Fed Implied Market Prices and Risk Premia

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Abstract

We introduce FDIF, a measure of Fed communication surprise based on the text of FOMC statements. FDIF measures the difference between text-implied and actual values of key market variables. Positive FDIF of countercyclical variables (e.g., credit spreads) is associated with negative macroeconomic forecast revisions; the opposite holds for procyclical variables. Industries that hedge bad FDIF news earn low returns on FOMC announcement days, but high returns on non-FOMC days. The opposite holds for FDIF-exposed industries, and the return differences are large. Controlling for FDIF exposure, rate-based policy surprise measures are not priced in the cross-section of industry returns.

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Keywords: Monetary policy, asset pricing, text data, market expectations

The Online Appendix is available at https://sites.google.com/view/hmamaysky/research
The FDIF measures are available at https://sites.google.com/view/hmamaysky/data

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> "As long as the current overnight rate is stuck at or near zero, central bank communication about expected future rates becomes the essence of monetary policy."
>
> Blinder et al. (2008)

1 Introduction

The traditional instrument of monetary policy is the short-term rate at which central banks are willing to lend or borrow funds. Short-term interest rates respond to changing expectations about future policy rates, and market fluctuations in short-term rates thus convey information about future central bank monetary policy. Bernanke and Kuttner (2005) propose that Fed policy surprises can be measured by the change in Fed fund futures on the day of Fed policy announcements. A large literature, including Gürkaynak et al. (2005), Hanson and Stein (2015), and Nakamura and Steinsson (2018), extends their approach by looking at higher frequency changes and changes in other short-term interest rate instruments.

Figure 1 shows the evolution of the Fed funds target rate over the last several decades. The global financial crisis (GFC) of 2008–2009 pushed the target rate to its zero lower bound, where it then stayed for many years. A similar phenomenon occurred globally. With their main policy instruments thus constrained, central banks resorted to unconventional monetary policy, such as quantitative easing, asset purchases, and forward guidance. Information about these cannot be gleaned from the unchanging level of short-rates. However, news about central bankers' policy intent *can* be obtained from central bank speeches, statements, minutes, and press conferences. Systematic analysis of such central bank communications, which emerged as a field in the early 2000s, has taken on additional urgency in the low-interest rate regime. Even when interest rates are not constrained, changes in interest rates alone may not contain all the useful information available about central bank beliefs and intentions. That is especially true if central banks consciously use guidance, in addition to interest rate changes, as one of their policy tools.

Further, Fed communication not only provides news about monetary policy, it also contains information about the Fed's view of the state of the economy, and some combination of this information may not be known by the market in advance of Fed communications. Thus Fed communications can affect immediate market prices and predict future macroeconomic changes both because they communicate information about changes in

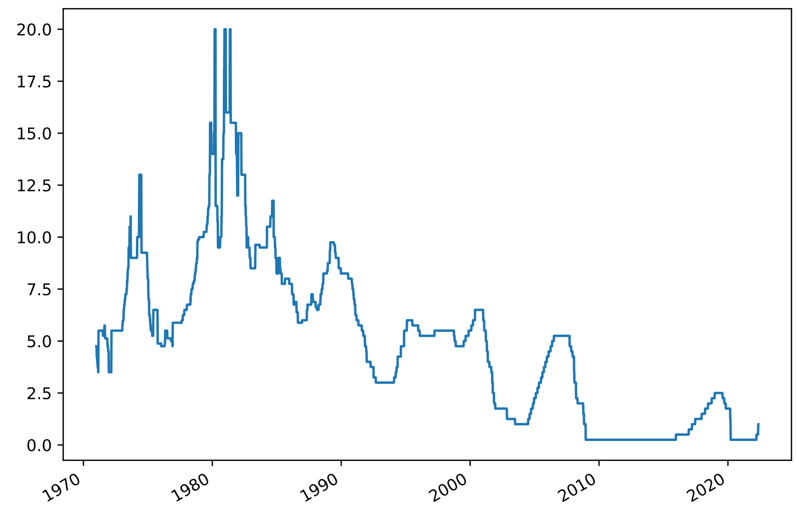

Figure 1: Fed funds target rate

Fed policy thinking and because they communicate information about the economy.

Early attempts to understand the impact of central bank communications, documented in Blinder et al. (2008), involved a manual scoring of written or spoken central bank communications as being dovish or hawkish, accompanied by an analysis of the impact of such measures on economic or market outcomes. This process, while a natural starting point, is subjective and cumbersome. Over the subsequent decade, researchers applied tools from natural language processing (NLP) to count the frequency of either dovish or hawkish words or phrases in central bank communications, thus automating the tone scoring process.[1] This method solved the slow throughput problem of hand-coding, but retained some element of subjectivity because the dovish and hawkish classification of words had to be imparted by the researchers themselves. These second-generation methods introduced a new problem: they lacked context. "Inflation" can be hawkish, but "lower than expected inflation" has the opposite meaning.[2] Finally, NLP models typically use unchanging measures of word flow to capture meaning, but the meaning of words changes over time, depending on the policy context, and new policy-relevant words come into existence. For example, "quantitative easing" is an important expression after the 2008 crisis, but was absent previously.

The insight of the present paper begins with the recognition that market prices contain information about central bank language, both its tone and context. Blinder et al. (2008) argue that market prices should depend on the information investors have about the

[1]See, for instance, Rosa (2013); Apel and Grimaldi (2014); Neuhierl and Weber (2019).

[2]Apel and Grimaldi (2012) and Tadle (2022) account for context in a limited way by introducing modifying words (e.g., "falling") that can change the tone of concept words (e.g., "unemployment").

economy (inflation, output, etc.) and a vector s_t of central bank signals (such as numerical inflation targets, or central bank language). It follows that market prices should be linked to the information contained in Fed communications that leads market participants to update their forecasts about the economy. In this paper, we provide such a mapping, focusing on the prices of seven major asset classes: the VIX index of short-term implied volatility of S&P 500 options, ten-year Treasury yields, the 2s10s curve (the difference between Treasury ten- and two-year yields), the three-month Treasury yield, the DXY dollar index whose value reflects the foreign currency price of the dollar (i.e., a higher DXY means the dollar has gained value against a basket of foreign currencies), and high yield and investment-grade corporate credit spread indexes.[3] What is required for Fed communication to impact the valuation of these asset classes?

Absence of arbitrage in securities markets implies that $P_t = \mathsf{E}_t[m_{t+1}(P_{t+1} + D_{t+1})]$ for any stochastic discount factor (SDF) m_{t+1} (see Cochrane 2009), where P_t is the time t security price and D_t is the time t dividend. From this, it is straightforward to show that

$$P_t = \frac{\mathsf{E}_t[P_{t+1} + D_{t+1}]}{1 + r_{f,t}} + \mathsf{cov}_t(m_{t+1}, P_{t+1} + D_{t+1}). \tag{1}$$

A security will trade below its expected discounted value, and have positive expected excess returns, if and only if its cum dividend payout covaries negatively with the SDF.

According to (1), the price P_t will be impacted by variation in s_t (in our example, a measure of Fed communication) if the latter is useful for forecasting future dividends or the future covariance between the SDF and security payouts (and thus the risk discount). The covariance term will be predictable if s_t can forecast future volatility of either the SDF or of security payouts, or the future correlation between the two. These mild conditions then justify the following decomposition. Consider the VIX, whose level is a function of S&P 500 option prices. If option prices are impacted by Fed communication and other, orthogonal information, we can write

$$VIX_t = f_t^{VIX}(s_t, \eta_t), \tag{2}$$

where η_t is a mean-zero (the mean is captured by f_t^{VIX}) vector of information orthogonal to s_t. The mapping f_t^{VIX} has a t subscript to indicate that such relationships are time-varying, which would occur if, for example, the functional form of conditional expectations changes over time.

[3]We exclude non-stationary series, like S&P 500 prices, as we explain shortly.

We propose to measure s_t using the text of Fed statements and minutes and to estimate f_t^{VIX} in rolling windows using a support vector regression (SVR). Armed with $\hat{f}_{t^-}^{VIX}$, estimated using information strictly prior to announcement day t, and s_t, we can calculate the level of the VIX implied by a Fed communication, assuming other variables are set to their long-run means:

$$VIX_t^{FED} = \hat{f}_{t^-}^{VIX}(s_t, 0).$$

This is preferable to using the closing level of the VIX as an indicator of Fed news on a Fed announcement day because the latter is contaminated by η_t. Our methodology allows us to obtain a "clean" measure of the VIX which reflects only Fed information. The mapping $\hat{f}_{t^-}^{VIX}$ recovers word tone as it is relevant for the VIX, and because s_t can contain the entirety of the Fed's communication, $\hat{f}_{t^-}^{VIX}$ can partially account for word context. We refer to VIX_t^{FED} as the Fed-implied VIX.

It is likely however that different components of the Fed's signal s_t are more or less relevant for different market variables. For example, while inflation talk may impact the VIX, it may be relatively more important for the determination of the 2s10s curve. To capture these additional dimensions of the Fed's signal s_t, we use a similar estimation procedure for our remaining six asset classes. For each of these market series we estimate its own SVR-based rolling $\hat{f}_{t^-}^{V}$, where V is the market variable in question (required to be stationary for the estimation of eq. 2). $\hat{f}_{t^-}^{V}$ yields domain-specific word tonality which captures the market implications of Fed word use for each market series V.

We show in Section 3.3 that the difference between the Fed-implied market variable on Fed announcement day t and the closing level of that same variable on the prior day measures the market's surprise about the Fed signal.[4] For example, for the VIX, our surprise measure is

$$FDIF_t^{VIX} = VIX_t^{FED} - VIX_{t-1}. \tag{3}$$

More generally, when referencing a market variable V we will write $FDIF_t^V$, and refer to this as the *Fed diff* measure. Because this measure uses the prior day's value of market variable V and because the Fed-market mapping is already known prior to the Fed communication day, FDIF avoids endogeneity issues that plague market-based measures of Fed communications surprise. A formal decomposition of FDIF into three components – communications surprises, model surprises, and measurement error – roughly along the lines of Bauer and Swanson (2021) provides motivation for our empirical tests, which show

[4]We ran an alternative specification using the mean closing level of V over the two days before the statement is released instead of V_{t-1} and found the results to be essentially unchanged.

the communications surprise component of FDIF to be a key driver of Fed risk pricing.

Our empirical analysis shows that Fed diff variables are associated with contemporaneous revisions in a cross-section of macroeconomic forecasts that we obtain from the Philadelphia Fed's Survey of Professional Forecasters (SPF). Positive innovations in Fed diff measures derived from countercyclical market variables (e.g., credit spreads) are associated with negative revisions in macroeconomic forecasts, while positive innovations in Fed diff measures derived from procyclical market variables (e.g., the level of interest rates) are associated with positive macroeconomic forecast revisions. The first principal component of our seven Fed diff variables is also associated with contemporaneous changes in SPF forecasts, but is not uniformly more informative than individual Fed diff measures for specific survey components. A single-dimensional measure of Fed policy surprise is therefore unlikely to capture all relevant information contained in the cross-section of the Fed diff variables.

We next employ our Fed diff measures to analyze the extent to which Fed risk is priced in markets. If our Fed diff measures capture important macroeconomic news – either about the state of the macroeconomy or about monetary policy – that are not known to the market beforehand, then exposure to Fed diff risk should be priced. We focus on the returns of 49 value-weighted U.S. industry portfolios obtained from Ken French's website. An advantage of using industry portfolios rather than individual stocks is that, as Fama and French (1997) point out, industry-level risk loadings are more precisely estimated than firm-level ones. Given that Fed risk can be measured only when the Fed communicates with the market, these more precisely estimated factor loadings are particularly appealing. We find that Fed risk has dramatically different effects on different industries (e.g., utilities behave very differently from coal miners) suggesting that firm-level Fed risk (analyzed in Ozdagli and Velikov 2020 and Ai et al. 2022) contains a strong industry component.

Using these 49 industry portfolios we perform a Fama and MacBeth (1973) analysis with first-stage betas that reflect the covariance between industry returns and Fed diff measure on FOMC announcement days. We document strong evidence that each of our seven Fed diff variables is a priced risk for the cross-section of industry returns on Fed announcement dates. Countercyclical Fed diff variables, which are associated with negative macroeconomic forecast revisions (e.g. credit spreads), command a negative price of risk, suggesting that industries which help hedge adverse macroeconomic news on Fed announcement days earn negative returns on those days on average. Procyclical Fed diff variables, associated with good macroeconomic news, command positive risk premia. These results are consistent with a consumption-based asset pricing explanation:

FOMC announcement days are associated with important macroeconomic news releases; securities which allow investors to hedge against bad news act as insurance and offer low average returns; securities which are exposed to bad economic news are risky and earn high returns.

In robustness tests, Fed diff variables remain a priced risk even when we control for (1) the lagged value of the market variable associated with the respective Fed diff measure and (2) traditional, interest-rate based measures of Fed policy surprise (such as changes in Fed fund futures as in Bernanke and Kuttner 2005 and changes in two-year yields as in Hanson and Stein 2015). Fed diff measures capture Fed news risk more effectively than do traditional rate-based measures.

We classify as "Fed-risky" those industries that have, on average, positive (negative) loadings on Fed diff measures with a positive (negative) price of risk. Industries with positive (negative) loadings on Fed diff variables with a negative (positive) price of risk are classified as "Fed-safe". Our industry classification uses information from all seven Fed diff measures to reflect multiple dimensions of Fed monetary policy communications. By construction, Fed-risky (safe) industries, on average, do well (poorly) on Fed announcement dates. An examination of these industries shows that Fed-risky industries are highly cyclical, including those exposed to commodity or housing-related businesses. Fed-safe industries consist of staples like food and utilities, as well as growth sectors like software and medical equipment. Fed-safe and risky industry classifications are stable over time.

While Fed-risky industries outperform Fed-safe industries on Fed announcement dates, the effect is reversed on all other trading days, during which Fed-risky industries strongly underperform Fed-safe industries. A long-short strategy that goes long Fed-risky industries and short Fed-safe industries on announcement dates, but reverses the position on all other trading days, earns an annual risk premium of 7.5% (9%) in the full (late) sample. Though this trading strategy has high turnover, its large economic magnitude suggests that exposure to Fed risk is an important determinant of industry-level returns.

In contrast, when we measure our Fed diff variable on Fed minutes release dates, we find no evidence of priced risk, even though the information content of minutes-based Fed diff variables for SPF forecast revisions is similar to that of the Fed diff variables derived from statements. News about FOMC meetings is largely learned when FOMC statements are released; minutes provide more detail three weeks later, but apparently not enough to cause large market responses.

1.1 Relation to the Literature

The present paper presents an alternative approach to traditional, interest-rate based measures of monetary policy. Our Fed diff measure captures multiple dimensions of Fed communications and drives out rate-based measures, such as Bernanke and Kuttner (2005) and Hanson and Stein (2015), as proxies for priced Fed risk. The paper is part of a growing literature that applies NLP tools to central bank communications. Many papers use dictionary-based methods where researchers identify the tone of words a priori, and use these to measure the tone of central bank communications: Apel and Grimaldi (2012), Correa et al. (2017), Goldfarb et al. (2005), Lucca and Trebbi (2009), Schmeling and Wagner (2019), Sharpe et al. (2017), Stekler and Symington (2016), and Tadle (2022). We build on these methods by estimating the implications of words directly from the relationship between Fed communication and market variables. Furthermore, we control for most words in Fed communications, thus partially capturing context, and also allow the impact of different words to vary depending on the market variable in question (e.g., some words matter more for the VIX and others for 2s10s) and over time.

Our work relates to a new literature at the intersection of finance and NLP that uses supervised learning techniques applied to market data to capture the semantic content of text. An early example of this approach, applied to equities, is Jegadeesh and Wu (2013). Recent papers that use market information to learn about word meanings include Ke et al. (2018), Garcia et al. (2020), and Glasserman et al. (2020).

A methodologically related paper is Manela and Moreira (2017) who use an SVR to estimate how the VIX index loads on the text of Wall Street Journal articles, and then use the coefficients from this mapping to estimate an implied level of the VIX using news stories from time periods when the VIX index did not exist. Our approach similarly allows us to calculate multiple Fed-implied market variables, which can be used to derive clean measures of the Fed's communications along different dimensions.[5] Aruoba and Drechsel (2022) use a similar methodology to us and to Manela and Moreira (2017) to project the Fed funds rate on the texts of Fed documents (e.g., Green book, Teal book, etc.) available to policymakers ahead of Fed meetings, but explicitly leave out the text of Fed minutes (and presumably statements) to focus only on information, as opposed to policy language. Their measure of monetary policy surprise is the residual from a ridge regression (similar to our SVR) of the Fed funds rate on macroeconomic and text-based information. Aruoba and Drechsel (2022) is complementary work to ours, but the focus differs. They do not

[5] Our approach is also reminiscent of Jegadeesh and Wu (2017), who apply topic modeling to estimate 8 different dimensions of policy from the text of Fed minutes.

analyze the out-of-sample properties of their estimator (recall our Fed-implied market mapping is known ahead of each meeting), nor do they analyze multiple dimensions of the Fed's communications or how such information is priced in markets. Furthermore, our focus on Fed statements and minutes yields information about *both* monetary policy and the Fed's evaluation of the state of the economy.

Two recent papers use text-based approaches to measure Fed communication surprises. Cai et al. (2021) use a lasso regression (very similar to an SVR) to estimate how the Fed funds rate loads on the embedding that results from a BERT neural network model applied to the text of FOMC statements and New York Times articles about monetary policy. They then project changes in interest rates around an FOMC announcement on the difference in the expected movements coming from the text of the FOMC statement and from the text of relevant New York Times articles (the latter serve as a benchmark). They interpret this projected part of rate moves as the policy surprise, and show that this surprise measure can account for a substantial amount of interest rate variation around FOMC announcements. Rather than using the text of New York Times articles as the benchmark against which to compare the information content of FOMC statements, we use the pre-announcement day values of several key market variables and show that our FDIF measure is naturally motivated by asset pricing theory. Furthermore our use of multiple market signals yields multifaceted insights into Fed communications, and conveys more information than measures of only a single dimension of Fed policy.

Doh et al. (2020) use sentence embeddings and alternative FOMC statements, which are labeled by Federal Reserve Board staff as being more dovish or hawkish than the released statement, to extract the monetary policy tone of Fed language. They then use high-frequency bond price changes around FOMC statement releases to construct a benchmark market expectation for the language of the FOMC statement release; the benchmark consists of a weighted average of the dovish and hawkish alternative statements with weights chosen to best match actual bond price changes around statement releases. Using this framework, they conduct counterfactual analysis of the potential market impact of alternative statements from those actually released. We differ from this analysis via our use of multiple market-based benchmarks to evaluate Fed tone, our focus on how professional forecasters' expectations respond to Fed policy surprises, and our analysis of how Fed risk is priced.

Our risk premium results are most closely related to a nascent literature focused on understanding how Fed risk is priced in markets. Ai et al. (2022) measure firm-level sensitivity to FOMC announcements as the difference between option-implied variance ahead of an announcement day relative to recent implied variance from options maturing prior to the announcement day. Like us, they find that firms that are highly exposed to upcoming FOMC announcements earn higher average returns on announcement days (in fact their long-short announcement day portfolio return of 31.40 basis points is very close to our estimates of 2.75%/8 in Table 6). However, they find that long-short FOMC sensitivity portfolios do not earn abnormal returns on non-FOMC days. On the other hand, using a high frequency version of the Bernanke and Kuttner (2005) policy surprise measure from Gürkaynak et al. (2005), Ozdagli and Velikov (2020) estimate firm-level monetary policy exposure (MPE) that conditions on firm characteristics, such as cash-flow duration or operating profitability. They show that high MPE stocks (which do well when the Fed announces expansionary monetary policy, i.e., Fed-risky in our parlance) do poorly on average during all trading days. This is consistent with our finding that Fed-risky industries do poorly on non-FOMC announcement days, though our FDIF measures drive out interest-rate based measures in Fama and MacBeth (1973) tests.[6]

Our paper extends the Fed-risk literature in several ways. First, we perform our analysis at the industry, as opposed to the individual stock, level. This gives our tests more power because industry betas are better estimated than individual stock betas, and importantly shows that Fed risk pricing has a strong industry component. Our classification of Fed-risky (e.g., commodity-related) and Fed-safe (e.g., staples) industries is both novel and very intuitive. Second, we use a different measure of Fed sensitivity than either of these two papers, and we show that rate-based Fed risk (as in Bernanke and Kuttner 2005) is not priced after controlling for Fed diff exposure, suggesting that Fed diff better captures surprises in Fed policy. The text-based FDIF measure is a key methodological contribution of our work. Third, while Ai et al. (2022) focus on FOMC announcement days, and Ozdagli and Velikov (2020) focus on all other days, we show that the Fed risk effect is present on both sets of days, but its sign on FOMC and non-FOMC days is reversed. A theoretical explanation of how Fed risk is priced must account for this fact. Such a theoretical explanation does not yet exist.

Our paper is also related to a recent literature that seeks to understand the information content of Fed policy announcements. Nakamura and Steinsson (2018) show that hawkish Fed policy surprises, measured using high-frequency changes in interest rates around FOMC announcements, are associated with upward revisions in growth expectations, sug-

[6] Chava and Hsu (2020) show that financially constrained firms perform poorly in surprise increases in the Fed funds rate compared to financially unconstrained firms. Financially constrained firms are thus Fed-risky, and should earn high returns on average on FOMC announcement days and low returns on all other days.

gesting that positive rate changes around FOMC announcements convey positive economic news to the market, which contradicts the interpretation that such rate increases signal a hawkish Fed, and therefore bad news.[7] Bauer and Swanson (2021) show that introducing controls for macroeconomic information into the Nakamura and Steinsson (2018) regression reverses the sign on the rate-based policy surprise variable, and suggest that rate increases around FOMC announcements reflect policy surprises and are, indeed, bad economic news after controlling for other macro information. Using the correlation between FDIF and changes in the underlying market variable on Fed announcement days, we argue FDIF measures capture a combination of these two influences, that is, both information about changes in Fed policy and news about the state of the economy.

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 describes our text analysis and support vector regression methodology, and explains the validity of our measure. This section introduces our FDIF variables discusses their behavior. Section 4 analyzes how Fed diff variables are associated with changes in beliefs about future macroeconomic outcomes. Section 5 analyzes the pricing of FDIF risk at the industry level and conducts out-of-sample portfolio tests. Section 6 concludes. An appendix contains technical details about the SVR regression. An Online Appendix contains supporting information. The FDIF measures are available on the authors' websites.

2 Data

The Fed textual sources we analyze consist of FOMC statements and minutes from February 2, 2000 to August 27, 2020. Statements are immediate explanations of policy provided at the end of FOMC meetings. Minutes are more detailed descriptions of FOMC meetings released with a lag. We do not include Fed officials' speeches in our analysis. Speeches don't follow a regular format or schedule, and they are expressions of individual opinion rather than a reflection of the FOMC's overall thinking. Previous analyses of text flow from speeches shows that they follow markedly different word use patterns from statements and minutes (Calomiris and Mamaysky, 2019).

Scheduled FOMC meetings occur at regular six-week intervals, and in recent years, statements are released at the end of the FOMC meeting as part of the FOMC's public

[7] Other papers attempt to disentangle monetary policy versus information surprises by using responses of non-interest-rate variables. Jarociński and Karadi (2020) show that conditioning on contemporaneous high-frequency stock price responses differentiates hawkish policy shocks into bad information surprises (when associated with negative stock price reaction) and good information surprises (when accompanied by positive stock price reactions). Acosta (2022) uses a measure of GDP forecast revisions derived from newspaper articles as the additional conditioning variable.

communication of its policy stance. FOMC statements receive immediate and widespread attention from market participants. Minutes for each FOMC meeting are released three weeks after the FOMC statements.

As Wynne (2013) shows, 2000 marked the beginning of a distinct disclosure regime in which statements were released after each FOMC meeting (implying eight regular FOMC statement releases per year). As he discusses, prior to the second half of 1999, the FOMC never released statements when it was not making a change to the stance of monetary policy. Further, between 1994 (when the FOMC first released a statement) and May 1999, the statements were very short, serving almost solely to describe the committee's decision about its monetary policy stance. Thus, 2000 is the first year in which the FOMC released a statement after each meeting and in which statements served not only to describe the committee's monetary policy stance, but also to provide information about its view on the state of the economy. By beginning our sample period in 2000, we ensure a consistent disclosure regime comprised of statements with similar levels of detail. All of the market impact measures we use to measure the impact of Fed words (e.g., the VIX) were available by the late 1990s. Our analysis of the market impact of Fed statements and minutes from 2000 to the present, therefore, permits us to examine the market impact of Fed word choice under a consistent meeting, disclosure and reporting regime, and using a consistent set of market variables to measure the relationships between Fed communications and other variables. This period is also of particular interest because it is a time when communication became especially important as a means of implementing policy. The post-GFC period saw interest rates stuck at their lower bound, and communications related to quantitative easing and forward guidance became central aspects of Fed policy.

Occasionally (e.g., during the 2008-2009 crisis) the FOMC met at unscheduled times. We include the statements from those meetings in our analysis of how Fed language impacts macroeconomic forecast revisions in Section 4 and in our beta estimates in Section 5. However, we exclude unscheduled meetings when analyzing risk premia associated with statement releases in Section 5 because the timing of emergency meetings was not known in advance, and thus market participants could not have demanded risk-premia in anticipation of such meetings.

To extract the text of Fed communications, we used Python to scrape statements and minutes from the Fed's website and to construct a list of words and bigrams for each document.[8] Using the package `BeautifulSoup`, we extracted the links that point to the

[8] https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm for recent years and https://www.federalreserve.gov/monetarypolicy/fomc_historical_year.htm for earlier years.

statement and minute text from the HTML of the main web pages. We then extracted the text of the communication by stripping HTML and other extraneous text from the beginning and end of each document.[9] Next, we removed capitalization, punctuation and stop words (using the Python `nltk` package). In addition to standard English stop words (e.g., "the", "and", "for"), we removed a list of FOMC-specific quasi-stop words. These include "committee", "trillion", as well as names of months, cities and Fed governors and presidents; the complete list is shown in Online Appendix Section A1. After these text processing steps, we use word and bigram counts for each Fed communication – either statements or minutes – as a proxy for s_t, the Fed information vector.

Summary statistics about these documents can be found in Panel A of Table 1. We have 180 Fed statements and 165 Fed minutes in our sample. Statements are on average 441 words, while minutes are on average 6,832. Because they are longer and less scripted, minutes contain about 20 times more words and bigrams than do statements.

The list of financial market indicators we use to estimate our Fed implied variables is intended to span the main categories of financial market outcomes: the short-term and longer-term government bond yields, the slope of the yield curve, the value of the dollar, bond credit spreads for different classes of bonds, and stock market risk. Candidate financial variables must be stationary (which precludes use of stock market indices).

Specifically, our list of market indicators includes seven measures: VIX, DXY, ten-year and three-month Treasury yields, 2s10s treasury spread, investment grade credit spread and high yield credit spread. We obtain the treasury yields, as well as the ICE Bank of America U.S. High Yield Index option-adjusted spread (i.e., the high yield credit spread) from the FRED website of the St. Louis Fed. We obtain DXY, Moody's Aaa and Baa indices from Bloomberg, and the VIX index from the CBOE website. To compute the 2s10s spread, we subtract the two-year yield from the ten-year yield and to compute the investment grade spread we subtract the Moody's Aaa index from the Moody's Baa index.

To calculate the Fed surprise measure proposed by Bernanke and Kuttner (2005) (BK surprise), we use futures data obtained from Bloomberg. Following their paper, the surprise is given by:

$$\text{BK Surprise}_d = \frac{D}{D-d}(FF_d - FF_{d-1}),$$

where D is the total number of days in the month and d is the day of the month on which the meeting occurs. This accounts for the fact that the Federal funds contract's settlement price is based on the monthly average Federal funds rate, so the change in the

[9]For example, we remove from each statement the text "For release at 2pm EST".

implied futures rate must be scaled up by a factor related to the number of days in the month affected by the change. Also following Bernanke and Kuttner (2005), if the change falls on one of the last 3 days of the month, the unscaled change from day $d-1$ to day d of the next month's future price is used in order to minimize end-of-month noise. We also use a measure suggested by Hanson and Stein (2015). We obtain two-year Treasury yields from the FRED website, and then calculate the difference between the closing yield on the day of the announcement (d) relative to the closing yield of the prior day ($d-1$).

We obtain all macroeconomic forecasts data from the Survey of Professional Forecasters website maintained by the Philadelphia Federal Reserve Bank. These are used in Sections 4 to understand the relevance of our FDIF measures for expectations about macroeconomic outcomes. The survey is sent quarterly following the Bureau of Economic Analysis (BEA) advance GDP estimate, which occurs at the end of the first month of every quarter. We scraped the exact release dates from the BEA website. We obtain the survey deadline from the Philadelphia Federal Reserve website, so that we are able to identify the start and end date for each survey period. We use forecasts for the mean growth of all variables except for CPI, where we use the forecasts for the mean level (both for core CPI and for CPI5YR, which is the annual average rate of headline CPI inflation over the next five years).

In Section 5 we use industry-level returns to estimate industry Fed sensitivity and risk premia. For this we we use the daily returns for 49 industry portfolios and factor returns from the Fama and French (2015) five-factor model and the Jegadeesh and Titman (1993) momentum factor obtained from Ken French's website.

3 Fed-implied market variables

This section discusses how we estimate the time-varying f_t^V function in (2) for all seven of our market variables. We assume that each market variable loads linearly on the text vector s_t which is obtained from the word and bigram counts of each Fed communication

$$V_t = a_V + b_V^\top s_t + \eta_t. \tag{4}$$

Here b_V is a vector of coefficients, one for each token that appears in our corpus. Because the length of Fed statements (see, for example, Smales and Apergis 2017) or minutes can itself be informative, we represent each communication as a vector of token counts, instead of token fractions. We use as V_t the closing value of the market variable on the day of the Fed communication release.

To allow for the possibility that f_t^V varies over time we estimate (4) in rolling windows. The trade-off for choosing the size of the window is the desire to capture high-frequency variation with the need to have enough data to estimate the function. We use overlapping windows of 20 observations each, which represents roughly two and a half years since there are typically eight annual meetings. We then set

$$\hat{f}_t^V(s) = \hat{a}_V^{[t]} + \hat{b}_V^{[t]\top} s, \tag{5}$$

where the regression in (4) has been estimated over the day t meeting and the 19 prior ones. We tried alternative specifications with 15, 25 and 30 meeting windows and the fit of the SVR was unchanged. We also tried using expanding (instead of rolling) windows and found that the fit worsened, which is consistent with the idea that the mapping between words and market outcomes is time-varying and must be estimated using Fed communications from nearby dates, reflecting similar economic regimes, and not from the entire sample.

The problem with regression (5) is that the dimensionality of s_t is much higher than the number of available observations, making the regression minimization problem poorly specified. In this paper, we have 20 observations, and the dimensionality of s is 7,531 for the statements, and 174,221 for minutes. To overcome this difficulty we use a support vector regression (SVR). The SVR allows for estimation of such high-dimensional systems because it imposes additional constraints on the typical ordinary least squares (OLS) minimization problem. First, the SVR treats all model fits that are within ε of the dependent variable as zero errors. This is natural in the present context because getting the right-hand side of (4) close enough to V_t is sufficient, as we do not believe Fed communication should perfectly explain the level of market variables. Second, the SVR imposes a ridge regression type penalty for coefficient deviations away from zero. This regularization helps to solve the minimization problem for high dimensional inputs. The optimal solution in the SVR is to set $\hat{b}$ in (4) to a linear combination of the s_ts in the training window, with some of the weights set to zero. Hastie et al. (2009) is a classic introduction to the method. Some technical details are in Appendix Section A.

3.1 Examination of Fed-implied variables

Figure 2 shows the Fed-implied market variable on Fed announcement day t (when either a statement or minutes transcript is released), calculated using $\hat{f}_{t-\delta}^V(s_t)$. This is the Fed-implied function for asset V from (5), estimated using the 20 Fed communications up to and including announcement day $t-\delta$, where δ represents the number of days between consecutive Fed statement or minute releases. $\hat{f}^V_{t-\delta}(\cdot)$ is therefore already known prior to day t, which means that the Fed-implied measure is an out-of-sample estimate and would have been available to investors or policy makers in real time. The figure also shows the closing value V_t of the market variable on the day of the Fed communication. The Fed-implied and actual market series are highly correlated, with correlations ranging from the 65% to 95%. The correlation, while high, is imperfect because the end-of-day value of V_t on a Fed communication day reflects not only information about the Fed's statement, but also other information such as that reflected in η_t in (2). Therefore, even if the true $f^V_t(\cdot)$ were known, we would not expect the Fed-implied and closing value of V to be identical.

Part of the difference comes from the reaction of V_t to the price response of other markets to the Fed communication. Therefore V_t can not be used as an exogenous instrument for Fed information. Regressing changes in other market variables on changes in V_t to gauge the sensitivity of the former to Fed information suffers from endogeneity problems. The literature addressed this issue by looking at price response of markets that are predominantly driven by Fed policy, such as short-term interest rates (Bernanke and Kuttner 2005; Hanson and Stein 2015), as well as looking at high-frequency responses to Fed announcements to control for other potential influences (Gürkaynak et al. 2005; Nakamura and Steinsson 2018). However, such measures do not capture important policy information in the Fed's communication if it isn't relevant for short-term rates. Furthermore, even short-term interest rate movements on the days of (or even half hour windows surrounding) Fed policy announcements may suffer from similar endogeneity problems.

Our solution to these issues to to apply the $\hat{f}^V_{t-\delta}$ mapping estimated over the prior 20 meeting or statement releases (strictly prior to day t) to the current vector s_t of the Fed's communication. This avoids the endogeneity issues that confound market-based measures of the effects of Fed communications (including those based on short-term interest rates and their futures prices) because both the mapping $\hat{f}^V_{t-\delta}$ and the Fed's communication are exogenous to market or economic events on day t. Furthermore, the Vs cover multiple, key markets, allowing us to measure the impact of the Fed's policy along multiple dimensions.

Table 2 gives some insights into the types of tokens (words or bigrams) that are selected by the SVR in (4) for Fed statements. We use the same methodology as in Manela and Moreira (2017) to define the variance contribution of each token as

$$h(i) = \frac{Var[\hat{v}_i(t)]}{\sum_{j \in All\ tokens} Var[\hat{v}_j(t)]}, \tag{6}$$

where $\hat{v}_i(t) \equiv \bar{b}_i s_t(i)$ is the average $\hat{b}_i$ across our rolling SVR regressions (denoted $\bar{b}_i$) multiplied by the time t count of token i. $h(i)$ is a proxy for how much of the variance of V_t can be attributed to variation in the incidence of the ith token. For each of our seven market variables, Table 2 shows the tokens with the highest variance contribution. The (+) and (-) next to each token indicate the sign of the $\bar{b}_i$ coefficient. Focusing on the column labeled "HY Spread Terms," the top variance contributing words associated with higher high-yield spreads are: economic, conditions, securities, growth, and available. The top variance contributing words associated with lower levels of high-yield spreads are: inflation, remains, continues, expectations, and bank. It is inappropriate to focus too much on the impact of a single token – recall there are 7,531 of them in the statements corpus – because tokens tend to co-occur and it is the combined effect that matters. Nevertheless the top variance contributors across all seven markets are important economic words, suggesting that the SVR is capturing salient features of the textual data.

3.2 Sudden shifts in Fed language

Our Fed-implied market mapping in (5) is estimated over rolling 20-meeting windows. Here we examine how quickly the mapping responds to market regime shifts, in which the Fed may adopt new language to which the SVR model may not have been exposed. Figure 3 shows the actual VIX and the Fed-implied VIX during the global financial crisis of 2008 and 2009, and the COVID-19 pandemic of 2020. The figure uses the same timing convention as Figure 2, with the Fed-implied series on announcement day t given by $\hat{f}^V_{t-\delta}(s_t)$ and the value of market variable V_t shown as of the close of day t.

In 2008, the VIX began to rise by the sixth scheduled Fed meeting. Following the bankruptcy of Lehman Brothers on September 15, 2008, the Fed held a regularly scheduled meeting on September 16, 2008. The VIX was then at 30.3, but the Fed-implied VIX series we estimate was not yet elevated because the language the Fed was using to express economic concerns was unknown to the model. Technically, this means that the s_t vector contained words which were set to zero in the $\hat{b}_V^{[t-\delta]}$ vector. For example, on October 8, 2008, the new tokens, i.e., those which had not been seen in the 20 meetings up to and including the September 16 one, included the words: "crisis", "turmoil", and "unprecedented". In the December 16, 2008 statement, the first to discuss quantitative easing, the new words included: "purchase", "large", and "quantities" (the context being "the Federal Reserve will purchase large quantities of agency debt and mortgage-backed securities to provide support to the mortgage and housing markets"). After seeing these and similar words in two successive meetings, the SVR learned that such words were associated with high levels of the VIX index, and the Fed-implied VIX rose to a level similar to its market counterpart. Table A1 in the Online Appendix shows the new tokens at every Fed meeting in 2008.

During the COVID-19 pandemic of 2020, the VIX began to spike by February. However, the SVR model was unaware of the new set of Fed crisis words. In the March 3 meeting "coronavirus" was a new word, and on March 15 new words included, "challenging", "disrupted", "harmed", "health" and "outbreak". As these new words were introduced and these statements were incorporated into the training sample, the model was again able to learn that the words were associated with high levels of the VIX. The Fed-implied VIX rose to an elevated level by the March 19 meeting, and to an extremely elevated level by the March 23 one. Table A2 in the Online Appendix reports the new Fed tokens that entered the Fed's communication in 2020.

This analysis of two major crises suggests that the text model is able to identify new Fed language, but with a brief lag. Changes in our Fed-implied series therefore occur due to some combination of two reasons: a changing $\hat{f}^V_{t-\delta}(\cdot)$ mapping and changing communication s_t from the Fed. We now explore these channels in greater detail.

3.3 FDIF decomposition

Based on our analysis in Section 1, a variable V_t that is derived from market prices can be written $V_t = f^V_t(s_t, \eta_t)$. If we assume that this mapping is (approximately) linear, we can write $V_t = a_{V,t} + b^\top_{V,t} s_t + c^\top_{V,t}\eta_t$.[10] We further assume s_t and η_t are conditionally independent. From standard results (see Cochrane 2009), we can write

$$V_{t-1} = \frac{1}{1 + r_{f,t-1}} \mathsf{E}^*_{t-1}[a_{V,t} + b^\top_{V,t} s_t + c^\top_{V,t}\eta_t], \tag{7}$$

where $r_{f,t}$ is the time t risk-free rate and E^*_t is the expectation under the risk-neutral measure. Now consider our FDIF variable from (3), and use the approximation that over one day $r_{f,t-1} \approx 0$:

$$\begin{aligned} FDIF^V_t &= \hat{f}^V_{t-\delta}(s_t) - V_{t-1} \\ &= \hat{a}^{[t-\delta]}_V - \mathsf{E}^*_{t-1} a_{V,t} + \hat{b}^{[t-\delta]\top}_V s_t - \mathsf{E}^*_{t-1}[b^\top_{V,t} s_t] - \mathsf{E}^*_{t-1}[c^\top_{V,t}\eta_t], \end{aligned}$$

[10]For example, log zero coupon bond prices are affine in the state variables in a wide class of term-structure models (e.g., Duffee 2002). Even the presence of higher order terms in V_t is not a problem as long as the one-day ahead risk-neutral expectations of these (which would show up in equation 8) are not too volatile. Given the short-term predictability of higher order moments, this is plausible.

where the second equality uses (5) and (7) (recall δ is the number of days between Fed statement or minutes releases). We can rewrite this in a more intuitive way by subtracting and adding $\hat{b}_V^{[t-\delta]\top}\mathsf{E}^*_{t-1}[s_t]$

$$FDIF_t^V = \underbrace{\hat{b}_V^{[t-\delta]\top}(s_t - \mathsf{E}^*_{t-1}[s_t])}_{\text{macro information surprise}} + \underbrace{\hat{a}_V^{[t-\delta]} - \mathsf{E}^*_{t-1}a_{V,t} + \mathsf{E}^*_{t-1}[s_t^\top(\hat{b}_V^{[t-\delta]} - b_{V,t})]}_{\text{model surprise}} - \underbrace{\mathsf{E}^*_{t-1}[c_{V,t}^\top \eta_t]}_{\text{noise}}. \tag{8}$$

This decomposition applies to our seven variables because the related securities prices are approximately linear in our measurement variables (e.g., Treasury prices are approximately linear in yields, corporate bond prices are approximately linear in option-adjusted spreads, VIX futures are approximately linear in the level of the VIX, etc.). Note that the $\hat{a}_V^{[t-\delta]}$ and $\hat{b}_V^{[t-\delta]}$ terms, estimated up to and including the time $t-\delta$ statement or minutes release, are know as of time $t-1$.

In a regime where a_V and b_V have not changed since the prior meeting, which we expect will be the case when no major economic event takes place, the model surprise term in (8) is roughly zero, and FDIF is a noisy measure of the surprise component of the Fed's time t communication. However, when economic regime changes happen, as in the case of the two examples in Section 3.2, there is also a change in how the market responds to Fed communication, i.e., $a_{V,t}$ and $b_{V,t}$ change, and this too is reflected in FDIF. We refer to this as the model surprise. There is an additional noise term in FDIF, reflecting the market's belief about η_t, the component of prices orthogonal to s_t; this is an unavoidable measurement error that results from differencing out V_{t-1}.

Since the expectations in (8) are under the risk-neutral measure, there is an additional risk premium component in FDIF, which reflects distortions in the risk-neutral relative to the physical probabilities (typically, risk neutral probabilities overweight negative events). However, the risk distortion in one-day ahead risk-neutral expectations is unlikely to contribute much time series variation to FDIF, and therefore we interpret systematic variation in FDIF as being driven largely by realizations that differ from investor expectations.

The decomposition in (8) is loosely analogous to the three drivers of monetary policy surprise discussed in Bauer and Swanson (2021). Our macro information surprise term reflects a combination of two components, the first of which they and Nakamura and Steinsson (2018) call the Fed information effect, which occurs when the Fed releases information about the state of the economy which differs from the market's expectation, as well as a second component, monetary policy shocks, which represent a policy choice different from the market's expectation. We emphasize that, as we discussed previously, our methodology does not permit us to disentangle in any particular Fed text what is the relative importance of these two components within our macro information surprise measure. Our model surprise, which measures the difference between the market's estimate and our own estimate of the mapping from Fed communication to the value of market variables, is related to what Bauer and Swanson (2021) call the difference between the market's assessment of and the Fed's actual policy response function. The analogies are not exact, but the connections are illuminating.

3.4 FDIF around historical episodes

We now present evidence that our FDIF measures capture both macro information and model surprises. Figure 4 shows the evolution of the FDIF variables for our seven asset classes, both for statements (the left column) and minutes (the right column). To give context for these variables, five important economic and political events that were addressed in Fed communications are labeled in the plots as follows:

A. the Lehman Brothers bankruptcy (September 15, 2008),

B. Greece's sovereign rating downgrade (April 9, 2010),

C. the Brexit referendum (June 23, 2016),

D. the repo market volatility episode (September 16, 2019), and

E. the first FOMC meeting addressing COVID-19 (March 3, 2020).

A notable feature of the FDIF series is that the procyclical ones are right-skewed and the countercyclical ones are left-skewed. The FDIF series for three-month and ten-year rates are right skewed (have upward jumps), while the FDIF series for the DXY, VIX, investment grade (IG) and high yield (HY) spreads, and 2s10s are left skewed (have negative jumps). Panel B of Table 1 gives summary statistics for the FDIF variables for both statements and minutes, and the same characteristics are visible there.

The observed jumps cluster around crises or sudden changes in the economic regime. When economic regimes change, model surprises occur as the Fed modifies the language it uses to communicate with the market. New tokens are introduced (e.g., "crisis" or "coronavirus") to describe new economic and social phenomena. For example, the two negative spikes in FDIF^{VIX} at points A and E are the same episodes that are shown in Figure 3. The model surprise part of (8) shows a large negative spike in both cases since the loading of $\hat{b}_V^{[t-\delta]}$ on the new words in the Fed's time t communication is mechanically zero, while $\mathsf{E}^*_{t-1} b_{[V,t]}^\top s_t$ anticipates the new language contribution to a higher VIX level. FDIF jumps will also be negative for the DXY, because the dollar appreciates in times of global crises. The two credit risk spread series also spike downward in crises, for a reason similar to the VIX. 2s10s will experience negative jumps in crises reflecting loosening monetary policy and a steepening yield curve. However, the ten-year and three-month rate FDIF series will exhibit positive spikes since the $\mathsf{E}^*_{t-1} b_{[V,t]}^\top s_t$ loading on new words during crises will be negative for interest rate variables to reflect their procyclical behavior.

The model surprise component of FDIF is prominent during regime shifts, but, as expected, largely disappears after a few meetings that expose the model to new Fed language. Variation in FDIF outside of such regime shifts is due to macro information surprises and noise. To interpret the macro information surprise component of FDIF, note first that the VIX, 2s10s, DXY, and IG and HY spreads are all countercyclical variables that are higher in bad times and lower in good times. The three-month rate and ten-year rate tend to be procyclical, with higher rates being associated with good economic times, and low rates being associated with bad economic times.[11]

The macro information surprise in (8) reflects what Nakamura and Steinsson (2018) and Bauer and Swanson (2021) refer to as the Fed information effect and policy surprises. Our methodology does not permit us to disentangle these two parts of the macro information surprise for any particular FOMC release, though we expect that both types of news are present, and the relative weight of each may vary over time and across asset classes. We can, however, observe which component of the macro information surprise dominates on average for a given FDIF measure. Consider the following variable:

$$\text{DIFV}_t^V = V_t - V_{t-1},$$

where t is the Fed announcement day. DIFV is analogous to FDIF, except FDIF uses the Fed-implied value of V on day t whereas DIFV uses the closing level of V_t in the market.

The last column of Panel B of Table 1 reports the correlation between FDIF and DIFV for Fed statement releases for all seven asset classes. The correlations are generally low, suggesting that FDIF captures information that is largely orthogonal to that reflected in the closing level V_t of the market variable. Of the four correlations that are significant, all

[11]This result follows from standard macrofinance models where real short rates increase with the rate of time preference and consumption growth, but decrease with consumption growth volatility.

are negative. The strongest correlation is between the FDIV^{3m} and DIFV^{3m} variables for the three-month rate. We show in Section 4 that FDIF^{3m} is associated with positive revisions in expectations about economic growth. When the Fed reveals a more dovish policy stance, that news can have negative implications for short-term rates and positive implications for economic growth. In contrast, when FDIF simply reveals positive information about the macroeconomic state (not Fed policy), then the short-term interest rate should rise. This logic and the negative correlation between FDIV^{3m} and DIFV^{3m} suggest that the macro information surprise in FDIF^{3m} conveys dovish news about monetary policy. We show in Section 4 that FDIF^{10Y} is also associated with positive economic surprises, and therefore the negative correlation between this variable and DIFV^{10Y} also suggests that innovations in FDIF^{10Y}, on average, convey policy surprises.

We find in Section 4 that FDIF^{VIX} and FDIF^{hy} are associated with negative revisions in expectations about economic growth. A pure macro information shock that caused downward revisions in growth expectations would likely be associated with increasing VIX and HY spread levels. A pure hawkish monetary policy shock would also be associated with downwards revisions in growth expectations and increases in VIX and HY spread levels. Instead, the negative correlation between FDIF^{VIX} and FDIF^{hy} and their respective DIFV measures suggests a combination of a negative surprise about the macroeconomic state *and* a dovish monetary policy surprise. The former is associated with negative revisions in growth expectations and the latter can lead to improving financial conditions (i.e., lower VIX, lower HY spreads) even in the face of negative news about the macro state.

Our paper thus provides a potential reconciliation of the divergent views in Nakamura and Steinsson (2018) and Bauer and Swanson (2021). When seen through the lens of rate-based measures, Fed communication surprises appear to convey information about monetary policy; but when seen through the lens of non-rate-based measures, Fed communications surprises appear to convey news about both macroeconomic conditions and monetary policy. Given the relatively low correlations between FDIF and DIFV measures, we do not want to oversell our results. We also hasten to point out that none of our analysis of Fed communications-related risk hinges on whether FDIF variation mainly conveys information about the state of the macroeconomy or the monetary policy stance. Nevertheless, our results shed new light on an existing debate in the literature.

Finally, we note that the correlation between FDIF and DIFV for Fed minutes releases is virtually zero which suggests that the information content of minutes is not systematically perceived as novel by market participants, a point we return to in our risk pricing analysis in Section 5.

4 FDIF and macroeconomic expectations

If the macro information surprise is an important component of the FDIF decomposition in (8), then Fed diff variables must contain important macroeconomic information. However, to gauge whether the Fed diff associated with market V is good or bad news, it is not enough to check that FDIF^V forecasts either good or bad macroeconomic outcomes, because such outcomes may already have been widely anticipated. A better question is whether FDIF^V is associated with market participants revising their *expectations* of macroeconomic outcomes up or down. This is the point made by Nakamura and Steinsson (2018) and Bauer and Swanson (2021), and we follow their approach. These papers use Blue Chip Economic Indicators survey, while we use the Philadelphia Fed's Survey of Professional Forecasters (SPF).[12] The SPF asks forecasters to submit predictions about a wide range of macroeconomic and market variables. Of these we focus on the following: corporate profitability (CPROF), change in nonfarm payrolls (EMP_AVG), growth in industrial production (INDPROD), housing starts (HOUSING), growth in real GDP growth (RGDP), the chain-weighted residential investment and government expenditures portion of GDP (RRESINV and RFEDGOV), 5-year ahead forecasts for annual headline CPI (CPI5YR), and the change in core CPI (CORECPI).[13] With the exception of CPI5YR, these are all one-year ahead estimates. Panel C of Table 1 gives summary statistics about the SPF variables used in our analysis.

The SPF is conducted after the quarterly release of data from the Bureau of Economic Analysis (BEA), which occurs at the end of the first month of every quarter (January, April, July, October). The SPF is due in either the second or third week of the middle month of each quarter (February, May, August, November). The exact start and end dates of each survey are available from the BEA and the Philadelphia Fed's website, respectively. To study how changes in SPF forecasts are related to each of our FDIF variables we sum FDIF^V from the end of the SPF survey in quarter q (around the end of the middle month in the quarter) to the start of the next survey in quarter $q+1$ (around

[12]The Blue Chip survey is monthly, while the SPF is quarterly. However, the SPF covers more categories than does the Blue Chip. For example, the Blue Chip survey does not contain data on residential investment, government expenditures, or change in nonfarm payrolls.

[13]The SPF separates the survey into growth (i.e., how much will GDP grow in the next n quarters) and level (i.e., how much will GDP be in n quarters). CPI is only reported in levels (where level means the inflation rate), whereas most other variables are reported both ways. The forecasters are generally asked to report their forecasts in levels and then the SPF staff convert these to growth rates.

the beginning of the middle month of the quarter), and then regress changes in the survey from quarter q to quarter $q+1$ on the summed Fed diff variable $FDIV^{V}_{q:q+1}$. Fed meetings or minutes that are released during the (approximately) two week period when the survey is live are excluded from this analysis. Our FDIF sum is thus measured strictly after the end of the quarter q survey and strictly before the start of the quarter $q+1$ survey.[14] This ensures that the quarter q forecasters have not seen the Fed statement when making their forecast, but that the quarter $q+1$ forecasters have. This process excludes 46 out of a total of 160 Fed meetings during the time interval 2002–2020.

4.1 Results

Our main empirical specification is

$$S_{q+1} - S_q = a + b \times FDIF^{V}_{q:q+1} + \epsilon_{q+1}, \tag{9}$$

for each survey variable S_q and the summed FDIF variable associated with market component V observed between the end of the quarter q survey and the beginning of the quarter $q+1$ (the measurement window). We analyze two alternative forms of (9), one that uses Fed diff measures from FOMC announcement days, and the other that uses Fed diff measures from minutes release days. For this analysis, we include scheduled and unscheduled meetings because both should be sources of news to the market. To test for commonality among the FDIF measures, we also run a version of (9) where the right-hand side variable is the summed first principal component (PC1) of the seven Fed diff measures, with PC1 estimated over the full sample. Finally, we estimate (9) by using the average BK surprise or the average change in two-year yields on Fed announcement days that fall in the measurement window.

Table 4 shows the results of (9) for the FOMC meetings. Each column of the table corresponds to one right-hand side variable, and each row of the table corresponds to a different SPF survey. For example, the upper left cell shows that a one unit increase in FDIF^{VIX} is associated with a -0.0512 drop in corporate profitability forecasts. The R^2 of this regression is 0.0168. Looking down the first column shows that FDIF^{VIX} innovations are associated with negative revisions in economic growth forecasts (corporate profitability, payrolls, industrial production, housing starts, real GDP growth, residential investment, and Federal government expenditures) and positive revisions in inflation

[14] If the quarter q survey is taken between January 31 and February 10, and the quarter $q+1$ survey is taken between April 30 and May 10, we use Fed meetings or minutes between February 10 and April 30.

forecasts (for 5-year ahead CPI and year-ahead core CPI). We interpret this as likely reflecting that negative revisions of growth expectations are associated with dovish revisions in expected monetary policy, and thus upward revisions in inflation expectations. The behavior of FDIF^{HY} and FDIF^{IG} is almost identical to FDIF^{VIX}: negative for revisions to expectations about macroeconomic growth measures and positive for revisions to inflation expectations. FDIF^{DXY} displays similar outcomes, as does FDIF^{2s10s} for the revisions in growth expectations though many FDIF^{2s10s} results are not significant. The market variables associated with these FDIF measures are countercyclical – high in bad times and low in good times – and the associated FDIF variables are associated with negative growth and (mostly) positive inflation expectation revisions.

On the other hand, FDIF^{10y} and FDIF^{3M} have the opposite behavior. The associated interest rate series are procyclical – high in good times and low in bad times – and the respective FDIF variables are associated with positive revisions in growth expectations, and negative revisions in inflation expectations. The inflation mechanism is presumably the same: higher growth expectations are associated with more hawkish monetary policy expectations, which are then associated with negative revisions to inflation expectations. The first principal component of the Fed diff series also conveys positive macroeconomic news, and is associated with positive revisions in growth forecasts and negative revisions in inflation expectations. However, this aggregate Fed diff measure does not perform uniformly better in explaining contemporaneous forecast revisions compared to the market-level Fed diff measures. The cross-section of FDIF measures thus captures unique aspects of Fed policy that a single Fed diff factor is unable to convey.

The BK surprise and the two-year change variables behave similarly to the FDIF measures associated with countercyclical market variables – positive innovations in these rate-based measures signal negative growth and positive inflation expectation revisions, though the latter are only marginally significant. Our BK surprise and two-year growth expectation results are opposite in sign to findings of Nakamura and Steinsson (2018), but are consistent with the preferred specification of Bauer and Swanson (2021) that controls for potential omitted variable bias (their Table 4).[15]

[15] Both our BK surprise and two-year change measures are associated with negative revisions in GDP growth expectations and insignificant (though also negative) revisions in payrolls expectations. This is the opposite effect documented in Nakamura and Steinsson (2018) (NS) and in the replication of their results in Bauer and Swanson (2021). However, our inflation effects, though only marginally significant, go in the same direction as the findings in Table 1 of Bauer and Swanson (2021). There are several differences in methodology that may explain this: we use a different survey (SPF versus their use of the Blue Chip survey) which may exhibit different behavior; our analysis is at the quarterly level, while theirs is monthly and thus ignores any lagged influences of policy surprise on future revisions; our measures are daily while the NS measures are in 30 minute windows around the policy announcement; we consider many different

The R^2s of the regressions in Table 4 show that our FDIF variables explain a substantial portion of the variation in revisions in expectations, with values ranging from close to 0% to 45% (FDIF^{VIX} for payrolls growth). The rate-based measures have a similar range of R^2s, suggesting that for some macroeconomic forecast revisions, monetary policy surprises can explain a large portion of the observed variation.

Table A3 in the Online Appendix shows the results of (9) for FOMC minute releases. The results are qualitatively similar, though generally of lower magnitude and significance, and with some variables, like BK surprise, having quite different behavior. We interpret this finding as reflecting that news contained in minutes (released long after statements) is necessarily less important, although it still may be useful for helping market participants to deepen their understanding of the news they first encountered in a prior Fed statement.

The results in Table 4 are summarized in the "Change in macro expectations" column of Table 3. Positive innovations in FDIF measures associated with countercyclical market variables are bad macroeconomic news, whereas positive innovations in the procyclical FDIF measures are good macroeconomic news. However, as Bauer and Swanson (2021) point out, we also recognize that it is possible that there is an omitted variable bias in the specification in (9) because the Fed policy and macroeconomic forecasts may be reacting to the same underlying economic news.

Recognizing that possibility, to verify that investors perceive our FDIF measures as containing new information, we investigate the risk premia associated with the cross-section of FDIF exposures during Fed information events. Our logic follows the consumption-based asset pricing literature (see Campbell 2017). If countercyclical FDIF measures are indeed bad news, and if procyclical ones are indeed good news, then securities that help to hedge adverse FDIF shocks should command negative risk premia, and those that do well during positive shocks should contain positive risk premia. If, on the other hand, FDIF simply reflects news already known to market participants, i.e., surprises in (8) which come from model staleness, then there should be no risk premium associated with FDIF innovations.

We have a natural setting to test these hypotheses: we can distinguish between the risk premia associated with FDIF measures around FOMC announcements and those around FOMC minutes releases. The macro information surprise components of the statements

growth surveys and they all go in the same direction; finally, our time period is different because our Fed text data only start in 2000. Our growth expectation results *are* consistent with the impact of the NS surprise measure on GDP (negative) and unemployment (higher) expectations in Table 4 of Bauer and Swanson (2021) which controls for other macroeconomic variables that can impact expectation revisions. Bauer and Swanson (2021) argue this last specification captures most accurately the impact of the NS surprise measure.

and minutes FDIF variables are likely to be quite different – minutes, after all, are "old news" – and the associated risk premia are likely to be different as well. Presumably exposure to the release of old news should not command a risk premium. We turn to this analysis next.

5 Fed risk premia

Section 4 showed that the FDIF variables contain important information for forecasting revisions in macroeconomic expectations. These results are summarized in the "Change in macro expectations" column of Table 3. Consider FDIF^{HY}, which conveys negative economic information when its value is positive. Securities that do well on Fed announcement days when FDIF^{HY} is high serve as hedges against bad economic surprises. Investors should be willing to accept lower average returns from holding these hedging securities heading into Fed announcement days. The Fed announcement risk premium for FDIF^{HY} should therefore be negative. The same is true for the risk premia associated with the other FDIF variables that signal negative economic news. On the other hand, consider FDIF variables that signal positive economic news, such as FDIF^{3M}. Securities that do well on Fed announcement days with positive values of FDIF^{3M} are economically sensitive – they will do poorly when the Fed-implied economic news is bad – and investors should expect to be compensated more for holding such securities heading into Fed announcement days. The risk premium associated with the positive news FDIF variables should thus be positive. These predictions are summarized in the "Price of risk" column in Table 3. We now turn to an analysis of these implications.

Rather than work with firm-level stock data, we focus our analysis on the 49 U.S. industry portfolios obtained from Ken French's website.[16] The primary reason for this choice is that we need to measure securities' sensitivity to our FDIF variables on Fed announcement days. Since there are only eight such days per year, industry-level analysis allows us to obtain more accurately-measured FDIF sensitivities.[17] We first show that exposure to our FDIF variables is a priced risk factor for the cross-section of value-weighted

[16] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[17] Ai et al. (2022) overcome this same measurement issue by looking at the "expected implied variance reduction" (EVR), the difference between the implied variance of short-dated options that expire after the Fed announcement and the median implied variance of the same maturity options in the weeks prior to the announcement when their expiries did not overlap. While EVR is available at the firm-level, the measure does not directly classify a firm as being Fed-safe or Fed-risky, since either type of firm may be very sensitive to Fed policy surprises. With industry-level analysis, we are able to obtain a directional measure of Fed surprise exposure.

industry returns on Fed announcement dates, even after controlling for traditional asset pricing factors. Then, we classify industries as being "Fed-safe" or "Fed-risky" based on the risk-compensation that they earn on Fed announcement dates; our industry classification scheme is very intuitive. Using this classification, we propose a trading strategy that is based only on historically available information, and show that this strategy generates significant risk-adjusted returns.

5.1 Cross-sectional asset pricing

To evaluate whether the exposures to our FDIF variables are priced in the cross-section, we employ the Fama and MacBeth (1973) (henceforth, FMB) two-stage regression procedure using 49 U.S. industry portfolios as test assets. In the first step of the FMB procedure, betas are estimated using the full sample:[18]

$$r_{i,t+1} = c_i + \boldsymbol{\beta}_i' \boldsymbol{f}_{t+1} + \epsilon_{i,t+1}, \text{ for a given } i, \ \forall\ t, \tag{10}$$

where $r_{i,t+1}$ is the one-day return around the FOMC announcement for industry i in period $t+1$ and $\boldsymbol{f}_{t+1}$ is a vector of common factors. In the second step, we run a pooled OLS regression of raw industry returns on betas:

$$r_{i,t+1} = \alpha + \boldsymbol{\lambda}' \boldsymbol{\beta}_i + \nu_{i,t+1}, \tag{11}$$

where the slope coefficient $\boldsymbol{\lambda}$ represents the market prices of risk. As the error terms are likely to be cross-sectionally correlated at a given time, we follow Petersen (2009) and Cochrane (2009) in reporting standard errors clustered by time for the pooled regressions.

The use of estimated betas in the second stage introduces the classical errors-in-variables problem. In this case, estimating risk premia with more precise factor loadings will produce less biased risk premia estimates. Therefore, to increase the precision of the beta estimates in the first stage of the FMB procedure we use one-day returns around all FOMC meetings (scheduled and unscheduled). In the second stage, we only use one-day returns for scheduled FOMC meetings, because investors were not likely to demand a risk premium for holding securities going into meeting days that were unanticipated.

[18] Instead of running a single time-series regression for each asset return, Fama and MacBeth (1973) use rolling 5-year regressions, but one can also use the technique with full-sample betas (see, for instance Cochrane, 2009; Lustig et al., 2011).

Univariate analysis

Table 4 reports the asset pricing results obtained using a univariate version of the FMB procedure applied to the 49 U.S. industry portfolios, where the sole priced factor is assumed to be a particular FDIF variable around Fed announcements. FDIF sensitivites are estimated using (10) on Fed announcements dates using the realized FDIF variable as the only factor. These results are reported in the bottom row of the table ("FM Univariate"), which shows estimates of the risk-compensation in basis points per unit of risk, defined as the market price of risk λ times the standard deviation of β, for each FDIF variable.

All FDIF variables, including the first principal component FDIF^{PC1}, represent priced risks for the cross-section of industry returns on Fed announcement dates. The risk-premia are highly statistically significant and economically large, with risk compensations ranging from 8 basis points for FDIF^{VIX} to 12 basis points for FDIF^{3M} per unit of standard deviation of the first-stage FMB betas. As a benchmark, we report the risk-premium for the BK surprise measure and for changes in two-year yields. As can be seen in the last two columns of Table 4, BK surprise is priced in the cross-section of industry returns, with a risk compensation of 4.6 basis points per unit of beta standard deviation. Since this is directly comparable to our FDIF risk premiums, the lower magnitude of the BK surprise risk premium (less than half of the FDIF ones) suggests that FDIF does a better job capturing policy surprises. Exposure to changes in two-year yields is not priced.

The striking pattern in Table 4 is how the prices of risk of Fed communication surprise measures relate to the sign of the relationship between those surprise measures and macroeconomic expectation revisions. Countercyclical $FDIF$ measures, e.g., FDIF^{HY}, are associated with negative growth expectation revisions and with negative prices of risk; BK surprise follows a similar pattern. But procyclical measures, such as FDIF^{10Y} and FDIF^{PC1}, which are associated with positive revisions to growth expectations command positive prices of risk. This is consistent with the predictions summarized in Table 3.

In Table A3 of the Online Appendix we repeat the same analysis using FDIF variables derived from Fed minutes releases. In contrast to the results in Table 4, we find no evidence of priced risk for the FDIF variables, BK surprise, or for two-year yield changes. This is puzzling because the information released on Fed minutes days is sufficient to cause revisions in some SPF forecasts, though the revisions are smaller than those that result from statement releases. Yet, the information released from minutes is not a priced risk in markets. Perhaps, professional forecasters overreact to the information content of minutes; or perhaps market participants underreact. But the responses of these two groups do not appear to be fully consistent.

Multivariate analysis

Table 5 reports the results for the multivariate versions of the FMB regressions. In every column, we report the the risk-premium associated with each FDIF variable, controlling for other pricing factors: (1) the day $t-1$ value of the market variable associated with the respective FDIF measure; (2) traditional, interest-rate based measures of Fed policy surprise (BK surprise and two-year change) on the announcement day t; (3) the iShares 7-10 Year Treasury Bond ETF excess return (IEF_Rf) on day t; and (4) the market excess return (Mkt_Rf) on day t. All of these variables are included in the $\boldsymbol{f}_{t+1}$ vector in the first-stage FMB regression in (10). Columns (1)-(7) report the results for FDIF variables measured on Fed statement release dates, and columns (8)-(14) report the results for FDIF variables measured on Fed minutes release dates.

As can be seen in Table 5, the FDIF variables remain priced risk factors on FOMC announcement days, even after controlling for the additional pricing factors. The magnitudes of risk premia, in basis points per unit of beta standard deviation, fall slightly relative to the univariate analysis of Tables 4 and A3, but the signs and economic and statistical significance of the risk premia remain comparable. Importantly, BK surprise and two-year change, the traditional measures of Fed policy surprise, are no longer statistically significant once we control for the FDIF variables; in fact, the magnitude of the BK risk premium effectively falls to zero. This result implies that the FDIF measures capture Fed news-related risk more effectively than do traditional rate-based measures.

As in the univariate analysis of Table A3, there is no evidence of priced Fed risk on minutes announcement days. This confirms our macro information surprise hypothesis with respect to the novelty of statement versus minutes releases. There is a strongly priced risk premium around statement releases, exposure to which can be captured using our Fed diff variables. However, there is no risk premium associated with exposure to minutes releases, though these also are associated with macroeconomic forecast revisions. Another piece of corroborating evidence is that market beta is strongly priced on Fed statement, but not on Fed minutes, release days. Savor and Wilson (2014) document that beta is strongly priced on important macroeconomic news announcement days (which include FOMC statement days) but not on other days, suggesting that Fed minutes releases are not perceived by the market as being important macroeconomic news days.

5.2 Returns to Fed-safe versus Fed-risky industries

We now analyze the returns of portfolios sorted on the average risk-compensation associated with our FDIF variables. We define Fed-safe industries as those which do well, on average, on Fed announcement days when there are positive FDIF values of countercyclical variables, e.g., FDIF^{HY}, and negative FDIF values of the procyclical variables, e.g., FDIF^{10Y}. Fed-risky industries have the opposite behavior. We use individual industries' unconditional risk compensations on Fed announcement days – defined as their betas from (10) multiplied by the market prices of risk from the second-stage FMB regressions in (11) – to rank industries from Fed-safest to Fed-riskiest. By construction, Fed-risky industries earn positive returns on average on Fed announcement days, and Fed-safe industries earn negative returns on average on Fed announcement days.

After we classify industries from safest to riskiest for each one of our seven FDIF variables, we compute the average risk compensation rank across different FDIF measures for every industry. This aggregate ranking is in the spirit of the results from Section 4 that each Fed diff variable captures a unique aspect of Fed monetary policy. Figure 5 presents the average risk compensation rank for every industry using the full sample (Mar 2002–Jun 2020, gray bars) and only the first half of the sample (Mar 2002–Feb 2011, red line). A closer examination of these industries shows that, as one would expect, Fed-risky industries (industries with high average ranks) are highly cyclical, including those exposed to commodity or housing-related businesses. Fed-safe industries (industries with low average ranks) consist of staples like food and utilities, as well as growth sectors like software and medical equipment. The similarity of the full- and early-sample rankings suggests Fed-safe and risky industry classifications are stable over time.[19]

Long-short trading strategies for FDIF portfolios

We allocate industries to five portfolios based on their average risk compensation ranks across different FDIF measures, shown in Figure 5. Portfolio 1 contains industries with the lowest risk compensation ranks (Fed-safe industries). Portfolio 5 contains industries with the highest risk compensation ranks (Fed-risky industries). Portfolio (1-5) is long portfolio 1 and short portfolio 5. Table 6 documents the excess returns and alphas (relative to the Fama and French 2015 model plus momentum from Jegadeesh and Titman 1993) of the portfolios. Panel A reports the results for the full sample (Mar 2002–Jun 2020), and Panel B reports the results for the late sample (Mar 2011–Jun 2020), where the portfolios are

[19] Table A4 in the Online Appendix shows the $\beta \times \lambda$ scores for each industry for each FDIF measure in the full sample, confirming that industry risk pricing is stable across different FDIF measures.

constructed using the average ranks computed in the early sample (Mar 2002–Feb 2011). To gauge the impact of the return earned in the one-day window around FOMC days, we report the results for three different holding periods: (1) FOMC days; (2) all days; and (3) non-FOMC days. Note that the late-sample results in Panel B are completely out-of-sample as the industry classifications would have been known in real time.

We find that Fed-risky industries outperform Fed-safe industries on FOMC days, but the effect is reversed on all other trading days, during which Fed-risky industries do poorly relative to Fed-safe industries, underperforming by roughly 3% per year in the full sample (Panel A) and by 8% per year in the late sample (Panel B). For "all days" and for "non-FOMC days", our results support the results of Ozdagli and Velikov (2020) who find that stocks with a more positive reaction to expansionary monetary policy surprises (Fed-risky in our terminology) earn low average returns. In contrast to our paper, they do not report how stock prices respond to monetary policy surprises realized on FOMC announcement days and they use the BK measure to measure monetary policy surprise, while we find the BK rate-based measure is not priced after controlling for FDIF betas.

Given the empirical evidence that Fed-risky industries do particularly well relative to Fed-safe industries on Fed announcement dates, but do poorly relative to the Fed-safe industries on all other trading days, we construct a long-short strategy that goes long Fed-risky industries and short Fed-safe industries on FOMC days, but reverses the position on all other trading days. Table 7 documents the excess returns and alphas of strategies based on: (1) the average risk compensation ranks for our seven FDIF variables; (2) the risk compensation rank for the BK surprise (each industry j is ranked by its BK surprise first-stage β_j times the second stage price of risk λ); and (3) the risk compensation ranks for the two-year change (same as for BK surprise except using two-year changes as the risk factor). As can be seen in the table, for the full sample, the FDIF long-short strategy earns an annual risk-adjusted return of 7.6%, after controlling for the five Fama and French (2015) factors plus the Jegadeesh and Titman (1993) momentum factor. This is highly statistically and economically significant. The two-year change and BK portfolios earn positive alphas, though the magnitudes are less than half of the FDIF strategy's alpha and neither is significant after adjusting for the six factor model.

To alleviate data mining concerns, we also test the out-of-sample performance of our trading strategy. We use the first half of the sample to estimate the risk compensations used in the portfolio sorts. We report the performance of the three strategies in the second half of the sample in the last three columns of Table 7. Interestingly, the long-short strategy based on our FDIF variables earns a risk-adjusted return of 9% per year in the late sample, compared to 3.6% for the portfolio based on the two-year change ranks and 0.2% for the portfolio based on the BK surprise ranks. The performance of our Fed-risk strategy appears very persistent.

One worry is that our long-short strategy is no longer profitable after taking into account transaction costs. According to Hagströmer (2021), the round-trip effective bid/ask spread for S&P 500 stocks in a weekly sample in 2015 is 3 basis points. Since our strategy requires 16 trades per year, this implies an annual net, risk-adjusted return of 8.79% in the late sample ($9.27\% - 16 \times 0.03\%$) if trades can be implemented at prevailing bid/ask prices. Price impact from larger trades would decrease profitability, but since the strategy requires trading industry portfolios and not individual stocks, an efficient trading implementation is likely possible. For market makers and high-frequency traders, who earn rather than pay bid/ask spreads, our trading strategy would be particularly attractive. We don't view these high returns as indicative of a true riskless profit opportunity. Rather, we interpret them as reflecting compensation for bearing industry-level Fed risk.

6 Conclusion

We have constructed a new way to measure word flow in Fed statements and minutes by using the historical relationship between Fed language and market outcomes. Our measures do not suffer from problems of endogeneity that complicate the interpretations of market-based measures of the effects of Fed communications (such as those related to interest rate changes). Our methodology allows us to estimate exogenous, real-time Fed-implied market variables from statements and minutes, using the relationships between Fed word choices and the values of market variables observed in the recent past. For the period 2000-2020 we use this approach to construct our FDIF measures, which represent flexible and consistent gauges of the degree of surprise contained in Fed communications. Our approach relies on Fed communications s_t being an important conditioning variable for investor expectations in (1).

We employ seven FDIF measures, one for each asset class we consider. Interestingly, we find that Fed communications have unique implications for each of the market measures, and that the implications of Fed policy are only fully captured by seeing the totality of FDIF variables. In forecasting revisions in economic expectations, measured by changes in forecasts from the Survey of Professional Forecasters, we find that individual Fed diff measures capture different dimensions of macroeconomic forecast revisions, and an aggregate FDIF measure does not perform uniformly better than the combination of the individual ones. In other words, there is not one way to read Fed statements, but rather there are several distinct dimensions to Fed communications, depending on which outcome one is interested in understanding. Focusing only on interest-rate based measures, as is standard in most of the literature, will not fully capture all relevant information. The same is true of focusing on only a single Fed diff measure, while ignoring the information content of the others.

We establish several novel facts about the pricing of Fed risk in securities markets. Fed-safe industries, those than do well on Fed announcements days with negative economic surprises, earn negative risk premia on Fed announcement days and positive risk premia on all other days. The finding is reversed for Fed-risky industries. A strategy that exploits the Fed risky-safe dichotomy on announcement and non-announcement days earns significant statistical and economic returns, after adjusting for standard risk factors. While Fed risk is priced on FOMC statement days, it is not priced on minutes release days. These findings extend our understanding of how Fed risk is priced in markets, and can help guide theoretical developments.

We hope that our text-based FDIF measures will be useful tools for practitioners, policy makers, and researchers to understand the economic news contained in Fed, and other central bank, communications.

A Support vector regression

Schölkopf and Smola (2004) gives a thorough description of the technical details of SVRs. Hastie et al. (2009) is an excellent introduction. SVRs allow us to estimate (4) with high-dimensional regressors. The SVR's objective function defines an acceptable error (denoted ε) and minimizes the $l2$-norm of the coefficient vector (denoted $b_V^\top$). Formally, given training data $(s_1, V_1), \ldots, (s_N, V_N)$, where we assume here that s_i contains a constant, with $s_i \in \mathbb{R}^K$ and $V_i \in \mathbb{R}$, linear SVR minimizes the following objective function:

$$\frac{1}{2}||b_V^\top||^2 + C\sum_{i=1}^{N}|\xi_i|$$

subject to

$$|V_i - b_V^\top s_i| \leq \varepsilon + |\xi_i|,$$

where ε and C are the hyperparameters that must be chosen in advance. ε is the error threshold and C determines the tolerance for errors above ε. ξ_i is the deviation of the actual errors, η_i, from ε, given that their absolute value is larger than ε:

$$\xi_i = \begin{cases} |\eta_i| - \varepsilon & \text{if } |\eta_i| > \varepsilon \\ 0 & \text{if } |\eta_i| \leq \varepsilon \end{cases}$$

By focusing on minimizing $||b_V^\top||^2$ instead of the sum of squared errors and imposing an error threshold as a constraint, SVR is feasible for problems where OLS is not, notably where $K \gg N$. Our implementation of the SVR is from the Python `sklearn` package. We chose $\varepsilon = 0.05$ and $C = 1$ for all our regressions. We found that our results were robust to choosing any small ε (between 0 and 0.5) and to choosing any value of C.

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Tables and Figures

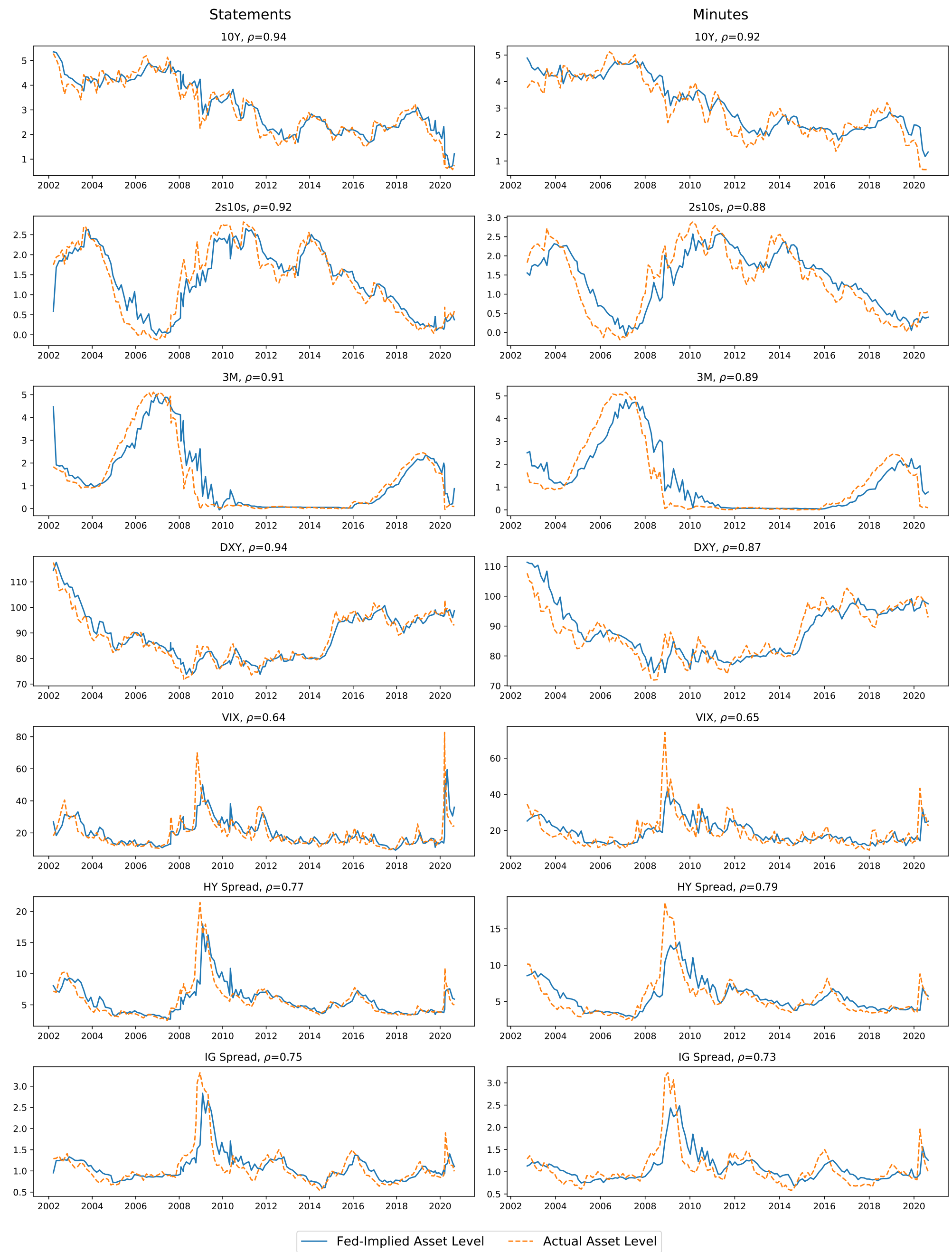

Figure 2: SVR fit for statements and minutes

This figure plots the actual and Fed-implied levels of the seven assets that we use in our analysis. The actual asset levels are measured as of the close of the day of the FOMC release (either statement or minutes). ρ measures the Pearson correlation between the actual asset value and its corresponding Fed-implied value.

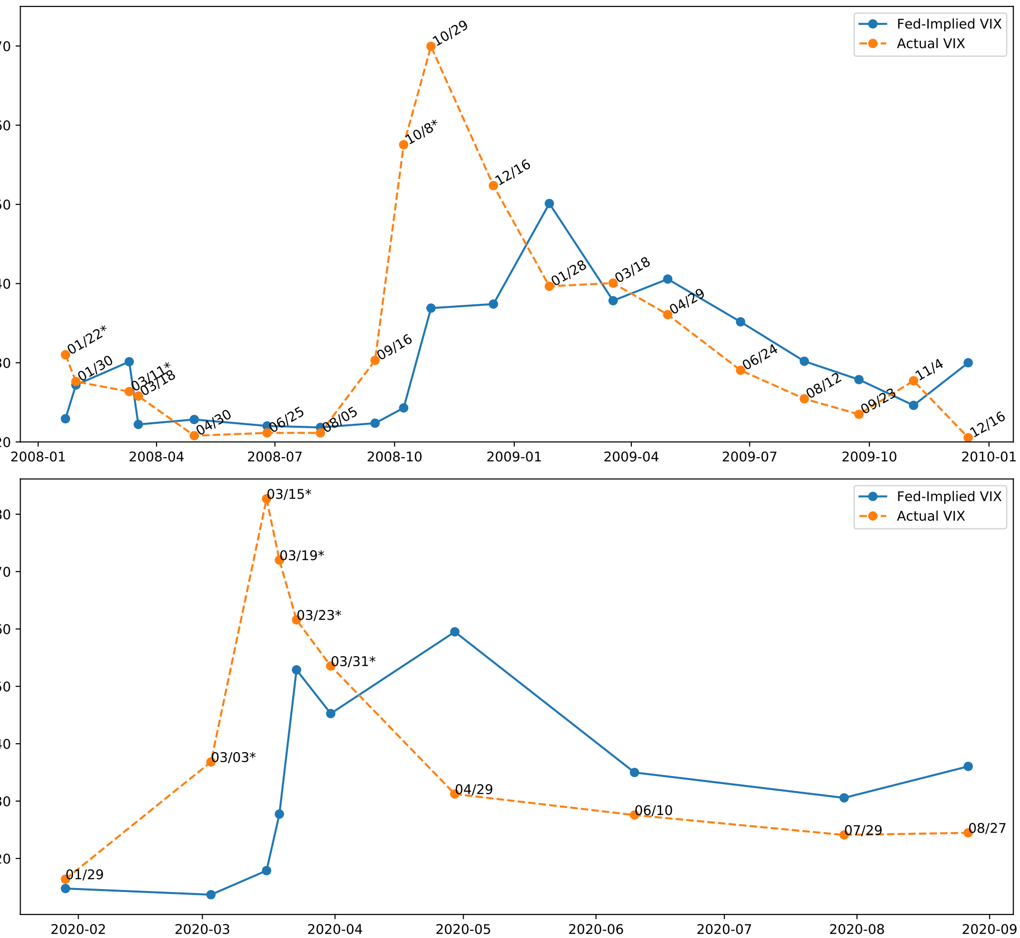

Figure 3: Predicted and actual VIX (from statements) in 2008/2009 and 2020

This Figure plots the actual and fed-implied (from statements) levels of the VIX around two recent crises: the 2008/2009 financial crisis and the 2020 coronavirus pandemic. Stars (*) indicate an unscheduled meeting. The Fed-implied series on announcement day t is given by $\hat{f}^V_{t-\delta}(s_t)$, where δ is the number of days elapsed from the prior Fed announcement day, and the value of the market variable V_t is shown as of the close on day t.

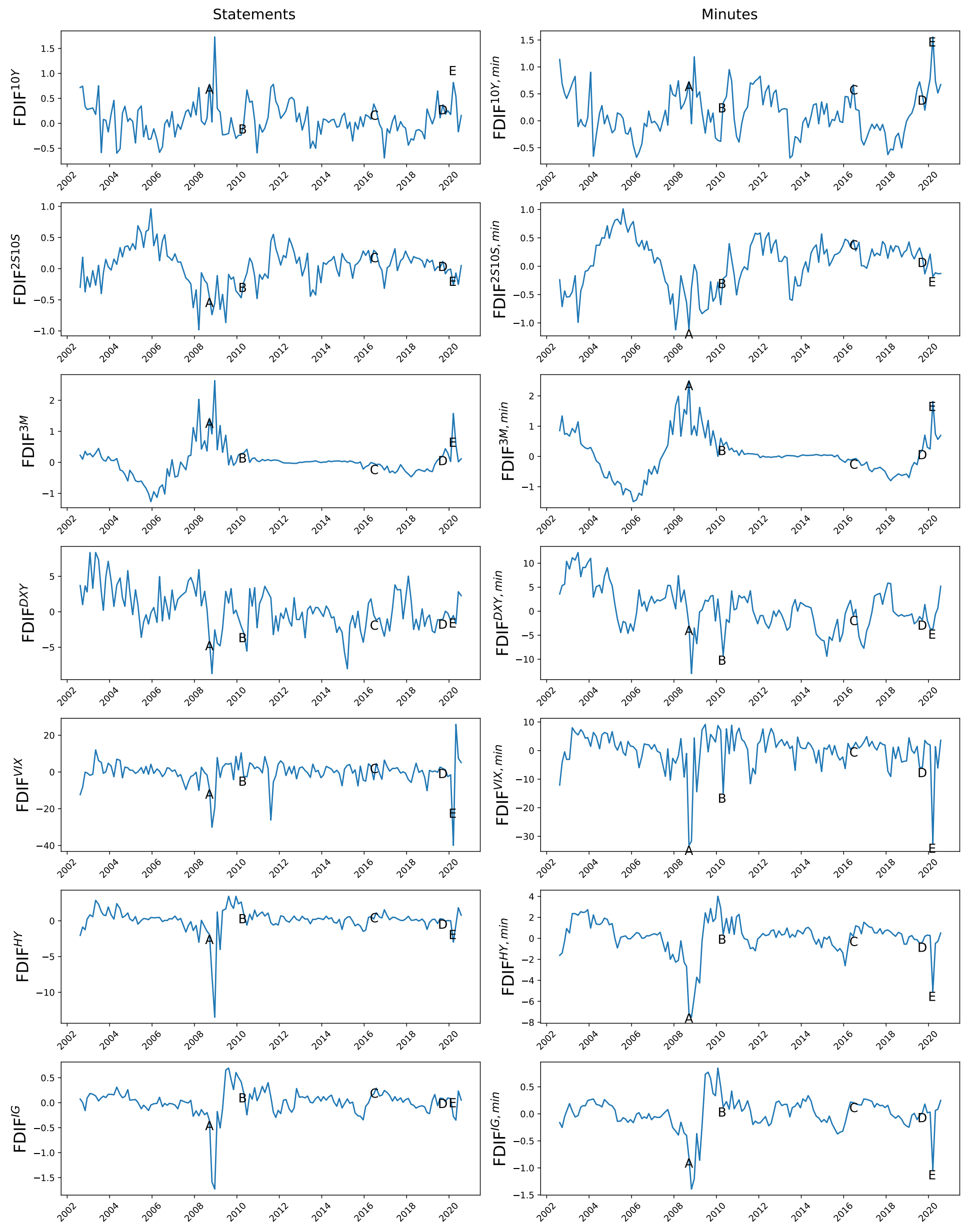

Figure 4: Time series of FDIF variables

The markings show important macroeconomic events: A is the Lehman Brothers bankruptcy (September 15, 2008), B is when Fitch downgraded Greece's credit rating from BBB+ to BBB- (April 9, 2010), C is the Brexit referendum (June 23, 2016), D is the repo market meltdown (September 16, 2019) and E is the first FOMC meeting addressing the coronavirus pandemic (March 3, 2020). For the dates that do not coincide with FOMC communications, the label is placed at the first communication following the event.

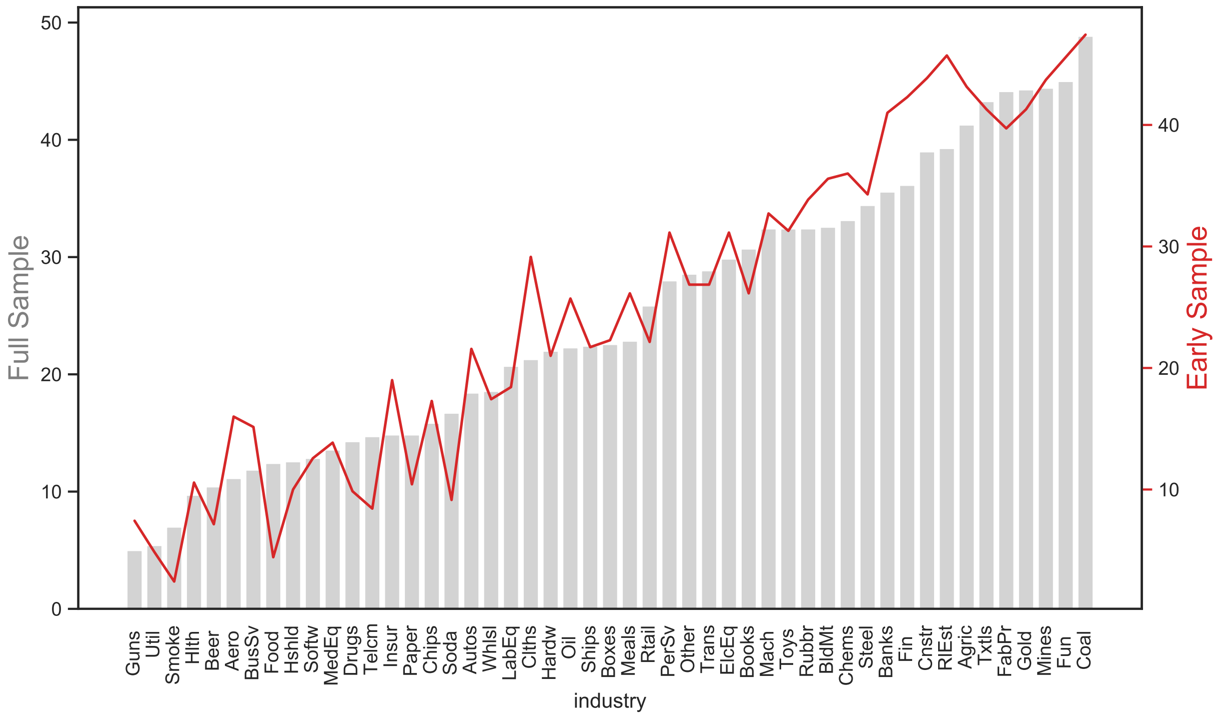

Figure 5: Average risk compensation ranks for the 49 U.S. industry portfolios

This figure plots the average risk-compensation rank across different Fed measures for every industry portfolio. For every FDIF measure, we rank industries in the cross-section in terms of risk-compensation (risk-compensation= price of risk $\times$ β_j, for $j = 1, \ldots, 49$), with 1 being the lowest risk compensation rank and 49 being the highest risk compensation rank. We then compute the average rank for every industry across different FDIF measures. The gray bars show the full sample (Mar 2002–Jun 2020) analysis, and the red line shows the early sample (Mar 2002–Feb 2011) analysis.

Table 1: Summary statistics

In Panel B, *corr* refers to the correlation of FDIF_t^V and $V_t - V_{t-1}$ for market variable V_t on day t. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Statements and minutes text

	Statements	Minutes
Number of observations	180	165
Average word count	441	6,832
Std. dev. of word count	319	2,379
Number of unique words and bigrams (no stopwords)	7,531	174,221
First meeting date	Feb 2, 2000	Feb 2, 2000
Last meeting date	Aug 27, 2020	Jul 29, 2020

Panel B: FDIF variables

	count	mean	std	min	25%	50%	75%	max	corr
FDIF^{VIX}	160	-1.07	8.30	-48.72	-2.59	0.11	2.77	25.93	-0.14^{*}
FDIF^{DXY}	160	0.32	3.10	-8.71	-1.55	0.15	2.74	8.36	0.03
FDIF^{10Y}	160	0.10	0.37	-0.69	-0.12	0.08	0.27	1.73	-0.25^{***}
FDIF^{2s10s}	160	-0.01	0.34	-1.27	-0.17	0.05	0.19	0.96	-0.04
FDIF^{3m}	160	0.10	0.60	-1.27	-0.21	0.03	0.23	2.63	-0.28^{***}
FDIF^{hy}	160	-0.03	1.84	-13.48	-0.38	0.23	0.64	4.41	-0.14^{*}
FDIF^{ig}	160	0.00	0.29	-1.73	-0.10	0.04	0.12	0.69	0.06
$\text{FDIF}^{VIX,min}$	145	-0.04	6.69	-33.17	-1.84	1.31	3.31	9.16	-0.03
$\text{FDIF}^{DXY,min}$	145	0.62	4.46	-12.99	-2.28	0.28	3.12	12.23	0.11
$\text{FDIF}^{10Y,min}$	145	0.14	0.42	-0.69	-0.15	0.11	0.45	1.56	0.02
$\text{FDIF}^{2s10s,min}$	145	0.06	0.43	-1.12	-0.18	0.14	0.36	1.01	0.1
$\text{FDIF}^{3m,min}$	145	0.05	0.69	-1.50	-0.36	0.03	0.35	2.50	0.07
$\text{FDIF}^{hy,min}$	145	0.15	1.67	-7.52	-0.27	0.31	0.94	4.02	-0.12
$\text{FDIF}^{ig,min}$	145	0.01	0.30	-1.39	-0.11	0.02	0.18	0.85	-0.01

Panel C: SPF variables

	count	mean	std	min	25%	50%	75%	max
CPROF Growth	75	6.700	4.852	1.175	3.967	5.395	8.274	37.095
EMP_AVG Growth	68	163.878	77.590	6.137	136.825	158.320	185.210	629.838
INDPROD Growth	75	3.308	0.978	1.398	2.573	3.224	4.001	6.269
HOUSING Growth	75	11.183	13.339	-6.293	1.135	7.501	18.744	43.612
RGDP Growth	75	2.890	0.528	1.786	2.566	2.840	3.160	4.612
RRESINV Growth	75	5.641	5.325	-2.746	1.522	4.608	10.459	15.226
RFEDGOV Growth	75	1.403	1.300	-1.909	0.836	1.376	2.154	4.754
CPI5YR	61	2.262	0.230	1.876	2.093	2.218	2.445	2.751
CORECPI	55	2.019	0.262	1.337	1.933	2.068	2.186	2.421

Table 2: Top variance driving n-grams for each Fed tone measure in statements

The table shows the top tokens by their variance share $h(i)$, defined in equation (6). The sign in parentheses indicates whether a given token is associated with a higher or lower level of the asset (positive or negative coefficient in the SVR). The words are shown in descending order of $h(i)$ for each of our seven market series.

10Y Terms	2s10s Terms	3M Terms	DXY Terms	VIX Terms	HY Spread Terms	IG Spread Terms
inflation (+)	market (+)	inflation (+)	inflation (-)	inflation (-)	inflation (-)	economic (+)
growth (-)	labor (+)	conditions (-)	economic (+)	economic (+)	economic (+)	inflation (-)
rate (+)	economic (-)	pressures (+)	growth (-)	growth (+)	conditions (+)	rate (+)
economic (-)	labor_market (+)	securities (-)	available (+)	rate (-)	securities (+)	bank (-)
market (+)	pressures (-)	labor (-)	economic_growth (+)	remain (-)	growth (+)	available (+)
labor_market (+)	action (-)	growth (-)	currently (+)	conditions (+)	available (+)	financial (+)
securities (-)	bank (+)	potential (+)	markets (-)	financial (+)	credit (+)	credit (+)
labor (+)	conditions (+)	inflation_pressures (+)	prices (-)	bank (+)	financial (+)	activity (+)
lower (-)	earlier (+)	market (-)	remain (-)	available (+)	sustainable_economic (+)	economic_activity (+)
agency (-)	inflation (-)	activity (-)	longer (-)	pace (+)	mortgage (+)	pace (-)
employment (-)	rate (+)	bank (-)	pace (-)	central (+)	rate (+)	prospects (+)
remains (-)	potential (-)	labor_market (-)	risks (-)	banks (+)	remains (-)	continues (-)
outlook (-)	energy (-)	economic_activity (-)	appears (-)	credit (+)	continues (-)	economic_growth (+)
developments (-)	economic_growth (-)	earlier (-)	rate (+)	activity (+)	agency (+)	sustainable_economic (+)
support (-)	inflation_pressures (-)	price (-)	support (-)	remains (-)	backed_securities (+)	expectations (-)
mortgage (-)	available (-)	contained (+)	sustainable_economic (+)	pressures (-)	prospects (+)	growth (-)
pace (+)	gradually (-)	agency (-)	expansion (+)	longer (-)	economic_growth (+)	markets (-)
backed_securities (-)	contained (-)	economic (-)	expectations (-)	economic_activity (+)	expectations (-)	spending (+)
basis (-)	growth (+)	mortgage (-)	basis (-)	labor (-)	spending (+)	remains (-)
long (+)	securities (+)	core (+)	currently_available (+)	continues (-)	bank (-)	inflation_expectations (-)
still (+)	risks (+)	spending (-)	expected (-)	price (+)	economic_activity (+)	sustainable (+)
action (-)	employment (-)	quarters (-)	meeting (+)	weakness (+)	activity (+)	agency (+)
conditions (-)	improved (+)	support (-)	goals (+)	funds_rate (-)	backed (+)	action (-)
months (+)	continues (+)	market_conditions (-)	bank (+)	currently (+)	pace (-)	mortgage (+)
mortgage_backed (-)	spending (+)	backed (-)	earlier (-)	agency (+)	currently (+)	price_stability (+)

Macro directionality and price of risk of FDIF measures

FDIF variable	Change in macro expectations	Price of risk
VIX, 2s10s, IG, HY, DXY	negative	negative
three-month, ten-year rates	positive	positive

Table 3: The "Change in macro expectations" summarizes the direction of economic surprises from an increase in each FDIF variable. This is discussed in Sections 3 and 4. The "Price of risk" column shows the sign of the predicted risk premium associated with each FDIF variable. This is discussed in Section 5.

Table 4: Univariate Regressions of SPF Forecast Changes on FDIF (Statements)

Univariate regression coefficients of forecast revisions on FDIF from statements. The fed variables used are those where the meeting occurs between the survey deadline of quarter q's survey and the BEA advance release that occurs in quarter $q+1$ (which is the earliest possible date the survey can start). The right hand side variables are the sum of the FDIF variables in this period. The forecast change is the difference between the forecast from quarter $q+1$ and quarter q. All forecasts are made over a one year horizon except CPI5YR. FDIF^{PC1} is the first principal component of the FDIF series estimated over the full sample. Standard errors are adjusted according to Newey and West (1987) with three lags. P-values are in parentheses and R^2s are in brackets. The Fama-MacBeth univariate coefficient reports the cross-sectional pricing results for the linear factor model based on Fed measures computed from FOMC statements and minutes, where the test assets are the 49 Fama-French industry portfolios. Factor risk prices are obtained by FMB cross-sectional regressions, and are reported in basis points per unit of standard deviation of the first-stage FMB beta. FMB standard errors are clustered by time. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.

Forecast Variable	$FDIF^{VIX}$	$FDIF^{DXY}$	$FDIF^{10Y}$	$FDIF^{2s10s}$	$FDIF^{3M}$	$FDIF^{HY}$	$FDIF^{IG}$	$FDIF^{PC1}$	BK Surprise	2Y Change
CPROF Growth	-0.0512**	0.0483	0.7647	-1.5135***	0.9***	-0.2422	-1.3169	0.2436*	-3.6762	4.9074
	(0.0214)	(0.7773)	(0.3961)	(0.0031)	(0.0085)	(0.1501)	(0.1069)	(0.0801)	(0.5042)	(0.4807)
	[0.0168]	[-0.0118]	[-0.0065]	[0.0109]	[0.0193]	[0.0082]	[0.0017]	[0.0135]	[-0.0081]	[-0.0004]
EMP_AVG Growth	-2.5144**	-3.8355	41.3835	-21.2176	26.6747	-7.975	-17.2485	8.1358	-241.4587	-141.1335
	(0.0345)	(0.3427)	(0.3097)	(0.4056)	(0.2965)	(0.3701)	(0.6007)	(0.3222)	(0.388)	(0.3977)
	[0.4509]	[0.0511]	[0.116]	[0.014]	[0.159]	[0.1346]	[0.0016]	[0.1773]	[0.134]	[0.0514]
INDPROD Growth	-0.0218**	-0.0263	0.4547	-0.2576	0.2772	-0.0839	-0.2447	0.0851	-2.565	-1.4449
	(0.0184)	(0.3613)	(0.1614)	(0.195)	(0.1572)	(0.2224)	(0.3426)	(0.1808)	(0.2425)	(0.2641)
	[0.3569]	[0.0243]	[0.1566]	[0.034]	[0.196]	[0.1624]	[0.022]	[0.2082]	[0.1687]	[0.0635]
HOUSING Growth	-0.1086***	-0.2271	3.2467***	-1.474	1.4936*	-0.7098***	-3.6696**	0.607***	-28.7973***	-20.5091***
	(0.0)	(0.1408)	(0.0045)	(0.1693)	(0.0629)	(0.0022)	(0.0107)	(0.0048)	(0.0)	(0.0)
	[0.1503]	[0.0372]	[0.1417]	[0.0142]	[0.0952]	[0.212]	[0.1299]	[0.1884]	[0.3977]	[0.2645]
RGDP Growth	-0.0133**	-0.0154	0.264	-0.1101	0.1332	-0.0441	-0.1008	0.0451	-1.9011*	-1.4432**
	(0.0244)	(0.3796)	(0.1847)	(0.4157)	(0.3076)	(0.3259)	(0.5401)	(0.287)	(0.0984)	(0.0368)
	[0.395]	[0.0251]	[0.1564]	[0.0121]	[0.1296]	[0.1303]	[0.0042]	[0.171]	[0.2832]	[0.2144]
RRESINV Growth	-0.0425***	-0.1267**	1.1115**	-0.5235	0.514	-0.2296**	-1.1966**	0.2126**	-14.1969***	-10.1645***
	(0.0001)	(0.0239)	(0.0364)	(0.3072)	(0.1683)	(0.0232)	(0.0264)	(0.0227)	(0.0)	(0.0)
	[0.1165]	[0.0684]	[0.0807]	[0.0046]	[0.0532]	[0.1088]	[0.0655]	[0.1148]	[0.5049]	[0.3406]
RFEDGOV Growth	-0.0094***	-0.0437***	0.2535	-0.0592	0.1232*	-0.0717***	-0.4293***	0.0585***	-1.2021**	-0.5158
	(0.0033)	(0.0021)	(0.1425)	(0.5935)	(0.0824)	(0.0001)	(0.0002)	(0.0011)	(0.0255)	(0.3798)
	[0.0381]	[0.0655]	[0.0262]	[-0.0118]	[0.0175]	[0.0832]	[0.0691]	[0.0654]	[0.0165]	[-0.0063]
CPI5YR	0.0021***	0.0082**	-0.09***	-0.0048	-0.0289	0.0145***	0.0929***	-0.0126***	0.2872	0.2712*
	(0.0)	(0.0256)	(0.0052)	(0.859)	(0.161)	(0.0023)	(0.004)	(0.0056)	(0.1439)	(0.0633)
	[0.0762]	[0.0617]	[0.1597]	[-0.0165]	[0.0418]	[0.1268]	[0.1247]	[0.1153]	[0.0453]	[0.0495]
CORECPI	0.0042***	0.0135**	-0.107**	0.0533	-0.0563**	0.0243***	0.1375***	-0.0216***	0.4124	0.2017
	(0.0)	(0.0147)	(0.0152)	(0.1884)	(0.0388)	(0.0)	(0.0005)	(0.0)	(0.1259)	(0.2809)
	[0.2973]	[0.158]	[0.1837]	[0.02]	[0.1515]	[0.3203]	[0.2447]	[0.3055]	[0.0897]	[0.0118]
FM Univariate	-8.274**	-9.742***	10.702***	-12.230***	12.340***	-11.268***	-11.277***	11.850***	-4.629**	0.209
	(0.017)	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)	(0.039)	(0.943)

Table 5: Cross-sectional asset pricing with controls

The table reports cross-sectional pricing results for the linear factor model based on Fed measures computed from FOMC statements and minutes. The test assets are the 49 Fama-French industry portfolios. FDIF sensitivities are calculated in the first-stage FMB regression using (10). The Mkt_Rf and IEF_Rf sensitivities are also calculated in the FMB first stage where these regressors are part of the $\boldsymbol{f}_{t+1}$ factor. Factor risk prices are obtained by FMB cross-sectional regressions using (11). All risk-premia are reported in basis points per unit of standard deviation of the first-stage FMB betas. P-values are reported in parentheses. Standard errors are clustered by time.

	Statements							Minutes						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Intercept	-0.486	-5.636	-4.146	-5.686	-5.813	-6.063	-4.726	7.058	6.411	7.994	3.744	5.856	3.347	0.754
	(0.958)	(0.511)	(0.637)	(0.516)	(0.503)	(0.486)	(0.580)	(0.426)	(0.463)	(0.354)	(0.676)	(0.460)	(0.702)	(0.937)
FDIF^{10Y}	6.565**							1.427						
	(0.035)							(0.539)						
FDIF^{2s10s}		-7.401**							-1.483					
		(0.033)							(0.450)					
FDIF^{3M}			9.173***							-0.033				
			(0.005)							(0.987)				
FDIF^{DXY}				-5.069*							2.205			
				(0.098)							(0.263)			
FDIF^{VIX}					-3.313							1.043		
					(0.240)							(0.649)		
FDIF^{HY}						-6.522**							0.413	
						(0.011)							(0.758)	
FDIF^{IG}							-6.951**							1.078
							(0.028)							(0.468)
10Y_{t-1}	-4.444**							2.167						
	(0.048)							(0.352)						
2s10s_{t-1}		-0.710							-1.910					
		(0.699)							(0.242)					
3m_{t-1}			-2.204							3.982				
			(0.264)							(0.126)				
DXY_{t-1}				2.420							1.503			
				(0.209)							(0.395)			
VIX_{t-1}					8.843***							1.167		
					(0.003)							(0.549)		
hy_{t-1}						7.900***							1.154	
						(0.008)							(0.491)	
ig_{t-1}							8.383***							0.221
							(0.008)							(0.892)
BK Surprise	-1.834	0.187	-0.251	-0.117	-0.067	0.476	0.100	-0.622	-1.569	-0.391	-1.679	-1.561	-1.536	-1.185
	(0.447)	(0.925)	(0.896)	(0.956)	(0.972)	(0.782)	(0.957)	(0.714)	(0.338)	(0.826)	(0.284)	(0.368)	(0.355)	(0.455)
2Y Change	-1.620	-2.616	-1.837	-0.743	-0.848	-1.829	-1.694	0.144	-0.638	0.548	-1.757	-1.187	-1.518	-1.630
	(0.602)	(0.406)	(0.514)	(0.813)	(0.766)	(0.565)	(0.592)	(0.953)	(0.803)	(0.824)	(0.471)	(0.639)	(0.577)	(0.554)
Mkt_Rf	7.297**	8.413***	7.769***	8.266***	7.867***	7.536***	7.111***	-1.053	-0.721	-1.246	-0.085	-0.593	0.123	0.869
	(0.014)	(0.004)	(0.008)	(0.008)	(0.008)	(0.003)	(0.004)	(0.780)	(0.849)	(0.737)	(0.982)	(0.868)	(0.974)	(0.827)
EIF_Rf	4.946	3.981	2.811	5.928*	3.575	4.906	5.853	1.426	2.328	0.792	2.982	3.139	3.614	3.728
	(0.116)	(0.186)	(0.309)	(0.075)	(0.223)	(0.155)	(0.104)	(0.658)	(0.493)	(0.815)	(0.380)	(0.336)	(0.314)	(0.310)
R-squared	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.001	0.001	0.001	0.001	0.001	0.001	0.001
F-statistic	6.763	6.898	7.077	6.685	6.961	7.098	7.113	0.825	0.868	0.889	0.894	0.636	0.602	0.612
Prob(F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.550	0.518	0.502	0.498	0.702	0.729	0.721
N	7105	7105	7105	7105	7105	7105	7105	6958	6958	6958	6958	6958	6958	6958

Table 6: FDIF portfolios

This table reports, for each portfolio j, the average return (Mean), the risk-adjusted return controlling for the market excess return (Alpha CAPM), the Fama and French (1993) five-factor model (Alpha FF5), and the Fama and French (2015) five-factor model plus the momentum factor (Alpha FF5+UMD). All moments are annualized and reported in percentage points. Newey and West (1987) standard errors (allowing auto-correlation up to lag 20) are reported in parentheses. The portfolios are constructed by sorting industries into five groups based on unconditional risk-compensations as described in Section 5.2. Portfolio 1 contains industries with the lowest risk-compensations. Portfolio 5 contains industries with the highest risk-compensations. Portfolio (1-5) is the long-short portfolio (long portfolio 1, short portfolio 5). We report summary statistics for portfolios formed on average risk-compensation ranks across different FDIF measures for different holding periods. The sample period is March 2002-June 2020 for the full sample and March 2011-June 2020 for the late sample. For the late sample, we use average ranks derived from the first half of the sample.

Panel A: Full Sample	FOMC days						all days						non-FOMC days					
Portfolio	1	2	3	4	5	(1-5)	1	2	3	4	5	(1-5)	1	2	3	4	5	(1-5)
Mean	1.25*	2.24**	2.16*	2.79*	4.00**	-2.75**	11.31***	10.57**	11.14**	9.60*	10.82*	0.49	10.06***	8.32**	8.98**	6.81	6.82	3.24
	(0.70)	(0.99)	(1.14)	(1.54)	(1.85)	(1.22)	(3.44)	(4.20)	(4.35)	(5.26)	(5.83)	(3.52)	(3.44)	(4.20)	(4.40)	(5.31)	(5.87)	(3.54)
Std. Dev.	2.68	3.38	3.57	4.33	5.11	3.42	16.41	19.41	20.08	23.74	26.40	16.02	16.18	19.10	19.75	23.32	25.87	15.62
Sharpe Ratio	0.45	0.65	0.59	0.64	0.77	-0.82	0.61	0.48	0.49	0.35	0.36	-0.05	0.55	0.37	0.39	0.24	0.22	0.13
Cumul. Return	24.78	48.98	46.43	63.57	102.22	-40.13	513.13	385.83	426.18	243.57	279.25	-13.54	391.39	226.09	259.34	110.05	87.54	44.41
Alpha CAPM	-0.49**	-0.07	-0.25	-0.10	0.83	-1.32**	4.49***	2.18**	2.57**	-0.42	0.38	4.11	5.10***	2.24**	2.77**	-0.45	-0.72	5.82**
	(0.23)	(0.15)	(0.26)	(0.39)	(0.57)	(0.63)	(1.24)	(0.94)	(1.10)	(1.58)	(2.60)	(2.89)	(1.21)	(0.92)	(1.09)	(1.59)	(2.64)	(2.92)
Alpha FF5	-0.41	-0.05	-0.06	0.12	0.98*	-1.39**	2.95**	1.93**	1.58*	-0.69	0.66	2.29	3.40***	1.95**	1.68*	-0.81	-0.44	3.84
	(0.27)	(0.13)	(0.21)	(0.22)	(0.52)	(0.58)	(1.21)	(0.89)	(0.88)	(1.21)	(2.36)	(2.70)	(1.18)	(0.86)	(0.88)	(1.21)	(2.37)	(2.69)
Alpha FF5+UMD	-0.41	-0.05	-0.06	0.13	0.99*	-1.40**	2.91**	1.95**	1.60*	-0.65	0.70	2.22	3.37***	1.97**	1.69*	-0.78	-0.42	3.79
	(0.27)	(0.13)	(0.21)	(0.22)	(0.52)	(0.58)	(1.20)	(0.86)	(0.89)	(1.16)	(2.33)	(2.64)	(1.17)	(0.84)	(0.88)	(1.16)	(2.33)	(2.63)
Nobs	146	146	146	146	146	146	4590	4590	4590	4590	4590	4590	4444	4444	4444	4444	4444	4444
Panel B: Late Sample using Ranks from Early Sample																		
	FOMC days						all days						non-FOMC days					
Mean	0.08	1.20*	0.53	0.49	2.05	-1.98***	12.91***	15.34***	11.14*	9.74	6.82	6.09	12.84***	14.14**	10.61*	9.25	4.77	8.07*
	(0.77)	(0.65)	(0.74)	(1.23)	(1.29)	(0.60)	(3.98)	(5.76)	(6.17)	(7.09)	(7.03)	(4.87)	(4.04)	(5.84)	(6.32)	(7.24)	(7.12)	(4.82)
Std. Dev.	2.64	3.24	3.45	4.12	4.58	2.88	14.70	19.13	19.12	21.99	22.53	14.51	14.46	18.85	18.80	21.60	22.05	14.20
Sharpe Ratio	0.02	0.36	0.15	0.11	0.44	-0.69	0.84	0.77	0.55	0.42	0.28	0.38	0.85	0.72	0.53	0.40	0.19	0.53
Cumul. Return	0.38	11.19	4.45	3.84	19.74	-17.06	197.88	247.46	135.85	96.34	48.31	59.15	196.74	212.49	125.82	89.09	23.86	91.89
Alpha CAPM	-0.72**	0.12	-0.60*	-0.84	0.60	-1.32***	3.38*	1.85*	-2.06	-5.09**	-7.78***	11.16***	4.10**	1.77	-1.48	-4.31**	-8.53***	12.63***
	(0.34)	(0.11)	(0.35)	(0.66)	(0.59)	(0.37)	(1.99)	(1.08)	(1.50)	(2.15)	(2.92)	(3.96)	(1.94)	(1.08)	(1.50)	(2.15)	(2.84)	(3.89)
Alpha FF5	-1.07**	0.26***	-0.22	-0.26	1.12***	-2.19***	1.53	1.67	-0.08	-2.26	-3.34	4.88	2.39	1.51	0.13	-2.10	-4.66*	7.04**
	(0.44)	(0.10)	(0.17)	(0.54)	(0.42)	(0.33)	(1.65)	(1.02)	(1.15)	(1.73)	(2.74)	(3.44)	(1.63)	(1.01)	(1.13)	(1.70)	(2.63)	(3.34)
Alpha FF5+UMD	-1.07**	0.26***	-0.22	-0.26	1.13***	-2.20***	1.56	1.68*	-0.12	-2.32	-3.47	5.02	2.41	1.51	0.09	-2.16	-4.79*	7.21**
	(0.43)	(0.09)	(0.16)	(0.54)	(0.37)	(0.35)	(1.63)	(1.02)	(1.11)	(1.64)	(2.56)	(3.22)	(1.62)	(1.01)	(1.09)	(1.62)	(2.46)	(3.14)
Nobs	74	74	74	74	74	74	2326	2326	2326	2326	2326	2326	2252	2252	2252	2252	2252	2252
Holding days (per year)	8	8	8	8	8	8	252	252	252	252	252	252	244	244	244	244	244	244

Table 7: Long-short strategy

This table reports, for each portfolio j, the average return (Mean), the risk-adjusted return controlling for the market excess returns (Alpha CAPM), the Fama and French (1993) five-factor model (Alpha FF5), and the Fama and French (2015) five-factor model plus the momentum factor (Alpha FF5+UMD). All moments are annualized and reported in percentage points. Newey and West (1987) standard errors (allowing auto-correlation up to lag 20) are reported in parentheses. The portfolios are constructed by sorting industries into five groups based on unconditional risk-compensations. The first portfolio contains industries with the lowest risk-compensations. The last portfolio contains industries with the highest risk-compensations. For these long-short portfolios, we are long portfolio 1 and short portfolio 5 when there is no FOMC Statement release. For days with FOMC Statement releases, we do the opposite strategy: long portfolio 5 and short portfolio 1. We report results for portfolios formed on average risk-compensation ranks across different Fed diff measures, the risk compensation rank for the change in the two-year treasury rate on the day before the announcement from Hanson and Stein (2015), and the risk-compensation for the Bernanke and Kuttner (2005) surprise. The sample period is March 2002-June 2020 for the full sample and March 2011-June 2020 for the late sample. For the late sample, we use average ranks derived from the first half of the sample.

	Full Sample			Late Sample		
	FDIF	2Y Change	BK Ssurprise	FDIF	2Y Change	BK Surprise
Mean	5.99	2.36	1.98	10.05**	3.56	0.22
	(3.72)	(2.29)	(2.82)	(4.97)	(2.76)	(3.06)
Std. Dev.	16.02	9.89	11.39	14.50	8.58	9.33
Sharpe Ratio	0.30	0.11	0.06	0.65	0.35	-0.04
Cumul. Return	135.73	40.57	27.54	129.49	34.26	-1.98
Skewness	0.00	0.01	-0.00	-0.01	-0.01	-0.02
Kurtosis	0.02	0.02	0.02	0.02	0.03	0.02
Alpha CAPM	9.27***	4.33**	3.15	14.62***	6.11**	2.25
	(3.19)	(2.09)	(2.63)	(4.14)	(2.46)	(2.67)
Alpha FF5	7.64**	2.81	3.26	8.94**	3.51	0.16
	(3.01)	(2.02)	(2.36)	(3.67)	(2.14)	(2.51)
Alpha FF5+UMD	7.58**	2.80	3.23	9.06**	3.57*	0.18
	(2.99)	(2.04)	(2.33)	(3.52)	(2.16)	(2.49)
Nobs	4590	4590	4590	2326	2326	2326
Number of Trades (year)	16	16	16	16	16	16