Demystifying Monetary Policy Surprises: Fed Response to Financial Conditions and Wait and See for New Economic Data*

Zhengyang Chen†

Forthcoming in Journal of Macroeconomics

Abstract

Why are supposedly exogenous monetary policy surprises, measured by changes in short-term financial contracts within short windows around FOMC announcements, partially predicted by pre-meeting economic and financial information? We propose a new explanation: the Federal Reserve targets economic variables by responding primarily to financial conditions while adopting a "wait-and-see" approach to recent economic data. When markets expect the Fed to target economic variables directly, this creates the predictable component of policy surprises. Using daily-frequency economic and financial data from 2000-2019, we find three pieces of supporting evidence: First, the previously documented strong predictors are reflected in financial markets and not in the Fed's private information. Second, controlling for financial conditions, recent real economic surprises negatively predict policy surprises, which supports the "wait-and-see" hypothesis over a more aggressive response to economic news (Bauer and Swanson, 2023b). Third, financial conditions alone predict policy surprises as effectively as all other documented predictors combined.

JEL Classification: E3, E4, E5, G1

Keywords: Monetary Policy Surprises, Predictability Puzzle, Monetary Policy Identification, High-Frequency Event Study, Financial Conditions, Real Surprises.

*Acknowledgments: I thank Bryce Kanago for his careful reading and comments on earlier drafts. I also benefited from discussions with Victor J. Valcarcel, John Keating, and A. Lee Smith on how the Fed operates. Participants at the annual meetings of the Southern Economic Association, Missouri Valley Economic Association, and Midwest Economic Association offered useful feedback. All errors are mine.

†Wilson College of Business, University of Northern Iowa. Email: zhengyang.chen@uni.edu

1 Introduction

Monetary policy surprises capture the gap between what markets expect and what the Federal Reserve actually decides. These measures are obtained by unexpected changes in short-term financial contracts (such as federal funds futures and Eurodollar contracts) within a narrow time window around Federal Open Market Committee (FOMC) announcements.

First introduced by Kuttner (2001), monetary policy surprises have become important tools that extend well beyond financial studies. They serve as crucial instruments for identifying exogenous monetary policy shocks in, for instance, proxy structural vector autoregressions (Proxy SVARs) (Gertler and Karadi, 2015; Faust et al., 2004) and proxy local projections (Proxy LPs) (Kilian and Kim, 2011; Plagborg-Møller and Wolf, 2021). Additionally, these surprises allow market participants to gauge unexpected shifts in the Fed's stance and gain insight into the policy reaction functions (Cieslak and Vissing-Jorgensen, 2021; Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023b).

In theory, these surprises measure the exogenous policy actions at the Fed's discretion. Therefore, they should not be predictable, even partially, by economic news or financial fluctuations that predate the FOMC announcements. However, a growing body of research has found empirical evidence that they are partially yet significantly predicted by pre-announcement information.

Such (partial) predictability presents a puzzle. Two competing explanations have emerged in the literature. The first highlights information asymmetry due to the Fed's private information (Romer and Romer, 2000; Campbell et al., 2012; Nakamura and Steinsson, 2018; Miranda-Agrippino and Ricco, 2021), suggesting that monetary policy surprises reflect the Fed's superior knowledge about the state of economy. The second argues that monetary policy surprises stem from misperceptions about how the Fed responds to economic news (Bauer and Swanson, 2023a,b; Cieslak, 2018; Schmeling et al., 2022), contending that market participants systematically underestimate the Fed's responsiveness to economic developments, especially during recessions.

Both explanations face a challenge. These predictable patterns have persisted since 1994, when the Fed began issuing post-meeting statements. Why haven't markets learned to anticipate them after three decades? According to the efficient market hypothesis, systematic predictability should create arbitrage opportunities that would gradually disappear as traders exploit them. However, the evidence indicates that monetary policy surprises remain partially predictable by information available before FOMC announcements in a manner that is systematic, persistent, and seemingly permanent. Therefore, a more permanent institutional justification is required.

We resolve this contradiction with a new explanation: To achieve the targeting of economic variables, the Fed primarily responds to financial market conditions while taking a wait-and-see approach to economic data. Meanwhile, markets consider the Fed directly target the economic variables.

The underlying rationale for why "the Fed's response to financial conditions" is not learned by markets is presented in Fed Chair Jerome Powell's statement during his press conference after the FOMC meeting on May 3, 2023:

> "We do look at financial conditions very broadly, and we do that because they're important for the achievement of our goals, but we don't target them. We have our eye on maximum employment and price stability, and we use financial conditions as an important piece of information in assessing the likely path of the economy."

He makes three key points: first, the Fed responds to financial conditions; second, improving financial conditions is not a third goal; and third, the Fed assesses economic prospects via current financial conditions. A natural question arises: what if the private sector takes the "don't target financial conditions" literally so that it is not fully aware of the Fed's response to financial conditions? This under-disclosed approach to policy goals may lead to persistent gaps between market expectations and actual Fed policy responses.

We model accordingly. Through monitoring the broad financial conditions, the Fed evaluates what policy actions that markets expect and learns how markets believe the economy will evolve. Responding to financial conditions helps the Fed achieve targeting of economic variables. In this sense, the Fed adopt a "wait-and-see" approach for new economic data, as it does not need to react instantly to every pre-announcement data release until that information has influenced financial conditions. Meanwhile, financial markets believe that the Fed sticks to the policy goals for economic outcomes and does not have additional mandate of financial stability. This means markets may miss how the Fed truly responds to economic data through the lens of financial conditions. The discrepancy in the understanding of the Fed's policy reaction to economic data creates the predictable component of monetary policy surprises. Specifically, the predictability arises from three factors that the market tends to overlook: the Fed's learning of market expectations, the time-varying relationship between financial and economic data, and financial stress shocks. Importantly, this explanation emphasizes the distinct interpretations of the Fed's strategy to achieve its policy goals rather than relying on the slow and inefficient learning of the private sector.[1]

[1]Following Bauer and Swanson (2023b), learning is specifically referred to the process of figuring out the

Our empirical analysis yields three principal findings that support the testable hypotheses in the aforementioned model while contradicting the arguments presented in the two competing explanations:

First, financial markets price in all available information before FOMC announcements. We find that the predictors of policy surprises documented by Bauer and Swanson (2023b) do not contain information unavailable to the private sector; these strong predictors also strongly predict the level of financial stress the day before FOMC announcements and thus are not Fed's private information. This finding aligns with Bauer and Swanson (2023a) 'no private information' evidence.

Second, after controlling for financial fluctuations, there is no systematic bias in the Fed's response to news but novel evidence of the Fed's wait and see. The findings are threefold. First, when controlling for financial fluctuations, an adjacent positive real activity surprise predicts an expansionary monetary policy surprise while the Fed's response to news explanation suggests the opposite. Digging deeper, we confirm that the Fed does not immediately react to surprises in real economic data released shortly before an FOMC meeting. In contrast, real surprises released more than two weeks before a scheduled meeting are fully incorporated, and their impacts are properly anticipated before announcements.

Second, after purging the information available in financial markets, all predictors summarized in Bauer and Swanson (2023b), especially the real economic variables like non-farm payroll annual growth and surprise, become non-predictive of monetary policy surprises, suggesting that market participants properly learn how monetary policy reacts to relatively distant economic news.

Third, monetary policy surprises orthogonal to Bauer and Swanson (2023b) predictors and policy surprises orthogonal to financial conditions, serving as external instruments in SVAR identification, generate qualitatively identical impulse responses. The latter even exhibits a lesser degree of the output puzzle, in which real output increases (and unemployment declines) after a contractionary monetary policy shock. The mixture of financial and economic predictors do not contribute to better refinement on the identification of monetary policy shocks than financial conditions.

Those findings point that the private sector does not capture the Fed's response to financial conditions and thus incur the predictability puzzle. We do not observe the difficult

true response parameter of the policy reaction function. However, these different interpretations represent a structural barrier to convergence in understanding between the Fed and markets, rather than simply a learning problem that can be resolved over time. We cannot rule out that this persistent divergence may result from the Fed's intentional communication strategy.

and slow learning of financial markets; instead, we witness the Fed's prudential and delayed reaction to new economic data.

Third, the Fed systematically responds to financial conditions or stress levels in markets. Two financial variables, one measuring financial stress and the other evaluating the upside and downside risks in the economic outlook, are highly significant in predicting monetary policy surprises and exhaust all the predictive power of documented predictors. Both financial variables exhibit sensible signs: heightened financial stress and downside economic risk predict an expansionary monetary policy surprise. Additionally, we provide evidence that these surprises are not due to time-varying risk premia on short-term financial contracts, as suggested by Miranda-Agrippino (2016); instead, the risk premia respond to monetary policy shocks after FOMC announcements. In this sense, at the time of the announcement, investors' risk appetite is stable and unaffected by the prior financial conditions. So it does not help predict surprises beyond the biased expectation of how the Fed responds to financial conditions.

These findings suggest that financial markets serve as critical conduits for transmitting economic information to the Fed. For researchers seeking to identify exogenous policy shocks, we recommend using surprises purged of their correlation with pre-announcement financial conditions as instrumental variables. When analyses include unscheduled meetings — where the "wait-and-see" strategy becomes more pronounced — an additional control for recent real activity surprises is warranted. Importantly, our results demonstrate that once financial information and real surprises are accounted for, incorporating other economic predictors yields little additional benefit for shock identification.

Our empirical results would not be observable without addressing both information insufficiency and frequency mismatch issues in existing predictors. Previous approaches either used comprehensive but low-frequency economic data (monthly macroeconomic variables and Greenbook forecasts) or high-frequency financial variables with limited information content (stock indexes, yield curve slope). Our approach combines high frequency with information richness by employing three daily measures: the OFR Financial Stress Index, real activity surprise index, and Treasury skewness. This novel combination enables a more granular and thorough investigation of monetary policy surprise predictability.

The rest of the paper is organized as follows. Section 2 reviews the literature on monetary policy surprises by introducing established measures and discussing explanations for their predictability. Section 3 presents a theoretical model that formalizes our "Fed's response to financial conditions" and "wait-and-see strategy" hypotheses. The model provides testable predictions that distinguish our explanation from alternatives. Section 4 introduces the high-frequency indicators used to capture financial stress, the economic outlook, and real activity

surprises. Section 5 demonstrates that financial markets incorporate predictive information in documented predictors before FOMC announcements. Section 6 investigates the Fed's response to financial conditions and refutes the time-varying risk premia hypothesis. Section 7 examines the Fed's approach to economic news, finding evidence for the "wait-and-see" strategy and against the "response to news" effect. Section 8 concludes.

2 Literature Review

Our work builds on established measures of monetary policy surprises to investigate their puzzling predictability. We evaluate the two prevailing explanations—the Fed's private information advantage and markets' overestimation of the Fed's reaction to economic news—and identify their key limitations. We then propose the Fed's systematical response to financial conditions as another explanation.

2.1 Measures of Monetary Policy Surprises

The study of monetary policy surprises began with the seminal work of Kuttner (2001), who used changes in federal funds futures contracts around FOMC announcements to isolate unexpected policy actions.

To investigate the Fed's private information, Nakamura and Steinsson (2018) develop a key measure (NS) based on 30-minute changes in short-term interest rates, specifically the current month and 3-month ahead Fed Funds futures rates and the 2, 3, and 4-quarter ahead Eurodollar futures rates. Their approach focuses exclusively on scheduled FOMC announcements, excluding unscheduled meetings to maintain consistency in announcement formality.

Gürkaynak et al. (2005) introduced a decomposition method that extracts two factors from high-frequency changes in interest rate futures around policy announcements. Their approach yields a "target" factor representing surprises in the current policy rate and a "path" factor capturing surprises in the anticipated future trajectory of policy rates. Like the NS measure, this decomposition typically focuses on scheduled meetings to ensure regularity in the analysis.

These high-frequency identification approaches rely on the assumption that in a narrow window around policy announcements (typically 30 minutes), the primary driver of asset price movements is the monetary policy news itself. However, researchers have recognized that these measures may still contain components predictable by pre-announcement information.

Addressing this concern, Bauer and Swanson (2023b) construct a baseline measure (MPS) as the first principal component of changes in Eurodollar futures rates around both scheduled and unscheduled FOMC announcements with policy rate decisions. Their key contribution is the orthogonalized version (MPS_orth), which is obtained by regressing MPS on economic and financial variables known before the FOMC announcement and taking the residuals. This procedure aims to purge the monetary policy surprise of any correlation with pre-announcement information.

Taking a different approach to purging, Jarociński and Karadi (2020) propose a decomposition that separates policy surprises into pure monetary policy shocks (JK_MP) and information shocks (JK_Info) based on the comovement of interest rates and stock prices around announcements. Their method identifies surprises that move in the same direction with stock prices as "information shocks," thought to reflect the Fed's private information about the economy, while those moving opposite to stock prices are classified as "pure monetary policy shocks."

In our analysis, we employ all these different high-frequency measures focusing short-term financial contracts —Nakamura and Steinsson (2018) raw measure, Gürkaynak et al. (2005) target and path factors, Bauer and Swanson (2023b) MPS and MPS_orth, and Jarociński and Karadi (2020) JK_MP and JK_Info—to evaluate the sources of predictability in monetary policy surprises.

2.2 Fed's Private Information Hypothesis

The first explanation for the predictability puzzle emphasizes information asymmetry. Romer and Romer (2000) pioneer this view by showing that the Fed possesses superior information about future inflation compared to commercial forecasters. This information advantage hypothesis was further developed by Campbell et al. (2012), who introduced the concept of "Delphic" forward guidance—communication that reveals the central bank's information about future economic conditions rather than its policy intentions.

Nakamura and Steinsson (2018) formalize this mechanism as the "Fed's information effect." They collect evidence that FOMC announcements convey information about economic fundamentals beyond the policy action itself. Positive monetary policy surprises, which are supposed to reduce output expectations, led to increased private GDP forecasts, a finding consistent with the market's interpretation of Fed actions as revealing positive economic news.

Miranda-Agrippino and Ricco (2021) extend this framework by highlighting the role of sluggish information processing of the private sector. They proposed that monetary policy

surprises combine the Fed's private information about economic prospects with genuine policy shocks. Distinguishing those two components requires more sophisticated identification approaches. Their solution involves the orthogonalization of policy surprises to Greenbook forecasts to remove the component related to the Fed's information advantage.

However, this explanation has faced increasing scrutiny from Bauer and Swanson (2023a), who demonstrate that Greenbook forecasts do not predict monetary policy surprises after controlling for other publicly available information. Moreover, no evidence exists that Greenbook forecasts surpass private sector forecasts in predicting future economic developments.

Furthermore, Lunsford (2020) finds evidence for the information effect in the early 2000s but not in later years. Cieslak and Schrimpf (2019) decompose monetary policy surprises and found that information shocks play only a minor role in FOMC announcements, though they are more significant in minutes releases and Fed chair speeches.

Our study contributes to this debate by demonstrating that information contained in predictors of monetary policy surprises is already priced into financial markets before FOMC announcements. Thus, their predictive power is not because they are private to the Fed or because the private sector is sluggish to learn.

2.3 Fed's Response to News Hypothesis

The second explanation focuses on how markets perceive the Fed's reaction function. Cieslak (2018) documents that financial markets consistently underestimate how responsive the Fed would be to economic variations, particularly to large negative shocks. Such underreaction leads to ex post predictability of monetary policy surprises by economic news that occurred before FOMC announcements.

Market expectations of monetary policy, claimed by Schmeling et al. (2022), fail to fully incorporate public information about the economic outlook. The resulting systematic pattern of expectation errors indicates that markets tend to underestimate both the magnitude and persistence of the Fed's response to economic news.

Bauer and Swanson (2023b) present evidence for the proposed "Fed's response to news" effect: monetary policy surprises can be predicted by a parsimonious set of publicly available economic and financial variables. They constructed the monetary policy surprises orthogonalized to this predictable component and found them better representing genuine policy shocks.

A theoretical model proposed by Bauer and Swanson (2023a) explains that the complexity of the Fed's reaction function, combined with infrequent policy actions, makes learning difficult for market participants.

This explanation faces a fundamental challenge: why does such predictability persist over decades? If markets are aware of their consistent underestimation of the Fed's reactions to economic variables, what drives them persistly doing so?

We claim this market inefficiency does not exist by showing that, after controlling for financial conditions, there is no evidence of systematic bias in the magnitude of the Fed's response to economic news. Furthermore, there is a delay in the Fed's response to recent economic data.

2.4 Fed's Response to Financial Conditions Hypothesis

An increasing amount of research suggests that the Fed systematically responds to financial market instability beyond their traditional dual mandate. These studies provide an alternative perspective on policy surprise predictability.

Caldara and Herbst (2019) state that the systematic component of monetary policy includes a direct and significant reaction to changes in corporate credit spreads during the Great Moderation. Failure to account for this endogenous reaction leads to an attenuated estimated effects of monetary policy shocks. This financial response component, present but not emphasized in Gertler and Karadi (2015), remains largely overlooked despite its importance for properly identifying monetary policy effects.

From a theoretical perspective, Caballero et al. (2024) develop a model where it becomes optimal for the central bank to target financial stability beyond their direct targeting on output and inflation. Their counterfactual analysis finds that Financial Conditions Index (FCI) targeting could significantly reduce macroeconomic volatility by enabling arbitrageurs to trade more aggressively against financial noise.

Brunnermeier et al. (2021) provide additional evidence with a structural VAR model. They show that negative reduced-form responses of output to credit growth stem primarily from the Fed's systematic tightening in response to credit expansion. This explains why credit and output growth remain positively associated on average, despite their apparent negative relationship in reduced-form analysis.

In line with this emerging research, we provide a theoretical model that incorporates the Fed's direct response to financial conditions but not targeting them, and present empirical evidence that supports this model.

3 A Model of Fed's Response to Financial Conditions

In this section, we present a model that formalizes our hypothesis that the Fed responds primarily to financial conditions to achieve its policy goals and delays reaction to new economic data. It reconciles the contradiction between predictability and market efficiency and provides testable hypotheses for the empirical studies.

3.1 Model Setup

We begin by modeling how investors form expectations about the policy rate. They take the Fed's policy goals such as the dual mandate literally and follow a Taylor-rule-type policy reaction function as

$$E^m(i_t^{post}) = \alpha_1 X_{1,t}^{pre} + \alpha_2 X_{2,t}^{pre} \tag{1}$$

where *pre* (*post*) means prior to (after) a FOMC announcement at date t, $E^m(i_t^{post})$ represents the policy rate expected by market participants, and X_t^{pre} denotes the economic data the Fed targets and is released before the FOMC announcement. Prior to every FOMC meeting, economic data X_t^{pre} is continuously released to the public. The variable $X_{1,t}^{pre}$ represents news released in close proximity to the meeting, while $X_{2,t}^{pre}$ represents news released relatively further in time from the meeting. Financial markets learn from experience that the policy rate responds to economic data with different timing, as captured by the perceived feedback rule parameters α_1 and α_2. These parameters are estimated based on historical information and are known to both the Fed and the financial market.

The Fed's decision-making process is modeled in accordance with Jerome Powell's statement; i.e., the Fed considers financial conditions comprehensively to achieve its policy goals for economic variables since financial conditions reflect the most up-to-date market reaction to economic news. The Fed seeks information about the future evolution of target variables $X_{1,t}^{post}$ from financial conditions rather than from realized economic data $X_{1,t}^{pre}$:

$$i_t^{post} = \beta_1 S_t^{pre} + \beta_2 X_{2,t}^{pre} + \varepsilon_t^{MP} \tag{2}$$

$$S_t^{pre} = \gamma_t E^m(X_{1,t}^{post} | E^m(i_t^{post})) + \eta_t^{pre} \tag{3}$$

where i_t^{post} is the policy rate set by the Fed, S_t^{pre} represents the financial conditions prior to the announcement, η_t^{pre} is a financial stress shock, and ε_t^{MP} is the pure monetary policy shock which is unknown before the FOMC meeting. β_1 indicates a time-invariant response to financial conditions. The pre-announcement financial conditions reflect a financial stress

shock η_t^{pre} and the market's expectation of the future economic conditions $E^m(X_{1,t}^{post})$ given the expected policy action $E^m(i_t^{post})$.

This framework highlights the critical trade-off facing the Fed. Although responding to current financial conditions allows policymakers to harness market expectations and forward-looking information, it could also risks policy reactions to transitory financial stress that may be unrelated to underlying economic fundamentals.

Regarding recent data release $X_{1,t}^{pre}$, the Fed adopts a wait-and-see approach, waiting until new data influences the financial conditions[2]. Specifically, the Fed does not directly respond to $X_{1,t}^{pre}$; instead, it reacts to the economic prospects $E^m(X_{1,t}^{post})$ indicated by the financial conditions S_t^{pre}. The time-varying coefficient γ_t that relates financial conditions with economic news is inherently stochastic. Additionally, the Fed prudently responds to remote news $X_{2,t}^{pre}$ with reaction parameter β_2.

3.2 Derivation of Monetary Policy Surprises

The monetary policy surprise can be expressed as the difference between the Fed's policy rate decisions and market expectations, which for our model equals

$$\begin{aligned} mps_t^{post} &= i_t^{post} - E^m(i_t^{post}) \\ &= \beta_1\gamma_t E^m(X_{1,t}^{post}|E^m(i_t^{post})) - \alpha_1 X_{1,t}^{pre} + \beta_2 X_{2,t}^{pre} - \alpha_2 X_{2,t}^{pre} + \beta_1\eta_t^{pre} + \varepsilon_t^{MP} \quad (4) \\ &= \beta_1\gamma_t E^m(X_{1,t}^{post}|\alpha_1, X_{1,t}^{pre}) - \alpha_1 X_{1,t}^{pre} + \beta_1\eta_t^{pre} + \varepsilon_t^{MP} \quad (5) \end{aligned}$$

Since an efficient financial market is capable of learning how the Fed responds to remote news, $\alpha_2 X_{2,t}^{pre}$ equals $\beta_2 X_{2,t}^{pre}$ with no arbitrage opportunity. Since both expectations in $E^m(X_{1,t}^{post})$ and $E^m(i_t^{post})$ are generated by financial markets, we can combine these expectation operators and simplify $E^m(X_{1,t}^{post}|E^m(i_t^{post}))$ to $E^m(X_{1,t}^{post}|\alpha_1, X_{1,t}^{pre})$.[3] Thus, we obtain Equation (5).

In our model, the predictability of policy surprises stems from three key market oversights due to the under-disclosed response to financial conditions. First, markets fail to account

[2]Admittedly, the notion that the Fed should respond to financial conditions or stability is a behavioral assumption and might not represent the optimal strategy for the central bank. Bauer et al. (2023) and Adrian and Liang (2016), among other studies, focus on the transmission of monetary policy through risk premia, risk-taking behaviors and financial markets. However, less theoretical work like Caballero et al. (2024) has been conducted on the Fed's choice of information between financial fluctuations and recent economic data in their policy reaction function.

[3]Since the older economic news should be fully priced in, we ignore the impact of older economic news $\alpha_2 X_{2,t}^{pre}$ on $E^m(X_{1,t}^{post})$.

for how their own policy expectations influence the target variables. What if investors accounted for its own influence on policy? In this sense, agents respond to $E^m(X_{1,t}^{post}|\alpha_1, X_{1,t}^{pre})$ rather than just $X_{1,t}^{pre}$. This implies markets should anticipate the coefficient β_1 such that $\beta_1\gamma_t = \alpha_1$. The impact of market-expected policy actions on policy rate should be neutralized ($\beta_1\gamma_t E^m(X_{1,t}^{post}|\alpha_1, X_{1,t}^{pre}) - \alpha_1 E^m(X_{1,t}^{post}|\alpha_1, X_{1,t}^{pre}) = 0$). Second, given the former ignorance, the market fails to recognize that the time-varying relationship between financial conditions and economic data (γ_t) is incorporated in monetary policy decisions. These two factors inherent from financial conditions explain why the private sector cannot fully learns the Fed's policy reaction function despite decades of observation; that is, by responding to financial conditions, the Fed continuously learns from evolving market expectations while burdens the uncertainty in financial markets. Lastly, markets overlook the influence of financial stress shocks ($\beta_1\eta_t^{pre}$). Controlling for other factors, an exogenous increase in financial stress should generate a negative policy surprise because β_1 is negative in Equation (2), reflecting the Fed's accommodative response to financial distress.

3.3 Fed's Private Information and Response to News

Alternative hypotheses in the literature are modeled as follow. If the Fed possesses private information, as suggested by Romer and Romer (2000) and Nakamura and Steinsson (2018), the market expectation remains the same but the Fed responds not only to public information about the target variables ($X_{1,t}^{pre}$ and $X_{2,t}^{pre}$) but also to their private information $X_t^{Fed,pre}$:

$$i_t^{post} = \beta_1 X_{1,t}^{pre} + \beta_2 X_{2,t}^{pre} + \beta_3 X_t^{Fed,pre} + \varepsilon_t^{MP} \tag{6}$$

As markets can anticipate the Fed's response to public information, $\alpha_1 = \beta_1$ and $\alpha_2 = \beta_2$. The monetary policy surprise is expressed as:

$$mps_t^{post} = \beta_3 X_t^{Fed,pre} + \varepsilon_t^{MP} \tag{7}$$

According to Miranda-Agrippino and Ricco (2021), if the Fed's private information $X_t^{Fed,pre}$ were partially derived from economic information before announcements, economic news would predict policy surprises.

Alternatively, if the Fed responds to economic news more aggressively than markets expect, as proposed by Cieslak (2018) and Bauer and Swanson (2023b), the market expectation and the Fed reaction function can be represented as:

$$E^m(i_t^{post}) = \alpha_{1,t} X_{1,t}^{pre} + \alpha_2 X_{2,t}^{pre} \tag{8}$$

$$i_t^{post} = \beta_{1,t} X_{1,t}^{pre} + \beta_2 X_{2,t}^{pre} + \varepsilon_t^{MP} \tag{9}$$

Importantly, markets do not observe $\beta_{1,t}$ directly and must form beliefs about this parameter based on the history of observed economic data and policy decisions. The policy surprise then becomes

$$mps_t^{post} = (\beta_{1,t} - \alpha_{1,t}) X_{1,t}^{pre} + \varepsilon_t^{MP} \tag{10}$$

Bauer and Swanson (2023b) argue that if the private sector underestimates the Fed's responsiveness to economic news $X_{1,t}^{pre}$, then policy surprises mps_t^{post} will exhibit *ex post* positive correlation with procyclical business cycle indicators. While Bauer and Swanson (2023a) develop a theoretical model explaining the difficulty of learning the Fed's reaction function, they do not fully address why market participants consistently and persistently underestimate the Fed's responsiveness over multiple decades.

The financial conditions hypothesis presented in our model offers a resolution to this puzzle by suggesting that the Fed's primary response is to financial conditions rather than directly to economic data. Thus, this creates a fundamental disconnect between market expectations based on economic news releases and the Fed's actual policy decisions.

3.4 Testable Hypotheses

Our theoretical framework generates several testable predictions that distinguish our financial conditions hypothesis from alternative explanations.

First, we test the Fed's private information hypothesis by comparing Equations (2) and (6). If the Fed possesses private economic information unavailable to markets before announcements, then $X_t^{Fed,pre}$ should not be fully reflected in financial conditions S_t^{pre}. To evaluate this in Section 5, we assess whether pre-announcement financial conditions already incorporate these economic data. If so, then the Fed likely lacks substantial private information that isn't already embedded in market prices—in formal terms, $X_t^{Fed,pre}$ would be a subset of S_t^{pre}.

Second, we compare the financial conditions model in Equation (5) with the response to news model in Equation (10) to distinguish between these competing explanations. According to the news response theory, predictability arises only from the persistent gap between actual Fed's actual responsiveness $\beta_{1,t}$ and market expectations of that responsiveness $\alpha_{1,t}$.

In contrast, our hypothesis attributes predictability to the under-communicated response to financial conditions and the policy surprises are predictable due to the stochastic relationship γ_t between financial variables and economic outcomes, along with market mispricing of expected policy impacts on future economic conditions $E^m(X_{1,t}^{post}|\alpha_1, X_{1,t}^{pre})$ and financial shocks η_t^{pre}. These differences yield three specific empirical tests:

1. *Response to financial conditions*: If the Fed responds primarily to financial conditions ($\beta_1 < 0$ in our model), then financial stress should negatively predict monetary policy surprises. Section 6 confirms this prediction.

2. *Negative partial effect of economic surprises*: When the pre-announcment financial state is controlled for, the financial shock η_t^{pre} and the time-varying component of γ_t are taken out of Equation (5). The time-invariant component $\bar{\gamma}_t$ should be learnable and thus $\beta_1\bar{\gamma}_t = \alpha_1$ without loss of generosity. The predicted effect of adjacent economic data $X_{1,t}^{pre}$ is negative under our model. This occurs because high economic realizations raise expected policy rates $E^m(i_t^{post})$, which in turn reduces expected future economic conditions $E^m(X_{1,t}^{post})$, making $\alpha_1[E^m(X_{1,t}^{post}|\alpha_1, X_{1,t}^{pre}) - X_{1,t}^{pre}] < 0$. In contrast, the response to news channel would predict $\beta_{1,t} > \alpha_{1,t}$ in Equation (10), suggesting positive coefficients on economic surprises regardless of financial controls. Section 7.1 reports negative coefficients on real economic surprises after controlling for financial conditions.

3. *Informational sufficiency of financial conditions*: Our model predicts that older economic data $X_{2,t}^{pre}$ should not significantly affect monetary policy surprises, as markets have fully incorporated this information. Section 7.2 confirms this prediction, showing that real economic surprises released two weeks prior to announcements have no predictive power for policy surprises. We further find that the majority of documented predictors are relatively distant from the announcement dates[4]. Section 7.3 shows evidence that previously strong predictors—especially economic variables like non-farm payroll growth over last 12 months and non-farm payroll surprises—become insignificant after controlling for financial conditions. Furthermore, our proxy-SVAR analysis demonstrates that monetary policy surprises purged using only financial conditions perform equally well as those purged using both financial and economic predictors, as evidenced by the absence of price and output puzzles that typically plague standard monetary SVAR models.

These testable hypotheses require appropriate empirical measures for evaluation. In Section 4, we introduce three high-frequency indicators that capture financial stress, the economic outlook, and real activity surprises. Sections 5-7 then empirically test our hypotheses

[4]For instance, the non-farm payroll surprise is a strong predictor. The non-farm payroll data is release on the first Friday of each month. The scheduled FOMC meetings are held once in 1.5 months. It is seldom that the payroll data is seldom released shortly before a FOMC meeting date.

against competing explanations using these indicators.

4 High-frequency Indicators for Financial Stress, Economic Outlook and Real Activities

Previous research on the predictability of monetary policy surprises suffers from two main shortcomings: information insufficiency and frequency mismatch. High-frequency financial variables alone are inadequate to summarize the economic news and forecasts considered in the Fed's monetary policy reaction function, while lower-frequency economic data lacks the granularity to establish causality between data releases and FOMC announcements. Some studies, such as Miranda-Agrippino (2016) and Miranda-Agrippino and Ricco (2021), address information insufficiency by using a dynamic factor model to extract information from a large set of monthly macroeconomic variables. However, this approach introduces a frequency mismatch when predicting irregular policy surprises.

To examine the predictability of monetary policy surprises in a high-frequency and information-rich environment, we employ three daily variables that capture key aspects of the economic and financial circumstances leading up to each FOMC announcement: the OFR Financial Stress Index (Monin, 2019), which provides a comprehensive gauge of global financial conditions; Bauer and Chernov (2024) option-implied skewness of 10-year Treasury yields, reflecting asymmetries in investors' views about future economic conditions; and the real activity surprise index of Scotti (2016), capturing the real-time flow of information about evolving real economic conditions relative to market expectations.

4.1 Financial Stress

While Fed chairs have consistently emphasized that the Fed's primary focus is on the real economy and price stability, there is growing recognition that financial conditions play a crucial role in the transmission of monetary policy and can have significant effects on the real economy. This raises the question of whether the Fed's response to financial stress could be a source of monetary policy surprises, as market participants may have different perceptions of the extent to which the Fed incorporates financial conditions into its reaction function.

To investigate the potential role of Fed's response to financial conditions in driving the gap between market expectations and the Fed's actual policy decisions, it is essential to include a high-frequency measure of financial stress in a model of monetary policy surprises. Capturing the information available in financial markets right before FOMC announcements

requires a measure that can track systematic movements in global financial markets at a daily frequency. While most financial stress indexes and financial condition indexes are updated monthly or weekly, such as the Kansas City Fed Stress Index (Hakkio and Keeton, 2009), the St. Louis Fed Stress Index (Kliesen and Smith, 2010), and the financial condition index (Hatzius et al., 2010), there are a few exceptions that provide daily updates. These include the OFR Financial Stress Index (Monin, 2019), the Bloomberg Financial Conditions Index, and the excess bond premium (Gilchrist et al., 2022).

In this study, we adopt the OFR Financial Stress Index (FSI) instead of the Bloomberg Financial Conditions Index because the variables included in the latter are a subset of those in the former.[5] As a convenient feature of the dynamic factor model, the OFR Financial Stress Index can be decomposed into five sub-indexes that represent different dimensions of global financial stress, such as credit spreads, equity valuation, constraints in funding markets, safe assets valuation, and volatility. We further consider these sub-indexes as indicators of different aspects of financial markets and evaluate what types of information they respond to. For robustness, we also employ the excess bond premium, which is used in Gertler and Karadi (2015) proxy-SVAR with the financial sector. By examining its relationship with monetary policy surprises at a daily frequency, we investigate whether the instrument exogeneity condition holds.

4.2 Economic Outlook

Miranda-Agrippino and Ricco (2021) and Sastry (2022) find that economic forecasts are predictive of policy surprises, suggesting that the forward-lookingness of the Fed's policy decisions may not be fully captured by the public. This finding motivates the inclusion of a measure of market-perceived economic outlook.

Following Bauer et al. (2023), we use option-implied skewness of Treasury yields, particularly for medium-term maturities like the ten-year yield, to provide valuable information about investors' perceptions of the economic outlook. The ten-year Treasury yield reflects market expectations about future economic conditions and monetary policy over a longer horizon. This measure captures asymmetries in investors' views about the distribution of possible economic outcomes. Positive skewness indicates that investors see upside risks to the economic outlook and interest rates, while negative skewness points to downside risks.

[5]We do not directly use VIX or VXX to evaluate uncertainty in financial markets because they only reflect the volatility of stock markets. While this information is incorporated in the FSI measure, we prefer the FSI for its comprehensive coverage of stress in global financial markets across multiple asset classes and regions.

Compared to traditional economic forecasts, option-implied skewness of Treasury yields has several advantages. It swiftly incorporates the latest information and shifts in market sentiment through real-time prices of options on Treasury futures. It aggregates the perspectives of a diverse set of market participants, providing a broader view of future economic conditions than forecasts based on a limited panel of experts. Additionally, its sensitivity to changes in investors' risk perceptions enables it to promptly reflect shifts in the perceived balance of risks surrounding the economic outlook.

Since the Treasury skewness reflects a higher-moment fluctuation in financial markets and may supplement the first-order information contained in the FSI index, we include both to measure financial conditions.

4.3 Real Activities

To test the impact of adjacent economic data releases ($X_{1,t}^{pre}$ in our model), we employ the real activity surprise index of Scotti (2016). It provides a high-frequency, real-time gauge of the degree to which real activity is evolving relative to market expectations. By capturing the real-time flow of information about macroeconomic conditions, the surprise index allows us to examine whether policy surprises can be explained by the arrival of macroeconomic news.

The surprise index offers several key advantages as a measure of real activity surprises. First, extracted from a dynamic factor model, it aggregates information from a range of important macroeconomic indicators that provide timely signals about the state of real activity, including GDP, industrial production, employment, retail sales, and purchasing managers' indexes. The weights assigned to each indicator are based on the indicator's time-varying contribution to the underlying real activity factor, ensuring that surprises in the most informative and timely indicators receive the greatest weight.

Second, the surprise index is available at a daily frequency, updating every time a new macroeconomic data release occurs. This high-frequency feature is particularly valuable for studying the predictability of policy surprises, as it allows us to capture the real-time evolution of economic conditions leading up to each monetary policy announcement.

Third, compared to market-based measures like the Citi Economic Surprise Index, the surprise index used here provides a more direct and objective gauge of real activity surprises, depending only on the economic data surprises themselves rather than their market impact.

Despite the advantages of these high-frequency indicators in capturing financial stress, the economic outlook, and real-time economic developments, it is important to acknowledge

limitations in data availability. The financial stress index (FSI) begins in January 2000. The real activity surprise index is available from June 2003 to the Pandemic. We end the sample to 2019 to avoid the dramatic swings in real output and labor statistics during the Pandemic [6]. We also exclude the Pandemic period to make our results comparable to past research. Our sample period includes two recessions and covers both the effective zero lower bound and normalized interest rate periods, capturing a range of economic conditions. Thus, the observed response to financial conditions is not likely to be caused by a specific economic regime.

5 No New Information in Existing Predictors

We test the first prediction of our model: if markets are efficient, then the information content in previously documented predictors should already be reflected in financial conditions before FOMC announcements. This test is crucial for evaluating the Fed's private information hypothesis.

The existing literature has documented many economic and financial variables that predict upcoming monetary policy surprises. Importantly, the relevant data was available to financial markets prior to the FOMC announcement itself (Bauer and Swanson, 2023a; Cieslak, 2018; Bauer and Chernov, 2024). Based on this line of research, Bauer and Swanson (2023b) propose a parsimonious and robust set of predictors that also bear an intuitive relationship to the Fed's monetary policy rule.

If the predictors contain information not already reflected in financial markets, this would support the Fed's private information hypothesis. Conversely, if the broad financial condition already incorporate all information in these predictors, this would indicate that the Fed and financial markets have access to the same information set.

We test this information gap between the Fed and the market with a high-frequency event study regression on FOMC announcements.

$$FSI_t^{pre} = \alpha + \beta' X_{2,t}^{pre} + \epsilon_t \tag{11}$$

where t indexes FOMC announcements in our sample, Financial stress index FSI_t^{pre} denotes a measure of the financial stress or conditions prior to announcement t and ϵ_t is a regression residual. $X_{2,t}^{pre}$ contains the following six predictors that are publicly known by the private sector prior to the announcement t.

[6] In an unreported test including the post-Pandemic sample, the Fed's response to financial conditions is robust.

The six predictors of monetary policy surprises included in the Bauer and Swanson (2022) are as follow. We keep them, and even the sample period up to December 2019, the same to maintain the consistency with the literature.

- Yield curve slope: the change in the slope of the yield curve from three months before the FOMC announcement to the day before the FOMC announcement, measured as the second principal component of one- to ten-year zero-coupon Treasury yields from Gürkaynak et al. (2007).

- S&P 500 : the log change in the S&P500 stock price index from three months (65 trading days) before the FOMC announcement to the day before the FOMC announcement.

- Commodity prices: the log change in the Bloomberg Commodity Spot Price index (BCOMSP) from three months before the FOMC announcement to the day before the FOMC announcement.

- Employment growth: the log change in nonfarm payroll employment from one year earlier to the most recent release before the FOMC announcement, as used in Cieslak (2018).

- Nonfarm payrolls surprise: the surprise component of the most recent nonfarm payrolls release prior to the FOMC announcement, measured as the difference between the released value of the statistic minus the median expectation for that release from the Money Market Services survey.

- Treasury skewness: the implied skewness of the ten-year Treasury yield, measured using options on ten-year Treasury note futures with expirations in 1–3 months, averaged over the preceding month, from Bauer and Chernov (2024).

Since these predictors contain information dating back from one month to one year before announcements, we categorize them as distant data releases $X_{2,t}^{pre}$.

We find that these six strong predictors of monetary policy surprises are also strong predictors of systematic financial stress in global markets. The results from seven different versions of regression are reported in Table 1. The first column considers the excess bond premium (EBP) over our sample of 146 FOMC announcements from Auguest 2002 to December 2019. The adjusted R-squared is 47 percent, and most predictors are statistically significant, with the signs of the estimated coefficients being intuitive. A strong stock market predicts a relief in the EBP, while an increasingly steep yield curve slope predicts a widening of credit spreads. The second column reports results for our primary measure of financial

condition, the FSI index, over a sample of 169 FOMC announcements from Janurary 2000 to December 2019. The adjusted R-squared is higher at 57 percent, and the signs of the coefficients are similar to those for the EBP, with strong nonfarm payroll employment, a strong stock market, and high commodity prices predicting a relief in financial stress. When the yield curve becomes more upward-sloping (i.e., when short-term interest rates fall relative to long-term rates, as they do during monetary easing cycles), financial conditions deteriorate.

Table 1: Financial Stress and Documented Predictors of Monetary Policy Surprises

$$FSI_t^{pre} = \alpha + \beta' X_{2,t}^{pre} + \epsilon_t$$

	EBP	FSI	FSI Sub-Indexes				
			Credit	Equity	Safe Asset	Funding	Volatility
SLOPE_3M	0.19*	0.17*	0.13	0.24*	-0.14	0.20	0.10
	(2.47)	(2.37)	(1.97)	(3.37)	(-1.28)	(1.79)	(1.60)
SP500_3M	-0.42**	-0.56**	-0.77**	-0.51**	-0.19	-0.42**	-0.49**
	(-4.40)	(-6.28)	(-13.84)	(-5.48)	(-1.38)	(-3.05)	(-7.65)
BCOM_3M	-0.27*	-0.12	-0.03	-0.12	0.35*	-0.17	-0.16
	(-2.13)	(-0.80)	(-0.34)	(-1.11)	(2.37)	(-0.86)	(-1.73)
TR_SKEW	0.06	0.11	-0.05	0.09	0.03	0.15	0.13**
	(0.67)	(1.44)	(-0.98)	(1.03)	(0.26)	(1.38)	(2.68)
NFP_12M	-0.20	-0.24**	0.04	-0.18	-0.12	-0.12	-0.42**
	(-1.66)	(-2.90)	(0.64)	(-1.49)	(-1.23)	(-1.24)	(-8.57)
NFP_SURP	-0.06	-0.12**	-0.06	-0.12*	-0.23*	-0.10*	-0.08
	(-1.34)	(-3.19)	(-1.94)	(-2.59)	(-2.07)	(-2.34)	(-1.94)
Obs.	146	169	169	169	169	169	169
Adj. R2	0.47	0.57	0.68	0.48	0.11	0.31	0.66
Max VIF	2.18	1.69	1.30	1.64	2.59	2.05	1.27

Note: * and ** denote significance at 5% and 1%. β in the regression $FSI_t^{pre} = \alpha + \beta' X_{2,t}^{pre} + \epsilon_t$ are reported. The standardized coefficients are reported (the variances of dependent and independent variables are equal to one). The HAC-robust t-statistics are enclosed in parentheses. The sample of daily EBP ranges from 2002:08 to 2019:12, while the sample of FSI and its subindexes spans from 2000:01 to 2019:12. The Max VIF reports the highest VIF statistics among all regressors.

The third through seventh columns report results for sub-indexes of the FSI. An increase in these indexes indicates widening credit spreads, declining equity valuation, increasing safe asset valuation, tightening funding markets, or swelling volatility in global financial markets. We notice that an increasingly steep yield curve slope predicts the widening of credit spreads and the decline of global equity valuation. Gains in the S&P 500 index diminish financial stress in all measures except safe asset valuation. In contrast, only safe asset valuation

reflects commodity price movements. A robust labor market instills faith in the financial markets, with nonfarm payrolls surprises alleviating all dimensions of financial conditions and employment growth reducing volatility across financial markets. The information content in these predictors, except for Treasury skewness, is incorporated into at least one feature of financial stress and is in turn reflected in the aggregate FSI. It is unreasonable to argue that their ability to predict monetary policy surprises is due to the Fed's unique information that is unavailable in the market. The maximum variance inflation factor (VIF) for each regression is well below three, indicating that multicollinearity is not a concern in our analysis.

The Treasury skewness, however, is not significantly reflected in the FSI or its sub-indexes, except for a modest impact on volatility. The Treasury skewness provides a forward-looking assessment of potential tail risks and asymmetries in market expectations. The higher-moment information captured by the Treasury skewness is distinct from the first-moment financial stress that captured by the FSI. So, we include the Treasury skewness in our high-frequency measures alongside the FSI to ensure a more comprehensive measure of financial conditions (i.e., S_t^{pre} combines the information in FSI_t^{pre} and $skew_t^{pre}$).

6 Response to Financial Conditions

This section examines our core hypothesis that the Fed systematically responds to financial conditions. According to our model, if the Fed primarily responds to financial stress and the economic outlook as reflected in financial markets ($\beta_1 < 0$ in Equation (2)), then heightened financial conditions should predict accommodative monetary policy surprises.

We use the representative monetary policy surprise measures introduced in Section 2.1 at the event study frequency from the first FOMC meeting in 2000 to the last meeting in 2019, including 163 scheduled meetings and six unscheduled meetings with policy rate changes. Table 2 considers regressions regarding the pre-announcement financial stress and market risk perception of the form

$$mps_t^{post} = \mu + \lambda FSI_t^{pre} + \delta skew_t^{pre} + u_t \tag{12}$$

where t indexes FOMC announcements, mps_t^{post} denotes a type of monetary policy surprise from the literature, FSI_t^{pre} records the level of the OFR financial stress index on the day before each announcement, and $skew_t^{pre}$ is the average of the daily Treasury skewness in the 30 days preceding announcements. Note that mps_t^{post} is constructed with high-frequency changes in the 30-minute window surrounding the FOMC announcement at date t, while FSI_t^{pre} and $skew_t^{pre}$ measure changes at a daily frequency.

Table 2: Financial Conditions Predict Monetary Policy Surprises (High-Frequency Event Study)

$$mps_t^{post} = \mu + \lambda FSI_t^{pre} + \delta skew_t^{pre} + u_t$$

	MPS	MPS_orth	JK_MP	JK_Info	NS	Target	Path
FSI	-0.25**	0.04	-0.13	-0.23*	-0.31**	-0.15**	-0.27**
	(-3.18)	(0.49)	(-1.78)	(-2.35)	(-6.06)	(-2.64)	(-4.97)
TR_SKEW	0.21**	0.03	0.15	0.12*	0.18**	0.07	0.17*
	(3.74)	(0.49)	(1.93)	(2.00)	(2.91)	(1.20)	(2.18)
Obs	169	169	169	169	163	163	163
R2	0.11	0.00	0.04	0.07	0.12	0.03	0.08
Max VIF	1.28	1.00	1.28	2.69	1.06	1.00	1.02

Note: * and ** denote significance at 5% and 1%. λ and δ in the regression $mps_t^{post} = \mu + \lambda FSI_t^{pre} + \delta skew_t^{pre} + u_t$ are reported. The standardized coefficients are reported (the variances of dependent and independent variables are equal to one). The HAC-robust t-statistics are enclosed in parentheses. With the same sample period (2000:01 - 2019:12), MPS, MPS_orth includes six unscheduled FOMC meetings with policy rate changes, while NS, Target and Path only consider scheduled meetings. The Max VIF reports the highest VIF statistics among all regressors.

We first verify that both financial variables, the financial stress index (FSI) and the Treasury skewness (TR_SKEW), are strong predictors of unprocessed monetary policy surprises (i.e., MPS and NS). These surprises are similarly constructed as the first principal component of a range of federal funds futures and Eurodollar contracts. The R-squared values for MPS and NS are 11% and 12%, respectively.

The target and path decomposition of the NS, following Gürkaynak et al. (2005), indicates that surprises in the interest rate target and the expected path of future interest rates are both negatively related to financial stress level. In other words, unanticipated dovish interest rate decisions and accommodative forward guidance accompany alleviated financial stress. However, only the path factor, not the target factor, reflects the Treasury skewness, with upside economic risk predicting hawkish surprises in interest rate guidance.

Bauer and Swanson (2023b) and Jarociński and Karadi (2020) provide two viable approaches to purge the predictability from monetary policy surprises. This is illustrated by the insignificant results in the columns of MPS_orth and JK_MP. It seems that the information content in the financial stress level vastly overlaps with that in the set of financial and economic variables listed in Bauer and Swanson (2023b) and information shocks identified in Jarociński and Karadi (2020).

We have a different interpretation of the component of monetary policy surprises that

move in the same direction as the equity market (i.e., JK_Info). Jarociński and Karadi (2020) identify JK_Info as the Fed's private information shock, which is unknown to investors before FOMC announcements. However, we find that it is strongly predictable by financial conditions before announcements, suggesting that its information content is not exclusive to the Fed but also available to financial markets.

6.1 The Hypothesis of Time-Varying Risk Premia

A potential criticism to the Fed's response to financial conditions may come from Miranda-Agrippino (2016). They argue that time-varying risk premia may drive the predictability of monetary policy surprises. This hypothesis posits that the information content in FOMC announcements could trigger a sudden movement in financial stress and in turn lead to a variation in the risk premia embedded in the policy rate or its expected path. Then an unanticipated monetary policy surprise emerges.

However, the empirical evidence presented contradicts the time-varying risk premia hypothesis. We consider a regression of the form

$$mps_t^{post} = \rho_1 \Delta FSI_t^{FOMC} + \rho_2 \Delta FSI_t^{FOMC+1} + e_t \tag{13}$$

where ΔFSI_t^{FOMC} and ΔFSI_t^{FOMC+1} denote the change of FSI index on the announcement day and that on the next day. Importantly, ρ_1 indicates the causality of concern while ρ_2 only represents correlation.

Table 3 presents the results for various measures of monetary policy surprises. None of the monetary policy surprises are caused by changes in the systematic risk perceived by financial markets, as measured by the daily change in the FSI index on the announcement date (ΔFSI_t^{FOMC}). In fact, the FSI barely fluctuates on announcement dates. In contrast, the movement of the FSI on the day following the announcement is highly correlated with the monetary policy surprise, exhibiting the expected sign. These results indicate that while financial stress does indeed decline following a dovish monetary policy surprise, this decline occurs not on the announcement day itself, but rather on the subsequent days. Therefore, the changes of financial stress following FOMC announcements appears to be a consequence, rather than a cause, of the monetary policy surprise, refuting the hypothesis that time-varying risk premia contribute to the emergence of policy surprises.

Our evidence that risk premia do not cause monetary policy surprises is consistent with the empirical arguments of Cieslak (2018) and Bauer and Swanson (2023a), who contend that the changes in risk premia would need to be implausibly large to explain the observed predictability. Similarly, Piazzesi and Swanson (2008) find that risk premia in federal funds

Table 3: Time-Varying Risk Premia

$$mps_t^{post} = \rho_1 \Delta FSI_t^{FOMC} + \rho_2 \Delta FSI_t^{FOMC+1} + e_t$$

	MPS	MPS_orth	JK_MP	JK_Info	NS
FSI_t^{FOMC}	-0.03	0.06	0.08	-0.05	0.09
	(-0.61)	(0.75)	(1.26)	(-0.48)	(1.40)
FSI_t^{FOMC+1}	0.37**	0.33**	0.31**	0.11	0.32**
	(4.75)	(4.01)	(3.13)	(1.16)	(3.33)
Obs.	169	169	169	169	163
R	0.13	0.12	0.10	0.00	0.12

Note: * and ** denote significance at 5% and 1%. $mps_t^{post} = \rho_1 \Delta FSI_t^{FOMC} + \rho_2 \Delta FSI_t^{FOMC+1} + e_t$ are reported. The standardized coefficients are reported (the variances of dependent and independent variables are equal to one). The HAC-robust t-statistics are enclosed in parentheses. With the same sample period (2000:01 - 2019:12), MPS and MPS_orth include six unscheduled FOMC meetings with policy rate changes, while NS only consider scheduled meetings. JK_MP and JK_Info have shorter sample ending in June 2019.

futures contracts are relatively small. To the other end, the results indicating that monetary policy surprises lead to variations in risk premia are consistent with a rapidly growing literature on the transmission of monetary policy through risk premia (Bernanke and Kuttner, 2005; Cochrane and Piazzesi, 2005; Hanson and Stein, 2015; Nakamura and Steinsson, 2018; Drechsler et al., 2018; Jarociński and Karadi, 2020; Lagos and Zhang, 2020; Bianchi et al., 2022; Pflueger and Rinaldi, 2022).

Given that monetary policy surprises are not attributable to market participants altering their risk preferences, the discrepancy must arise from another source, possibly the divergent views on how the Fed responds to financial conditions.

7 Rethinking the Fed's Response to News Effect

This section tests another implication of our model: after controlling for financial conditions, the market does not systematically misperceive how the Fed responds to distant economic news but miscalculate the policy response to close data releases. In comparison, the Fed's response to news explanation predicts that, if we control for financial conditions, both recent and distant economic data releases retain the predictive power.

7.1 The Partial Effect of Recent Economic News

Our first test focuses on the sign of the relationship between recent economic data releases and monetary policy surprises. Our model predicts that after controlling for financial conditions, recent economic surprises should have a negative relationship with monetary policy surprises. This contrasts with the Fed's response to news hypothesis, which would predict a positive relationship regardless of financial controls due to the Fed's more aggressive response to economic data than markets anticipate.

To evaluate this prediction, we assess the impact of real data releases on policy surprises controlling for financial conditions. Table 4 considers a parsimonious regression of the form

$$mps_t^{post} = \phi + \zeta real_t^{pre} + \theta FSI_t^{pre} + \iota skew_t^{pre} + \eta_t \tag{14}$$

where $real_t^{pre}$ denotes the real activity surprise index on the day before announcement dates. This additional variable captures the surprises in real macroeconomic data that is release on or right before FOMC meetings. Note that if multiple data releases may exert effect at date t, the weights for aggregation in the surprise index exhibit an intuitive time decay feature so that the impact of a surprise gradually fades over time.

Table 4: Predictability of Monetary Policy Surprises (High-Frequency Event Study)

$mps_t^{post} = \phi + \zeta real_t^{pre} + \theta FSI_t^{pre} + \iota skew_t^{pre} + \eta_t$							
	MPS	MPS_orth	JK_MP	JK_Info	NS	Target	Path
FSI	-0.30**	0.00	-0.22	-0.18*	-0.36**	-0.22*	-0.31**
	(-5.49)	(-0.06)	(-1.69)	(-2.32)	(-3.33)	(-2.24)	(-3.52)
TR_SKEW	0.21**	0.00	0.14*	0.12	0.20**	0.10	0.18
	(4.67)	(-0.05)	(2.15)	(1.68)	(2.62)	(1.39)	(1.93)
REAL_SURP	-0.19**	-0.28**	-0.21*	0.04	-0.17*	-0.08	-0.16**
	(-3.35)	(-4.98)	(-2.16)	(0.67)	(-2.37)	(-0.78)	(-2.78)
Obs	139	139	139	139	133	133	133
R2	0.13	0.06	0.07	0.05	0.16	0.05	0.12
Max VIF	1.84	1.69	2.71	3.77	3.67	1.81	1.65

Note: * and ** denote significance at 5% and 1%. ζ, θ and ι in the regression $mps_t^{post} = \phi + \zeta real_t^{pre} + \theta FSI_t^{pre} + \iota skew_t^{pre} + \eta_t$ are reported. The standardized coefficients are reported (the variances of dependent and independent variables are equal to one). The HAC-robust t-statistics are enclosed in parentheses. The real surprise series is only available since June 2003. With the same sample period (2003:06 - 2019:12), MPS and MPS_orth include six unscheduled FOMC meetings with policy rate changes, while NS, target and path only consider scheduled meetings. The Max VIF reports the highest VIF statistics among all regressors.

Table 4 reports that, across all monetary policy surprises except the target measure, a positive real activity surprise predicts a dovish monetary policy surprise.[7]. This finding contradicts the stabilizing role of monetary policy illustrated by the textbook monetary policy curve: i.e., the Fed needs to overshot the policy rate to contain the inflation. In addition to the scheduled FOMC announcements included in the Nakamura-Steinsson measure, the MPS and MPS_orth measures further includes those critical unscheduled FOMC meetings. It appears that real activity surprises do a better job in predicting monetary policy surprises in those unscheduled ones compared to those scheduled FOMC announcements.

When comparing the two approaches to purging the predictability of monetary policy surprises, we notice that the Bauer and Swanson (2023b) orthogonalized MPS (MPS_orth) is still predicted by real activity surprises, while the Jarocinski-Karadi (JK) monetary policy shock (JK_MP) is less explained by real activity surprises. This implies that the JK approach is more effective in isolating the unpredictable component of monetary policy surprises.

Comparing the results of the target and path factors, we find that all three predictors have a stronger inference on the path factor than on the target factor. This implies that financial conditions and economic news are more strongly reflected in the expected path of future interest rates than in the immediate target rate decision.

The FSI remains a strong predictor of monetary policy surprises across most measures, with negative coefficients indicating that higher financial stress is associated with more dovish monetary policy surprises.

Importantly, we do not observe the Fed's excessive response to economic news after the financial conditions is accounted.

7.2 Fed Wait and See Strategy for New Data Release

The negative coefficient on real activity surprises suggests that the Fed adopts a wait-and-see approach to recent economic data releases ($X^{pre}_{1,t}$). Specifically, upon a positive real activity surprise, investors might swiftly adjust expectations, looking for a tighter monetary policy. The Fed, instead, maintains its current position. It prefers to await further evidence to confirm the economic trajectory. This very mismatch between market expectations and the Fed's actual response can result in what appears as an unexpected easing by the Fed. By examining the timing of real activity surprises relative to FOMC announcements, we can further confirm this temporal element of the Fed's reaction function directly.

We investigate the time frame over which the Fed incorporates real activity surprises into

[7] In an unreported test, the results are robust to the alternative indicator of financial stress – Gilchrist et al. (2022) daily excess bond premium

Table 5: Fed Wait and See Strategy

$\zeta_j: \ mps_t^{post} = \phi + \theta FSI_t^{pre} + \iota skew_t^{pre} + \zeta_j real_{t,j}^{pre} + \eta_t$						
j=	1	3	7	14	21	28
MPS	-0.24**	-0.06**	-0.25**	-0.31**	-0.03	0.02
	(-3.35)	(-5.51)	(-2.48)	(-4.27)	(-0.27)	(0.50)
JK_MP	-0.33*	-0.29**	-0.08	-0.20**	-0.02	-0.05
	(-2.16)	(-2.08)	(-0.75)	(-2.72)	(-0.31)	(-0.71)
NS	-5.09*	-3.80*	0.01	-4.20*	1.09	1.33
	(-2.37)	(-2.61)	(0.01)	(-2.53)	(0.34)	(1.24)
Path	-4.66**	-4.44*	0.51	-4.44*	3.15	2.32
	(-2.78)	(-2.55)	(0.21)	(-2.03)	(0.84)	(1.41)

Note: * and ** denote significance at 5% and 1%. ζ_j in the regression $mps_t = \phi + \theta FSI_{t-1} + \iota skew_{t-} + \zeta_j real_{t-j} + \eta_t$ are reported with different value of j. j denotes how many days before a FOMC announcment the real activity surprise is released. MPS includes the unscheduled FOMC meetings but NS and Path does not. The HAC-robust t-statistics are enclosed in parentheses.

its monetary policy decisions in the form

$$mps_t^{post} = \phi + \theta FSI_t^{pre} + \iota skew_t^{pre} + \zeta_j real_{t,j}^{pre} + \eta_t \tag{15}$$

where $real_{t,j}^{pre}$ denotes the real activity surprise j days before each FOMC announcement and other variables are identical to those in the previous equation. The coefficient ζ_j captures the Fed's responsiveness to real activity surprises incurred j days before an announcement.

Given the symmetric information of real activity surprises, the question of concern is when the Fed and the public incorporate new information into their monetary policy decisions and expectations, respectively. For a given positive real activity surprise released at time j days before announcement t, we consider three possible scenarios:

- If both the Fed and the market fully incorporate the surprise or if the Fed responds more aggressively (as the "Fed response to news" effect suggests), we should observe either an insignificant or positive ζ_j. The coefficient would not be negative in either case.

- If the Fed incorporates the news while markets fail to price it in, the positive real activity surprise would lead to a positive monetary policy surprise ($\zeta_j > 0$).

- If the Fed adopts a "wait-and-see" approach while the market overestimates the expected interest rate hike, this miscalibration would cause an unexpected monetary

easing, leading to $\zeta_j < 0$. Until the Fed fully responds, so ζ_j where j is large would be a zero.

Table 5 presents the estimates of ζ_j for alternative measures of monetary policy surprises and real activity surprises at different time lags (ranging from one day to four weeks). The results indicate that for real activity surprises within two weeks before an FOMC announcement, the coefficients ζ_j are significant and negative across all measures of monetary policy surprises. This finding reveals that the Fed's "wait-and-see" approach is not fully anticipated by financial markets. Notably, the results are more pronounced for the MPS measure, which includes unscheduled FOMC meetings, compared to the NS measure. This difference suggests that unscheduled meetings may be more focused on addressing concerns about future economic developments rather than reacting to the most recent realized economic data.

Interestingly, the negative relationship between real activity surprises and monetary policy surprises dissipates for real surprises occurring more than two weeks before an FOMC announcement. This pattern indicates that the Fed does eventually incorporate older economic data into its policy decisions, as anticipated by financial markets. For real activity surprises three weeks or earlier from FOMC announcements, the coefficients ζ_j become insignificant and even turn positive, consistent with the conventional view.

As a robustness check, we match the timing of financial stress index with that of the real data surprise and summarize the results in Table 6. In this sense, the $FSI^{pre}_{t,j}$ does not contain information of real surprises from 0 to j days before an announcements and thus the regression in Table 6 constitutes a clearer inference on $real_{t,j}$. The overall results are consistent – no evidence of the Fed's responding to real surprises released within two weeks before an announcement. Focus on those scheduled meetings, NS measure particularly demonstrates the process of wait and see strategy: the negative coefficient of real surprise in the first two weeks (14 days) prior to an announcement suggests that, unlike what the market expects, the Fed does not incorporate the most recent real news into its decision; the positive coefficient in the third week and significant positive result in the fourth week indicate that the Fed prudentially responds to real news and when they respond, they tend to be more aggressive than market anticipates, manifesting the Fed's response to news effect.

Our results provide support for the Fed's wait and see scheme for adjacent economic news rather than the aggressively response. As to relatively distant economic data, the markets are capable to predict its impact on policy decisions.

Table 6: Fed Wait and See Strategy
(Match Timing of FSI and Real Surprises)

ζ_j : $mps_t^{post} = \phi + \theta_j FSI_{t,j}^{pre} + \iota skew_t^{pre} + \zeta_j real_{t,j}^{pre} + \eta_t$					
j=	1	7	14	21	28
MPS	-0.31**	-0.07**	-0.26**	-0.02	0.04
	(-3.35)	(-3.11)	(-4.06)	(-0.10)	(1.32)
JK_MP	-0.33*	-0.16	-0.33*	-0.03	-0.05
	(-1.96)	(-1.12)	(-2.45)	(-0.32)	(-0.58)
NS	-5.09*	-0.07	-4.37*	1.35	1.80*
	(-2.37)	(-0.06)	(-2.67)	(0.67)	(2.11)
Path	-4.66**	0.65	-4.46*	3.34	2.70
	(-2.78)	(0.25)	(-2.10)	(0.91)	(1.37)

Note: * and ** denote significance at 5% and 1%. ζ_j in the regression $mps_t^{post} = \phi + \theta_j FSI_{t,j}^{pre} + \iota skew_t^{pre} + \zeta_j real_{t,j}^{pre} + \eta_t$ are reported with different value of j. j denotes how many days before a FOMC announcement the real activity surprise is released. $FSI_{t,j}^{pre}$ instead of FSI_t^{pre} is specified in the model to avoid recent FSI index including the impact of $real_{t,j}^{pre}$. MPS includes the unscheduled FOMC meetings but NS and Path do not. The HAC-robust t-statistics are enclosed in parentheses.

7.3 The Information Sufficiency of the Financial Conditions

The third test is whether financial conditions are informationally sufficient for predicting monetary policy surprises. Our model predicts that once we control for financial conditions, other documented predictors, which are mostly distant from FOMC announcements and falls into $X_{2,t}^{pre}$, should lose their predictive power, as financial markets have already incorporated all relevant information.

We compare predictive power with and without controlling for financial conditions. We start with a baseline regression where monetary policy surprises are regressed directly onto Bauer and Swanson (2023b) predictors:

$$mps_t^{post} = \mu + B^{'} X_{2,t}^{pre} + \epsilon_t \tag{16}$$

Second, we tease out the components in those predictors that are explained by changing financial conditions and then regress monetary policy surprise onto the residuals as

$$X_{2,t}^{pre} = \tau S_t^{pre} + \upsilon skew_t^{pre} + e_t \tag{17}$$

$$mps_t^{post} = \phi + \chi e_t + \varepsilon_t \tag{18}$$

Table 7: Predictive Power of Bauer and Swanson (2023b) Predictors

Adj. R^2	MPS	JK_Info	NS	Target	Path
No Control	12.3%	7.7%	12.0%	3.4%	7.3%
Control	3.4%	0.0%	0.6%	0.7%	0.0%
Obs.	169	169	163	163	163

Note: The reported adjusted R^2 are based on HAC-robust standard deviations. "No Control" indicates the regression onto Bauer and Swanson (2023b) predictors, such as $mps_t^{post} = \mu + B' X_{2,t}^{pre} + \epsilon_t$. It has no control for the financial conditions. "Control" indicates the regression onto the same predictors purged from financial conditions, i.e., $X_{2,t}^{pre} = \tau S_t^{pre} + \upsilon skew_t^{pre} + e_t$ and $mps_t^{post} = \phi + \chi e_t + \varepsilon_t$. It controls for variations in financial conditions.

Table 7 reports the adjusted R^2 of both regressions. In the sample 2000:01 to 2019:12, those predictors bear strong predictive power on monetary policy surprises as shown in row "No Control". After purging the financial conditions from them, the predictive power evaporates. The highest adjusted R^2 (3.4%) is for the surprises including unscheduled meetings, while other cases were all below 1%. As to those regularly scheduled FOMC meetings included in the NS measure, financial conditions exhausted the predictability of monetary policy surprises.

This raises the question: Why do those predictors still have a tiny predictive power on MPS after controlling for financial fluctuations? To investigate this further, we take a granular look at Eurodollar futures one to four quarters out, whose high-frequency variations are used to compose monetary policy surprises. The regressions are similar to Equations (16) – (18) with the only difference being that the dependent variables are high-frequency surprises of Eurodollar contracts.

The upper panel of Table 8 shows results for all meetings, while the lower panel demonstrates those for scheduled meetings only. Consistent with what we find in Table 7, after accounting for the information from financial conditions, the explanatory power of those predictors dramatically declines. The residuals, after removing the influence of financial conditions, are predictive of the surprises in ED1 and ED2 contracts when unscheduled meetings are considered, while only the ED1 surprise is mildly explainable for scheduled meetings. This remaining predictability in the near-term Eurodollar contracts might be due to the Fed's wait-and-see strategy for new economic data as such strategy is more prominent in MPS than NS (as shown in Section 7.2) and its effect is parallel to the Fed's response to

Table 8: Predictive Power on Eurodollar Contracts

Raw predictors: $X_{2,t}^{pre}$					Residuals $e_t : X_{2,t}^{pre} = \tau FSI_t^{pre} + vskew_t^{pre} + e_t$				
	ED1	ED2	ED3	ED4		ED1	ED2	ED3	ED4
SP500_3M	23.86*	23.15*	20.16*	17.05*	SP500_3M	26.69	21.64	14.97	9.37
	(2.02)	(2.11)	(2.28)	(2.02)		(1.55)	(1.35)	(1.19)	(0.84)
SLOPE_3M	-1.88	-1.95	-1.86	-1.42	SLOPE_3M	-2.05	-1.91	-1.64	-1.09
	(-1.91)	(-1.81)	(-1.86)	(-1.48)		(-1.86)	(-1.46)	(-1.28)	(-0.90)
BCOM_3M	-3.71	1.19	5.88	9.10	BCOM_3M	-3.23	0.87	4.86	7.62
	(-0.58)	(0.21)	(1.10)	(1.41)		(-0.70)	(0.18)	(0.89)	(1.09)
NFP_12M	-0.11	-0.06	-0.06	-0.04	NFP_12M	0.02	-0.01	-0.06	-0.09
	(-0.42)	(-0.18)	(-0.17)	(-0.12)		(0.09)	(-0.02)	(-0.18)	(-0.28)
NFP_SURP	0.01	0.01	0.01	0.01	NFP_SURP	0.01	0.01	0.01	0.01
	(1.85)	(1.48)	(1.08)	(0.73)		(1.73)	(1.33)	(0.97)	(0.65)
obs.	169	169	169	169	obs.	169	169	169	169
R^2	12.0%	11.3%	10.1%	8.1%	R^2	7.3%	2.8%	0.0%	0.0%

Raw predictors:$X_{2,t}^{pre}$					Residuals $e_t : X_{2,t}^{pre} = \tau FSI_t^{pre} + vskew_t^{pre} + e_t$				
	ED1	ED2	ED3	ED4		ED1	ED2	ED3	ED4
SP500_3M	11.03	13.63*	16.73*	19.09*	SP500_3M	9.14	7.13	7.01	7.63
	(1.81)	(2.03)	(2.07)	(2.13)		(1.10)	(0.85)	(0.70)	(0.69)
SLOPE_3M	-0.91	-1.34*	-1.67*	-1.66	SLOPE_3M	-0.71	-0.88	-1.03	-0.91
	(-1.54)	(-2.13)	(-2.21)	(-1.88)		(-1.30)	(-1.12)	(-1.05)	(-0.81)
BCOM_3M	1.75	4.24	6.54	8.06	BCOM_3M	1.63	3.46	5.31	6.60
	(0.31)	(0.84)	(1.12)	(1.28)		(0.27)	(0.51)	(0.66)	(0.76)
NFP_12M	0.10	0.09	0.03	-0.02	NFP_12M	0.16	0.10	0.02	-0.05
	(0.60)	(0.38)	(0.10)	(-0.05)		(0.85)	(0.41)	(0.06)	(-0.16)
NFP_SURP	0.01	0.01	0.01	0.00	NFP_SURP	0.01	0.01	0.00	0.00
	(1.78)	(1.39)	(0.89)	(0.58)		(1.61)	(1.14)	(0.68)	(0.40)
obs.	163	163	163	163	obs.	163	163	163	163
R^2	9.2%	9.3%	8.7%	8.7%	R^2	3.7%	0.0%	0.0%	0.0%

Note: * and ** denote significance at 5% and 1%. The HAC-robust t-statistics are enclosed in parentheses. Left panels reports B in the regression onto Bauer and Swanson (2023b) predictors, such as $mps_t^{post} = \mu + B^{'} X_{2,t}^{pre} + \epsilon_t$ with no control for the financial conditions. Right panels reports coefficients χ in the regression onto the same predictors purged from financial conditions, i.e., $X_{2,t}^{pre} = \tau FSI_t^{pre} + vskew_t^{pre} + e_t$ and $mps_t^{post} = \phi + \chi e_t + \varepsilon_t$ with control for variations in financial conditions. Upper panels consider all FOMC meetings, while the lower panels consider scheduled meetings only.

financial condition[8].

In sum, we find limited evidence for the additional predictive power of documented predictors beyond the information in financial conditions.

7.4 Identification in Proxy-SVAR

This subsection explores the implications of our findings for macroeconomic modeling. We test whether monetary policy surprises purged of their correlation with financial conditions perform as well as or better than those purged using economic predictors in structural VAR identification.

We employ Nakamura and Steinsson (2018) high-frequency surprises (NS measure) as external instruments in a Proxy Structural Vector Autoregression (SVAR) framework.[9] The monetary policy variable is represented by the Wu and Xia (2016) shadow rate to accommodate the zero lower bound restriction. Our endogenous variables include industrial production (log), unemployment rate, Consumer Price Index (log), and a commodity price index. Except for the commodity index from the Commodity Research Bureau, all variables come from the St. Louis FRED Database, consistent with Coibion (2012) and Ramey (2016).

The VAR is estimated in levels with 12 lags from January 1995 to December 2023, while the identification sample covers January 2000 to December 2019. Responses are normalized for a 1% policy rate increase on impact. Figure 1 shows the impulse responses using three different instrument specifications: raw NS surprise (dashed yellow), NS surprise orthogonal to Bauer and Swanson (2023b) predictors (NS_BSorth, dark blue dash-dotted), and NS surprise orthogonal to financial conditions (NS_FCorth, red).

[8]However, including $real_t^{pre}$ reduces our sample, we include real surprises $real_t^{pre}$ in Equation (17) and rerun the regressions in an unreported test. Those three variables exhaust the predictive power of the listed predictors across all measures of policy surprises and Eurodollar contracts with the highest adjusted R^2 of 0.6%.

[9]We opt for the NS measure instead of the MPS measure because the former does not include unscheduled FOMC meetings and is less influenced by the Fed's wait-and-see strategy. This allows us to avoid orthogonalizing real economic surprises, which have a shorter sample period compared to the FSI and Treasury skewness.

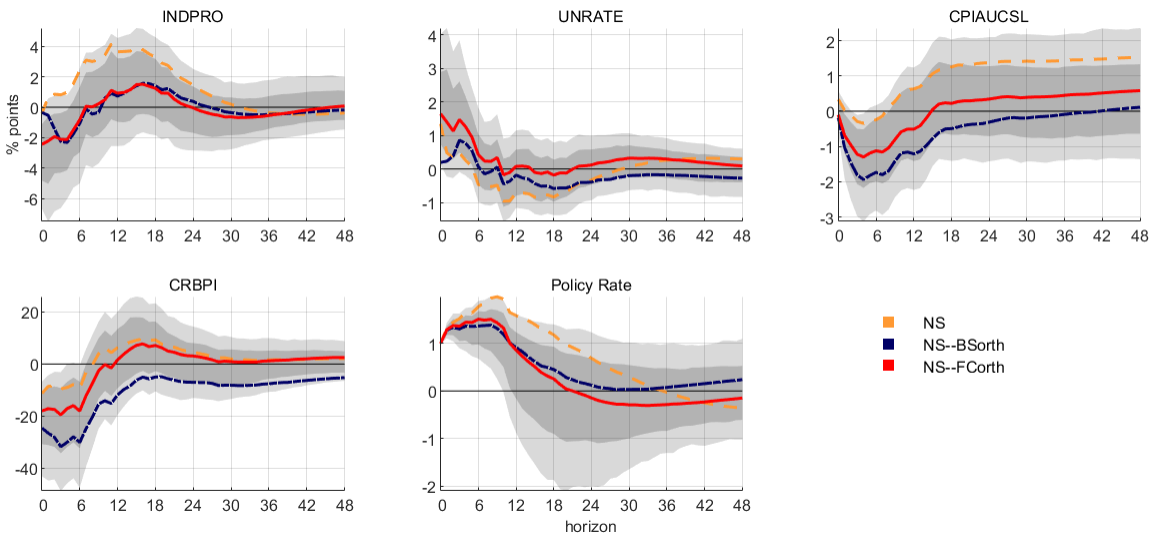

Figure 1: Impulse responses to monetary policy shocks in proxy SVAR

The disparities between the three identification schemes are notable. The impulse response functions (IRFs) derived from the raw NS measure lie outside the 68% confidence bands of NS_FCorth in most instances, particularly for the shorter horizons. The endogeneity/predictability issues highlighted for the raw measures, coupled with a small, presumably informationally deficient VAR, produce distorted and counterintuitive responses for both industrial production and the CPI price level. In contrast, the IRFs obtained from orthogonalized proxies are devoid of puzzling responses for all variables, exhibiting non-positive responses of industrial production, CPI, and commodity price levels, as well as a non-declining unemployment rate following a contractionary monetary policy shock. In the shorter horizons, surprises orthogonal to financial conditions constitute a more suitable proxy compared to the BS measure, as they generate more conventional real responses to the same policy tightening, such as a contractionary output gap and an increase in cyclical unemployment. It is worth noting that the sample includes the two periods restricted by the zero lower bound, and the Wu and Xia (2016) shadow rate is often associated with price and output puzzles when used as the policy indicator in monetary SVAR models. However, no puzzles are observed in the cases utilizing orthogonalized proxies.

The results suggest that financial conditions contain information content for monetary policy shock identification that is comparable to, and potentially superior to, other documented predictors. Purging variations in financial conditions proves sufficient to approximate a conventional monetary policy shock that is free of output and price puzzles.

This section exhibits evidence supporting the Fed's response to financial conditions and

refuting the response to news effect. First, the Fed does not instantly respond to new real surprises so that a negative partial effect is found with no sign of over-reacting to economic news. Second, controlling for financial fluctuations, previously documented predictors lose all or most of their predictive power of monetary policy surprises, suggesting the response to distant economic news is learned by markets. Third, policy surprises purged of those predictors do not appear to constitute better external instruments than those purged of financial conditions in identification of monetary policy shocks in structural VAR models.

8 Conclusion

This paper reconciles the persistent predictability of monetary policy surprises with the long-term efficiency of financial markets: i.e., markets can learn efficiently but may misunderstand the Fed's insufficiently communicated approach to achieve its goals. We demonstrate that the Fed responds systematically to financial conditions to achieve its policy goals rather than instantly reacting to new economic data releases. When market participants take the Fed's policy goals literally and presume that the Fed responds directly to economic data, this creates the predictable component of monetary policy surprises.

Our theoretical model identifies three distinct market blind spots that are stem from the under-disclosed response to financial conditions. 1) Markets underestimate how the Fed learns from their own policy expectations. 2) They overlook the varying connection between financial conditions and economic outcomes. 3) They also miss the Fed's inevitable response to financial stress shocks. These oversights produce testable predictions that set our explanation apart from competing theories.

We test these predictions with high-frequency data on financial stress, Treasury yield skewness, and real economic surprises. The evidence strongly supports our "Fed's response to financial conditions" explanation. All or most information in previously documented predictors already exists in financial markets before FOMC announcements – a fact indicates that the predictive power is not stem from the Fed's private information. Financial stress remains stable on announcement days, which challenges the time-varying risk premia hypothesis. When we control for financial conditions, recent economic data shows a negative relationship with monetary policy surprises, and other predictors that are not closely adjacent to the announcements lose their predictive power completely. This implies that the Fed's "wait-and-see" approach to close economic data release and the private sector can predict the policy reaction to relatively remote news, opposing the Fed's aggressive response to economic news.

Our model and findings might reshape the understanding of monetary policy mecha-

nisms and offer tangible guidance for identifying exogenous policy shocks. To isolate pure policy shocks, we recommend that researchers purge surprises of their correlation with pre-announcement financial conditions. When an analysis includes unscheduled meetings, where the impact of the "wait-and-see" strategy is more pronounced, an additional refinement is warranted: controlling for recent real activity surprises. Importantly, our results show that, after accounting for financial information and real surprises, purging other economic predictors offers little additional benefit. Financial markets overall serve as critical conduits for transmitting economic information to the Fed. We hope that this research advances the debate on monetary policy surprise predictability by providing an institutional explanation that does not contradict to long-term market efficiency.

References

Adrian, T. and N. Liang (2016): "Monetary policy, financial conditions, and financial stability," Publisher: CEPR Discussion Paper No. DP11394.

Bauer, M. and M. Chernov (2024): "Interest rate skewness and biased beliefs," *The Journal of Finance*, 79, 173–217, iSBN: 0022-1082 Publisher: Wiley Online Library.

Bauer, M. D., B. S. Bernanke, and E. Milstein (2023): "Risk appetite and the risk-taking channel of monetary policy," *Journal of Economic Perspectives*, 37, 77–100, iSBN: 0895-3309 Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2418.

Bauer, M. D. and E. T. Swanson (2023a): "An alternative explanation for the "fed information effect"," *American Economic Review*, 113, 664–700, iSBN: 0002-8282 Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

——— (2023b): "A reassessment of monetary policy surprises and high-frequency identification," *NBER Macroeconomics Annual*, 37, 87–155, iSBN: 0889-3365 Publisher: The University of Chicago Press Chicago, IL.

Bernanke, B. S. and K. N. Kuttner (2005): "What explains the stock market's reaction to Federal Reserve policy?" *The Journal of finance*, 60, 1221–1257, iSBN: 0022-1082 Publisher: Wiley Online Library.

Bianchi, F., M. Lettau, and S. C. Ludvigson (2022): "Monetary policy and asset valuation," *The Journal of Finance*, 77, 967–1017, iSBN: 0022-1082 Publisher: Wiley Online Library.

Brunnermeier, M., D. Palia, K. A. Sastry, and C. A. Sims (2021): "Feedbacks: financial markets and economic activity," *American Economic Review*, 111, 1845–1879, publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Caballero, R. J., T. E. Caravello, and A. Simsek (2024): "Financial Conditions Targeting," Tech. rep., National Bureau of Economic Research.

Caldara, D. and E. Herbst (2019): "Monetary policy, real activity, and credit spreads: Evidence from Bayesian proxy SVARs," *American Economic Journal: Macroeconomics*, 11, 157–192, publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425.

Campbell, J. R., C. L. Evans, J. D. Fisher, A. Justiniano, C. W. Calomiris, and M. Woodford (2012): "Macroeconomic effects of federal reserve forward guidance [with comments and discussion]," *Brookings papers on economic activity*, 1–80, iSBN: 0007-2303 Publisher: JSTOR.

Cieslak, A. (2018): "Short-rate expectations and unexpected returns in treasury bonds," *The Review of Financial Studies*, 31, 3265–3306, iSBN: 0893-9454 Publisher: Oxford University Press.

Cieslak, A. and A. Schrimpf (2019): "Non-monetary news in central bank communication," *Journal of International Economics*, 118, 293–315, iSBN: 0022-1996 Publisher: Elsevier.

Cieslak, A. and A. Vissing-Jorgensen (2021): "The economics of the Fed put," *The Review of Financial Studies*, 34, 4045–4089, iSBN: 0893-9454 Publisher: Oxford University Press.

Cochrane, J. H. and M. Piazzesi (2005): "Bond risk premia," *American economic review*, 95, 138–160, iSBN: 0002-8282 Publisher: American Economic Association.

Coibion, O. (2012): "Are the effects of monetary policy shocks big or small?" *American Economic Journal: Macroeconomics*, 4, 1–32, iSBN: 1945-7707 Publisher: American Economic Association.

Drechsler, I., A. Savov, and P. Schnabl (2018): "A model of monetary policy and risk premia," *The Journal of Finance*, 73, 317–373, iSBN: 0022-1082 Publisher: Wiley Online Library.

Faust, J., E. T. Swanson, and J. H. Wright (2004): "Do Federal Reserve policy surprises reveal superior information about the economy?" *Contributions in Macroeconomics*, 4, 20121011, iSBN: 1534-6005 Publisher: De Gruyter.

Gertler, M. and P. Karadi (2015): "Monetary policy surprises, credit costs, and economic activity," *American Economic Journal: Macroeconomics*, 7, 44–76, iSBN: 1945-7707 Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425.

Gilchrist, S., B. Wei, V. Z. Yue, and E. Zakrajšek (2022): "Sovereign risk and financial risk," *Journal of International Economics*, 136, 103603, iSBN: 0022-1996 Publisher: Elsevier.

Gürkaynak, R. S., B. Sack, and E. Swanson (2005): "The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models," *American economic review*, 95, 425–436, iSBN: 0002-8282 Publisher: American Economic Association.

Gürkaynak, R. S., B. Sack, and J. H. Wright (2007): "The US Treasury yield curve: 1961 to the present," *Journal of monetary Economics*, 54, 2291–2304, iSBN: 0304-3932 Publisher: Elsevier.

Hakkio, C. S. and W. R. Keeton (2009): "Financial stress: What is it, how can it be measured, and why does it matter," *Economic Review*, 94, 5–50, publisher: Citeseer.

Hanson, S. G. and J. C. Stein (2015): "Monetary policy and long-term real rates," *Journal of Financial Economics*, 115, 429–448, iSBN: 0304-405X Publisher: Elsevier.

Hatzius, J., P. Hooper, F. S. Mishkin, K. L. Schoenholtz, and M. W. Watson (2010): "Financial conditions indexes: A fresh look after the financial crisis," Tech. rep., National Bureau of Economic Research.

Jarociński, M. and P. Karadi (2020): "Deconstructing monetary policy surprises—the role of information shocks," *American Economic Journal: Macroeconomics*, 12, 1–43, iSBN: 1945-7707 Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425.

Kilian, L. and Y. J. Kim (2011): "How reliable are local projection estimators of impulse responses?" *Review of Economics and Statistics*, 93, 1460–1466, publisher: The MIT Press.

Kliesen, K. L. and D. C. Smith (2010): "Measuring financial market stress," *economic synopses*, publisher: Federal Reserve Bank of St. Louis.

Kuttner, K. N. (2001): "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market," *Journal of monetary economics*, 47, 523–544, iSBN: 0304-3932 Publisher: Elsevier.

Lagos, R. and S. Zhang (2020): "Turnover liquidity and the transmission of monetary policy," *American Economic Review*, 110, 1635–1672, iSBN: 0002-8282 Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Lunsford, K. G. (2020): "Policy language and information effects in the early days of Federal Reserve forward guidance," *American Economic Review*, 110, 2899–2934, iSBN: 0002-8282 Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Miranda-Agrippino, S. (2016): "Unsurprising shocks: information, premia, and the monetary transmission," Publisher: Bank of England working paper.

Miranda-Agrippino, S. and G. Ricco (2021): "The transmission of monetary policy shocks," *American Economic Journal: Macroeconomics*, 13, 74–107, iSBN: 1945-7707 Publisher: American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425.

Monin, P. J. (2019): "The OFR financial stress index," *Risks*, 7, 25, iSBN: 2227-9091 Publisher: MDPI.

Nakamura, E. and J. Steinsson (2018): "High-frequency identification of monetary non-neutrality: the information effect," *The Quarterly Journal of Economics*, 133, 1283–1330, iSBN: 0033-5533 Publisher: Oxford University Press.

Pflueger, C. and G. Rinaldi (2022): "Why does the fed move markets so much? a model of monetary policy and time-varying risk aversion," *Journal of Financial Economics*, 146, 71–89, iSBN: 0304-405X Publisher: Elsevier.

Piazzesi, M. and E. T. Swanson (2008): "Futures prices as risk-adjusted forecasts of monetary policy," *Journal of Monetary Economics*, 55, 677–691, iSBN: 0304-3932 Publisher: Elsevier.

Plagborg-Møller, M. and C. K. Wolf (2021): "Local projections and VARs estimate the same impulse responses," *Econometrica*, 89, 955–980, publisher: Wiley Online Library.

Ramey, V. A. (2016): "Macroeconomic shocks and their propagation," *Handbook of macroeconomics*, 2, 71–162, iSBN: 1574-0048 Publisher: Elsevier.

Romer, C. D. and D. H. Romer (2000): "Federal Reserve information and the behavior of interest rates," *American economic review*, 90, 429–457, iSBN: 0002-8282 Publisher: American Economic Association.

Sastry, K. (2022): "Disagreement about monetary policy," *Available at SSRN 3421723*.

Schmeling, M., A. Schrimpf, and S. A. Steffensen (2022): "Monetary policy expectation errors," *Journal of Financial Economics*, 146, 841–858, iSBN: 0304-405X Publisher: Elsevier.

Scotti, C. (2016): "Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises," *Journal of Monetary Economics*, 82, 1–19, iSBN: 0304-3932 Publisher: Elsevier.

Wu, J. C. and F. D. Xia (2016): "Measuring the macroeconomic impact of monetary policy at the zero lower bound," *Journal of Money, Credit and Banking*, 48, 253–291, iSBN: 0022-2879 Publisher: Wiley Online Library.