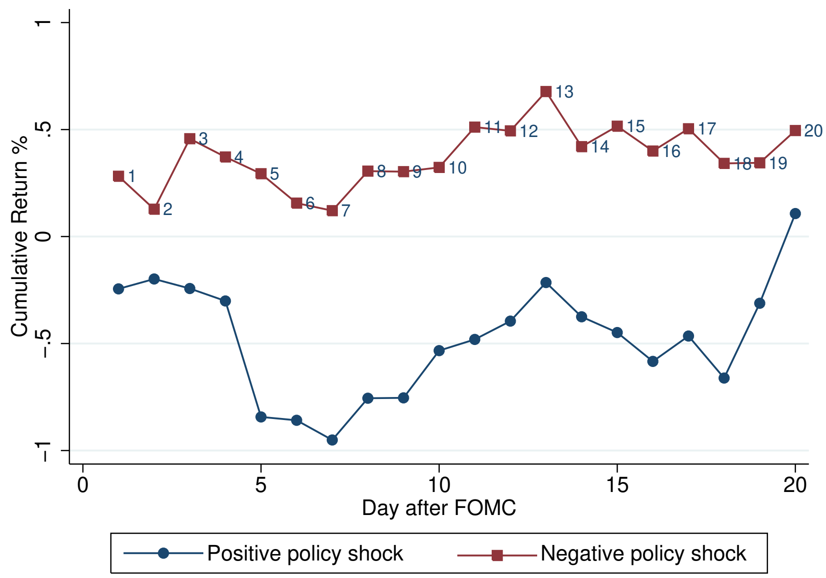
More generally, the new front of research provides another chance to examine the flow of new information in the financial market. The information, in this case, is about the Fed's view on the state of the economy, which is important for at least two reasons. First, the Fed may have a deeper understanding of the economy due to its possible information advantage. Secondly, the central bank is such an important policy maker and a deep-pocket player in the financial market that its views on

[1] The unexpected pessimism may lower the current stock price, when stock price rebounds after, it will cause a positive return.

economic conditions, whether they are accurate or not, can have profound impacts on financial prices simply because what it believes now can potentially decides what policy it chooses in the future.

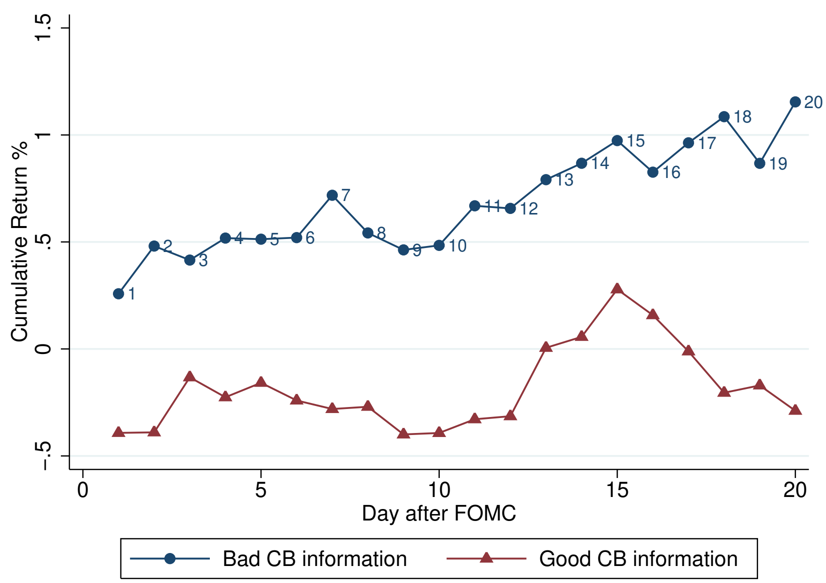
Our central bank news identification builds on the growing high-frequency identification literature that uses asset prices co-movements in a narrow window (Jarociński & Karadi, 2020 among others). Around a FOMC announcement, if the interest rate implied by federal funds futures goes up and the stock price goes up, the dominant information content in this particular FOMC event is positive central bank information concerning economic conditions or growth prospect. If on the other hand, the interest rate goes down and the stock price goes down, the dominant news is the central bank's unexpected pessimism regarding the economy. Similarly, we identify unexpected easing (tightening) through negative co-movements: if interest rates go down (up) while stock prices go up (down), we define these events as unexpected easing (tightening). We note that the simple sign restriction, relying solely on signs of co-movements between interest rate and stock prices, is easily implementable but is limited in that it can only identify the type of dominant information content, not all the information, nor does it provide any point estimate of underlying shocks. For robustness we will also use data from Jarociński and Karadi (2020), who provide estimates of policy and news shocks behind all FOMC announcements via sign restrictions in a VAR analysis (specifically, they provide the means of shocks that satisfy the sign restrictions as the estimates of shocks).

Figure 2.1: Post-FOMC drift after unexpected Fed easing or tightening



Note: Cumulative stock market returns for unexpected easing (negative) or tightening (positive) based on simple sign restriction.

Figure 2.2: Post-FOMC drift after unexpected good or bad information



Note: Cumulative stock market returns for different good/bad Fed news based on simple sign restriction.

We made two main findings in our paper. The first is that taking into account of the Fed information effect does not substantially alter findings reported in Neuhierl and Weber (2021) regarding return drifts after FOMC announcements. Using the sign restriction identified monetary policy surprises (i.e., among those FOMC events dominated by unexpected easing/tightening), as shown in Figure 2.1, we continue to find upward drift of stock returns after policy easing, though the pattern is less obvious relative to those in Neuhierl and Weber (2021). This finding is in line with Ma (2022) and others (e.g., Bauer & Swanson, 2020), who show that interest rate surprises primarily reflect unexpected monetary policy changes.

The more interest finding in our paper, as plotted in Figure 2.2, is what we call the "post-FOMC drift": following an announcement that reveals the Fed's unexpected pessimism about the state of the economy, stock returns (on average) drift upward for 20 days, achieving an average cumulative return of about 1.2%. On the other hand, following a good news announcement, stock returns go slightly down, losing an average of about 0.3%. There is thus a roughly 1.5% gap in stock returns between bad news announcements and good news announcements.

To ensure the post-FOMC drift (positive return drift following bad central bank news) is not driven by factors other than the revealing of the Fed's information though its announcements, we further control for macroeconomic data releases, corporate earnings announcements, and calendar days which may contain other news in a regression analysis. Results suggest the drift is likely caused by the Fed information. We further demonstrate the robustness of our findings by showing that the patterns of post-FOMC drifts hold in portfolios formed based on different industries, market betas, market capitalization, and book-to-market value. Additionally, we perform a tone analysis following a recent study by Hubert and Labondance (2021). In our sample, bad announcements, on average, have negative tones, while good announcements, on average, carry positive tones. Studies have shown that words used by central bankers play an important role in its monetary policy decisions, especially when there is uncertainty about future policy stances. By showing a positive return drift after the bad (negative tones) central bank announcements, we provide additional evidence that the "tone of central bank statements acts as a way to reveal central bank information," as augured in Hubert and Labondance (2021).

The post-FOMC drift can be exploited in a trading strategy that builds on the easily observable trading signal from analyzing high-frequency co-movements of federal funds futures and stock prices (available in real time with simple calculations). A trading strategy that buys the market portfolio after bad information FOMC announcements can earn an annual excess return of 2.5% in our sample period (1994-2016), which equals to more than 40 percent of the average U.S. equity premium. Moreover, the Sharpe ratio of the simple strategy is also higher than the leading risk factors documented by Fama and French (1993) and Fama and French (2015).

Why does the stock market go up following a bad central bank announcement? Motivated by the uncertainty-based explanations for pre-FOMC drifts (e.g., Laarits, 2020), we look into the Chicago Board Options Exchange's Volatility Index (VIX), the most popular measure for investors' perception of near-term stock market volatility. We find that VIX on average decreases on FOMC announcement days compared to other trading days, suggesting that FOMC announcements tend to lower stock market risks. This is consistent with the explanation of pre-FOMC drift in Neuhierl and Weber (2019) and others. More importantly, if we compare the good versus bad Fed announcements, the decreases in VIX are greater on good news announcement days than on bad news days. This suggests that the relatively higher returns following bad information announcements could be attributed to the *relative* increases in risks. However, it is also possible that the different drifts between good and bad news announcements are a result of market overreactions. In other words, stock prices rise too much after good news and fall too much after bad news, and the correction after the initial over reaction leads to the positive return after bad news and negative return after good news.

The remainder of the paper is organized as follows: Section 2.2 reviews the relevant literature, Section 2.3 explains the empirical methodology in the study and discusses the results, and Section 2.4 concludes.

2.2 Related Literature

Our paper is most closely related to two strands of literature. One studies the patterns of stock market returns on days around the central bank announcements (pre-FOMC drift in Lucca & Moench, 2015 and monetary momentum, both before and after the announcements, in Neuhierl & Weber, 2021). The other strand, mostly called the "Fed-information effect" literature, breaks down market reactions to central bank announcements into monetary policy surprises and central bank's assessment of economic conditions and prospects (Gürkaynak et al., 2005; Nakamura & Steinsson, 2018a; Cieslak & Schrimpf, 2019). Our contribution is to combine the two. Much of the FOMC stock drift/momentum literature ignores the Fed information effect, and is thus silent on whether and how the stock market behaves differently depending on types of information contents.

The Fed information effect literature builds on earlier studies that use high-frequency data to identify drivers of financial prices around central bank announcements. Pioneered by Kuttner (2001), the literature uses high-frequency financial prices (such as federal funds futures) as a proxy for monetary policy surprises, interpreting interest rate increases as surprise tightening, and decreases as surprise easing. More recent literature challenges that one-dimensional view and argues that the announcements made by central banks can do more than just state monetary policy stances; they can also convey other information, such as the central banks' assessment of future economic outlook and/or market risks (Cieslak & Schrimpf, 2019; Cieslak & Pang, 2020). Both information components (namely, monetary policy and central bank assessment) can affect financial prices.

As a result, multiple financial prices, not just short-term interest rates as stated in Kuttner (2001) are needed to uncover the underlying drivers. That extra information often entails movements in stock prices. Cieslak and Schrimpf (2019) find that about 40% of monetary policy decisions by the Fed and the European Central bank (ECB) are denominated by non-monetary news (i.e., news about future growth and risks). Another study by Jarociński and Karadi (2020) also relies on the co-movement between stock returns and interest rates to separately identify monetary policy shocks and central bank information shocks. A commonly used sign restriction in literature (Cieslak & Schrimpf, 2019; Cieslak & Pang, 2020; Jarociński & Karadi, 2020) is that negative co-movement between stock returns and interest rate changes is caused by monetary policy shocks, whereas positive co-movement is caused by central bank information shocks. In this paper, we follow this sign restriction to differentiate good central bank information (assessment of economic conditions/prospects) versus bad information, and then study the stock return drifts after the announcements.

The stock market's FOMC drift/momentum literature builds on earlier literature that investigates how FOMC announcements affect stock prices. Bernanke and Kuttner (2005), using daily interest rate and stock price data, find that an unexpected interest rate cut of 25 basis points leads to an increase of the overall market index by 1%. They attribute the stock price reaction to monetary policy's effect on equity premium, with an expansionary policy shock lowering equity premium. Using intraday data instead of daily data, Gürkaynak et al. (2005) find a similar size impact to the policy target factor that they identify using the higher frequency data.

Our paper is closer to the recent literature, which studies stock price drifts around FOMC announcements. Savor and Wilson (2013) and Savor and Wilson (2014) show that stock returns are significantly higher on macroeconomic announcement days and, in particular, only on the FOMC announcement days, the security market line (the plot of CAPM beta against average excess return) is upward sloping. Lucca and Moench (2015) document the well-known pre-FOMC announcement drift, indicating that almost 80% of the equity premium is earned in the 24 hours before the actual FOMC announcement. Cieslak, Morse, and Vissing-Jorgensen (2019) find pre-announcement drift is part of a broader bi-weekly pattern that stock returns are higher on even weeks around FOMC announcements. Neuhierl and Weber (2019) show that faster policy easing predicts positive stock returns.

In a more recent paper, Neuhierl and Weber (2021) document the "monetary momentum" before and after FOMC announcements. Specifically, they find that stock prices tend to rise before expansionary monetary policy surprises and then drift in the same direction for another 15 days. Their study does not take into account the Fed information effect, interpreting decreases in interest rates as unexpected easing. In this paper, we will follow the newer literature to treat the same decrease in interest rate differently depending on whether it coincided with an increase in stock prices or with a decrease, interpreting the former as a reaction to policy easing and the latter as a reaction to central bank pessimism.

From a pure empirical perspective, we help check whether the post-FOMC drift reported in Neuhierl and Weber (2021) holds up or not when the Fed information effect is considered. More importantly, there is now an entirely new front of research: how does the stock market respond to Fed information, or more specifically, the surprise components in the Fed's assessment of economic conditions and market risks? To the best of our knowledge, our paper is the first to document the stark positive return drifts following the revelation of bad news by the Fed. This will improve our understanding about how financial markets react to the arrival of new information, which in this case is the Fed's private information made known to the public.

Many studies have attempted to explain the puzzling stock drifts around FOMC and other important macroeconomic announcements. Using a theoretical model, Ai and Bansal (2018) suggest the pre-FOMC announcement represents a "resolution of macroeconomic uncertainty" that could be related to the Fed's informal communications. Likewise, Cieslak et al. (2019) provide substantial evidence of information leaks from the Fed on even weeks. Wachter and Zhu (2018) explain the macro announcement premium as investors' reactions to a "latent disaster probability" stemmed from pre-scheduled events. In a recent study, Laarits (2020) shows that the pre-FOMC drift actually represents the risk premium associated with the uncertainty about announcement type (i.e., monetary policy action versus Fed's expectation about future economic condition). We also investigate the underlying mechanism behind the post FOMC drift by studying the behaviour of VIX. Our analysis suggests that the positive return following bad announcements could be attributed to the relatively heightened risks, though we cannot rule out overreaction by financial markets either.

Lastly, our paper contributes to the literature on stock market reactions to news. In a theoretical model, Veronesi (1999) shows that in equilibrium "stock prices overreact to bad news in good times." Using individual firm-level data, Frank and Sanati (2018) find that stocks are slow to absorb bad news relative to good news because investors tend to under react to the bad news.[2] By showing a positive return

[2]Frank and Sanati (2018) document negative drifts following both good and bad new announce-

drift following bad FOMC announcements, our findings suggest that the market may indeed overreact to the bad news revealed by the FOMC announcements.

2.3 Empirical Strategy and Results

2.3.1 Identify Fed information and policy surprises

Our central bank news identification is based on high-frequency co-movements between stock prices and interest rates. In a tight window around the FOMC announcement, if both the interest rate and the stock price go up, we interpret the movements as market reactions to the Fed signaling positive assessment of economic conditions or prospects (i.e., good news); if the interest rate and the stock price both go down, the news concerning future growth is likely to be negative. Likewise, we identify the Fed's unexpected easing/tightening if the interest rate and stock prices move in opposite directions.

The sign-based simple identification rule is summarized in Table 2.1. Specially, we follow the literature (e.g., Gertler & Karadi, 2015) and use unexpected changes in the 3-month ahead federal funds future, $ff4$, as an indicator for interest rate surprises. As noted by Gertler and Karadi (2015), the use of $ff4$ captures surprises to not only the current policy rate, but also some degree of forward guidance. For the stock price, we use the broad market index S&P 500. Following the convention in the high-frequency identification literature (Gürkaynak et al., 2005), all the surprise changes are measured in a 30-minute window starting 10 minutes before and 20 minutes after the announcement. We obtain all the 30-minute window changes in $ff4$ and S&P500 from Jarociński and Karadi (2020).[3]

Table 2.1: Sign restrictions to identify central bank announcement information

	good news	bad news	tightening	easing
interest rate ($ff4$)	↑	↓	↑	↓
stock price (S&P500)	↑	↓	↓	↑

ments and interpret their findings as "positive news shocks tend to produce overreaction, while negative news tends to produce under-reaction."

[3] Jarociński and Karadi (2020) provide high-frequency changes in in $ff4$ and S&P500 up to the FOMC meeting in December 2016.

Note that our sign restriction based identification method is only able to identify news content in some of the announcements (i.e., when non-monetary/monetary news is the *dominant* force for the financial price co-movements). If, for instance, the interest rate goes down while the stock price goes up, we cannot directly observe and conclude the news embedded in the announcement is good or bad. In contrast, Jarociński and Karadi (2020), using the same intuition, *fully* identify good/bad central bank information for each FOMC meeting in a Bayesian VAR. Technically, sign restrictions in a VAR can only identify a set of shocks that satisfy the restrictions (i.e., the method cannot yield point estimates for policy and news shocks). The point estimates in Jarociński and Karadi (2020) are actually the means of the set of shocks that satisfy the conditions. We will use our simple sign restriction to generate the baseline result for its ease of implementation, and will use shocks from Jarociński and Karadi (2020) for robustness tests.

The Fed holds 8 scheduled FOMC meetings per year. From 1994 to 2016, we have a total of 184 policy announcements.[4] The first two columns of Table 2.2 show the classification of the 184 FOMC meeting based on our sign restriction. We identify 96 (or about 50%) FOMC announcements, to which interest rates and stock prices reacted in the same direction. According to our sign restrictions, the positive co-movement indicates that the dominant information content is about Fed information on the economy. Of these 96 events, 59 of them indicate unexpected pessimism by the Fed (i.e., negative Fed information); only 37 indicate positive Fed information.[5] Because we have relatively few observations for good news announcements, we will focus mostly on bad news announcements. The sign restriction also identifies 88 events dominated by monetary policy news (i.e., when stock prices and interest rates move in opposite direction). Among them, 40 FOMC announcements are dominated by unexpected policy tightening, 48 dominated by policy easing.

Table 2.2 also presents findings based on the policy and central bank information shocks identified by Jarociński and Karadi (2020). We simply classify a FOMC

[4]From 1994 to May 1999, the FOMC only releases a statement if there is a change in the federal funds rate. After May 1999, the FOMC releases a statement after each scheduled meeting.

[5]Around 52 FOMC announcements in our sample period, high-frequency changes in $ff4$ are 0. For those events, we classify a FOMC to have good (bad) news if the high-frequency stock return is positive (negative). Among them, 29 have bad news (event window stock returns are negatives), and 23 have good news (event window stock returns are positive).

to be a good (or bad) news event as long as the estimated information shock is positive (or negative) for that particular FOMC meeting. Similarly, we classify all FOMC meeting to have unexpected tightening (or easing) as long as the policy shock is negative for that event. We note that a direct comparison between the simple sign-restriction approach and the Jarociński and Karadi (2020) approach is not possible: the simple sign restriction distinguishes events dominated by Fed information and those dominated by policy surprises. It does not classify a FOMC announcement as a good news event unless the dominant information content in that FOMC announcement is the Fed information. The shocks identified by Jarociński and Karadi (2020), in contrast, will classify a FOMC as good news as long as the estimated Fed information shock is positive (even if the co-movement is dominated by policy surprises).

Table 2.2: Identified good or bad news events and tightening or easing events

	Good news	Bad news	Tightening	Easing
Simple sign restriction	37	59	40	48
Jarociski and Karadi VAR	80	104	93	91

Table 2.3 presents summary statistics for the key variable of our interest—the 20-day excess returns calculated as in equation (2.1), where m and r represent daily stock and T-bill returns, respectively.[6] The reason for choosing the 20-day excess return is twofold. First, there are 8 scheduled FOMC meetings per year, roughly 6 to 8 weeks apart; we chose the 20-day window, a roughly 4- to 5-week period, to avoid overlapping of the FOMC meetings. Second, as documented by Neuhierl and Weber (2021), stock returns 15 days *before* the FOMC could predict the direction (positive/negative) of the monetary policy surprise. We can potentially overcome these issues by looking at the 20-day excess return. Notice that we focus on excess returns *after* the FOMC announcements (i.e., from the first trading day after the FOMC announcement to the twentieth trading day after the FOMC announcement) to distinguish our findings from the well-known pre-announcement drifts documented in

[6]The daily stock and treasury bill return data is from Kenneth French data library and CRSP. The sample starts in 1994, which is corresponding to the year that the FOMC began to formally release its policy decisions.

Lucca and Moench (2015).

$$20dayExcessReturn = 100 * [((1+m_{t+1}) * ... * (1+m_{t+20}) - (1+r_{t+1}) * ... * (1+r_{t+20})] \quad (2.1)$$

Over the 23-year period, the 20-day excess returns following FOMC announcements (0.281%) are about half of the sample average (0.597%) and days excluding FOMC days (0.607%), indicating the excess returns we are looking at are somewhat special for days following FOMC announcements. Looking at the events dominated by monetary policy shock (rows 4 and 5), on average, the excess returns are higher for expansionary surprises (0.301%) than for contractionary surprises (-0.119%). However, both returns are not statistically different from 0, as shown in Table 2.4. Visually, Figure 2.1 in the introduction section plots the cumulative returns following unexpected easing/tightening identified from our simple sign restriction. The positive return drift following unexpected policy easing is in line with Neuhierl and Weber (2021).

Focusing on the good/bad news announcements identified with our simple sign restrictions (rows 6 and 7), the returns are quite pronounced. Notably, following a bad news announcement (when a central bank announcement is accompanied by decline in both interest rates and stock prices), the 20-day excess return is surprisingly high, reaching around 1% on average; whereas the average excess return is negative following a good announcement. Moreover, as evident in t-Tests summarized in Table 2.4, excess returns following bad information announcements are statistically different from zero. Figure 2.2 in the introduction visualizes the diverging trajectories showing, on average, a positive drift after bad news and a negative drift after good news.

As noted earlier, we will use shocks from Jarociński and Karadi (2020) for robustness tests. Jarociński and Karadi (2020) use a similar sign restriction in their VAR analysis and provide the means of estimated monetary policy shocks and central bank information shocks for all FOMC events that satisfy the sign restrictions on high-frequency financial data (i.e., a surprise tightening raises interest rates and reduces stock prices; a positive central bank information raises both). Thus, their shocks allow us to test the robustness of our findings. We distinguish unexpected easing/tightening based on the sign of the monetary policy shock and classify the FOMC to have good (bad) news if the information shock is positive (negative). In general, our findings based on our simple sign restrictions (i.e., for the FOMC announcements dominated by monetary/information shocks) still hold.

Table 2.3: Summary statistics

20-day excess returns	Obs	Mean	Std Deviation	Min	Max
All days	5980	0.597	4.529	-28.568	24.268
All FOMC days(t+1 to t+20)	183	0.281	4.061	-18.441	8.016
All days other than FOMC	5797	0.607	4.543	-28.257	24.268
Sign positive CB surprise	39	-0.119	4.276	-10.271	8.016
Sign negative CB surprise	48	0.301	3.723	-13.073	7.745
Sign good CB information	37	-0.397	3.943	-9.318	6.636
Sign bad CB information	59	0.953	4.251	-13.073	7.745
JK positive CB surprise	92	0.125	4.480	-18.441	7.745
JK negative CB surprise	91	0.438	3.611	-10.271	8.016
JK good CB information	80	-0.556	4.187	-18.441	8.016
JK bad CB information	103	0.931	3.860	-13.073	7.745

Table 2.4: t-Test: 20-day excess return=0

t-Test	p-Value
Sign positive CB surprise=0	0.87
Sign negative CB surprise=0	0.36
Sign good CB information=0	0.54
Sign bad CB information=0	0.09*
JK positive CB surprise=0	0.79
JK negative CB surprise=0	0.25
JK good CB information=0	0.24
JK bad CB information=0	0.02**

Note: ** statistically significant at 5% level; * statistically significant at 10% level.

Based on the Jarociński and Karadi (2020) shocks, Figures 2.5 and 2.6 in the Appendix depict average cumulative stock returns for 20 days after FOMC announcements. Again, we find that stock returns drift upward following expected policy easing. In addition, we can see that following a bad news announcement, stock return continues to rise, reaching more than 1% in 20 days. On the other hand, the stock return dropped 0.5% following good news released by the Fed. The result is similar to our baseline result plotted in Figure 2.2, which uses data from the easily implementable sign restrictions, though the pattern is somewhat less pronounced. This is to be expected, because Figure 2.2 uses only events in which central bank news dominates policy surprises, while Figure 2.6 uses all FOMC events, including those in which central bank news is just a bit player, meaning that market movements are driven more by policy surprises instead of Fed information about the economy.

To our knowledge, no study has looked at the stock return patterns induced by the informational content of the central bank announcements. This finding, higher excess return following bad central bank information, is particularly interesting and motivates the more detailed analysis. From now on, we will refer to such FOMC events as bad news central bank announcement. Here "news" is are the about central bank's assessment of economic conditions/growth prospect, or market risks.

2.3.2 Robustness checks: linking the drift to Fed information

Our earlier analysis is based on sample averages. To see whether the post-FOMC drift (positive returns following bad news) could have been driven by extreme values, Figure 2.7 in the Appendix shows a scatter plot of 20-day excess returns for all the sign-identified bad central bank announcements. There are indeed some large negative returns that happened in the recent two crises (the dot-com bubble and the Great Recession). To avoid confounding external shocks, we drop the FOMC meetings during the crises.[7] The remaining 52 bad information events have an average 20-day excess return of 1.7%, which amounts to about 30% of the equity

[7] In the scatter plot, the two extreme negative returns in 2001 and 2002 correspond to periods encompassing 9/11 and "the great telecoms cash." https://www.economist.com/weeklyedition/2002-07-20

premium. It is thus clear that extreme values are not the reason behind the post-FOMC drift after bad news announcements.

Next, we test whether those 20-day returns following the bad information is statistically different from the rest of trading days by regressing 1-day excess return on a dummy variable that is equal to 1 if the day falls in the 20-day period following bad news announcements. Results are summarized in Table 2.5. Column (1) includes all 59 bad central bank announcements dummies. It seems that the daily excess return on these 1180 days is about 3 basis points higher, but the difference is statistically insignificant. After dropping announcements falling into crisis periods as discussed earlier, as shown in column (2), the difference between bad announcement days and other days increases to about 7 basis points and becomes statistically significant. Thus, we can conclude that stock returns in the 20-day period after observing bad central bank information (not in crisis) are indeed higher than normal days. However, is the bad news announcement the cause of the higher-than-normal return?

Table 2.5: Results: regress daily excess return on 20-day (after bad news) dummy

	(1) 1-day ex return	(2) 1-day ex return
Bad CB information Dummy	0.025	
	(0.61)	
Bad CB information Dummy (no recession)		0.067*
		(1.75)
Constant	0.026	0.020
	(1.63)	(1.18)
N	6000	6000
R^2	0.0001	0.0005

Note: Heteroskedasticity robust t-Statistics are reported in parentheses. * statistically significant at 10% level.

To rule out other potential factors that may contribute to the abnormal high returns, we follow Cieslak et al. (2019) to further control the relevance-weighted number of macroeconomic data releases in column (2), number of earnings announcements and the fraction of positive announcements in column (3), and day of the week, day of the month, last day of the month, last day of the quarter, last day of the year fixed effects in column (4).[8] All the controls are taken from Cieslak et al. (2019). From the results shown in Table 2.6, adding additional controls does not affect the significant 7 basis points difference. And only the relevance-weighted number of macroeconomic data releases contributes about 1 basis. Therefore, high excess returns on days following bad announcements are unlikely caused by other factors.

[8]The relevance-weighted number of macroeconomic data releases are constructed using the Bloomberg macroeconomic data releases. Earnings announcements are from Institutional Brokers' Estimate System (I/B/E/S) database. See Cieslak et al. (2019) II.A for details.

Table 2.6: Ruling out non-Fed explanations

	(1)	(2)	(3)	(4)
	1-day ex return	1-day ex return	1-day ex return	1-day ex return
Bad CB information Dummy (no recession)	0.067*	0.072*	0.068*	0.067*
	(1.75)	(1.87)	(1.79)	(1.76)
Relevance-weighted macro releases (Bloomberg)		0.014**		
		(2.06)		
Number of corporate quarterly EPS announcements (/10,000)			0.938	
			(0.45)	
Fraction of positive EPS announcements per day			0.075	
			(1.07)	
Constant	0.020	-0.009	-0.026	-0.008
	(1.18)	(-0.45)	(-0.66)	(-0.09)
Day of the week/month/ end of month/ quarter/year	No	No	No	Yes
N	6000	6000	6000	6000
R^2	0.0005	0.0011	0.0007	0.0095

Note: Heteroskedasticity robust t-Statistics are reported in parentheses. ** statistically significant at 5% level; * statistically significant at 10% level.

Moreover, Cieslak et al. (2019) document a striking bi-weekly pattern: stock returns are higher in weeks 0, 2, 4, and 6 in the FOMC cycle regardless of the content of the announcement. They provide ample evidence that ties their findings to the Fed's "systemically informal communication." To test whether our novel finding - high returns following bad news - is driven by the bi-weekly cycle, we further include interaction terms of dummy variables for week 0 (day t+1 to t+3 after FOMC announcement) and week 2 (day t+9 to t+13) and dummies for week 0 and week 2 separately.[9] Results in Table 2.7 suggest that the supposedly high return week 0 week 2 days are not the driver for the high 20-day excess returns following bad news.

Table 2.7: Ruling out bi-weekly pattern

	(1)	(2)	(3)
	ex return	ex return	ex return
Bad CB information Dummy (no recession)	0.067*	0.045	0.045
	(1.75)	(0.96)	(0.96)
Bad CB Dummy*Dummy week 0 & 2		0.055	
		(0.78)	
Bad CB Dummy*Dummy week 0 (=1 if t+1 to t+3)			0.028
			(0.26)
Bad CB Dummy*Dummy week 2 (=1 if t+9 to t+13)			0.072
			(0.90)
Constant	0.020	0.020	0.020
	(1.18)	(1.18)	(1.18)
N	6000	6000	6000
R^2	0.0005	0.0006	0.0006

[9] Cieslak et al. (2019) define week 0 as day t-1 to day t+3, relative to FOMC announcement day t.

Note: Heteroskedasticity robust t-Statistics are reported in parentheses. * statistically significant at 10% level.

2.3.3 Potential mechanism behind the drift

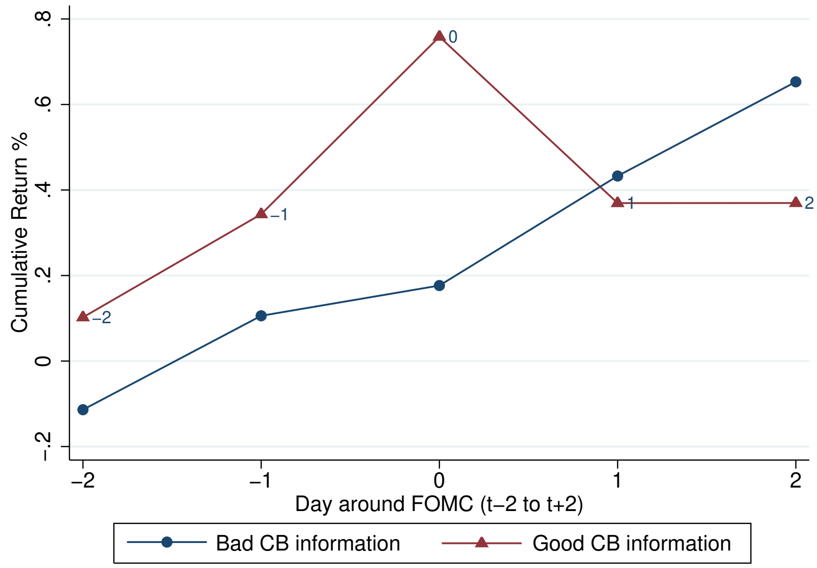
Similar to the uncertainty-based explanations for the pre-announcement drift (e.g., Laarits, 2020), a potential mechanism behind the post-announcement drift is that bad news announcements heighten investors' risk perception and thus increase the required rate of return for holding stocks. One supportive evidence is the behaviour of VIX, one of the most popular measures for investors' perception of near-term stock market volatility, around the FOMC announcements. Specifically, in Table 2.8, we show the changes in daily closing VIX comparing to its last 5-day moving average.

Table 2.8: Difference between VIX and its last 5-day moving average

Changes in VIX	Obs	Mean	Std Dev	Min	Max
All trading days	5785	-0.002	2.021	-15.758	22.894
All days exclude FOMC	5601	0.009	2.030	-15.758	22.894
FOMC days	184	-0.336	1.711	-6.124	4.734
Sign good CB information	37	-0.375	1.380	-3.544	3.694
Sign bad CB information	59	-0.174	1.961	-6.124	4.734
JK good CB information	80	-0.547	1.530	-3.922	3.952
JK bad CB information	104	-0.174	1.830	-6.124	4.734

From Table 2.8, several findings are worth noting. First, FOMC announcement days appear to be special. Compared to all other trading days, the VIX, on average, decreases by 0.34 units on the FOMC announcement days. Second, good or bad central bank announcements move VIX differently. On average, the VIX decreases more than doubled on good Fed announcement days (-0.375 units) than on bad news announcement days (-0.174 units). These differences are more pronounced if we use Jarociński and Karadi (2020) identified information shocks. With the *relatively* smaller decrease in VIX associated with bad news announcements, the high returns thus could be attributed to the *relative* increases in risk perception.

Figure 2.3: Return drift from 2 days before FOMC announcement to 2 days after



Note: Cumulative stock market returns from 2 days before to 2 days after FOMC announcements.

Another piece of evidence comes from the behaviour of stock returns encompassing the FOMC announcements. As shown in Figure 2.3, the pre-announcement drift (from the day before FOMC announcements to the day of FOMC announcements, labeled as -1 and 0, respectively) seems to be pronounced only for good news announcements. As suggested by Laarits (2020), the pre-announcement drift represents a risk premium earned from the uncertainty resolution. Here, we find that the pre-announcement return for bad news announcements is smaller, which corroborates our argument that bad news announcements resolve a *relatively* smaller amount of uncertainty.

One shortcoming of this uncertainty-based explanation is that it explains only the relative difference, not the absolute levels of returns. In terms of absolute levels, the average return after bad news announcements rises even though the average level of VIX declines, which would presumably indicate a lower level of risks and thus a lower required rate of return for holding stocks.

This apparent inadequacy of uncertainty-based explanation to account for the full pattern of post-FOMC drift leads us to an alternative explanation based on market overreactions. Specifically, the stock market overreacts to central bank news in either direction; its price rises too much after good news and falls too much after bad news. The subsequent correction is then responsible for the diverging pattern of post-FOMC drifts seen in Figure 2.2.

Here, we note an interesting contrast between the overreaction to bad news we document and the underreaction to bad news that Frank and Sanati (2018) report. The difference is that we look at the broad stock market reaction to central bank news. Frank and Sanati (2018), on the other hand, examine the reaction of individual firms' stocks to news stories concerning themselves. Part of their finding is that the initial price decline after bad news is followed by further declines, thus a downward drift in cumulative returns. Here we find the opposite, an upward drift after bad central bank news. The different responses may be caused by the scope of the news and investor attention. Specifically, investors may underreact to news regarding individual firms, but overreact to the news revealed by the Fed about the entire economy.

2.3.4 Tone of announcements

A growing literature has shown that tones of central bank announcements play an important role in revealing its private information to the public. Following Hubert and Labondance (2021), we used the well-established central bank tone analysis dictionary in Apel and Blix-Grimaldi (2014) to identify the positive and negative words used in FOMC statements.[10] With the number of positive and negative words identified in each FOMC statement, we then construct the tone of each announcement as in equation (2.2), which is the same way as Hubert and Labondance (2021).

$$Tone_t = (PositiveWords_t - NegativeWords_t)/(PositiveWords_t + NegativeWords_t) \tag{2.2}$$

By construction, the measure of the tone is bounded between [-1,1]. A positive tone of a given FOMC statement reflects optimism in the language used, while a negative

[10] Examples of positive words: increas*, accelerat*, fast*, strong*; examples of negative words: decreas*, decelerat*, slow*, weak*.

tone reflects pessimism.[11]

Figure 2.4: FOMC Tone: bad news announcements

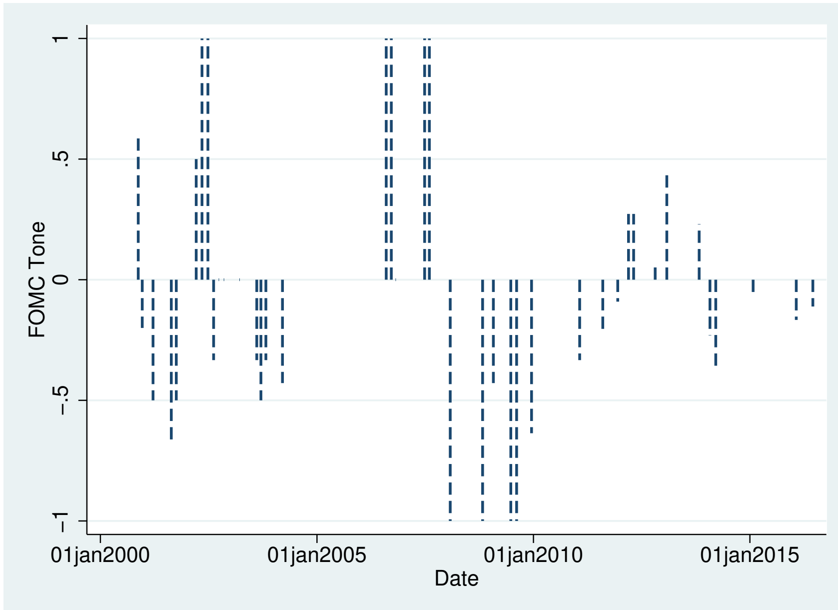


Figure 2.4 depicts the tone index for sign identified bad news announcements. We find that the bad announcements, on average, have negative tones, while good announcements, on average, carry positive tones. This simple relationship is not enough to draw any definitive conclusions, but the following examples may be able to provide additional anecdotal evidence to support that when the Fed uses negative words more, the market is likely to perceive a bad future prospect, which in turn puts pressure on the current stock prices.

- FOMC statement on 2008-10-29, tone: -1; high-frequency changes in $ff4$: -0.05999%; high-frequency changes in S&P500 -2.61509%

> "The pace of economic activity appears to have *slowed* markedly, owing importantly to a *decline* in consumer expenditures. Business equipment spending and industrial production have *weakened* in recent months, and *slowing* economic activity in many foreign

[11] As argued by Hubert and Labondance (2021), "policymakers could use positive and negative words for mentioning increasing growth the same way they could use positive and negative words for decreasing growth." The FOMC statement tone measures "whether policymakers use positive or negative words independently of the message they release."

> economies is damping the prospects for U.S. exports. Moreover, the intensification of financial market turmoil is likely to exert additional restraint on spending, partly by further *reducing* the ability of households and businesses to obtain credit."

- FOMC statement on 2013-03-20, tone: 0.27; high-frequency changes in $ff4$: 0.005%; high-frequency changes in S&P500: 0.09572%

> "Information received since the Federal Open Market Committee met in January suggests a return to moderate economic growth following a pause late last year. Labor market conditions have shown signs of *improvement* in recent months but the unemployment rate remains elevated. Household spending and business fixed investment advanced, and the housing sector has *strengthened* further, but fiscal policy has become somewhat more restrictive. Inflation has been running somewhat below the Committee's longer-run objective, apart from temporary variations that largely reflect fluctuations in energy prices. Longer-term inflation expectations have remained stable."

2.3.5 Trading strategy

Based on previous analysis, we conjecture that a trading strategy, which buys U.S. broad stock market index when observing bad FOMC news and holds for 20 days, could be profitable. In Table 2.9, we compare several different trading strategies, including the famous pre-announcement drift and our post-announcement drift. Note that in Lucca and Moench (2015)'s pre-FOMC drift, they calculate stock returns in a 24-hour window before the actual FOMC announcement. In our listed trading strategy B, we harvest the pre-announcement drift in two full trading days encompassing the 24-hour window: the day before the FOMC announcement and the FOMC announcement day.

Table 2.9: Performance of some trading strategies

Trading Strategy	Days	Avg Annu Excess Return	Std	Sharpe Ratio
A: Hold stocks on all days	6000	8.44	18.71	0.45
B: Hold stocks on the day and the day before FOMC	366	3.56	5.97	0.60
C: Hold stocks for 20 days after each FOMC	3660	2.29	12.41	0.18
D: Hold stocks for 20 days after bad CB information	1180	2.49	5.80	0.43
E: Hold stocks 20 day good CB information	740	-1.03	5.40	-0.19
F: Hold stocks pre-FOMC drift and 20 days after bad CB information	1546	6.10	8.80	0.69

Table 2.10: Performance of Fama French risk factors

Risk Factor	Days	Avg Excess Return	Std	Sharpe Ratio
A: Small minus Big	6000	-0.86	10.65	-0.08
B: High minus Low	6000	1.45	14.26	0.10
C: Robust minus Weak	6000	2.46	11.16	0.22
D: Conservative minus Aggressive	6000	1.05	10.49	0.10
E: Momentum	6000	3.67	16.88	0.22

Not surprisingly, the pre-FOMC drift harvested in strategy B earns an average excess return of 3.56% per year, leads to a Sharpe Ratio of 0.6. If we focus on the 20-day window after each FOMC announcement, returns differences are quite stark: 2.29% for all the FOMC events (strategy C), 2.49% (about 40% of the equity premium) for the bad news Fed announcements (strategy D), and -1.03% for the good news Fed announcements (strategy E). In terms of Sharpe ratios, we can see clearly that our "buy following bad announcement" strategy earns one of the highest Sharpe ratios of 0.43, while “buy following good information” earns a negative Sharpe ratio of -0.19. Since both the pre-drift and the post-drift strategy can help investors earn positive excess returns, we can then combine the two by buying stocks the day before the FOMC announcement and decide whether to hold for 20-days after we identify the nature of the announcement. This strategy can earn an annual excess return of 6.1% with a high Sharpe ratio of 0.69. Not only is our post-FOMC drift strategy economically meaningful, we show in Table 2.10 that it can generate a Sharpe ratio that is even higher than the Sharpe ratios of leading risk factors.

2.3.6 Additional findings based on different portfolios

Table 2.11: 20-day cumulative returns for different portfolios after bad news announcements

	Cumulative Return%	t-Statistic
Beta1(highest beta)	1.835	1.709*
Beta5	1.267	1.890*
Beta10(lowest beta)	1.418	3.234***
High Tech	3.276	2.897***
Utility	0.639	1.130
Energy	1.721	1.675*
Manufacturing	2.051	2.609**
Durables	1.481	1.689*
Nondurables	2.080	2.982***
Telecom	2.884	2.330**
Shop	2.208	2.788***
Health	2.229	2.593***
Small(size) Low(book/mkt)	0.440	0.467
Small High	1.625	2.160**
Big Low	1.281	2.500**
Big High	0.500	0.603

Note: * statistically significant at 10% level; ** statistically significant at 5% level; ***

statistically significant at 1% level.

To ensure that the post-FOMC drift we uncovered is a market wide phenomenon, we tested the statistical significance of 20-day cumulative returns after bad news announcements for CRSP beta decile portfolios, different industry portfolios, and portfolios formed on size and book-to-market value.[12] Results are summarized in Table 2.11. All the portfolios have positive cumulative returns, most of them are statistically significant, indicating that the post-FOMC drift holds in the market.

In the Appendix, Figures 2.8 and 2.9 show the return drifts for the market highest beta (beta1) portfolio and market lowest beta (beta10) portfolio, respectively. Following bad news announcements, portfolios with different systemic risk levels all display a positive drift, which supports our risk-based explanation that the bad information may heighten the risk premium for the whole stock market. In addition, Figures 2.10 and 2.11 depict the return drifts for the high tech industry and utility industry, respectively. Clearly, we can see that the post-FOMC drift (i.e., the upward return drift following bad news) holds for a typical cyclical industry like high tech, and a non-cyclical industry like utility, although the magnitudes are quite different.

2.4 Conclusion

A growing body of literature has shown that information contained in central bank announcements is multidimensional: it does more than just describe the central bank's monetary policy stances; it can also convey to the market the central bank's assessments of economic conditions, growth prospects and market risks (i.e., the information effect). Yet another recent literature has documented prominent patterns of stock return drifts before and after days of U.S. Fed policy announcements. Most, however, does not differentiate the different types of information contained in Fed announcements, and is therefore silent on how and whether the stock return patterns can be different depending on the types of information conveyed by the central bank. Our contribution is to combine the two strands of literature, taking a nuanced and

[12]CRSP Beta Deciles are ranked with Portfolio 1 containing the securities with the largest positive betas and 10 containing securities with the smallest and most negative betas. 10 Industry, 25 Size and Book-to-Market portfolios are extracted from Kenneth French Data library.

multidimensional view on how the market extracts information from central bank announcements, while focusing on the U.S. stock market behaviours surrounding FOMC meetings. In addition to robustness-checking some results reported in the existing literature, our approach opens an entirely new front of research: how the stock market reacts to non-monetary news contained in central bank announcements. For example, does unexpected optimism or pessimism reflected in central bank decisions affect market uncertainty and thus, stock returns?

We identify policy surprises and unexpected Fed information (on the economy) using commonly used sign restrictions based on the co-movements of interest rates and stock prices in a narrow window around FOMC announcements. Confirming reports in the existing literature, we find that expansionary monetary policy surprises are associated with an upward drift of stock returns afterward. The novel finding in our paper is that following announcements that reveal an unexpected pessimistic assessment by the Fed, there is a significant positive stock return in a 20-day period. We call this post-FOMC drift. Various robustness tests and tone analysis of Fed statements tie the drift to Fed announcements instead of other confounding factors. We make similar finding in different industry portfolios, CRSP beta decile portfolios, and portfolios formed on size and book-to-market value. The post-FOMC drift can be exploited in an easy-to-implement trading strategy that holds the broad market after a bad-news announcement. On its own, the strategy has a historical record of earning 40% of annual equity premium. When combined with a strategy that exploits the well known pre-FOMC drift, the pre- and post-FOMC trading strategy generates a high average return, as well as a market beating Sharpe ratio.

Why does the return drift upwards following bad news announcements? By ruling out other confounding factors, we provide some evidence that the relatively heightened risk followed by the bad announcement could be the reason. Nevertheless, our finding is also consistent with the story of market participants overreacting to the news revealed by the Fed.

2.5 Appendix

(1) Calculating $ff4$

Following Gürkaynak et al. (2005) and Nakamura and Steinsson (2018a), first we need to calculate the FOMC announcement day current month federal funds future surprise $ff1$ where

m_0: number of days in the current month

d_0 : the day of the FOMC meeting

f^1: implied rate from current month federal funds future

$$ff1 = \frac{m_0}{m_0 - d_0}(f_t^1 - f_{t-\triangle t}^1) \tag{2.3}$$

if the FOMC meeting occurs on a day when there are 7 days or less left in a month, we need to use the unscaled change in the next month federal funds future to avoid multiplying $f_t^1 - f_{t-\triangle t}^1$ by a large factor (detailed explanations can be found in Gürkaynak et al., 2005).

To calculate announcement day $ff4$, the 3-month ahead federal funds future surprise

$$ff4 = \frac{m_1}{m_1 - d_1}[(f_t^3 - f_{t-\triangle t}^3) - \frac{d_1}{m_1} * ff1] \tag{2.4}$$

where

m_1: number of days in the month of next FOMC meeting

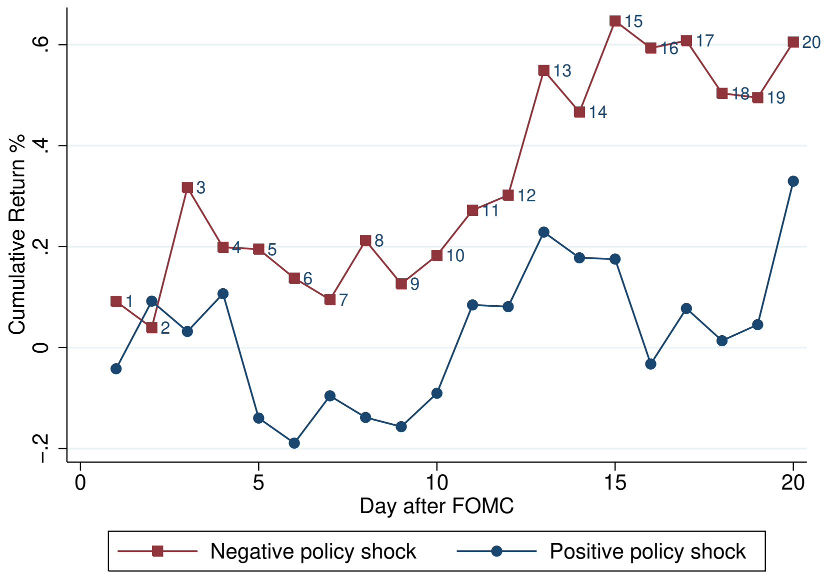
d_1 : the day of the next FOMC meeting

f^3: implied rate from 3 month ahead month federal funds future

again, if the FOMC meeting occurs on a day when there are 7 days or less left in a month, we need to use the unscaled change in the federal funds future.

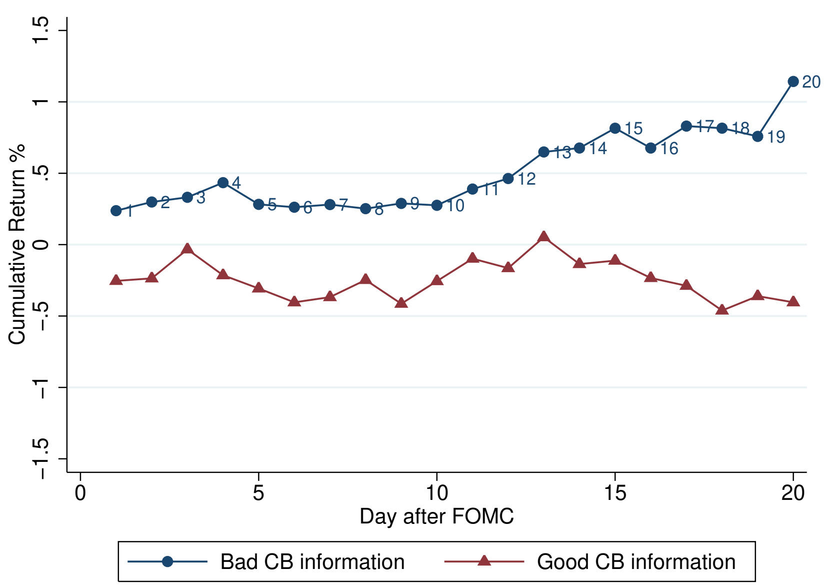
(2) Additional figures

Figure 2.5: Post-FOMC drift after unexpected Fed easing or tightening: all FOMC



Note: Cumulative market returns based on Jarociński and Karadi (2020) identified monetary policy shocks

Figure 2.6: Post-FOMC drift after unexpected good or bad information: all FOMC



Note: Cumulative market returns based on Jarociński and Karadi (2020) identified central bank information shocks

Figure 2.7: Scatter plot of 20-day excess returns after bad news announcements

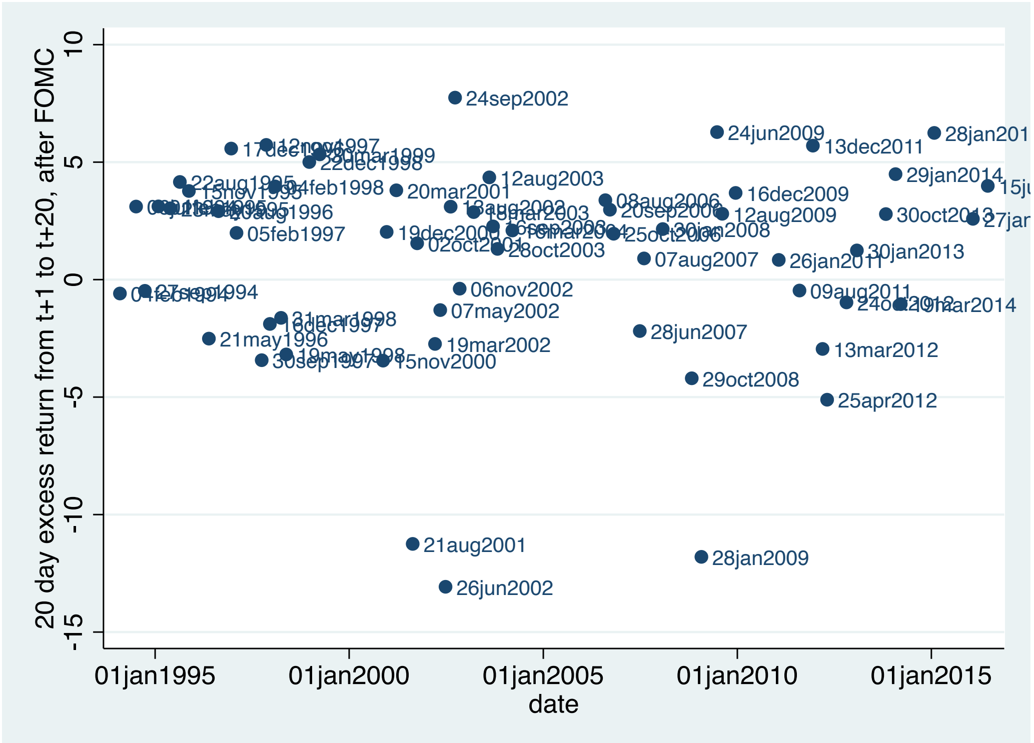
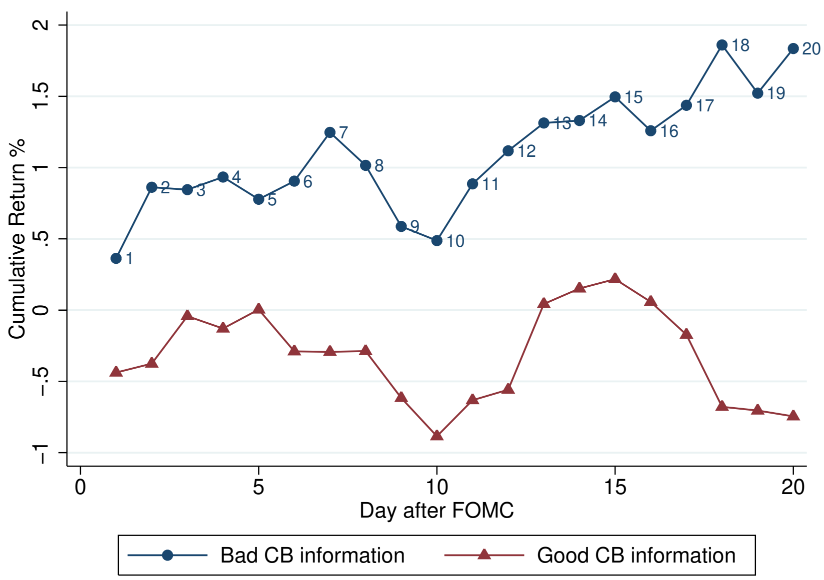
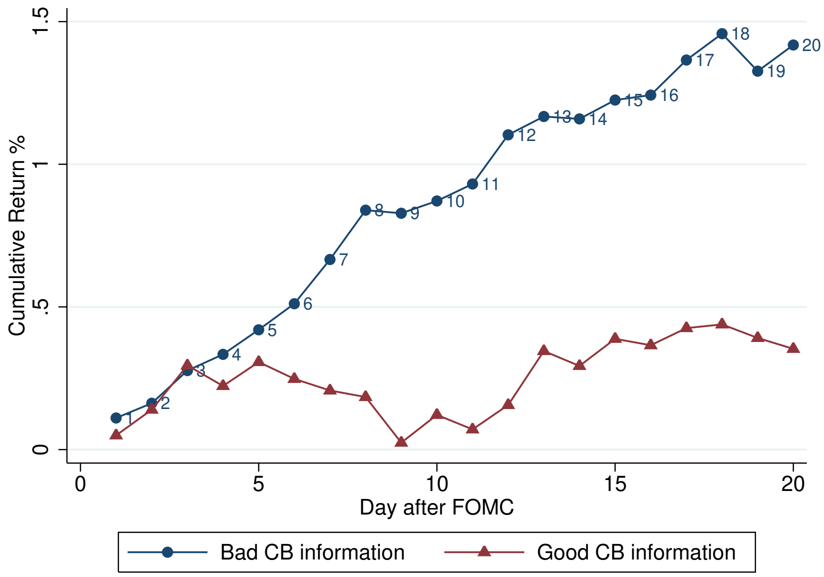


Figure 2.8: Post-FOMC drift for highest beta (Beta1) portfolio



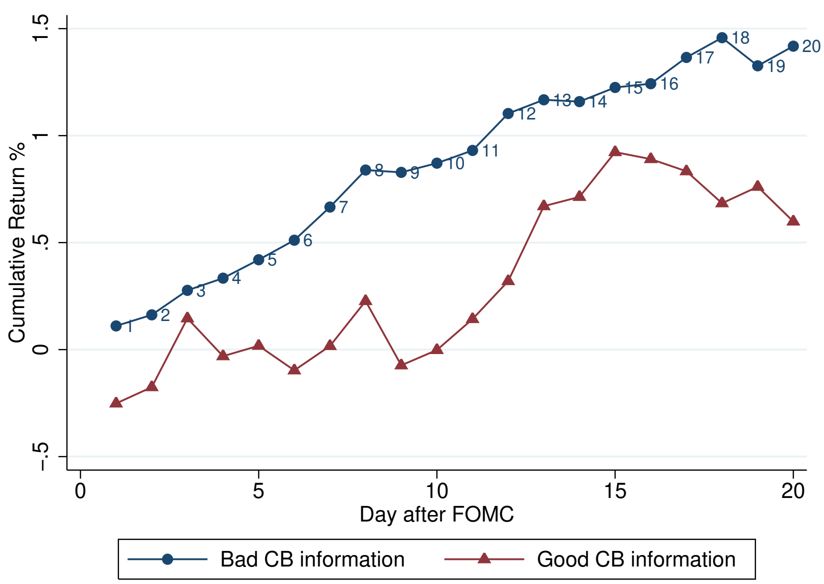
Note: Cumulative market returns for different central bank information.

Figure 2.9: Post-FOMC drift for lowest beta (Beta10) portfolio



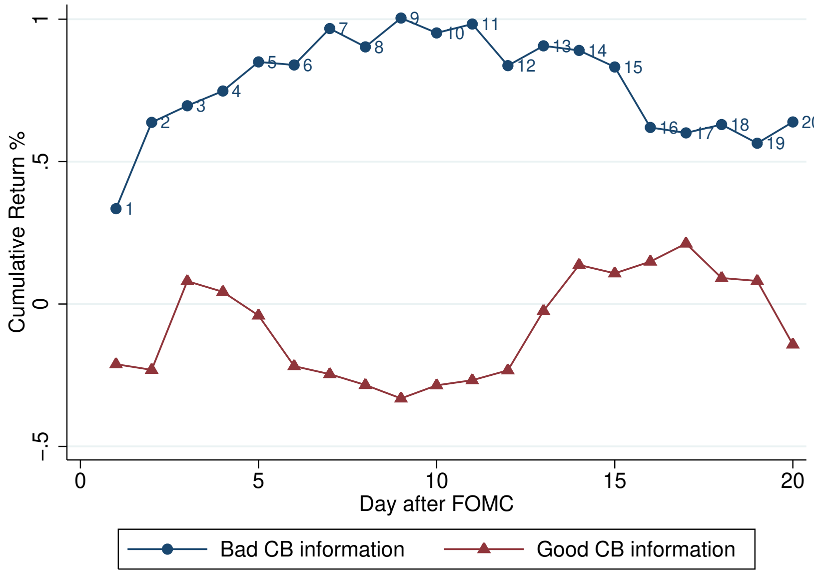
Note: Cumulative market returns for different central bank information.

Figure 2.10: Post-FOMC drift for high-tech portfolio



Note: Cumulative market returns for different central bank information.

Figure 2.11: Post-FOMC drift for utility portfolio



Note: Cumulative market returns for different central bank information.

Chapter 3

How do Financial Markets Process FOMC Announcements? Evidence from the Stock Market

Abstract

It is widely held that policy decisions made by the U.S. Federal Open Market Committee (FOMC) impact and shape financial markets and market trends. What information do the markets extract from FOMC announcements? The answer to this question sheds light on the influence of monetary policy on asset prices and the broader economy. In this paper, we analyze the co-movements of financial prices to the releases of FOMC announcements using an event study approach with tick-by-tick financial transaction data. Whereas much of the existing literature measures the surprise components in FOMC announcements with changes in federal funds rate futures, we take a broader view and allow the announcements to affect not just short-term risk-free rates, but also longer-term Treasury yields, corporate-to-Treasury credit spreads, and inflation expectations implied by the prices of Treasury Inflation Protected Securities (TIPS). Our findings show that the movements of these financial prices provide orthogonal information that helps to explain the reaction of the stock market to FOMC announcements, to the extent that the addition of information on top of short-term rates triples the model's goodness of fit, with the inclusion of inflation expectations having the biggest contribution. The results suggest that FOMC announcements contain non-federal funds rate information, and that the extra information, especially that which is related to inflation expectations, is important to the financial market. Moreover, the important role of inflation expectation suggests that the current literature of "Fed information effect," which largely ignores TIPS and uses stock prices and nominal rates to understand the information contents of FOMC announcements, may be too limited in the scope of information it uses. It is an interesting area of research to examine how FOMC announcements affect inflation expectations, and why the reactions of inflation expectations co-move substantially with stock prices.

3.1 Introduction

The U.S. Federal Open Market Committee (FOMC) holds eight scheduled meetings a year. Since February 1994, the Federal Reserve (hereafter, the Fed) began communicating to the public its decisions about the federal funds rate as well as justifications, economic forecasts, and future plans through after-meeting statements. FOMC statements are widely followed and can have immediate impacts on financial prices. An interesting question is what kinds of information the financial markets extract from those monetary policy announcements. Understanding the market interpretation of FOMC statements can help us apprehend the transmission of monetary policy in normal times and extraordinary situations.

This has been an active research question. Gürkaynak et al. (2005) study FOMC announcements' impacts on asset prices, while assuming that monetary policy surprises (information in FOMC statements that is not expected by the market) are completely captured by price changes of federal funds futures (and eurodollar futures) that expire within the next four quarters around the announcement time.[1] To parsimoniously represent policy surprises, they derive two factors, namely the "current federal funds rate target" factor and the "future path of policy" factor, from those future price changes and then regress asset (including short/long-term Treasury bonds and stocks) price responses on the two factors. Their findings suggest both factors have important impacts on asset prices, especially those of long-term Treasuries. Therefore, there are at least two components of information that are extracted by the financial market, the immediate changes in the Fed target, and changes in the future path of the overnight rate within a 1-Year horizon.

Such an assumption is a limited view of monetary policy announcements. The Fed has a history of spreading out their rate adjustments to a few years (see Figure 3.2 in the Appendix) and they may even signal plans for rate beyond the 1-Year horizon, which could include their views about the appropriate level of federal funds rate in the long-run (i.e., level of neutral real rate plus inflation target). These plans

[1] Fed funds futures are financial contracts that represent the market opinion of where the daily official federal funds rate will be at the time of the contract expiry. Similarly, eurodollar futures reflect the market gauge of LIBOR (London Interbank Offered Rate) anticipated on the settlement date of the contracts.

may be correlated with the two factors constructed by Gürkaynak et al. (2005), but the correlations would likely be imperfect. In other words, FOMC statements may contain elements that have little effect on those two factors but still affect the broader financial market.

Moreover, the assumption of Gürkaynak et al. (2005) is also restrictive given that they focus only on changes in risk-free rates. In fact, the central bank can influence credit costs through, for instance, its commitment to foster market liquidity.[2] Some of the impacts on credit costs are likely consequences of changes in overnight rates or the Fed's near-term plan, as assumed by Gertler and Karadi (2015). There are also theoretical models that articulate the link between the federal funds rate and credit spread (Drechsler, Savov, & Schnabl, 2018). However, past Fed policy actions suggest the possibility of the central bank to influencing credit spreads directly. For example, during the 2008-09 financial crisis, the Fed announced it would purchase a large amount of Mortgage Back Securities (MBS) and commercial papers with the aim of reducing market risk premium (Kacperczyk & Schnabl, 2010; Stroebel & Taylor, 2012).

Finally, many believed that the FOMC announcements contain the Fed's view about future economic growth (e.g., Melosi, 2016; Nakamura & Steinsson, 2018a). In other words, increases in the current target or future path of federal funds rate can either indicate a contractionary monetary policy or the Fed's optimistic view of future economy. To the extent that the market adjusts its expectation to incorporate the Fed's outlook, financial prices will be affected as well. In view of this, the two factors in Gürkaynak et al. (2005) are unlikely to be sufficient to differentiate these two scenarios. Indeed, it was confirmed by their own findings: changes in the future path of policy rates have only a small impact on the stock market - something they attribute to "revisions on investors assessment of the future path of output and inflation." And it is such revision that tempers the negative effect of a higher

[2] A good example is the FOMC statement on June 25, 2008, "the Federal Open Market Committee decided today to keep its target for the federal funds rate at 2 percent...the substantial easing of monetary policy to date, combined with ongoing measures to foster market liquidity, should help to promote moderate growth over time. Although downside risks to growth remain, they appear to have diminished somewhat, and the upside risks to inflation and inflation expectations have increased." Accessed through https://www.federalreserve.gov/newsevents/pressreleases/monetary20080625a.htm

interest rate on stock prices. Therefore, we need information on top of those two factors to analyze the information contained in the FOMC statements.

While most would agree on the possible existence of FOMC information contents that are not fully captured by near term path of the overnight rates, we need a way to know the relative importance of such information contents after taking into account their correlation with each other (i.e., how much they independently affect the financial market). For this purpose, we require a financial price that responds sensitively to a wide range of potential information contents in the FOMC announcements. Following insights from the Gordon growth model (Gordon, 1959), we use stock prices.[3] According to the model, equity prices are influenced by current and expected future interest rates, perceived risks, and expected future economic growth, precisely the kind of information contents that the existing literature has focused on.[4]

In this paper, we exploit the high-frequency co-movements of stocks with other financial prices. Particularly, we use some of the financial price movements as proxies of information contents. For instance, the changes in 3-Year rates are more closely correlated with changes in current and future overnight rates; changes in spreads between government bonds and corporate bonds are interpreted as changes in risk premium; changes in inflation expectations, on the other hand, are used in part for their correlation with revisions in growth prospects. Specifically, an increase in inflation expectation may indicate investors optimism over future economic growth, though the correlation is admittedly complex and likely state dependent.

The specific question we ask is: do these information contents have orthogonal components so as to explain the fluctuations of the stock price? In other words, do they each provide independent information that is important enough to shift stock prices? If the information contents related to the premium and inflation expectations have some unique information in addition to changes in the interest rate target and future path, then factors derived from the near-term overnight rates alone would be too narrow to describe the full impact of the monetary policy on stock prices.

[3]There are other empirical papers using stock prices as well, e.g., Cieslak & Schrimpf, 2019; Jarociński & Karadi, 2020.

[4]Cieslak and Schrimpf (2019) present a stylized macro-finance model to support the same argument, see their Appendix A for details.

Another question we ask is whether the monetary policy transmission mechanism on the premium operates as a result of changes in the short-term rates, as hypothesized by Gertler and Karadi (2015).[5] As stated earlier, there are reasons to believe that this may not offer a complete picture. But how significant is the direct impact compared to the standard channel (i.e., through interest rate changes)? Answering these questions is crucial for us to have a clear and more precise understanding of the transmission of monetary policy to the financial market and the broader economy.

Following a large and growing literature, we use high-frequency financial data around FOMC announcements to identify policy surprises (e.g., Gürkaynak et al., 2005; Nakamura & Steinsson, 2018a). This is different from the conventional approach - the recursive Vector Auto Regression (VAR) model - used in previous studies (e.g., Sims, 1980; Christiano et al., 1996). The recursive structure ordered the interest rate at the bottom of VAR amounts to assume that all variables in the Fed's information set (price and output, among others) will affect interest rates during the same period, whereas the impact of interest rates on other variables occurs with a lag of at least one period. When financial variables are included, this assumption cannot be justified due to the fact that financial prices are affected by interest rate contemporaneously.[6]

High-frequency identification (HFI) avoids some of the problems with VAR, which relies on monthly or quarterly data. With high-frequency data, the probability of other major events happening in the same narrow time window is fairly small. Specifically, we adopt the event study approach focusing on the release of FOMC statements and apply the regression method with movements of stock prices as dependent variable on the left, adding more price movements on the right hand side of the regression, in addition to the short-term rates. This allows us to orthogonalize the independent information contained in the right-hand side variables.

Consistent with the literature, we found that a rise in short-term rates has neg-

[5]Theoretical model in Drechsler et al. (2018) also supports a similar argument. By setting the nominal interest rate, central banks are able to affect liquidity in financial markets, which will in turn shift the cost of leverage for financial institutions, thus altering the risk premium. For example, lower nominal rates can lower risk premia.

[6]The problem persists even if we place the non-interest rate prices at the bottom: interest rates (central bank's policy decisions) could be influenced by current financial variables directly or other correlated variables outside of the VAR (Gertler & Karadi, 2015).

ative impacts on stock prices. The effect increases in magnitude when proxies for other information contents are included to capture future interest slopes, credit spreads, and inflation expectations (growth prospects) in each FOMC announcement. In addition, our analysis suggests that both the credit spreads and inflation expectations have significant contemporaneous impacts on stock prices, to the extent that the addition of information on top of interest rates triples the goodness of the fit of the model, which provides empirical evidence that the factors in Gürkaynak et al. (2005) are not enough to capture non-policy rate dimensions in FOMC statements, especially during the zero lower bound (ZLB) period.

Recent research in the "Fed information effect" (e.g., Cieslak & Schrimpf, 2019) tends to use co-movement between stock prices together with nominal interest rates (implied by Treasury or federal funds future) to disentangle different aspects of information contained in FOMC announcements, while ignoring the prices of real bonds (TIPS). Our finding, the important role of inflation played in explaining stock price movements, suggests the inclusion of real bonds, together with stocks and nominal rates, may provide additional insights.

The remainder of our paper is organized as follows: Section 3.2 reviews the relevant literature, Section 3.3 explains the empirical methodology and data used in the study, Section 3.4 presents and discusses the results, and Section 3.5 concludes.

3.2 Related Literature

This paper is closely related to the high-frequency identification (HFI) literature that uses high-frequency financial data to identify monetary shocks and examine their causal effects. Our contribution to the literature is to expand and examine the set of information used in the analysis.

Earlier literature focuses exclusively on short-term (overnight) interest rates, often the prices of derivatives that track the federal funds rate. An influential early contribution is Bernanke and Kuttner (2005), who analyze the response of the stock market to unexpected monetary policy surprises (implied by daily price changes of the current -month federal funds futures) on FOMC days. Using regression models (i.e., regress CRSP excess return on federal funds rate changes), they find a robust negative relationship between unexpected positive monetary policy surprises and broad stock indexes. Gertler and Karadi (2015) study the transmission of monetary policy in a VAR using high-frequency policy surprises (derived from 3 month ahead federal funds future) as external instruments. They find that modest movements in short interest rates can lead to significant changes in credit costs (including both the term premium and the risk premium).

The literature quickly moves beyond immediate changes in the federal funds rate since Fed announcements can contain information about future policy trajectories. Gürkaynak et al. (2005), for example, employs a factor model with tick-by-tick federal funds and eurodollar future data to decompose the policy information of FOMC announcements into two factors, the "current federal funds rate target" and the "future path of policy", which are both useful to explain fluctuations in bond yields and stock prices. In particular, the "future path of policy" factor - not associated with the current federal funds rate decision but could capture potential future expectations of monetary policy based on FOMC statements - has a much greater impact on longer-term Treasury yields.

The 2008-09 financial crisis powerfully demonstrates the importance of unconventional monetary policy. This reaffirms the importance of looking beyond movements in the near term interest rates. Swanson (2017) extended the factor model method used in Gürkaynak et al. (2005) to identify the effects of the Fed's unconventional monetary policies (i.e., forward guidance and large scale asset purchase) during the ZLB period. Just like Gürkaynak et al. (2005), the study continued to construct factors from derivatives tracking the short rates and medium to long term Treasury yields, equating rate reactions to policy surprises.

In contrast, the more recent literature of the Fed information effect suggests that interest rate changes around FOMC announcements are not all policy surprises. Nakamura and Steinsson (2018a) found that the so-called policy "tightening" that raises interest rate can paradoxically raise market expectations of future economic growth (i.e., Blue chip forecasts).[7] They interpret this anomaly as evidence of the

[7]The "proxy for monetary shock" or "policy news shock" in Nakamura and Steinsson (2018a) is the first principle component of unexpected interest rate changes over the 30-minute window implied by federal funds futures and eurodollar futures.

Fed information effect - in other words, the reason for the Fed to raise interest rates can reflect the central bank's optimism over growth prospect.

It is motivated by the Fed information effect that Cieslak and Schrimpf (2019), bring in stock prices as a way to decompose the FOMC information into policy and non-policy components. Using an event study approach, they collect time-stamped major monetary policy events from four leading central banks (the Fed, Bank of England, European Central Bank, Bank of Japan). For each event, they define a narrow time window and calculate the stock returns and yield changes minute-by-minute. Part of their identification assumption is that if high-frequency co-movements between stock prices increase (or decrease) together with short-term Treasury yields, it must be that the monetary policy events have information about future growth or market risk perception. Surprisingly, they find that 40% of the monetary policy announcements by the Fed and the European Central Bank (ECB) attempt to convey non-monetary news, which is an important driver of the financial market.[8] However, information contained within a single policy announcement can be multifaceted, and their approach can only identify the dominant piece of information.

Similarly, Jarociński and Karadi (2020) argue that high-frequency co-movements between interest rates (observed from 3 month ahead federal funds future) and stock prices can be useful to disentangle the monetary policy (rate) shock and the central bank information shock, where the latter is related to the central bank's information about future economic outlooks. Through imposing sign restrictions on interest rates and stock prices within a Bayesian structure VAR that includes macro variables, they find substantially different responses of macroeconomic indicators followed by the two different shocks.

In this paper, we include more than just stock and Treasury bond prices. We also look at corporate spreads, as well as inflation expectations measured through the prices of inflation indexed bonds relative to the regular bonds. It turns out that adding real bond to the analysis has a substantial impact in explaining stock price movements. Specifically, we use inflation expectation (implied by the real bond)

[8] They classify events according to the direction of the stock-yield co-movement and the effect on yield volatilities at different maturities in the 30-minute window around the monetary policy announcement. See their "central bank news classification matrix" for details.

as the dependent variable on the right-hand side of the regression because it reacts to a broad range of information, including current and future rates, risk premiums, growth prospects, and likely more. This points to a future research direction that incorporates real bond prices to analyze how the market processes information from the central bank.

3.3 Empirical Approach

How do financial markets process the information contained in the FOMC announcements? To measure the direct effects, we adopt the commonly used event study approach (e.g., Bernanke & Kuttner, 2005; Gürkaynak et al., 2005; Swanson, 2017) and we narrow the focus to monetary policy dates (i.e., FOMC statement days) to conduct the analysis.[9]

As emphasized by Jarociński and Karadi (2020), the response of the stock prices is a great indicator to assess the announcement effects. One of the simplest ways to gauge the impact is to regress stock market responses on the policy rate changes using Ordinary Least Squares (OLS). However, the main identification challenge is endogeneity, because both stock markets and monetary policies could be driven by other macroeconomic fundamentals, such as inflation or unemployment. Moreover, stock prices are very sensitive to new information in the market: even if daily data are used, the results would remain biased due to omitted explanatory variables.

Pioneered by Kuttner (2001), these problems can be mitigated by using high-frequency data in order to narrow down the time window of market responses. Since 1994, the FOMC started to release the after-meeting statement around 2:15pm EST to inform the general public of its monetary policy decision.[10] Therefore, this tradition inherently determines the most important time window. In particular, we follow the convention in the literature (e.g., Nakamura & Steinsson, 2018a) to choose a 30-minute window - 10 minutes before the release to 20 minutes after the release - to construct the surprises (unexpected changes) so that the probability of

[9]FOMC meeting dates are based on the FOMC calendar, which may be viewed at https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm

[10]See the website of the Federal Reserve Bank of San Francisco, https://www.frbsf.org/education/publications/doctor-econ/2006/april/federal-open-market-committee-fomc-short-term-interest-rate/ for details.

other major events happening is fairly small.[11]

In this paper, we employ Exchange Trade Funds (ETFs) tick-by-tick transaction data to conduct the analysis. All the ETFs tick data are extracted from the Trade and Quote (TAQ) database. Unlike derivatives, such as the federal funds futures or eurodollar futures that require margins to trade, ETFs are highly traded. In terms of dollar-value trading volume, ETF transactions increased dramatically, from about 5% of the whole market in 2002 to more than 30% in 2017; their popularity and high liquidity allow ETFs to be priced in a more informative way.[12]

There are many Treasury and index ETFs traded on the U.S. stock exchange. We pick the top 4 Treasury ETFs, SHY, SHV, IEF, and IEI, in terms of total assets (see Table 3.5 in the Appendix).[13] Moreover, our selection is based on their intrinsic features (i.e., different investment targets) that could characterize interest rates with different terms. To obtain a comprehensive view of stock market responses, we focus on returns of the most popular index in the U.S., Standard & Poor's 500, measured by the price changes of SPY.[14] To quantify different information contents embedded, TIP (which invests in Treasury Inflation Protected Securities, or TIPS, with average maturity close to 10 years) and LQD (which invests in U.S. investment grade corporate bonds, with an average maturity close to 10 years) are used as well.[15] Notice that these ETFs have different inception dates, as summarized in the Appendix Table 3.6. Consequently, this will only allow for a focus on monetary policy events (FOMC meetings) from August 2002 through December 2017.[16]

[11] Before 2011, FOMC statements were regularly released at 2:15pm EST, however, since the meeting on April 27, 2011, the Fed started to alternate the statement release time between 12:30pm and 2:15pm (depending on whether the meeting was followed by a press conference). From the meeting on March 20, 2013, the FOMC statements are published at 2:00pm EST. For each observation, we obtain the release time according to the FOMC minutes, which is available at https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm.

[12] Numbers are based on the Credit Suisse Trading Strategy, which may be viewed at http://on.ft.com/2jXxctA.

[13] IEF: iShares 7-10 Year Treasury Bond ETF; IEI: iShares 3-7 Year Treasury Bond ETF; SHY: iShares 1-3 Year Treasury Bond ETF; SHV: iShares Short Treasury Bond ETF. They are all from the same management company, iShares, owned by Black Rock.

[14] SPY: SPDR S&P 500 ETF, managed by State Street Global. SPY typically tops rankings for largest total asset among ETFs and greatest trading volume among the whole market, even though it is not a stock.

[15] TIP: iShares TIPS Bond ETF. LQD: iShares iBoxx Investment Grade Corporate Bond ETF.

[16] Our paper only considers the *scheduled* FOMC meetings. As Nakamura and Steinsson (2018a) point out, "unscheduled meetings may occur in reaction to other contemporaneous shocks."

Table 3.1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
S&P500	124	0.012	0.528	-1.811	1.601
10yr rate	124	-0.002	0.038	-0.240	0.131
7yr rate	88	-0.005	0.031	-0.104	0.057
3yr rate	124	-0.002	0.028	-0.078	0.101
1yr rate	88	-0.001	0.012	-0.054	0.055
interest slope	124	0.000	0.027	-0.193	0.067
risk premium	124	-0.001	0.020	-0.053	0.152
inflation	112	0.000	0.013	-0.043	0.079

Note: All variables are measured in % changes around FOMC.

Rather than using level changes, we convert all of the surprises into percentage changes, in order to overcome heteroskedasticity and to get more easily interpreted results (i.e., comparable dependent and independent variables). All of the percentage changes are calculated within the 30-minute window, as follows:

- *S&P500*: % change in S&P 500 index $=\frac{(PSPY_t - PSPY_{t-\triangle t})*100}{PSPY_{t-\triangle t}}$.
- $\mathbb{N}$ *yr rate*: approximated % change of $\mathbb{N}$-Year rate$=\frac{-(P_t - P_{t-\triangle t})*100}{\mathbb{N}*P_{t-\triangle t}}$, $\mathbb{N}$=1, 3, 7, 10.
- *interest slope*: % the change of interest slope, obtained by taking the difference between the *10yr rate* and *3yr rate*.[17]
- *risk premium*: % change of risk premium, calculated from the difference between yield changes implied by LQD (which invests in U.S. investment grade corporate bonds with average maturity close to 10 years) and *10yr rate*.

[17] Swanson (2017) provides empirical evidence that "the effects of the Fed's forward guidance (which mainly affect the future path of the interest rate) died out quickly, with a half-life of about 1–4 months." Therefore, the difference between 10-Year and 3-Year rates could be a good measure of the future interest path. Moreover, our construction of interest rate slope is similar to Fleming and Piazzesi (2005), which they define as the yield spread of 10-Year and 3-month treasuries.

- *real 10yr rate*: % change of 10 year real rate, constructed using TIP (which invests in TIPS bonds with average maturity close to 10 years).

- *inflation*: % change of inflation expectation, calculated from the difference between *10yr rate* and *real 10yr rate*.[18]

where the last transaction 10 minutes before is denoted by subscript $t - \triangle t$, and the first transaction 20 minutes after the announcement is denoted by subscript t.[19]

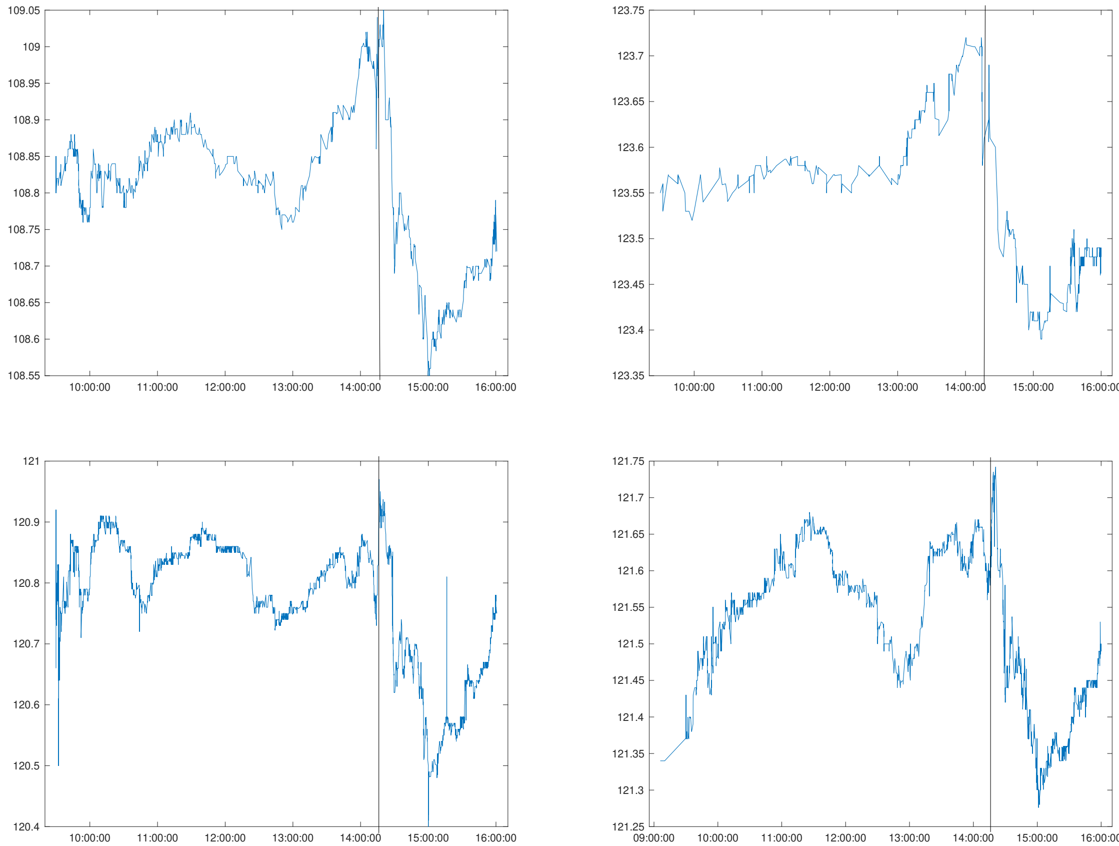
Table 3.1 presents the summary statistics for all the variables used in the study. Unsurprisingly, besides stock returns, the standard deviations of other surprises are very small. To quantify their impacts, we will analyze the contemporaneous responses on the financial market. Notice that our high-frequency changes could capture policy surprises independent of actual monetary policy actions. For instance, Figure 3.1 presents time plots of some tick-by-tick ETF prices on August 1, 2012. Although the Fed did not change its interest target on that day, the price patterns clearly show the existence of surprises around the FOMC statement release time.[20]

[18]Fleming and Piazzesi (2005) document empirical evidence that the FOMC announcements do have direct impacts on inflation expectations.

[19]In calculating the interest rate surprises, we approximate the price of the Treasury ETF as the price of a zero coupon bond with maturity equals to its longest investment target (i.e., price of IEF as the price of 10-Year zero coupon bond), thus, $P = \frac{F}{(1+r)^T} \approx Fe^{-rT}$, where P denotes the price of the bond, F is the face value, r is the corresponding interest rate (i.e., for IEF, r is the 10-Year interest rate), and T is the time to maturity (in years). Define $R = rT$, $P_{t-\triangle t} \approx Fe^{-R}$, $P_t = P_{t-\triangle t} + \triangle P \approx Fe^{-(R+\triangle R)}$, $\frac{P_{t-\triangle t}+\triangle P}{P_{t-\triangle t}} \approx \frac{Fe^{-(R+\triangle R)}}{Fe^{-R}}$ $=e^{-\triangle R}$, $\frac{\triangle P}{P_{t-\triangle t}} \approx e^{-\triangle R} - 1 \backsim -(\triangle R)$, because $\triangle R$ is fairly small. Rearranging the equation will yield $\triangle r \approx -\frac{1}{T} * \frac{(P_t - P_{t-\triangle t})}{P_{t-\triangle t}}$.

[20]As a validity check, we regress daily changes of Treasury yields on the constructed interest rate surprises, results are summarized in the Appendix Table 3.7. In most of the cases, R-squared is very high, indicating that a large proportion of the daily changes of long-term rates could be explained by the high-frequency identified interest rate changes.

Figure 3.1: Time plots of tick-by-tick ETF prices around a FOMC announcement



Note: (1) Plots are based on the ETF tick-by-tick transaction data on Aug. 1, 2012, horizontal layout as IEF(7-10 Year Treasury)-IEI(3-7 Year Treasury)-LQD(Corporate Bond)-TIP(TIPS Bond); (2) Black vertical lines correspond to 2:15pm EST, which is the FOMC statement release time.

With high-frequency data to deal with endogeneity, the baseline estimation function can be written as:

$$S\&P500 = \alpha + \beta X + \zeta \tag{3.1}$$

where X represents approximated % change of $\mathbb{N}$-Year rates; β is the parameter in this single factor model, which measures the effect of the FOMC statement on the stock market ($S\&P500$) relative to its effect on the monetary policy indicator (X). However, this simple regression model comes at the cost of making the coefficients hard to explain. For instance, the transmission of the interest rate changes to stock prices may work through credit costs (Gertler & Karadi, 2015) or other factors. To determine the underlying channels, it is convenient to consider the classic Gordon growth model (Gordon, 1959) used for equity valuation. According to the model, the price of the equity can be written as:

$$P = \frac{(1+g)\pi_0}{k-g}$$

where π denotes dividends, k denotes investors' required rate of returns including interest slope and equity risk premium (explicitly, $k =$*expected average of the short-term interest rates+interest slope/term premium+risk premium*), and g is the growth rate of future dividends. Jagannathan, McGrattan, and Scherbina (2001) show that, even if k and g are changing over time, this model still holds. Therefore, the possible effects of underlying information contents include:

- dividends discounting effect, equity prices are present value of future dividends, for the same dividend stream, a higher interest rate will cause the decrease of P.
- term premium effect (Gertler & Karadi, 2015), because equity investors generally focus on long-term returns, they should be compensated with the term premium; thus, an unexpected increase to the interest slope will decrease P.
- risk premium effect (Bernanke & Kuttner, 2005), when the Fed conveys to the market that it will keep the interest rate policy stable and gradual, it lowers risk premium, helping all asset classes. On the other hand, when uncertainties are high, the stock market will be hurt (i.e., an increase in risk premium may lead to a decline in stock prices).[21]
- expected growth effect (Nakamura & Steinsson, 2018a), all else the same, higher expected inflation is usually associated with higher expected growth. If the market thinks the FOMC's tightening policy conveys information about future growth, then the increase of g will increase P.

3.4 Empirical Results

Table 3.2 shows the full sample estimation results of equation (3.1). Clearly, the approximated 3-Year/7-Year/10-Year interest rate changes are shown to be better

[21]The change of risk premium around FOMC announcements is also documented in Fleming and Piazzesi (2005).

than 1-Year rate changes in explaining the volatility of the stock market performance because of the higher R-squared. With a 25-basis-point increase in the approximated 3-Year interest rate, the S&P 500 index will fall by about 1.6%. This finding seems a bit strange given that the literature suggests a larger effect (e.g., Bernanke & Kuttner, 2005 document an unanticipated 25-basis-point cut in the federal fund rates is associated with about a 1% increase in broad stock index). One explanation, as mentioned above, could be that the change of longer-term rate may contain a mix of information. Following the insights of Gertler and Karadi (2015), we chose the approximated changes of the 3-Year interest rate as the monetary policy indicator to capture both the changes in target rate and some degree of forward guidance.

Table 3.2: Results: regress FOMC announcement window stock returns on yield changes

	S&P500
10yr rate	-4.617***
	(1.235)
N	124
R^2	0.1092
7yr rate	-6.570***
	(2.413)
N	88
R^2	0.1290
3yr rate	-6.288**
	(2.470)
N	124
R^2	0.1088
1yr rate	-9.621*
	(5.072)
N	88
R^2	0.0418

Note: (1) *** p<0.01, ** p<0.05, * p<0.1; (2) Heteroskedasticity -consistent standard errors are reported in parentheses.

Table 3.3: Results: regress FOMC announcement window stock returns on yield changes and other proxies

	S&P500	**S&P500**	**S&P500**	**S&P500**
3yr rate	-6.288**	-6.385***	-7.187***	-10.670***
	(2.470)	(2.396)	(2.356)	(1.941)
interest slope		-2.714	-2.616	-6.190***
		(2.092)	(1.828)	(1.986)
risk premium			-5.782**	-5.335*
			(2.809)	(2.795)
inflation				14.580**
				(7.382)
N	124	124	124	112
R^2	0.109	0.128	0.174	0.305

Note: (1) *** p<0.01, ** p<0.05, * p<0.1; (2) Heteroskedasticity -consistent standard errors are reported in parentheses.

Table 3.4: Additional results: comparing normal and ZLB periods

	S&P500	**S&P500** (ZLB=0)	**S&P500** (ZLB=1)
3yr rate	-10.670***	-10.621***	-12.147***
	(1.941)	(2.550)	(2.516)
interest slope	-6.190***	-7.712	-4.618**
	(1.986)	(5.256)	(2.265)
risk premium	-5.335*	-2.933	-10.722**
	(2.795)	(3.568)	(5.342)
inflation	14.580**	20.512*	6.554
	(7.382)	(12.352)	(8.698)
N	112	56	56
R^2	0.305	0.202	0.498

Note: (1) *** p<0.01, ** p<0.05, * p<0.1; (2) Heteroskedasticity -consistent standard errors are reported in parentheses.

To simultaneously examine the above channels (i.e., whether each of the surprises provides unique information to explain the movements of the stock price), we estimate the following regression:

$$S\&P500 = \alpha + \beta 3yrrate + \gamma Z + \varepsilon \tag{3.2}$$

where Z denotes the constructed proxies (*interest slope, risk premium, inflation*). The Zs may be correlated but they all serve as explanatory variables so that we can isolate the orthogonal effects of the underlying information contents. The results are summarized in Table 3.3.

Unsurprisingly, adding the changes in the interest slope and risk premium increases the explanatory power by almost 8%, indicating the importance of credit costs. In addition, after controlling for changes in inflation expectations (growth prospects), the coefficient associated with our policy indicator (changes in 3-Year rates) decreases dramatically, meaning that the tightening rate policy actually contains a mix of information (i.e., a positive monetary policy surprise could possibly drive stock prices in two different directions, through increasing expected dividend growth rate or discount rate in the Gordon growth model). This pattern is quite similar to the simulated model that Nakamura and Steinsson (2018a) used to gauge the response of S&P 500 with the presence of the "Fed information effect."[22] Moreover, the impact of slope surprises become bigger and significant, implying that our measure of interest slope also contains mixed information - the term premium and inflation expectation - as suggested by Fleming and Piazzesi (2005). Furthermore, the coefficient associated with changes in inflation expectation is positive and highly significant, suggesting that when inflation responds positively to a higher rate, the stock market is more likely to respond positively.

Without accounting for changes in inflation expectations (growth prospects), the two types of cases are pooled together, thus weakening the explanatory power. Once controlling for inflation, the two cases can be differentiated and treated differently, yielding a substantial increase (13%) in the R-squared. From the last column of Table 3.3, all the surprises have statistically significant impacts on stock, which manifests the fact that the Fed does have controls over different information contents through FOMC statements. In addition, as shown in the Appendix Table 3.8, restricting the regressions to have the same sample period does not affect our findings.

Recent research (e.g., Cieslak & Schrimpf, 2019 and Jarociński & Karadi, 2020) tries to use the co-movement between stock prices together with nominal rates to disentangle different aspects of information contained in FOMC announcements. Our finding, the important role of inflation played in explaining stock price movements, suggests the inclusion of real bonds (e.g., TIPS) together with stocks and nominal rates may provide additional insights. In addition, it points to an interesting area of future research on why the reactions of inflation expectations co-move substantially

[22]Nakamura and Steinsson (2018a) find that "S&P500 falls by 6.5% in response to a policy news shock that raises the 2-Year nominal forward by 1%." In their calibrated model, "when monetary policy announcements convey information about both future monetary policy and future exogenous economic fundamentals stock prices fall by 6.8%"; "if monetary policy is assumed not to convey information about future exogenous fundamentals, stock prices fall by 11%."

with stock prices.

Finally, to determine whether the effects on credit costs are driven by unconventional policies during the recent financial crisis, we break the full sample into two subsamples covering the ZLB period (2008.12-2015.11), in which the Fed announced to keep the policy rate at 0 to 0.25 percent, and the normal period. Results are shown in Table 3.4. As we expected, the effects of future interest slope and risk premium are more prominent when the Fed is bounded by the zero nominal rate.

3.5 Conclusion

Despite the increasing predictability and transparency of U.S. monetary policy, investors still pay close attention to FOMC meetings. One of the interpretations in the literature is that the "words (path of policy rate within one year) actually speak louder than actions (current federal funds rate target)" (Gürkaynak et al., 2005). However, focusing on the federal funds rate (or within one year interest rates) is a limited view of monetary policy. Indeed, we provide empirical evidence that FOMC statements contain orthogonal information contents in addition to short-term interest rates.

By employing the high-frequency transaction data of several actively traded ETFs, we investigate how the stock market responses to the information contained in the FOMC announcements. Focusing on the 30-minute window, this approach allows us to examine the contemporaneous causal relationship, without the worry of other confounding factors.

In line with existing studies, we also find a consistent negative relationship between stock market performance and interest rate surprises. However, as Cieslak and Schrimpf (2019) point out, in almost half of the monetary policy announcements, non-monetary news (i.e., not directly related to policy rates) is the dominant force of driving financial market reactions. To quantify the information within non-monetary news and uncover the underlying transmission mechanisms, we also introduce several useful proxies to capture unanticipated changes in the inflation expectation (growth prospect), interest slope, and risk premium.

Our findings complement existing studies in two aspects. First, we show that the financial market could extract multiple dimensions of information from the FOMC announcements, not just about policy rates. More importantly, when assessing the stock market responses (to FOMC announcements), ignoring the roles of the future interest slope, risk premium, and inflation expectation will bias the estimates. The impacts of the future interest slope and risk premium are especially prominent during the ZLB period. Second, we find that the monetary policy transmission mechanism observed from the stock market is different from the one documented in Gertler and Karadi (2015). Their study concludes that the changes in credit costs (interest slope and risk premium in our paper) are consequences of policy rate movements. However, our results show that unexpected changes in interest slope and risk premium contain unique information in explaining the movements of stock prices.

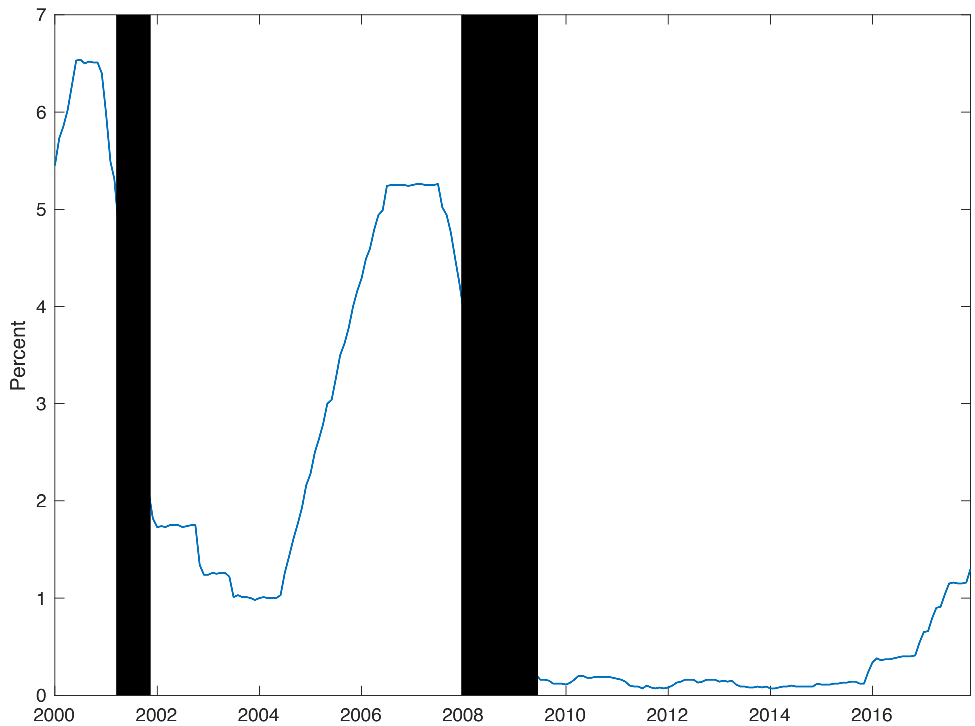
Another interesting finding is the strong evidence of the Fed information effect - when the inflation response is positive, the Fed's action to raise rates is perhaps regarded by the market as a show of confidence in the future, or from a theoretical perspective, an increase of the natural rate of interest rate (Nakamura & Steinsson, 2018a). This suggests that the response of financial markets to monetary policy surprises may depend on the state of the economy. Recent research (e.g, Jarociński & Karadi, 2020) often uses co-movements between stocks and nominal bonds to identify the Fed information shocks. Our finding calls for the inclusion of real bonds, because changes in inflation expectations also play an important role. Moreover, it points to an interesting area of future research on why the reactions of inflation expectations co-move substantially with stock prices.

Our study is also subject to some limitations. First, the empirical model using the high-frequency identification approach can only examine the contemporaneous relationship between different surprises and stock market performances. As investors, they may be more interested in the long-run impact of the surprises. Second, in the current study, it is difficult to distinguish the relative dominance of the interest slope and risk premium. Lastly, although we have found strong evidence of the Fed information effect, it is still unclear how stock market responses to monetary surprises depend on the state of the economy. These concerns are left for future research.

3.6 Appendix

Figure 3.2 is a time plot of the effective federal fund rate.

Figure 3.2: Monthly effective federal funds rate



Source: FRED, Federal Reserve Bank of St. Louis. Shaded areas indicate the U.S. recessions.

Table 3.5 presents brief information of the top Treasury ETFs. Table 3.6 presents the ETFs' inception dates.

Table 3.5: Brief information of top 10 treasury ETF

Symbol	**ETF Name**	**Total Assets ($MM)**	**Avg Volume**
SHY	iShares 1-3 Year Treasury Bond ETF	11,494	1,267,581
SHV	iShares Short Treasury Bond ETF	8,686	791,895
IEF	iShares 7-10 Year Treasury Bond ETF	8,117	2,422,397
IEI	iShares 3-7 Year Treasury Bond ETF	7,095	456,249
TLT	iShares 20+ Year Treasury Bond ETF	6,629	9,431,975
GOVT	iShares U.S. Treasury Bond ETF	5,289	1,367,248
TBT	UltraShort Barclays 20+ Year Treasury	2,338	3,195,594
SCHO	Schwab Short-Term U.S. Treasury ETF	2,191	410,359
BIL	SPDR Barclays 1-3 Month T-Bill ETF	1,951	367,588
VGSH	Vanguard Short-Term Government Bond ETF	1,914	212,246

Source: ETF Database (www.etfdb.com); Total Assets, Avg Volume are as of Feb 2, 2018.

Table 3.6: ETF inception dates

Symbol	**Inception date**
SPY	1993/1/22
IEF	2002/7/22
SHY	2002/7/22
IEI	2007/1/5
SHV	2007/1/5
TIP	2003/12/4
LQD	2002/6/22

Source: Yahoo Finance.

Table 3.7 shows the results of validity check: regressing daily yield changes on the high-frequency rate surprises.

Table 3.7: Validity check: regress daily yield changes on the rate surprises

	10yr Yield	**7yr Yield**	**3yr Yield**	**1yr Yield**	**3m Yield**
10yr rate	1.565***	1.720***	1.342***	0.421***	0.220***
	(0.221)	(0.214)	(0.106)	(0.072)	(0.083)
N	124	124	124	124	124
R^2	0.5255	0.5359	0.4541	0.1512	0.0419
7yr rate		2.230***	1.856***	0.602***	0.198*
		(0.410)	(0.213)	(0.126)	(0.118)
N		88	88	88	88
R^2		0.5007	0.5782	0.2357	0.0226
3yr rate			1.898***	0.894***	0.444***
			(0.176)	(0.138)	(0.127)
N			124	124	124
R^2			0.4881	0.3488	0.0918
1yr rate				0.151	-0.486
				(0.509)	(0.343)
N				88	88
R^2				0.0022	0.0206

Note: (1)*** p<0.01, * p<0.1; (2)Heteroskedasticity-consistent standard errors are reported in parentheses.

Table 3.8 contain additional results.

Table 3.8: Robustness: restrict to the same sample period

	S&P500	**S&P500**	**S&P500**	**S&P500**
3yr rate	-6.856**	-6.883**	-7.836***	-10.670***
	(2.821)	(2.730)	(2.650)	(1.941)
interest slope		-3.622**	-3.472**	-6.190***
		(1.823)	(1.532)	(1.986)
risk premium			-7.077**	-5.335*
			(3.066)	(2.795)
inflation				14.580**
				(7.382)
N	112	112	112	112
R^2	0.121	0.155	0.226	0.305

Note: (1) *** p<0.01, ** p<0.05, * p<0.1; (2) Heteroskedasticity -consistent standard errors are reported in parentheses.

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