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Central Bank Crisis Interventions and the Term Structure of Market Fear *

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Abstract

We study the impact of Fed crisis interventions on market fears — the perceived risk of large asset price drops. To do so, we develop a methodological framework that allows us to evaluate the causal effect of unexpected Fed actions on changes in market fears. We extract daily fear term structures from options markets with event horizons ranging from two weeks to ten years. We then use high-frequency price movements around crisis announcements for a wide range of financial assets, including FX, equity, and fixed income markets, to isolate the shock component of Fed interventions. We can measure the heterogeneous effects of various crisis tools by classifying Fed announcement shocks into five different policy groups. Applying this to the market turmoil of 2020, we find that the Fed impacts market fear via risk and information effects. The risk channel dominates at short to medium terms and works via asset purchases, whereas the information channel dominates at longer terms and operates via interest rate policies.

Keywords: financial crises; disaster risk; derivatives market; monetary policy; central bank communication

JEL classification: E52; E58; G12; G13.

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1 Introduction

Central banks have increasingly recognized the calming of market fear — the likelihood financial market participants attach to large asset price dislocations — as a critical part of their mission. They reason that sustained market stress is harmful, as the resulting high uncertainty hurts business investment and hiring and can cause the failure of systemically important financial institutions. This view dates back to the Bank of England's refusal to engage with the Panic of 1866, triggered by a collapse in railway stocks. The very high cost of that crisis prompted the government to force the Bank to develop a formal crisis response following Bagehot's (1873) classic exposition of the lender of last resort function. To date, the formal response has manifested itself in a versatile crisis toolkit. However, while these tools often put a floor under asset prices, preventing market participants from coordinating their expectations on worst-case scenarios, their use during crises is not without cost.

Focusing on the extreme market turmoil in the spring of 2020, we develop an empirical framework to relate the Fed's announcements of crisis interventions to changes in short and long horizon market fear. These daily fear measures are constructed by extracting the 10% risk-neutral quantiles of the S&P 500 index from options with terms ranging from two weeks to ten years. To quantify the impact of Fed crisis interventions on market fear for each term, we regress daily changes in market fear on Fed announcement shocks. We obtain a low-dimensional representation of these shocks using the first three principal components (PCs) extracted from high-frequency changes in futures and ETF prices around the announcements. These three PCs capture the majority of the price variation around Fed announcements and should thus summarize their key information content.

We run separate regressions of announcement shocks on horizon-specific market fear, obtaining a coefficient for each PC–horizon pair. Arranging these coefficients across maturities then allows us to trace how a given PC shapes fear across horizons, reflecting distinct channels via which the information revealed by Fed announcements affects risk perceptions over different horizons. Furthermore, we group Fed announcements into five distinct policy categories to capture the heterogeneous impact of different policy tools used by the Fed. Our results suggest the Fed faced two key trade-offs when using different policy tools in its crisis toolkit. First, when it used conventional policies to lower funding costs by providing liquidity, it also disturbed the markets via information effects, as the markets interpreted the interventions as signaling the Fed was more concerned than the market expected ex-ante. Meanwhile, when it used its newer unconventional policy tools, such as asset purchases, the markets did calm down. However, that action also caused the private cost of tail risk protection—hedging against extreme stock market outcomes—to fall, as seen by the long-term impact on options markets.

When investigating how the market perceives the Fed's interventions, we need financial instruments that contain information on the risk of significant losses across different event horizons. Options do precisely that. They encode information about the market's perception of significant price moves over pre-specified time horizons and how much market participants are willing to pay to insure against them. We focus on risk perceptions about the S&P 500 index, as it provides a natural focal point for market participants in times of crisis.

In this paper, we use a uniquely rich dataset on the over-the-counter (OTC) options markets provided by S&P Global's Totem service, allowing us to capture tail risk perceptions from two weeks ahead up to ten years into the future.[1] Options with such extreme contract terms are exclusively traded in the OTC market and are not available in standard option price datasets derived from exchange-based trading activity. We extract the risk-neutral distribution of future asset price moves from the option prices by applying standard methods that build on the insights of Breeden and Litzenberger (1978). Our primary interest is in the 10% quantile of the S&P 500 risk-neutral log return distribution for a given investment horizon. We refer to this 10% quantile as *market fear* and denote the entire schedule of fear across maturities as the *term structure of market fear*.[2]

We focus on the extreme market turmoil in 2020, using a sample of 125 trading days from 3 February to 31 July 2020 that spans 52 Fed announcement events. This choice is motivated by two considerations. First, to study the impact of Fed crisis interventions, we need heightened market turmoil as certain central bank tools, especially the broadly targeted lender of last resort interventions, are only deployed in crises. Market reactions to regular Fed actions, what we term conventional policies, such as interest rate decisions taken at pre-announced FOMC meetings, do not allow us to gauge how effective Fed interventions are in calming market fear at the peak of a crisis. Second, a range of non-conventional Fed crisis tools, such as the Fed's macroprudential levers, were only introduced after the 2008 financial crisis. The 2020 market turmoil is the first crisis where this broad range of tools was fully available.

Our goal is to quantify how different types of Fed crisis interventions impact market participants' perceptions of tail risk across multiple time horizons. Specifically, we measure how unexpected components of Fed announcements affect the term structure of market fear—the perceived probability and severity of large asset price drops from two weeks to ten years ahead. This requires us to address two fundamental measurement challenges.

The first challenge is isolating genuine Fed announcement effects from other factors. During the 2020 crisis, market conditions evolved rapidly, with multiple news events—pandemic developments, economic data releases, and policy responses—occurring simultaneously. Simply

[1] S&P Global's Totem service is the leading consensus pricing service for the over-the-counter (OTC) derivatives market. The option prices are the mid-quote estimates of the leading market makers, mostly large international banks. The data include prices for options with distant times-to-expiration and extreme strike prices corresponding to price drops in the underlying asset of more than 80%. For more information about the service, please see `https://www.spglobal.com/marketintelligence/en/mi/products/totem.html`.

[2] This usage of the term "fear" is close to how practitioners use it. In fact, the VIX measure is colloquially referred to as the "Fear Gauge," though other authors refer to the pricing kernel adjustment between the two measures as "fear" (see, e.g. Bollerslev and Todorov, 2011).

comparing fear levels on announcement days versus non-announcement days would conflate Fed effects with these confounding factors.

The second challenge is capturing the multidimensional nature of Fed crisis announcements. While conventional monetary policy operates primarily through the interest rate channel, crisis interventions activate channels that are largely absent from normal policy—portfolio balance effects from asset purchases, cross-border funding through FX swap lines, and regulatory relief through macroprudential measures. These channels operate alongside the interest rate channel, requiring a measurement approach that accommodates this richer transmission mechanism while remaining empirically tractable.

We address these challenges through high-frequency identification adapted from the monetary policy shock literature (Bernanke and Kuttner, 2005; Gürkaynak et al., 2005; Swanson, 2021). In narrow windows around Fed announcements—10 minutes before to 20 minutes after—we measure price changes across a comprehensive set of financial assets: interest rate futures (federal funds, Eurodollar, Treasury notes), foreign exchange futures, equity market futures, and a VIX ETF. These high-frequency price movements in the immediate announcement window capture market participants' reassessment of Fed policy and economic conditions, isolating the surprise component of announcements from other daily news flows.

To reduce dimensionality while preserving the rich information content, we apply principal components analysis (PCA) to these high-frequency price changes. The first three PCs—which we term the level, market, and slope factors—capture approximately 65% of the price variation around Fed announcements and have natural economic interpretations. The level factor reflects surprise changes in the interest rate level, the market factor captures unexpected shifts in broad risk perceptions, and the slope factor represents surprise changes in the term structure of interest rates.

With these surprise measures in hand, we estimate how each factor impacts market fear at different horizons by regressing daily changes in fear on the three factors, controlling for pandemic severity, macroeconomic news, and market volatility. Running separate regressions for each horizon reveals how a given type of surprise affects fear from two weeks to ten years ahead. We extend the baseline analysis to international equity indices and US sector ETFs, where cross-sectional heterogeneity in fear responses confirms the transmission channels identified in the baseline.

To understand how different Fed policies work through these channels, we classify the 52 announcement events into five policy categories based on Fed press releases: conventional interest rate policies (IR), lender-of-last-resort liquidity provision (LEN), asset purchases (AP), foreign exchange interventions (FX), and macroprudential regulation (MPR). We then decompose each principal component into contributions from these policy types, revealing which policies primarily operate through which transmission channels and how their effects evolve across the fear term structure.

We validate this identification strategy in multiple ways. First, we include comprehensive control variables in our daily regressions: lagged market variance, pandemic severity measures, and macroeconomic news surprises, with the robustness of our principal component coefficients to these controls suggesting that endogenous timing does not drive our main results. Second, we demonstrate through placebo tests using random timestamps that our results are specific to actual announcement times. Third, we directly measure fear changes in the same narrow announcement windows using minute-by-minute option prices, confirming that Fed announcements cause immediate, significant fear changes independent of daily market dynamics. This high-frequency analysis is limited to maturities of up to six months, however, which is why we rely on daily OTC option data for our baseline analysis of the full fear term structure extending to ten years.

We obtain three sets of results. First, crisis times are different. When we compare the impact of announcement surprises across horizons during crises to those at regular FOMC meetings outside crises, we find that Fed announcement surprises have little to no impact on market fear under normal market conditions but have large impacts during the crisis. Policy instruments and the targeted outcomes of the central bank's actions differ across economic conditions, and so does the nature of announcement surprises. When designing crisis intervention tools, it is necessary to calibrate them on crisis data.

Second, each of the three announcement surprise factors exerts a distinct impact on fear. While the level factor, the first principal component, captures most of the Fed announcement surprises, accounting for 33% of the variance, we still find that surprises picked up by the market and slope factors move fear significantly. For the level and slope factors, an unexpected easing, either via a lower level of interest rates or a flatter interest rate term structure, coincides with an increase in fear at all horizons. What would typically be thought of as accommodative Fed policies increase the cost of private tail risk protection. The market factor has a hump-shaped impact pattern, with the most substantial impact at shorter terms. Moreover, these findings generalize well across international equity markets and U.S. sectors, with cross-sectional heterogeneity: pronounced short-term responses in Canadian and Asian markets, stronger long-horizon effects in European indices, and amplified reactions in the financial sector – findings that closely align with established channels of monetary policy transmission.

Third, we find that the factors via which Fed announcement surprises impact fear differ significantly across policies. When we estimate policy attribution coefficients, we firmly reject the null hypothesis that policies are collectively indistinguishable from each other. Furthermore, even the sign of the average surprise created by different policies in a given factor can vary. For example, while interest rate related policies (IR), on average, create negative values for the slope factor, the Fed's asset purchase policy (AP), on average, creates positive values. The most surprising result is that both liquidity injections, targeted at the domestic sector (IR) and internationally (FX), on average increased fear, with FX exerting a powerful impact at the most extended maturities. By contrast, the policy most effective in reducing fear was asset purchases. Asset purchases primarily worked through the second PC, impacting fear via the market factor, while liquidity interventions increased fear through the first PC, the level factor. Finally, FX added fear via the third PC, the slope factor. This suggests that IR and FX's impact on fear primarily worked via Fed information effects, signaling to market participants that the long-term economic outlook is worse than expected (see Nakamura and Steinsson (2018) and Bauer and Swanson (2023)).

Taken together, we find that the Fed interventions strongly impacted fear, pointing to two types of trade-offs for crisis interventions. First, for conventional interest rate related policies, between easing funding conditions and scaring the market via negative information effects potentially blunting the effectiveness of interventions. Second, for non-conventional asset purchases, the trade-off is between calming immediate market fear at the cost of lowering the price of long-term tail risk insurance.

This paper aims to contribute to a better understanding of the functioning of the crisis toolkit of modern central banks. First, we introduce a methodological framework to empirically evaluate the heterogeneous impact of central bank crisis tools on risk perception. The existing literature explores the impact of conventional and unconventional Fed interventions (e.g. Hattori et al., 2016; Bekaert et al., 2013) and the introduction of specific 2020 crisis facilities (e.g. Haddad et al., 2021). Our study goes beyond this by examining the heterogeneous impacts of the central bank crisis toolkit. By emphasizing the unexpected component of Fed actions (Bernanke and Kuttner, 2005; Gürkaynak et al., 2005; Jarociński and Karadi, 2020; Swanson, 2021) and comparing the effectiveness of various crisis interventions, we contribute to a deeper understanding of the complexities involved in central bank policy during crises.

Second, we show that the way in which Fed actions affect risk perception differs significantly between crisis and non-crisis times. Building on the results in Bekaert et al. (2013) and Hattori et al. (2016) on the impact of monetary policy on risk perceptions, we highlight the importance of information effects during crises compared to normal market conditions. The state-contingent relationship between monetary policy and risk perceptions has implications for policy transmission. For example, seemingly identical policy actions, such as asset purchases, can have very different impacts on asset prices depending on market conditions.

Lastly, prior studies (Bekaert et al., 2013; Hattori et al., 2016; Hu et al., 2022) primarily focus on the effect on short-term risk perspectives (up to three months for equities). Similarly, Kelly et al. (2016) have documented significant risk premia in short-dated option prices due to implicit disaster insurance that the US government provides to the financial sector, echoing results for stock returns in Gandhi and Lustig (2015) and speaking to the possible long-term consequences of such interventions. However, we extend the analysis to evaluate both immediate and long-term perspectives, up to 10 years. This longer horizon of an investors' fear allows us to gauge the market participants' current view of the effect of the toolkit far beyond the duration of the current crisis. This allows us to provide a comprehensive assessment of the effectiveness of various Fed crisis management tools, shedding new light on their impact beyond the current crisis.

The remainder of the paper is organized as follows. First, Section 2 introduces the fear term structures we construct, the Fed policy announcements, and the identification strategy. Next, we discuss the empirical results in Section 3, cross-sectional evidence in Section 4, and the contribution of individual Fed policies to fear in Section 5. Section 6 concludes. Finally, the Appendix shows robustness checks and provides additional information on the Fed policies and announcement surprises.

2 Market fear and Fed interventions

Our empirical framework is based on regressions of the following type,

$$\Delta \text{Fear}_{t,\tau} = \alpha_\tau + \gamma_\tau \,\text{Fed crisis action}_t + \xi_\tau \,\text{Controls}_t + \epsilon_{t,\tau}, \tag{1}$$

where we regress contemporaneous daily changes in market fear, $\Delta\text{Fear}_{t,\tau}$, given time horizons τ (measured in months) on Fed crisis actions on day t and controls at time t. *Fed crisis action*$_t$ are represented by the high-frequency price shocks collected from futures prices around the announcement time. Our main object of interest is the coefficient γ_τ, measuring how a Fed action impacts fear over horizon τ. We thus obtain a collection of coefficients, which capture the *impact across horizons*. Finally, our final goal is to assess the more granular components of the regression coefficient γ_τ shocked by the different policy categories.

Our empirical strategy aims to identify the causal effect of Fed crisis interventions on market fear across multiple time horizons. This requires addressing two fundamental identification challenges: isolating genuine Fed announcement effects from contemporaneous market developments, and capturing the multidimensional nature of crisis policy interventions.

Our identification strategy is based on two key assumptions. First, within narrow time windows around Fed announcements, price changes in a comprehensive set of financial assets primarily reflect market participants' reassessment of Fed policy and economic conditions rather than other news or market developments. This assumption follows the high-frequency identification approach established in the monetary policy literature (Bernanke and Kuttner, 2005; Gürkaynak et al., 2005; Swanson, 2021). By focusing on price movements from 10 minutes before to 20 minutes after announcements, we minimize contamination from other news sources while capturing the immediate market reaction to Fed communications.

Second, we assume that the first three principal components of high-frequency price changes across our asset universe adequately span the space of Fed announcement surprises relevant for market fear. This dimensionality reduction is necessary because crisis interventions operate through multiple transmission channels simultaneously—affecting interest rate expectations, market liquidity, credit conditions, and cross-border funding. The three factors we extract—level, market, and slope—collectively capture approximately 65% of the price variation around announcements and have clear economic interpretations corresponding to distinct policy transmission channels. To implement this approach, we first need empirical measures of market fear and Fed crisis actions, which is the aim of the next two subsections.

2.1 Measuring market fear

We obtain our fear measure from the options market. As an option insures its owner against price moves, the option's price contains information on how likely the market deems the price move to be and how much market participants are willing to pay to insure against it. Given a sufficiently large range of strike prices for a given time to expiration, one can back out the risk-neutral (RN) distribution of possible price moves of the asset over the corresponding horizon as first pointed out by Breeden and Litzenberger (1978). While we have CBOE's intraday option prices for short horizons, we rely on data from S&P Global's Totem service. This is the leading consensus pricing service for the OTC derivatives market, an information aggregation service helping market participants to gauge the price of a particular option.[3] We opted for Totem instead of alternative sources because it contains options with long maturities and deep out-of-the-money strike prices on the S&P 500 index, which are crucial for capturing tail events but are not available in standard data sets derived from exchange-based trading activity (see, e.g. Dew-Becker et al., 2017).[4] We concentrate on the consensus prices of options written on the S&P 500 index, for which the Totem consensus pricing service features a notably higher number of submitters compared to other assets. Contracts with a 10 year horizon have on average 15 of the main brokers-dealers for this market submitting their best market going price.[5]

Our primary notion of fear over a particular time horizon τ is the negative of the 10% quantile of the RN excess log-return distribution of the S&P 500, $\text{Fear}_{t,\tau}$. Specifically, the excess log-return is given by the return from capital gains plus the dividend yield $\delta_{t,\tau}$ minus the risk-free rate for the corresponding horizon $r^f_{t,\tau}$, with current futures price for time-to-

[3] Totem collects end-of-day price estimates for a fixed grid of strike prices and maturities from the major dealers in the OTC market, where all contracts are valued at a single point in time, facilitating the construction of the RN densities.

[4] For existing studies adopting data from the Totem service, spanning several OTC derivatives, see Dew-Becker et al. (2017); Kremens and Martin (2019). Please note that previous studies may refer to the dataset as Markit Totem.

[5] Furthermore, Figure E1 in Appendix E depicts the transaction volume in long-dated contracts (maturities exceeding 500 days) on exchanges, showing that liquidity in long-dated options is highest during crisis times.

maturity τ given by $f_{t,t+\tau}$:

$$r_{t,\tau} := \ln \frac{S_{t+\tau}}{f_{t,t+\tau}} = \ln \frac{S_{t+\tau}}{S_t} + \delta_{t,\tau}\tau - r^f_{t,\tau}\tau.$$

Given the RN distribution of excess-log-returns, fear for a given horizon τ is then defined as:

$$\text{Fear}_{t,\tau} := -q^*_{t,\tau} \quad \text{where} \quad \mathbb{Q}_t\left(r_{t,\tau} \leq q^*_{t,\tau}\right) = 0.1, \tag{2}$$

where $\mathbb{Q}_t$ is the RN distribution of excess log-returns obtained from option prices. RN measures capture the key quantities by weighting markets' objective expectations about future events with a pricing kernel that adjusts those probabilities to reflect risk aversion. RN quantiles and VIX-type measures capture the markets' fears of these events.

Our focus on the 10% quantile is motivated by both economic interpretability and data reliability. A one-in-ten event provides a natural threshold for tail risk. More extreme quantiles, such as the 5%, are poorly identified in our data: at long maturities, the corresponding deep out-of-the-money strikes attract few contributors and exhibit large dispersion across quotes, while at short maturities, the coarse strike grid in daily Totem data prevents precise extraction of such extreme quantiles. The 10% quantile avoids these problems and, at short maturities, can be validated against high-frequency CBOE exchange-traded option data.[6]

Figure 1: One-year S&P 500 fear at the height of the financial turmoil

The RN cumulative distribution function on 19 and 20 March 2020 with a maturity of one year. The red line highlights the daily change in the RN 10% quantile.

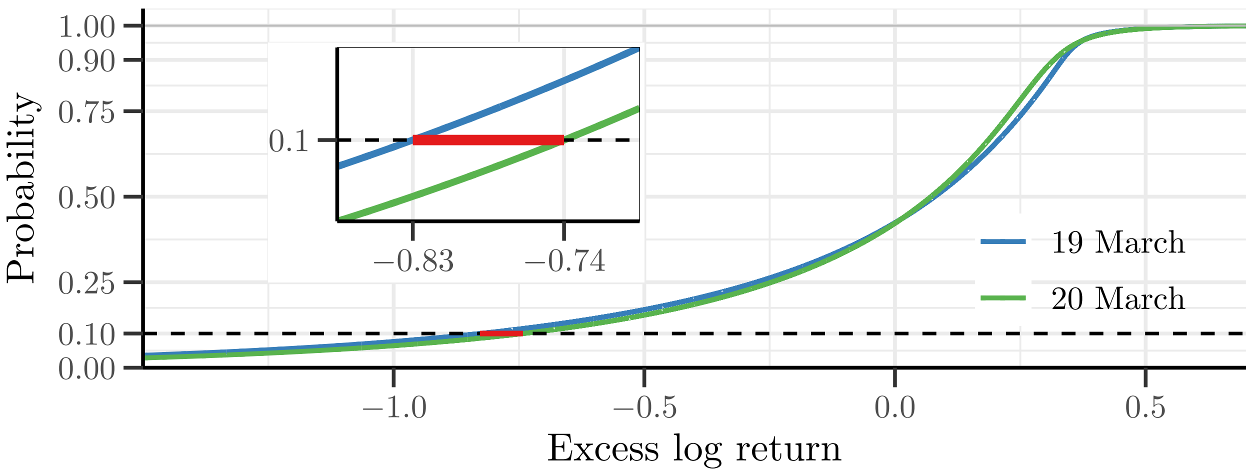


Figure 1 provides an example of fear in the S&P 500 index over a one-year horizon on two consecutive days at the height of the crisis, March 19 and 20, 2020. $\Delta\text{Fear}_{t,\tau}$, the daily change in fear, in this particular case, was:

$$\Delta\,\text{Fear}_{\text{March } 20,12} = \text{Fear}_{\text{March } 20,12} - \text{Fear}_{\text{March } 19,12} = 0.743 - 0.828 = -0.0850$$

[6]We validate these results using high-frequency options data in Section 3.2. We provide robustness checks adopting alternative quantile choices, and interquantile measures, in Section 3.3.

moving from a loss of $e^{-0.828} - 1 \approx -56\%$ to a loss of $e^{-0.743} \approx -52\%$, i.e., the market assessed on 19 March that there was a 10% chance of the S&P 500 dropping by over 56% over the subsequent year, that number fell to 52% the day after, a reduction in fear of 0.085 log return units.

Figure 2 shows how the market turmoil manifested itself in the term structure of fear. First, we see how different the main crisis days, here 18 March as an example, are from calmer days, such as 3 February. On a calm day, fear increases linearly, approximately at the rate of the square root of time. Likewise, fear increases across the maturity structure on the crisis day, but what stands out is the relatively higher increase at shorter immediate maturities, one month to three years, and the substantially higher level at longer maturities.

Figure 2: The term structure of fear before and during the 2020 crisis

The figure displays fear in the S&P 500 (y-axis) for horizons from 2 weeks to 10 years (x-axis) on 3 February 2020 (blue) and 18 March 2020 (green).

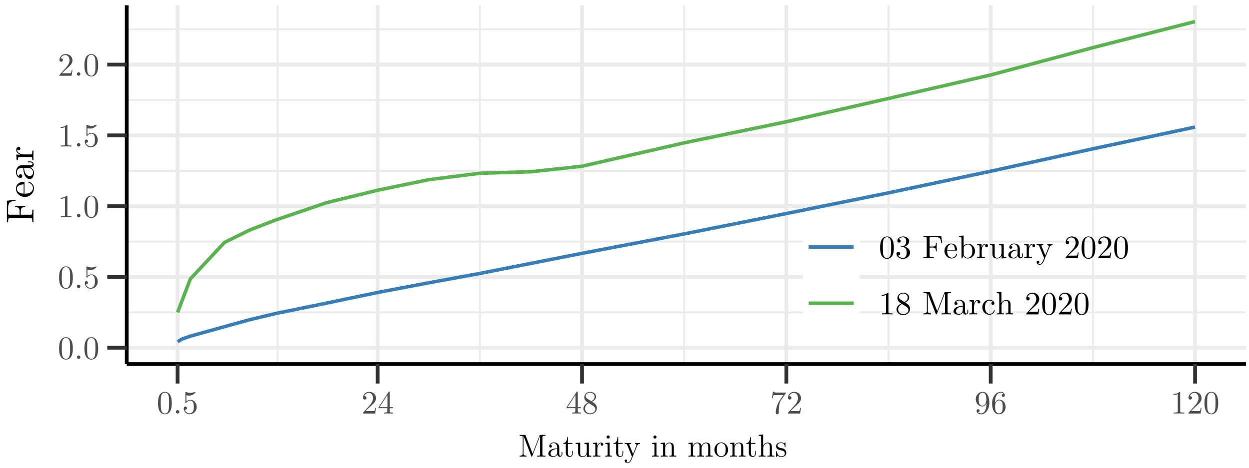
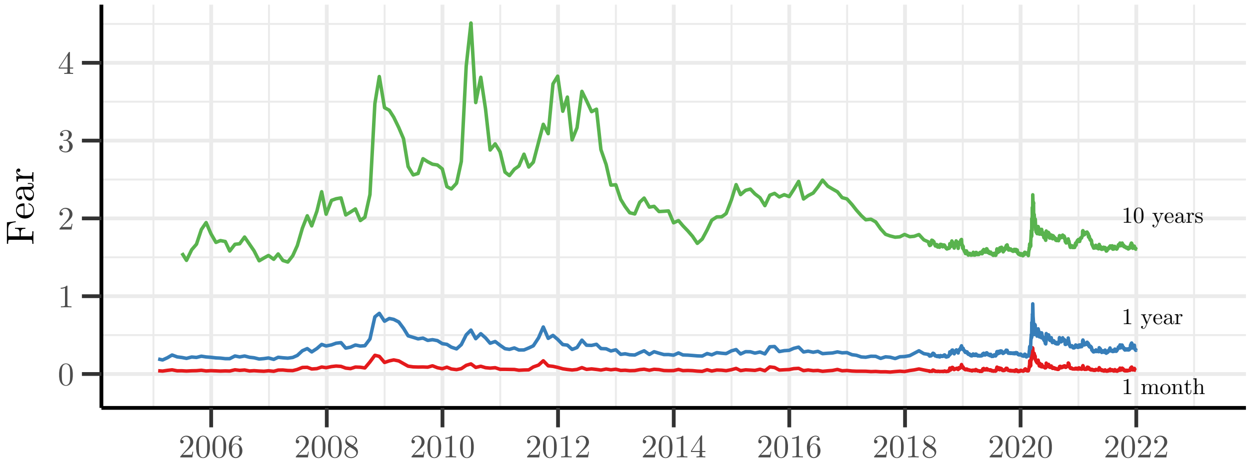


Figure 3 shows fear in the S&P 500 from 2005 until the end of 2021, monthly until 2018, and daily thereafter. The figure covers two crisis episodes, 2008 and 2020, and three maturities, one month, one year, and a decade. The two crises are visibly different from regular times, as fear spikes up sharply and only reverts slowly. There are important differences between the 2008 and 2020 crises. In the 2020 crisis, short-term fear is more pronounced, while in 2008, the strongest reactions were in long-term fear. Furthermore, while the flare-up of fear happens more quickly in 2020, it also reverts faster. These differences reflect the different nature of these two crises: a banking crisis and a crisis triggered by a significant liquidity demand shock. It might also reflect differences in the financial authorities' crisis interventions. In the following analysis, we do not compare the two episodes, both due to data limitations for the 2008 crisis — daily option price data for long-dated maturities are not available for that period[7] — and since the main Fed crisis-fighting tools only became available after the peak crisis of 2008 had passed.

[7] The Totem service has been providing S&P 500 daily option price data only since 2018.

Figure 3: S&P 500 term structure of fear, 2005-2021

The time series of S&P 500 fear for one month, one year, and ten years from 2005 to 2021. The data frequency is monthly until 2018, then daily.

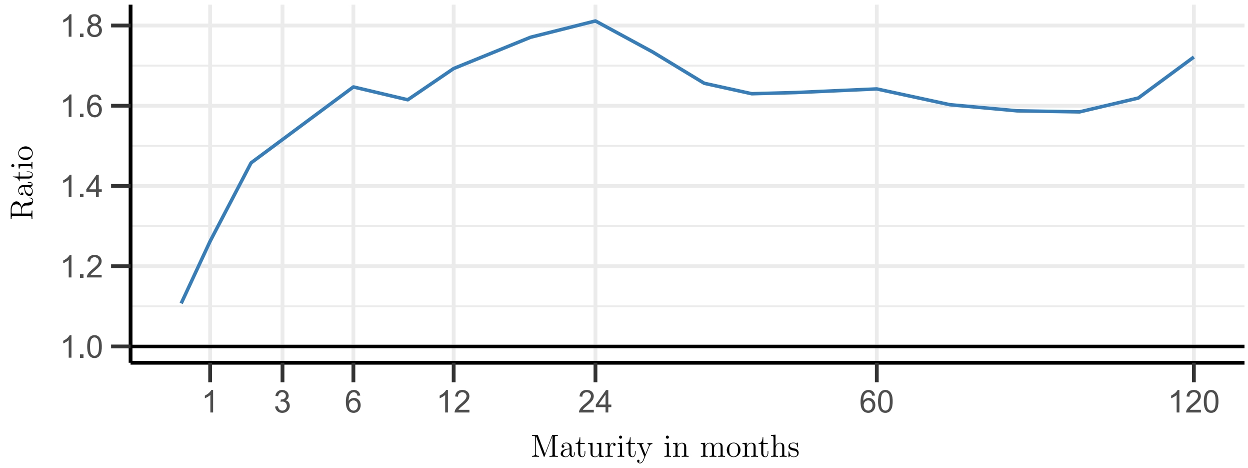


2.2 Fed announcements

Once it became clear in early spring 2020 that considerable market turmoil was on the way, most central banks reacted quickly. As an example of the speed of interventions, on the morning of 17 March, the Fed established the Commercial Paper Funding Facility. In the afternoon of the same day, the primary dealer credit facility was announced. Not only was the Fed quick to react, but the actions also appeared to have moved market fear. Figure 4 displays the ratio of change in fear on Fed announcement days versus non-announcement days. For short horizon fear, the average movement on announcement days was slightly larger than on non-announcement days. For the long horizon, on days with Fed announcements, fear moved almost twice as much as on days without announcements.

Figure 4: Change in S&P 500 fears on Fed announcement days

This figure shows the ratio of the average absolute change in daily fear on Fed announcement days to that on days without Fed announcements. The x-axis gives the horizon for fear displayed on a square root scale. The sample period is daily from 3 February 2020 to 31 July 2020.



The Fed intervened using a wide range of instruments. We collect all announcements of the Fed's economic and financial crisis policies from 3 February 2020 to 29 July 2020, including precise time stamps of when an announcement was made, from the press releases section of the Fed's website.[8] See Appendix A for the list of policy announcements and their time stamps.

With our market fear term structure measures and Fed policy actions in hand, the obvious way forward might be to directly use an announcement dummy in regression (1). However, that is not possible since, at the height of the crisis, the Fed made multiple interventions on the same day, while the fear measures are only available at a daily frequency. Furthermore, some announcements were presumably more important than others, and we want to be able to capture this intensive margin of Fed interventions. Consequently, we need an approach to pick up an announcement's timing and identify its importance. Lastly, Fed crisis announcements refer to various policy levers that impact financial markets differently. This means that announcement surprises are multidimensional and we need a measurement approach that captures this aspect.

2.3 Measuring announcement surprises

Thus, to overcome these empirical challenges, we propose a strategy for measuring Fed crisis interventions based on techniques to identify how monetary policy announcements affect asset prices, see, e.g., Bernanke and Kuttner (2005); Gürkaynak et al. (2005); Swanson (2021). To start, we collected several high-frequency futures and ETF prices, representing a broad spectrum of financial market activities, such as stock market returns and volatility, various aspects of the US money and government bond market, and foreign exchange.[9] The aim is to capture the broad transmission channels of Fed policies. For each asset, we measure how its price changes in a narrow window around the announcement (10 minutes before to 20 minutes after).[10] As an illustration, consider Figure 5, where we highlight the reaction of VIX ETF (VIXY) prices to different announcements of the Fed. In each panel, the black dots correspond to the minute-by-minute intraday aggregates of VIXY prices.

We z-score the panel of announcement surprises and perform a principal components analysis to reduce data dimensionality while preserving the most salient features. Table B2 shows the factor loadings of the first three principal components (PCs). Together, these PCs capture approximately 65% of the variation in the announcement surprises captured by the

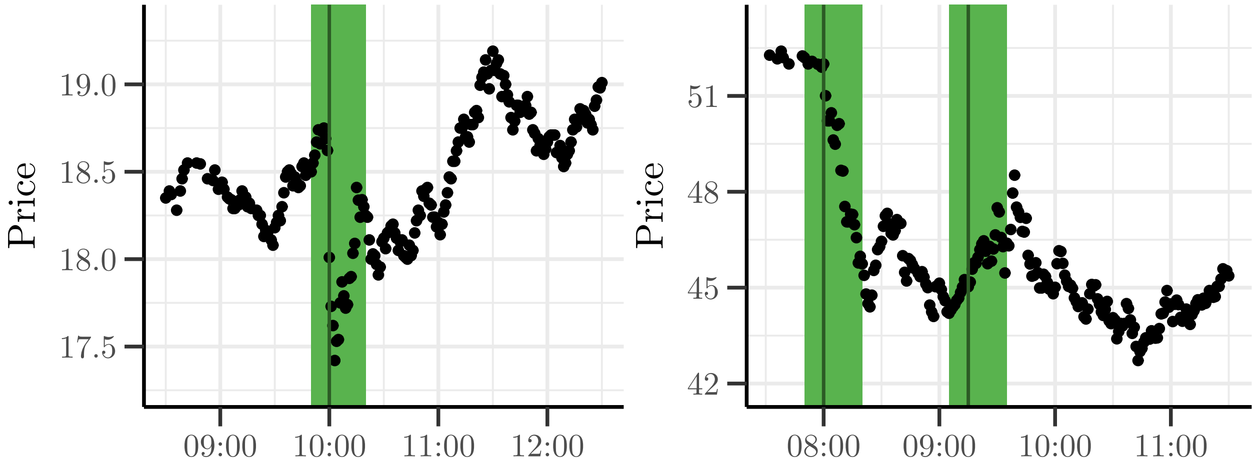
[8] See https://www.federalreserve.gov/newsevents/pressreleases.htm for more information.

[9] Our sample of financial assets consists of the VIXY ETF contract and the E-Mini, 1st Fed fund, 3rd Fed fund, 1st Eurodollar, 3rd Eurodollar, 2-year T-Note, 5-year T-Note, 10-year T-Note, USD/EUR, USD/Yen and USD/GBP futures contracts. Table B1 in Appendix B provides the pairwise correlations for the announcement shocks in these 12 contracts.

[10] One announcement was made on Sunday, 15 March, at 5 PM, when markets were closed, where we used the last available price before the announcement and the next available price after to calculate the price impact. We get similar results when we exclude this announcement.

Figure 5: Change in VIX ETF prices around Fed announcements

These figures illustrate the intraday changes in the VIXY ETF prices around Fed policy announcements, the intraday one-minute aggregates of the VIXY ETF prices (black dots) around the Fed announcements timestamps. The event window starts 10 minutes before and ends 20 minutes after the announcement and is displayed in green. The two days are (a) 3 March with an unscheduled FOMC meeting at 10:00 (IR), and (b) 23 March with two FOMC announcements, one at 08:00 (AP, LEN) as well as another one at 09:15 (MPR).



(a) 03 March 2020 (b) 23 March 2020

futures and ETF prices. More details on PC analysis and factor loadings can be found in the Appendix B.

Although PC analysis is a purely statistical technique for dimensionality reduction, the loadings in Table B2 in Appendix B show that the PCs have intuitive economic interpretations. PC_1 picks up surprise level shifts in the interest rate term structure. All interest rate futures, from the short end (Fed funds futures) to the long end (10y T-Note futures), have a loading of the same sign and magnitude. An increase in PC_1 corresponds to an unexpected lowering of interest rates. In what follows, we refer to PC_1 as the *level factor*.

PC_2 loads strongly on the equity markets, negatively on the VIXY ETF, and positively on the E-mini futures. Its loadings on interest rate surprises are significantly weaker than those of PC_1 and PC_3. An increase in PC_2 implies a surprise reduction in expected market volatility. These correlations are consistent with a broad reduction in risk perceptions across financial markets, and we refer to PC_2 as the *market factor*.

Lastly, PC_3 strongly loads on interest rate futures with opposite signs at the short and long end. An increase in PC_3 corresponds to a surprise steepening of the interest rate term structure. We refer to PC_3 as the *slope factor*.

Table B3 further highlights these economic factors by conducting univariate regressions. Specifically, we regress (i) the interest rate implied by the 1st Eurodollar futures contracts (ED 1st; in percentage points) on $\widetilde{PC}_1$; (ii) the VIXY ETF (VIX; in vol points) on $\widetilde{PC}_2$; and (iii) the spread between the implied yield of the 10y T-Note futures contract and the interest rate implied by the 1st Fed funds futures contract (TN 10-yr - FF 1st; in percentage points) on $\widetilde{PC}_3$. These regressions provide an economic scale for interpreting the regression coefficients in Section 3: a one-standard deviation increase in the level factor corresponds to a surprise decrease of five basis points in the short-term interest rate; a one-standard deviation increase in the market factor corresponds to a surprise decrease of 1.5 volatility points in the one-month VIX; and a one-standard deviation increase in the slope factor corresponds to a surprise three basis point flattening of the yield spread. To further cement the economic interpretation of the PCs, we also run a PCA on just the interest rate contracts to extract the first two PC's. These closely mimic the loading on the interest rate futures, representing the level and the slope changes in the interest rate term structure. Redoing the analysis with these two alternative PCs and the E-mini futures or VIXY ETF shocks produces quantitatively very similar results across horizons.

This approach adapts high-frequency identification methods from the monetary policy literature but differs in important ways that merit clarification. The canonical literature on monetary policy shocks (e.g., Bernanke and Kuttner, 2005; Jarociński and Karadi, 2020) aims to identify exogenous monetary policy shocks –deviations from the Fed's systematic reaction function—to trace their effects on macroeconomic variables like output and inflation.

Our objective differs from the monetary policy literature. We do not attempt to isolate exogenous monetary policy shocks in the traditional sense. Rather, we seek to measure the total effect of Fed crisis announcements—including both the direct policy component and any information revelation about the Fed's assessment of economic conditions—on market participants' tail risk perceptions. In crisis settings, information effects can be particularly important; when the Fed announces emergency interventions, market participants rationally update their beliefs about both policy support and the severity of economic conditions.

This is more modest modest than structural shock identification: we require only that high-frequency price changes around announcements primarily reflect reassessments of Fed policy and economic conditions rather than other contemporaneous news. Our measured effects capture the full impact of unexpected Fed communications on market fear, encompassing both the "risk channel" (direct policy effects on market functioning) and the "information channel" (signals about the Fed's private information). The contrast between how different policy types impact fear through our three factors, with conventional interest rate policies increasing fear while asset purchases reduce it, provides evidence that both channels operate during crises, sometimes in opposing directions.

We also differ from the structural shock literature in asset coverage. Swanson (2021) restricts his PCA to interest rate futures because his objective is to identify monetary policy shocks that operate through the yield curve. We deliberately include equity and foreign exchange surprises alongside fixed income. The narrow event window provides the identification: once we accept that price changes within these windows reflect the announcement—the standard assumption in this literature—there is no a priori reason to restrict which assets enter the factor decomposition. This broader coverage is necessary given our object of study. We analyze the full crisis toolkit, including FX swap lines, lending facilities, and regulatory measures, many of which do not primarily transmit through the yield curve. FX swap lines register in currency markets; lending facilities move the yield curve as well as the equity market. Restricting the PCA to fixed income would impose the assumption that all crisis interventions operate through the term structure of interest rates. Moreover, the broader asset coverage allows us to distinguish the economic channels through which announcements affect fear. Jarociński and Karadi (2020) demonstrate this principle in the monetary policy context, using equity responses to separate information effects from pure policy shocks. Our approach extends the same logic: by observing how announcements move equity and currency markets alongside interest rates, we can identify whether a given announcement reduces fear through direct risk reduction or increases it through adverse information revelation.

2.4 Threats to identification

Incomplete capture of Fed surprises

If our asset coverage does not span the relevant policy dimensions, our principal components may inadequately summarize the Fed announcement content, leading to measurement error and attenuation bias. We address this by deliberately selecting a broad asset universe covering fixed income (short-term federal funds and Eurodollar futures, medium- and long-term Treasury note futures), foreign exchange (dollar exchange rates against euro, yen and pound sterling), and equity markets (index futures and volatility). This comprehensive coverage ensures that we capture surprises operating through conventional interest rate channels, unconventional asset purchase programs, international spillovers via swap lines, and broad market risk perceptions. To further validate our approach, we compare results using our principal components against specifications employing individual asset surprises directly (federal funds futures, term structure slope, equity index changes, and exchange rate movements; Tables E1–E4 in Appendix E). The qualitative patterns align with our baseline results, confirming that our factors capture the salient dimensions of Fed announcements.

Endogenous Fed timing

The Fed intervened when market fear was elevated, raising concerns that our estimates capture reverse causality rather than Fed policy effects. Several features of our setting mitigate this concern. First, the vast majority of announcements (41 of 52 events) were unscheduled emergency interventions rather than pre-announced FOMC meetings, limiting the scope for systematic timing in response to intraday market conditions. Second, our high-frequency approach inherently reduces endogeneity concerns—the Fed cannot observe and respond to fear changes within our 30-minute event windows. Third, we include comprehensive control variables in our daily regressions: changes in realized market variance, pandemic severity measures, and macroeconomic news surprises. These controls capture observable factors that might trigger Fed interventions.

Contemporaneous news and events

During crisis periods, multiple significant events often occur simultaneously. If other major news arrives during our event windows, the measured price changes could reflect factors beyond Fed announcements. We address this threat in two ways. First, as mentioned earlier, we follow the standard approach in the high-frequency identification literature and extract announcement shocks from price movements in 30-minute windows around FOMC announcements (10 minutes before to 20 minutes after), as widely established (e.g. Gürkaynak et al., 2005; Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). This window strikes a balance between keeping the event window narrow enough to minimize contamination from confounding news and wide enough to allow asset prices to fully adjust to the information released during the announcement. However, some studies have considered wider windows to account for the slower incorporation of the information released during the FOMC press conferences (e.g. Hanson and Stein, 2015). In the following Section, we confirm that our results are not sensitive to alternative window choices and that the estimated effects on the fear term structure are specific to Fed announcement timing.

3 Impact of policy announcements on fear

Our empirical investigation is based on the regressing of daily changes in fear, $\Delta\text{Fear}_{t,\tau}$, on Fed announcement surprises, as captured by the first three principal components of price changes around announcements, and a set of controls. We modify (1) to incorporate the three surprise factors of the Fed announcement and the three controls,

$$\Delta\text{Fear}_{t,\tau} = \alpha_\tau + \gamma_\tau^{\text{level}}\,\widetilde{\text{PC}}_{1,t} + \gamma_\tau^{\text{market}}\,\widetilde{\text{PC}}_{2,t} + \gamma_\tau^{\text{slope}}\,\widetilde{\text{PC}}_{3,t} + \sum_{j=1}^{3} \xi_\tau^j\,\text{Controls}_t^j + \epsilon_{t,\tau}. \quad (3)$$

As discussed in Section 2, identifying the causal impact of Fed announcements on fear raises concerns about confounding news, endogenous Fed timing, and measurement error in the surprise extraction. To address these concerns, the baseline regressions control for the contemporaneous severity of the pandemic, news about the U.S. macro economy, and the first difference in realized stock market variance from $t-1$ to t.[11] In the regression, we

[11] We use the log of the 7-day rolling mean of new Covid-19 cases collected from the Johns Hopkins Coronavirus Resource Center, https://github.com/CSSEGISandData/COVID-19 and proxy for macroeconomic uncertainty using Bloomberg's economic surprise index (ECSU). To control for the endogenous response of the Fed to strong market volatility, we include the first difference of the previous day's realized variance of the S&P 500 obtained from Oxford-Man's realized variance library according to their measure of quadratic price variations over 10-minute intervals, see

normalize the PCs of the announcement surprise by their standard deviation and denote these normalized PCs by $\widetilde{PC}$. To control for residual serial correlation and heteroskedasticity, we use the Newey-West (HAC) estimator to calculate all standard errors.

Our interest is in the effectiveness of discretionary central bank actions in alleviating short-term financial market turmoil and the long-term consequences of such crisis interventions. To do this, we use regressions of the form (3) that relate daily changes in market fear in S&P 500 to Fed announcement surprises for a range of time horizons (two weeks to 10 years). The primary sample is daily observations from 3 February 2020 to 31 July 2020, when the Fed directly intervened to address significant financial market dislocations and support the wider economy.[12]

3.1 The impact of Fed announcements across horizons

We start by running regression (3) for varying horizons. The resulting collection of regression coefficients captures the *impact across horizons* of that factor. For a given maturity and factor, the regression coefficient gives the change in fear at that horizon caused by an announcement surprise captured by that factor. We present the empirical results of the impact of Fed announcements on fear across horizons in this section and show the impact by policy type in Section 5.

As the three factors are principal components, their units are not directly interpretable. To provide an economic scale, we use the univariate regressions reported in Table B3 (Section 2.3), which translate one-standard deviation PC movements into equivalent movements in interest rates, VIX, and the term spread. The regression coefficients γ_τ thus measure the change in fear at horizon τ caused by, for example, a surprise five basis point interest rate easing (level factor), a surprise 1.5 volatility point decrease in the VIX (market factor), or a surprise three basis point yield curve flattening (slope factor). As fear is measured by the negative of the 10% log return quantile, these changes are in units of (non-annualized) log returns over the corresponding horizon. A positive value implies an increase in fear.[13]

We present summary results for these regressions in Table 1, while Figure 6 displays the impact across horizons for the level (blue), market (yellow), and slope (red) factors. The sign of the impact coefficient for the level factor $\gamma_\tau^{\text{level}}$ is positive for all horizons and increases with

https://realized.oxford-man.ox.ac.uk/documentation/econometric-methods.

[12]The sample comprises 125 trading days spanning 52 Fed announcement events. The principal components of announcement surprises are non-zero only on the 40 trading days that contain at least one announcement within our event window; they equal zero on the remaining 85 non-announcement days, which contribute to the estimation of the control variable coefficients.

[13]If log returns were independently and normally distributed, fear would scale with the square root of maturity as it is a quantile of this distribution. If we assumed that a Fed announcement surprise permanently increases the variance of the log return distribution, then the impact coefficients would increase with the square root of maturity. A temporary impact of Fed announcement surprises induces a decreasing or hump-shaped pattern that converges to 0 for sufficiently long maturities. Appendix C provides more details on how to interpret the impact coefficients across horizons.

Table 1: Intervention impacts on market fear

The table reports the coefficient estimates of the announcement effects of Fed crisis actions on the market fear over horizon τ. Rows $\widetilde{\text{PC}}_1 - \widetilde{\text{PC}}_3$ give the impact coefficients, $\gamma_\tau^{\text{level}}$, $\gamma_\tau^{\text{market}}$, and $\gamma_\tau^{\text{slope}}$, from regression (3). Controls are $C_{t,\text{covid}}$, the rolling 7-day mean of the confirmed covid cases in the US, $C_{t,\Delta\text{ECSU}}$, the change in the Bloomberg economic surprise index, and $C_{t,\Delta\text{RV}}$, the change in realized variance from $t-1$ to t. The dependent variable is $\Delta\text{Fear}_{t,\tau}$ for maturities (τ) of 1,12,36, 60, and 96 months. Sample period: 3 February 2020 to 31 July 2020. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
$\widetilde{\text{PC}}_1$	0.008***	0.011*	0.010	0.012**	0.022***
	(0.003)	(0.006)	(0.006)	(0.006)	(0.005)
$\widetilde{\text{PC}}_2$	−0.015***	−0.036**	−0.029**	−0.021*	−0.017*
	(0.005)	(0.016)	(0.012)	(0.012)	(0.010)
$\widetilde{\text{PC}}_3$	0.007***	0.017***	0.018***	0.019***	0.026***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
C_{covid}	−0.001	0.028	0.042	0.037	0.037
	(0.018)	(0.029)	(0.037)	(0.034)	(0.033)
C_{ECSU}	0.005	0.006	0.002	0.002	−0.003
	(0.006)	(0.013)	(0.014)	(0.013)	(0.014)
$C_{\Delta\text{RV}}$	0.105***	0.160***	0.171***	0.171***	0.217***
	(0.019)	(0.032)	(0.035)	(0.032)	(0.040)
Constant	−0.002	−0.002	−0.001	−0.001	0.0005
	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	125	125	125	125	125
R^2	0.538	0.463	0.418	0.461	0.542
Adjusted R^2	0.514	0.435	0.389	0.434	0.518

maturity. An announcement that is more accommodating than expected, i.e. unexpectedly reduces interest rates, increases fear. At the ten-year horizon, a one-standard deviation increase in the interest level factor corresponding to a surprise five basis point interest level easing increases market fear by 0.03.

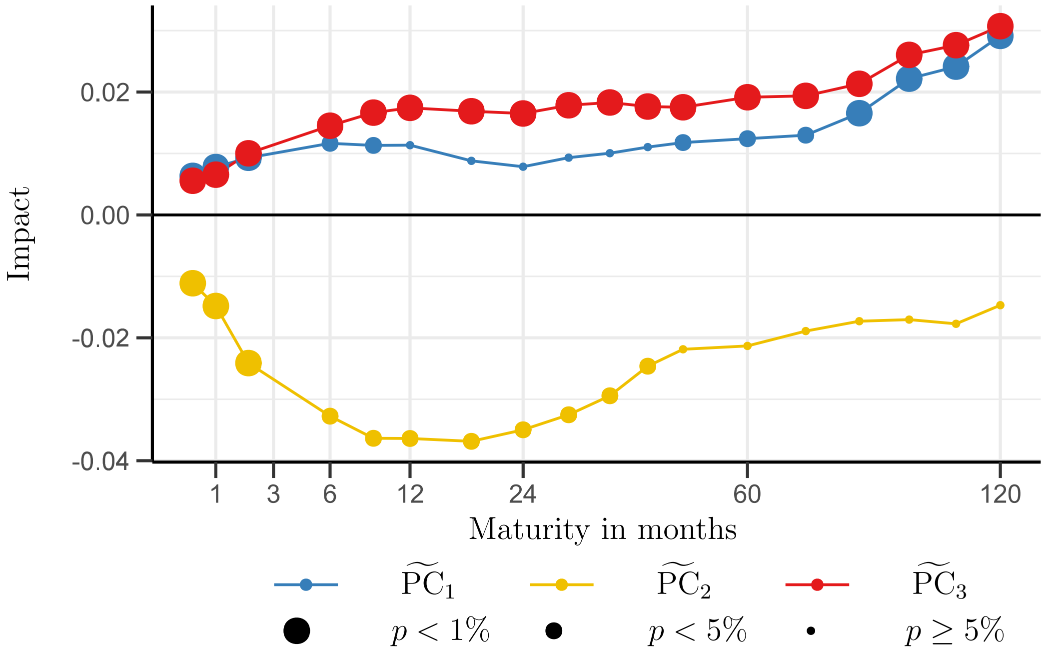
The sign of the impact coefficient for the market factor $\gamma_\tau^{\text{market}}$ is negative for all horizons, with a hump-shaped profile that peaks at intermediate maturities before decaying. An announcement that triggers a positive equity market surprise—for instance, by signaling stronger-than-expected policy support—reduces fear. At the one-year horizon, where the effect is strongest, a one-standard deviation increase in the market factor corresponding to a surprise decrease of 1.5 volatility points in the one-month VIX reduces market fear by 0.036.

The sign of the impact coefficient for the slope factor $\gamma_\tau^{\text{slope}}$ is positive for all horizons and increases monotonically with maturity. An announcement that unexpectedly flattens the yield curve increases fear. At the ten-year horizon, a one-standard deviation increase in the slope factor corresponding to a surprise three basis point flattening of the yield spread increases market fear by 0.026.

While the level factor captures most of the Fed announcement surprises — 33% of the standard deviation of announcement shocks compared to 19% and 12% for market and

Figure 6: Impact of Fed announcements on S&P 500 fear across horizons

This figure displays the impact of Fed announcement surprises on fear across horizons for the level (blue), market (yellow), and slope (red) factors. The y-axis provides the value of point estimates of the coefficients, $\gamma_\tau^{\text{level}}$, $\gamma_\tau^{\text{market}}$, and $\gamma_\tau^{\text{slope}}$. The x-axis gives the horizon on a square root scale. The bullet size •, ●, ⬤ indicate the significance level at 10%, 5% and 1% of the coefficients, respectively. The standard errors are calculated using robust standard errors based on Newey and West (1987).



slope factors respectively (see Appendix B) — Fed announcements also strongly impact fear via market and slope factors. The market factor has a hump shaped impact pattern, with the most substantial effects coming at the short to medium-term horizon. The slope factor's impact pattern, increasing with the horizon, is consistent with a long horizon effect of Fed surprises that operate via this factor.[14]

Regarding the impact of the slope factor, it is noteworthy that an unexpected flattening of the term structure of yields coincides with an increase in fear. The direction of this effect is consistent with an information channel of Fed surprises, whereby market participants extract signals about the state of the economy from the Fed's actions. Colloquially expressed by market participants as "Things must be terrible if the Fed does this." The fact that the effect is most potent for long-term fear suggests that such information extraction pertains primarily to the perceived probability of a protracted crisis.

When considering the temporal impact of the level and slope factors, neither point to a trade-off between calming shorter market fear at the expense of distorting long-term risk-taking incentives. In contrast, for both factors, an unexpected easing either via a lower level of

[14]Table B4 in Appendix B displays coefficient estimates for regression (3) augmented by including the (normalized) fourth PC of the announcement surprises ($\widetilde{\text{PC}}_4$). Tables E1–E4 in Appendix E report results from alternative specifications that replace the principal components with individual asset surprises (federal funds futures, term structure slope, S&P 500 futures, and USD/Yen exchange rate). The qualitative impact patterns across horizons are consistent with the baseline, confirming that our findings do not depend on the PCA-based factor construction.

interest rates or a flatter interest rate term structure causes an increase in fear at all horizons. What appear to be more accommodating Fed policies increase the cost of private tail risk protection. Instead, the results point to a different trade-off between relaxing funding costs and increasing market fear, as the former sends worrying signals about long-term economic prospects. This reiterates the difficulty already pointed out in the context of conventional interest policies, e.g. Nakamura and Steinsson (2018), that the effects of Fed information can reduce the effectiveness of accommodative policies.

By contrast, the impact of the market factor is to reduce fear. The impact is strongest at the short to medium-term horizons, but it does not die out rapidly, staying significant well beyond the immediate crisis horizon. The Fed likely intended to reduce short-term risk premia. However, the cheapening of private tail risk protection for longer-term horizons points to the potential costs of such relaxation.

Finally, as mentioned in Section 2.4, we confirm the robustness of our results along several dimensions. First, the vast majority of announcements were unscheduled emergency interventions rather than pre-announced FOMC meetings, limiting the scope for systematic timing in response to intraday market conditions. Excluding scheduled FOMC announcements from the baseline regression leaves our results qualitatively and quantitatively unchanged (Table E5 in Appendix E). Second, we verify that our findings are not sensitive to window choice by re-estimating the main specification using a wider event window (15–60 minutes around announcements), with results reported in Figure E2 in Appendix E. We find consistent patterns when adopting this alternative specification.[15] Third, we conduct placebo tests to rule out that our results merely reflect typical comovement between the futures prices entering the PCA and option-implied fear during the crisis. We draw random timestamps during trading hours on announcement days (excluding actual announcement times), extract pseudo-shocks from 30-minute windows around these placebo timestamps, and re-estimate our baseline regression. Table E6 in Appendix E reports the results: the pseudo-shocks bear no systematic relationship with fear changes, confirming that the estimated effects are specific to the timing of Fed announcements.

3.2 Validation through high-frequency fear measurement

Perhaps the most direct validation of our identification strategy comes from measuring fear changes at the same high-frequency as our announcement shocks. Using minute-by-minute CBOE option prices, we construct fear term structures for horizons up to six months and measure changes during the identical 30-minute announcement windows used to extract policy surprises. We then regress these high-frequency fear changes on our three principal components without any control variables—the narrow window eliminates concerns about

[15]Considering an alternative window choice, e.g. 15 minutes before to 60 minutes after the announcements, produces qualitatively and quantitatively similar results.

daily confounds.

The results (Table E7 in Appendix E) strongly confirm our identification approach. All three principal components remain highly significant ($p < 0.01$) with the same sign pattern as our baseline daily analysis. The R^2 values (89.0% –91.4%) indicate that the price changes in the announcement window explain the vast majority of the fear changes in the announcement window, validating that our asset price movements genuinely reflect policy-induced changes in tail risk perceptions. Moreover, the magnitudes align closely with our baseline estimates, though slightly larger for the level and slope factors, suggesting that our daily approach, if anything, somewhat understates these effects due to within-day noise.

While the high-frequency approach eliminates daily confounds and yields the most precise estimates, we retain the daily specification as our baseline for two reasons. First, exchange-traded CBOE options are available only for maturities up to six months, whereas our main analysis uses OTC option data extending to ten years. Our central findings—the monotonically increasing impact of the level and slope factors, the hump-shaped and subsequently decaying pattern of the market factor, and the resulting policy trade-offs—critically depend on the long end of the term structure that is unavailable at high frequency. Second, beyond the frequency issue, our approach offers a distinct methodological advantage: it links fear changes to announcement surprises through a principal component decomposition of asset price movements, which reveals through *which economic channels* announcements affect fear. For instance, the finding that unexpected interest rate easing increases rather than decreases fear identifies the information channel of Fed communication—a result that would not emerge from directly regressing high-frequency fear changes on policy dummies, which can establish that fear moved but not whether the underlying asset price surprise was perceived as positive or negative. It is the combination of the daily specification with the PC decomposition that enables this channel identification at long horizons. The high-frequency results thus serve as validation: they confirm that our daily approach successfully isolates Fed announcement effects for the horizons where both data sources overlap, supporting the credibility of our estimates at longer horizons where only daily OTC data are available.

3.3 Fear decomposition and alternative quantiles

To link our fear measure to the large literature that uses VIX as an uncertainty measure, (see, e.g. Bloom, 2009; Bekaert et al., 2013; Bruno and Shin, 2015; Miranda-Agrippino and Nenova, 2022), one can express the 10% quantile in terms of the mean, the variance, and higher moments of the return distribution,

$$\text{Fear}_{t,\tau} = -q^*_{t,\tau} = -\left[\mathbb{E}^{\mathbb{Q}}_t(r_{t,\tau}) + \text{std}^{\mathbb{Q}}_t(r_{t,\tau}) \times F^{-1}_{t,\tau}(0.1)\right].$$

Keeping in mind that $\text{VIX}^2_{t,\tau} = -\frac{2}{\tau}\mathbb{E}^{\mathbb{Q}}_t(r_{t,\tau})$, Figure D1 in Appendix D shows that the shift in the quantiles is due to the combined effects of the policies shifting the mean of the distribution of log returns, $\mathbb{E}^{\mathbb{Q}}_t(r_{t,\tau})$, upwards, reducing the dispersion of the log-returns, $\text{std}^{\mathbb{Q}}_t(r_{t,\tau})$, and changing the quantile of the standardized distribution, $F^{-1}_{t,\tau}(0.1)$. Fed announcements thus affect fear through all three channels—the mean, the dispersion, and the shape of the standardized distribution—so our quantile-based measure captures tail-specific effects that VIX alone would miss.

The sharpest evidence that our results reflect genuine downside tail risk comes from estimating regression (3) using the negative of the 90% quantile as the dependent variable, which captures upside rather than downside risk (Table E8 in Appendix E). All three factors flip sign relative to the baseline. For the level and slope factors, interest rate easing and yield curve flattening increase downside fear but *decrease* upside risk. This asymmetry is consistent with the information channel: market participants interpret unexpectedly accommodative policy as a negative signal about economic prospects, shifting the return distribution leftward rather than simply widening it. For the market factor, the market surprise compresses both tails—reducing downside fear and upside risk—consistent with a reduction in overall uncertainty. However, the magnitudes and horizon profiles differ across tails: the market factor's calming effect is stronger and more persistent for downside than for upside risk. These asymmetries confirm that our baseline results are not driven by symmetric distributional shifts.

As a robustness check, we re-estimate the baseline using the negative 20% quantile (Table E9 in Appendix E). All three factors retain the same sign patterns as in the 10% quantile specification, but with uniformly smaller magnitudes, and some coefficients at the long end lose statistical significance. The deeper into the left tail, the larger the effects of Fed announcements. This gradient confirms that our findings are not an artefact of the specific 10% cutoff, while demonstrating that more extreme quantiles are more sensitive to policy surprises.

To isolate the differential response within the left tail, we construct an interquantile measure defined as the difference between the 10% and 20% fear measures (Table E10 in Appendix E). This spread captures left-tail dispersion: how much more the extreme left tail moves relative to the moderate left tail. All three factors produce significant coefficients. The market factor compresses this spread, meaning that the market surprise reduces extreme-tail fear by more than moderate-tail fear. Conversely, the level and slope factors widen the spread, with effects that increase with horizon. Interest rate easing and yield curve flattening disproportionately affect the extreme left tail, amplifying the gap between the 10% and 20% quantiles.

Taken together, these results establish that our fear measure captures downside tail risk effects of Fed crisis interventions that go beyond shifts in the conditional mean (VIX) or symmetric changes in dispersion. The effects are strongest at the extreme left tail and are specific to downside risk.

3.4 Crisis times are different: Pre-crisis analysis

To verify that our main results reflect the market's reaction to Fed crisis interventions specifically, rather than a general impact of Fed communication on tail risks, we conduct a placebo robustness check using the pre-crisis period. If our main specification is correctly identified, we would expect the fear term structure to respond to extraordinary Fed actions during times of market stress, but not to monetary policy shocks during tranquil periods. With this in mind, we run an analogous analysis for the pre-crisis period from mid-2018 to January 2020, focusing on the effect of announcement surprises of regular FOMC meetings on fear. The construction of the fear term structure is as described in Section 2 and based on daily option pricing data provided by S&P Global's Totem service. We extract announcement shocks from price movements in futures and ETFs prices[16] in 30-minute windows around the 14:00 FOMC announcement (10 minutes before to 20 minutes after). In total, there are 16 FOMC announcements in this sample. Again, as in the main analysis, we perform a PCA on the series of announcement shocks to extract the main features of Fed announcement surprises, see Table B5 in Appendix B. We observe that a PCA on pre-crisis announcement shocks yields very different factor loadings than in crisis time.

We then regress daily changes in fear at varying horizons on the first three PCs of announcement shocks, that we normalize to have unit standard deviation. Thus, we have an analogue to regression (3),

$$\Delta \text{Fear}_{t,\tau} = \alpha_\tau + \gamma_\tau^1 \widetilde{\text{PC}}_{1,t} + \gamma_\tau^2 \widetilde{\text{PC}}_{2,t} + \gamma_\tau^3 \widetilde{\text{PC}}_{3,t} + \sum_{j=1}^{2} \xi_\tau^j \, \text{Controls}_t^j + \epsilon_{t,\tau},$$

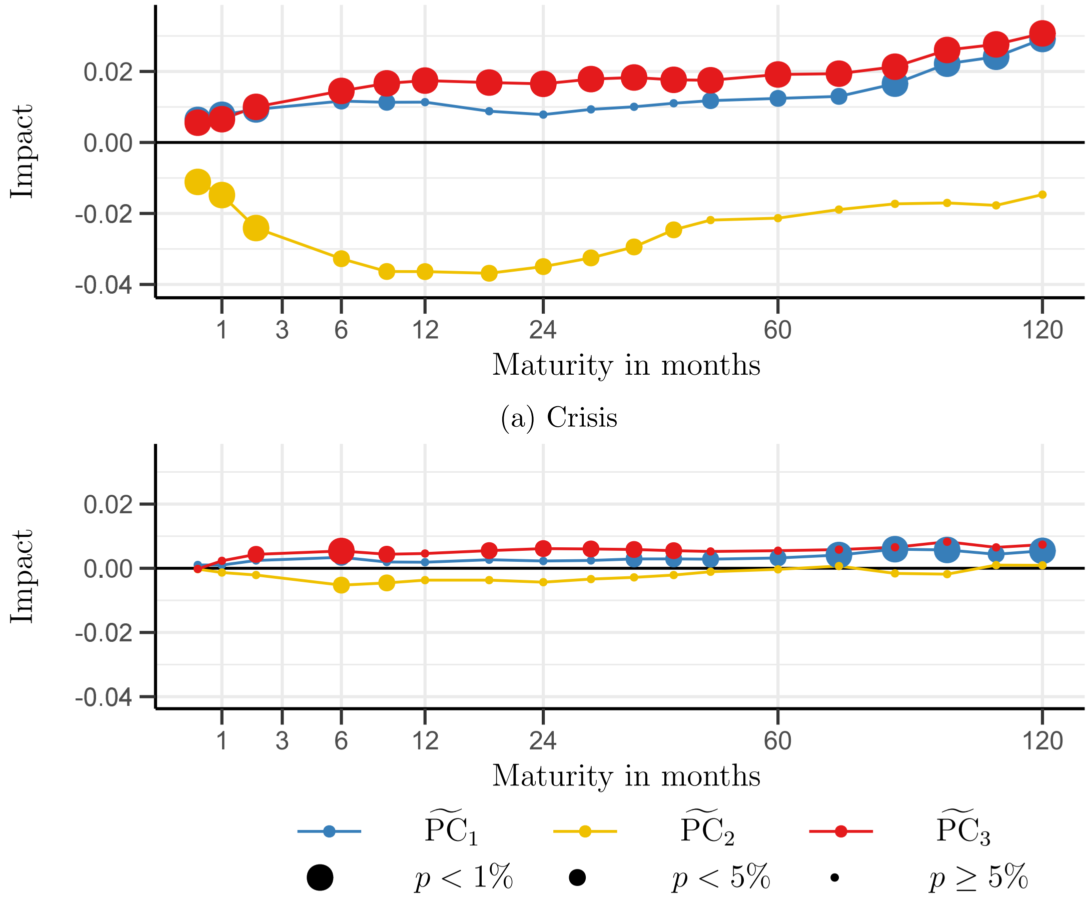
however the controls, for obvious reasons, do not include Covid cases. Figure 7 displays the impact across horizons for both the crisis and pre-crisis period.

We find that the impact of the regular FOMC meetings on the fear term structures is much smaller in magnitude relative to the crisis period. Crisis times are different. Policy instruments and the targeted outcomes of the central bank's actions differ across economic conditions, and so does the content of announcement surprises. Clearly, when calibrating crisis intervention tools, it is necessary to tune them on crisis data, not data generated in normal time.

[16]For the pre-2020 period we do not have access to FX futures prices.

Figure 7: Crisis and pre-crisis impact across horizons

The figure displays the impact of announcement surprises on fear across horizons at regular FOMC meetings for the period January 2018 to December 2019 (bottom panel) and reproduces the baseline crisis-period impact for comparison (top panel).



(a) Crisis

(b) Pre-crisis

4 International spillovers and sectoral heterogeneity

Our baseline results demonstrate that Fed crisis interventions significantly affected the term structure of market fear in U.S. equity markets. We now examine whether these effects extend beyond the S&P 500 by analyzing cross-sectional patterns in international equity markets and U.S. sector-specific indices. This analysis serves two purposes. First, it validates our identification strategy by testing whether Fed announcements produce systematic cross-sectional patterns consistent with the announced policies. Second, it addresses concerns about the generalizability of our findings beyond a single market index.

4.1 International equity markets

We first examine whether Fed crisis interventions affected market fear in international equity markets. If our high-frequency shocks genuinely capture Fed announcement surprises rather than generic crisis dynamics, we should observe systematic spillover effects that vary with countries' exposure to Fed policies. We extract fear term structures for equity indices in seven major economies available in our dataset: Australia (ASX200), France (CAC40), Germany (DAX30), the United Kingdom (FTSE), South Korea (KOSPI200), Japan (N225), and Canada (TSX60).

Figure E3 displays the impact across horizons for each country. The results reveal several important patterns. First, all three principal components of Fed announcement shocks significantly affect fear in international markets, with the same directional patterns observed for the S&P 500. The level factor (PC_1) increases fear across all horizons; the market factor (PC_2) reduces fear with the impact becoming stronger, and for some economies more negative, as the maturity increases, and the slope factor (PC_3) increases fear with effects strengthening at longer maturities.

The international spillover effects also reveal important heterogeneity across markets and factors, suggesting that Fed crisis interventions transmitted through multiple channels. For the level factor (PC_1), several international indices show stronger responses than the S&P 500. The Canadian (TSX60) and Australian (ASX200) indices exhibit significant effects across all maturities, while the S&P 500 effect concentrates at the short end. European indices (CAC40, DAX30) display particularly strong effects at longer maturities, from 24-month horizon onwards, suggesting heightened sensitivity to Fed signaling about long-term economic prospects. The market factor (PC_2) produces the most pronounced fear reductions in Asian markets, with Korean (KOSPI200) and Japanese (N225) indices showing effects across all maturities substantially stronger than the S&P 500. This pattern likely reflects these markets' acute sensitivity to dollar funding conditions and global risk sentiment. For the slope factor (PC_3), all international indices exhibit similar upward-sloping patterns across horizons, with the strongest effects at the 60- month horizon appearing in European markets (CAC40, DAX30).

These cross-sectional patterns are broadly consistent with known channels of international monetary policy transmission, though the short sample warrants caution in interpreting country-level variation. The strong market factor responses in Asian economies may reflect the dollar funding dependence of these markets: Bruno and Shin (2015) show that changes in global risk conditions affect the intermediation capacity of financial institutions with dollar-denominated liabilities, a channel that is particularly relevant for Korean and Japanese banks with large wholesale dollar funding needs. More broadly, Miranda-Agrippino and Rey (2020) document that U.S. monetary policy drives a global financial cycle through risk-taking and asset prices, with effects that are strongest in economies with open capital accounts and large financial sectors—a pattern consistent with the cross-country heterogeneity we observe. European indices respond most strongly to the level and slope factors at longer horizons, which may reflect deeper trade and financial linkages that amplify the information content of Fed actions about long-run economic prospects. The variation across countries also appears to correlate with access to Fed swap lines, as economies with direct Fed liquidity backstops tend to show more persistent fear reductions.

4.2 Sectoral heterogeneity in U.S. markets

We next examine whether Fed crisis interventions had differential effects across U.S. economic sectors. We construct fear term structures for six sector-specific ETFs included in the S&P 500: Energy, Financials, Health, Information Technology, Real Estate, and Utilities. We select these sectors to maximize variation in exposure to the pandemic and to Fed policy channels: Energy and Financials faced direct crisis exposure through collapsing oil prices and financial intermediary stress; Health and Information Technology exhibited differential pandemic sensitivity as beneficiaries of crisis-driven demand shifts; and Real Estate and Utilities are interest-rate sensitive sectors whose valuations depend heavily on long-term discount rates. This selection allows us to test whether sectors with greater exposure to specific Fed facilities exhibit stronger responses.[17]

Figure E4 presents the impact across horizons for each sector. The results reveal substantial sectoral heterogeneity, with particularly strong patterns in the financial sector. For all three PCs, the financial sector ETF exhibits the largest absolute responses, which are also statistically significant. The level factor (PC_1) is highly significant, with an effect that is three to four times larger than that observed for the aggregate S&P 500. The market factor (PC_2) lowers financial sector fear, with the strongest impact for horizons between 9 and 12 months. The slope factor (PC_3) similarly exhibits an effect that is roughly twice as strong as that for the aggregate S&P 500. This amplified sensitivity confirms that Fed crisis interventions are transmitted to the broader economy primarily through the financial system.

Other sectors show more moderate but still significant responses. Information technology and Real Estate, which tend to have longer-duration cash flows and greater cyclical sensitivity, exhibit particularly strong responses to the level factor (PC_1). All sectors show a strong and significant reaction to the slope factor (PC_3), which also increases with the horizon for sectors such as Real Estate, and Utilities. This pattern suggests that concerns about long-term economic conditions varied systematically across sectors in response to Fed announcements.

The amplified response of the financial sector provides direct evidence that Fed crisis interventions operated through their intended transmission channels. The finding that financial sector fear responds strongly to the market factor (PC_2) is particularly noteworthy, as we show in Section 5 that this factor is primarily driven by asset purchase announcements—suggesting that these interventions successfully targeted financial intermediary stress. This sectoral evidence complements our policy attribution analysis in Section 5 by demonstrating

[17] We examined all eleven S&P sector ETFs. The remaining five sectors—Communication Services, Consumer Discretionary, Consumer Staples, Industrials, and Materials—show no statistically significant responses to Fed announcement shocks, consistent with their more limited direct exposure to the pandemic and to the specific Fed facilities deployed during the crisis. The muted responses of these sectors provide additional support for our identification strategy.

that different Fed policy tools affected different parts of the financial system in economically interpretable ways.

Overall, the cross-sectional evidence strengthens our main conclusions in several ways. The systematic patterns across countries and sectors are difficult to reconcile with alternative explanations such as measurement error, confounding news events, or generic crisis dynamics. If our high-frequency shocks primarily reflected factors other than Fed announcements, we would not expect to see the observed geographic and sectoral patterns that align with economic linkages and policy exposure.

5 Announcement effects by policy type

Prior to the crisis in 2008, the Fed reacted to severe market stress with liquidity injections, both target rate cuts and short-term loans to banks. As conventional interventions proved insufficient in that crisis, the Fed has since developed a wide range of unconventional policies. Some were implemented in 2008, and others subsequently developed. Most were put to use in 2020, some for the first time, allowing us to identify their effectiveness in addressing market stress.

We use Fed press releases to classify all Fed announcements into five policy categories.[18] More specifically, we are interested in the impact of the different categories of Fed actions (IR, LEN, AP, FX, MPR), on the term structure of fear. That is, our final goal is to assess the more granular components of the regression coefficient γ_τ shocked by the different policy categories. IR captures conventional interest rate decisions, including forward guidance. Second, LEN is a lender-of-last resort type action that provides liquidity to stressed financial market participants, primarily banks and primary dealers, such as the Primary Dealer Credit Facility. Third, AP is asset purchases targeted at market functioning, especially for the US Treasury market, and at lowering longer-term borrowing costs, i.e., quantitative easing. One example is the Fed's new facilities for buying corporate bonds, the Primary and Secondary Market Corporate Credit Facilities. Fourth, FX is an intervention that provides dollar liquidity to foreign central banks and international organizations via the Fed's foreign exchange swap lines and FIMA repo facilities. Finally, MPR is macroprudential regulations. As the regulator of US bank holding companies, the Fed loosened macroprudential levers, such as excluding central bank reserves and US Treasury bonds from banks' supplementary leverage ratio calculations. Altogether there were 40 unique press releases and 52 policy events, 23 for LEN, 5 for IR, 10 for AP, 15 for MPR, and 5 for FX (see Appendix A).

[18] Our selection is similar to Cox et al. (2020), but we further include macroprudential policies and extend the set of included dates to the end of July.

5.1 Identifying policy attributions

The Fed's impact on fear differs across policy types because different policies transmit through different channels. In our framework, this operates through the three PCs of announcement surprises, level, market, and slope.[19] To identify how the various announcement surprises are picked up through the three (normalized) PCs, we regress them on policy type dummies,

$$\widetilde{\mathrm{PC}}_{i,n} = \beta_i^{\mathrm{IR}}\,\delta_n^{\mathrm{IR}} + \beta_i^{\mathrm{LEN}}\,\delta_n^{\mathrm{LEN}} + \beta_i^{\mathrm{AP}}\,\delta_n^{\mathrm{AP}} + \beta_i^{\mathrm{FX}}\,\delta_n^{\mathrm{FX}} + \beta_i^{\mathrm{MPR}}\,\delta_n^{\mathrm{MPR}} + \varepsilon_{i,n}, \tag{4}$$

where $i \in \{1,2,3\}$ identifies the PC, n refers to the n^{th} Fed announcement, and δ_n^p is a dummy variable for policy p, i.e. it is equal to 1 if the n^{th} announcement involved a policy of type $p \in \{\mathrm{IR}, \mathrm{LEN}, \mathrm{AP}, \mathrm{FX}, \mathrm{MPR}\}$ and 0 otherwise. The regression coefficient β_i^p then corresponds to the mean of $\widetilde{\mathrm{PC}}_i$ conditional on an announcement that only involved policy p. Intuitively, it gives the average size and direction of an announcement surprise in policy p during the 2020 market crisis that is captured by the given PCs.

Table 2 shows the regression coefficients for all five policies grouped by PC, along with an F-test for whether all policy coefficients for a given PC are the same, i.e., that the average announcement surprise captured by this PC does not depend on the type of policy that was announced. We show in Table E12 in Appendix E the p-values for whether each coefficient differs from zero. We see that interest rate (IR), foreign exchange (FX), and asset purchases (AP) created larger average surprises than lending (LEN) and macroprudential announcements (MPR). IR policies, on average, caused unexpected drops in the level of interest rates ($\mathrm{PC}_1 > 0$) together with a steepening of the term structure ($\mathrm{PC}_3 > 0$) while also causing risk perceptions to worsen ($\mathrm{PC}_2 < 0$). FX policies also lowered interest rate levels on average, but unlike IR, they flattened the interest rate term structure and improved risk perceptions. The strong effect of AP policies came through improving risk perceptions. The average impact on interest level and term structure was significantly weaker than for IR and FX-type policies except for the direct comparison between AP and FX for PC_3.

Figure 8 shows the average impact of a Fed intervention of a given policy type on fear. We obtain these policy specific impacts by multiplying the average surprise caused by the policy of type p in PC_i as given in Table 8 by the impact coefficient of PC_i for a corresponding horizon τ obtained in regression (4) and then summing across PCs, that is,

$$\left(\overline{\Delta\mathrm{Fear}_\tau}\,|\ \text{policy} = p\right) = \gamma_\tau^{\text{level}}\,\beta_1^p + \gamma_\tau^{\text{market}}\,\beta_2^p + \gamma_\tau^{\text{slope}}\,\beta_3^p \tag{5}$$

Overall, we see that asset purchases have been most effective in calming fears. On average,

[19] In Table E11 in Appendix E, we report results for regression (3) augmented by dummy variables that capture the policy type of an announcement. Including policy dummies does not change the impact coefficients across horizons, and policy dummies are statistically insignificant except for FX, i.e., they do not matter for the impact of the Fed announcement, given the PCs of announcement surprises.

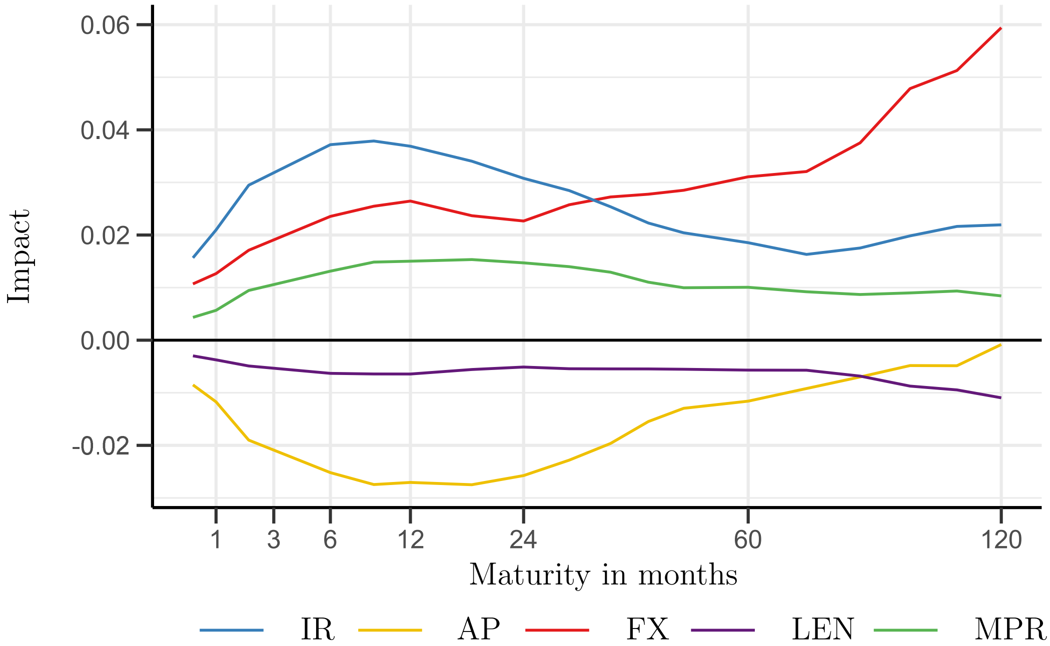
Table 2: Policy weights attributed to each factor

The table reports the coefficient estimates β_i^p for regression (4) where i refers to the PC (columns) and p to the policy (rows). The p-values of the F-test on all five coefficients are reported in the last row.

	level ($\widetilde{\text{PC}}_1$)	market ($\widetilde{\text{PC}}_2$)	slope ($\widetilde{\text{PC}}_3$)
IR	1.63	-1.17	-1.40
AP	-0.13	0.97	0.56
FX	0.81	0.11	1.22
LEN	-0.35	0.07	0.01
MPR	-0.10	-0.35	0.21
F-test (p-value)	0.00	0.03	0.02

Figure 8: Policy attribution

The figure displays the total expected impact on fear of an announcement of policy type p as given in equation (5). The x-axis reports the horizon on a square root scale.



they decreased fear by up to 0.03 log return units at the one-year horizon. The impact follows an inverted hump shape across horizons, with the most substantial effect at the one-year horizon and slowly dying off. Liquidity injections, both targeted at the domestic sector (IR) and internationally (FX), increased fear, with the impact increasing with the horizon, the strongest effects coming via the FX interventions beyond the five-year horizon. The overall impact of lending and macroprudential interventions on fear tends to be smaller, with the former decreasing on average, whereas the latter contributes to fear.

Asset purchases (AP) and liquidity interventions (IR, FX) have the opposite impact on fear because they operate through different factors. Asset purchases mostly relaxed fear via the market factor, where the pattern across horizons inherits the shape of the market factor. Liquidity interventions (IR and FX) increased fear through the level factor via an unexpected easing of interest rates. But FX added fear via the slope factor, whereas IR lowers fear through this channel, thus moderating the impact of IR policies on fear. Overall, this suggests that the impact on fear of these policies primarily worked via Fed information type effects, signaling to market participants that the long-term economic outlook is worse than expected. Table 2 shows that all the non-conventional policies (LEN, FX, AP, MPR) have negative coefficients for the slope factor, while IR's coefficient is positive, suggesting that for the Fed's interventions, non-conventional policies flattened the term structure of interest rates at the cost of unsettling markets, whereas conventional interest rate interventions steepened the interest rate term structure but calmed the market.

The contrast between liquidity policies (IR and FX) and asset purchases clarifies the types of trade-offs central banks face in their crisis interventions. The liquidity policies impact fear primarily via the level and slope factors, implying a trade-off between supporting the market by easing funding conditions and increasing fear by spooking the market, sending negative signals about the economic situation. On the other hand, asset purchases mainly operate via the market factor. To the extent that this factor has the biggest potential to reduce the private cost of tail risk protection, our results suggest that asset purchases are most costly in terms of the longer-term consequences that work via updated expectations about future central bank support. Ultimately, for these non-conventional policies, there is a trade-off between the short-term calming of market fear and the distortion of longer-term risk-taking incentives.

6 Conclusion

We study the impact of the Federal Reserve's 2020 crisis policy interventions on market fear. The analysis is based on the term structure of market fear, derived from a unique dataset on daily option prices covering extreme outcomes and horizons up to ten years into the future. We use high-frequency price movements around the Fed announcements to identify the importance of individual policy actions and classify them into five broad policy categories: lending, market liquidity, interest rate policies, foreign exchange policies, and macroprudential policies, and study their effects on the risk term structure.

The Fed's interventions had a strong impact on fear. Our results point to two types of trade-offs for crisis interventions. For conventional interest rate related policies, we find a trade-off between easing funding conditions and unsettling the market via negative information effects, potentially blunting the effectiveness of interventions. For non-conventional asset purchases, the trade-off is between calming immediate market fear at the cost of distorting long-term risk-taking incentives. A key message of this paper is that central banks should monitor the impact of their discretionary crisis actions on insurance premia across the full maturity spectrum, as different policy tools produce markedly different term structure profiles. Our results show that the choice of intervention instrument matters not only for the immediate calming of market fear but also for the long-term pricing of tail risk, with implications for the private sector's incentives to take on risk.

References

Bagehot, W. (1873). *Lombard Street.* London: H.S. King.

Bauer, M. D. and E. T. Swanson (2023). An alternative explanation for the "fed information effect". *American Economic Review 113*(3), 664–700.

Bekaert, G., M. Hoerova, and M. L. Duca (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics 60*(7), 771–788.

Bernanke, B. S. and K. N. Kuttner (2005). What explains the stock market's reaction to Federal Reserve policy? *The Journal of Finance 60*(3), 1221–1257.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica 77*(3), 623–685.

Bollerslev, T. and V. Todorov (2011). Tails, fears, and risk premia. *Journal of Finance 66*(6), 2165–2211.

Breeden, D. T. and R. H. Litzenberger (1978). Prices of state-contingent claims implicit in option prices. *Journal of Business*, 621–651.

Bruno, V. and H. S. Shin (2015). Capital flows and the risk-taking channel of monetary policy. *Journal of Monetary Economics 71*, 119–132.

Cox, J., D. L. Greenwald, and S. C. Ludvigson (2020). What explains the Covid-19 stock market? *NBER Working Paper*.

Dew-Becker, I., S. Giglio, A. Le, and M. Rodriguez (2017). The price of variance risk. *Journal of Financial Economics 123*(2), 225–250.

Gandhi, P. and H. Lustig (2015). Size anomalies in US bank stock returns. *The Journal of Finance 70*(2), 733–768.

Gürkaynak, R. S., B. Sack, and E. T. Swanson (2005). Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. *International Journal of Central Banking 1*(1), 55–93.

Haddad, V., A. Moreira, and T. Muir (2021). When selling becomes viral: Disruptions in debt markets in the Covid-19 crisis and the Fed's response. *The Review of Financial Studies 34*(11), 5309–5351.

Hanson, S. G. and J. C. Stein (2015). Monetary policy and long-term real rates. *Journal of Financial Economics 115*(3), 429–448.

Hattori, M., A. Schrimpf, and V. Sushko (2016). The response of tail risk perceptions to unconventional monetary policy. *American Economic Journal: Macroeconomics 8*(2), 111–36.

Hu, G. X., J. Pan, J. Wang, and H. Zhu (2022). Premium for heightened uncertainty: Explaining pre-announcement market returns. *Journal of Financial Economics 145*(3), 909–936.

Jarociński, M. and P. Karadi (2020). Deconstructing monetary policy surprises: the role of information shocks. *American Economic Journal: Macroeconomics 12*(2), 1–43.

Kelly, B., H. Lustig, and S. Van Nieuwerburgh (2016). Too-systemic-to-fail: What option markets imply about sector-wide government guarantees. *American Economic Review 106*(6), 1278–1319.

Kremens, L. and I. Martin (2019). The quanto theory of exchange rates. *American Economic Review 109*(3), 810–843.

Miranda-Agrippino, S. and T. Nenova (2022). A tale of two global monetary policies. *Journal of International Economics 136*, 103606.

Miranda-Agrippino, S. and H. Rey (2020). US monetary policy and the global financial cycle. *The Review of Economic Studies 87*(6), 2754–2776.

Nakamura, E. and J. Steinsson (2018). High-frequency identification of monetary non-neutrality: the information effect. *The Quarterly Journal of Economics 133*(3), 1283–1330.

Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Swanson, E. T. (2021). Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics 118*, 32–53.

A Announcements and classification

Table A1: Fed crisis announcements and policy classifications

Date and time	Category	Policy description
2020-03-03 10:00	IR	FOMC lowered the target range for the federal funds rate by 0.5%.
2020-03-15 17:00	AP	Fed tol increase holdings of Treasury and agency securities by at least $700 bn.
2020-03-15 17:00	FX,LEN	BoC, BoE, BoJ, ECB, Fed, SNB announce enhancement of USD liquidity swap lines.
2020-03-15 17:00	IR	FOMC lowered the target range for the federal funds rate by 1%
2020-03-15 17:00	LEN	The FOMC has instructed the OMD to expand its overnight and term repurchase agreement operations. Fed announced discount window and intraday credit for households and businesses.
2020-03-15 17:00	MPR	Fed encouraging banks to use their capital and liquidity buffers to lend.
2020-03-17 09:15	MPR	Banks allowed to ease capital buffers.
2020-03-17 10:45	LEN	Fed to establish a CPFF.
2020-03-17 18:00	LEN	Fed to establish a PDCF.
2020-03-18 23:30	LEN	Fed established MMLF.
2020-03-19 08:30	MPR	Interim final rule to ensure that financial institutions will be able to effectively use MMLF.
2020-03-19 09:00	FX,LEN	Fed announced temporary USD liquidity arrangements (swap lines) with several international central banks.
2020-03-20 10:00	FX,LEN	BoC, BoE, BoJ, ECB, Fed, SNB to enhance USD liquidity swap lines.
2020-03-20 11:00	LEN	Fed support for the flow of credit to the economy by enhancing the liquidity and functioning of money markets.
2020-03-23 08:00	AP	Fed announced PMCCF and SMCCF
2020-03-23 08:00	LEN	Fed $300 bn. to support the flow of credit to employers, consumers, and businesses.
2020-03-23 09:15	MPR	The Fed announces TLAC change.
2020-03-27 12:00	MPR	Actions to support the U.S. economy.
2020-03-31 08:30	FX,LEN	The Fed announced a temporary FIMA Repo Facility.
2020-04-01 16:45	MPR	Fed temporary change to supplementary LR.
2020-04-03 18:30	MPR	Regulatory flexibility for mortgage servicers with struggling consumers.
2020-04-06 09:00	MPR	Interim final rules for temporary relief to community banking organizations via temporarily lowering CBLR.
2020-04-06 14:00	LEN	The Fed will ease lending to small businesses via PPP.
2020-04-07 15:00	MPR	Interagency encouraging financial institutions to work with borrowers affected by COVID-19.
2020-04-08 11:30	MPR	Wells Fargo to make additional small business loans as part of PPP and MSLP.
2020-04-09 08:30	AP	Increase flow of credit to households and businesses
2020-04-09 08:30	LEN	Fed to provide up to $2.3 tr. to support the economy.
2020-04-09 09:30	MPR	Interim final rule to encourage lending to small businesses via PPP.
2020-04-14 18:00	MPR	Interim final rule to temporarily defer real estate-related appraisals and evaluations.
2020-04-17 16:30	LEN	Rule change to bolster the effectiveness of SBA and PPP
2020-04-23 17:30	LEN	Fed to increase intraday credit
2020-04-24 10:00	MPR	Fed rule to amend Regulation D to delete limit on convenient transfers
2020-04-27 16:30	AP	Fed $500 billion in lending to states and municipalities.
2020-04-29 14:00	AP,LEN	Fed continue to purchase Treasury and agency securities
2020-04-29 14:00	IR	Fed to maintain the target range for the federal funds rate.
2020-04-30 10:00	LEN	Fed announced an expansion to loan options to businesses.
2020-04-30 17:15	LEN	Fed expanded access to PPPLF.
2020-05-05 15:30	MPR	Fed announced a modified rule to LCR.
2020-05-15 17:45	MPR	Temporary changes to LR.
2020-06-03 13:00	LEN	Fed announced an expansion to eligibility of MLF.
2020-06-08 15:30	LEN	Fed expanded its MSLP to allow more SMB to receive support.
2020-06-10 14:00	AP,LEN	Fed continue to purchase Treasury and agency securities
2020-06-10 14:00	IR	Fed to maintain the target range for the federal funds rate.
2020-06-15 14:00	AP	Fed updates to SMCCF
2020-07-15 16:30	LEN	Fed extension to SBA PPP.
2020-07-17 10:00	LEN	Fed modified the MSLP.
2020-07-23 14:30	LEN	Fed broadedned eligibility to emergency lending facilities.
2020-07-28 09:30	AP	Fed 3-month extension of its PMCCF and SMCCF.
2020-07-28 09:30	LEN	Fed a 3-month extension of its lending facilities.
2020-07-29 14:00	AP,LEN	Fed increase holdings of Treasury and agency securities, OMD to continue repos.
2020-07-29 14:00	FX,LEN	Fed announced the extensions of its temporary USD liquidity swap and FIMA repo facility.
2020-07-29 14:00	IR	Fed decided to maintain the target range for the federal funds rate.

B Announcement shocks and principal components analysis

We calculate the price movements of 12 futures and ETF contracts in 30 minute windows around Fed crisis announcements, that is the price of a contract 20 minutes after the announcement minus the price of the contract 10 minutes before the announcement. The 12 contracts are (i) for the fixed income market, the 1st and 3rd Fed Funds futures (FF Fut 1st & 3rd), the 1st and 3rd Eurodollar futures (ED Fut 1st & 3rd) and the 2, 5, and 10 year T-Note futures (TN Fut 2-yr, 5-yr, & 10-yr), (ii) for the foreign exchange market the USD to Euro, Yen, and British Pounds futures (USD/EUR Fut, USD/Yen Fut, USD/GBP fut), and (iii) for the equity market the S&P 500 E-mini futures (E-Mini Fut) and the VIXY ETF. Table B1 provides the pairwise correlations for the announcement shocks in these 12 contracts.

Table B2 reports the PCA factor loadings. Table E12 reports the p-values for the hypothesis tests that the mean of a given PC does not differ across the two listed policies. That is, based on regression (4) in Section 5, the null hypothesis of the test for PC i and policies p and q is $H0 : \beta_i^p = \beta_i^q$. Table B3 shows the regression for the PCs.

Table B1: Pairwise correlations of announcement shock series

FF Fut 1st	1.00											
FF Fut 3rd	0.98	1.00										
ED Fut 1st	0.75	0.70	1.00									
ED Fut 3rd	0.84	0.81	0.96	1.00								
2-yr TN Fut	0.65	0.61	0.86	0.87	1.00							
5-yr TN Fut	0.83	0.79	0.94	0.96	0.89	1.00						
10-yr TN Fut	0.49	0.45	0.73	0.73	0.68	0.78	1.00					
VIXY ETF	0.24	0.18	0.40	0.30	0.37	0.43	0.15	1.00				
E-Mini futures	-0.01	0.00	-0.02	0.04	-0.06	-0.06	0.16	-0.79	1.00			
USD/EUR futures	0.56	0.53	0.69	0.70	0.54	0.64	0.66	-0.19	0.51	1.00		
USD/Yen futures	0.48	0.46	0.73	0.70	0.62	0.65	0.64	0.01	0.40	0.77	1.00	
USD/GBP futures	0.33	0.32	0.65	0.60	0.52	0.50	0.58	-0.19	0.40	0.84	0.75	1.00

Table B2: PCA factor loadings

This table reports the factor loadings for the 12 z-scored announcement surprise series of the first three PCs. The last row gives the percentage contribution of a given PC to total variance.

	PC_1	PC_2	PC_3
Fed fund futures 1st	0.30	-0.14	-0.52
Fed fund futures 3rd	0.29	-0.12	-0.57
Eurodollar futures 1st	0.35	-0.10	0.13
Eurodollar futures 3rd	0.36	-0.08	-0.06
2-year T-Note futures	0.32	-0.13	0.16
5-year T-Note futures	0.35	-0.15	-0.01
10-year T-Note futures	0.29	0.06	0.29
VIXY ETF	0.09	-0.56	0.31
E-Mini futures	0.05	0.59	-0.18
USD/EUR futures	0.30	0.31	0.02
USD/Yen futures	0.29	0.22	0.22
USD/GBP futures	0.26	0.32	0.30
S.D. (%)	32.86	19.01	11.98

Table B3: Economic interpretation of factors

This table reports regression coefficients from univariate regression (i) of the interest rate implied by the 1st Eurodollar futures contracts (ED 1st; in percentage points) on $\widetilde{PC}_1$ (1st column), (ii) the VIXY ETF (VIX; in vol points) on $\widetilde{PC}_2$ (2nd column), and (iii) the spread between the implied yield of the 10y T-Note futures contract and the interest rate implied by the 1st Fed funds futures contract (TN 10-yr - FF 1st; in percentage points) on $\widetilde{PC}_3$ (3rd column). *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:		
	ED 1st	VIX	TN 10-yr - FF 1st
$\widetilde{PC}_1$ − level	-0.052^{***}		
	(0.003)		
$\widetilde{PC}_2$ − market		-1.421^{***}	
		(0.126)	
$\widetilde{PC}_3$ − slope			-0.030^{***}
			(0.004)
Constant	-0.019^{***}	−0.139	0.005
	(0.003)	(0.125)	(0.004)
Observations	41	41	41
Adjusted R^2	0.909	0.758	0.622

Table B4: Impact across horizons with additional factor.

This table displays coefficient estimates for regression (3) augmented by including the (normalized) fourth PC of the announcement surprises ($\widetilde{PC}_4$). *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
$\widetilde{PC}_1$	0.008***	0.011*	0.010*	0.012**	0.022***
	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
$\widetilde{PC}_2$	−0.015***	−0.037**	−0.029**	−0.022*	−0.018*
	(0.005)	(0.015)	(0.012)	(0.012)	(0.010)
$\widetilde{PC}_3$	0.007***	0.017***	0.018***	0.019***	0.026***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
$\widetilde{PC}_4$	−0.001	−0.006	0.003	−0.002	−0.004
	(0.003)	(0.006)	(0.008)	(0.006)	(0.006)
C_{covid}	−0.001	0.029	0.042	0.037	0.038
	(0.018)	(0.030)	(0.037)	(0.034)	(0.034)
C_{ECSU}	0.005	0.006	0.003	0.001	−0.003
	(0.006)	(0.013)	(0.014)	(0.013)	(0.014)
$C_{\Delta\text{RV}}$	0.105***	0.160***	0.171***	0.171***	0.217***
	(0.019)	(0.031)	(0.036)	(0.032)	(0.039)
Constant	−0.002	−0.002	−0.001	−0.001	0.001
	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	125	125	125	125	125
R^2	0.538	0.468	0.419	0.462	0.543
Adjusted R^2	0.511	0.436	0.384	0.429	0.516

Table B5: Pre–2020 PCA factor loadings

This table reports the factor loadings for the 9 z-scored announcement surprise series of the first three PCs. Announcement surprises are price changes from 10 minutes before to 20 minutes after 2pm announcements at regular FOMC meetings from January 2018 to December 2019. The last row gives the percentage contribution of a given PC to total variance.

	PC_1	PC_2	PC_3
Fed fund futures 1st	-0.18	0.62	-0.39
Fed fund futures 3rd	0.41	0.03	-0.15
Eurodollar futures 1st	0.24	0.33	0.56
Eurodollar futures 3rd	0.46	0.11	-0.17
2-year T-Note futures	0.32	-0.55	0.20
5-year T-Note futures	0.44	0.09	-0.12
10-year T-Note futures	0.32	0.36	0.29
VIXY ETF	-0.11	0.23	0.49
E-Mini futures	0.35	0.05	-0.32
S.D. (%)	25.82	16.83	16.14

C Benchmarks for the impact across horizons

Here, we provide a simple model of normally distributed returns with a 3-factor structure to provide guidance on how to interpret the fear impact coefficients we obtain from regression (3) and display in Figure 6.

Assume that per-period excess log returns r_t are independently distributed under the RN distribution. Furthermore, let the per-period returns be the sum of 3 independent and normally distributed factors,

$$r_t = f_{1,t} + f_{2,t} + f_{3,t}, \quad \text{where} \quad f_{i,t} \sim N\left(\mu_{i,t}, \sigma_{i,t}^2\right).$$

Under the RN distribution, per-period returns are then normally distributed,

$$r_t \sim N\left(\mu_t, \sigma_t^2\right) \quad \text{where} \quad \mu_t = \sum_{i=1}^{3} \mu_{i,t} \quad \text{and} \quad \sigma_t^2 = \sum_{i=1}^{3} \sigma_{i,t}^2.$$

The τ period excess log returns $r_{t,\tau}$ are the sum of the independently and normally distributed per-period returns. Hence, they are also normally distributed with mean $m_{t,\tau}$ and standard deviation $s_{t,\tau}$, where

$$\mathbb{E}_t^{\mathbb{Q}}(r_{t,\tau}) = m_{t,\tau} = \sum_{j=0}^{\tau} \mu_{t+j} \quad \text{and} \quad \text{var}_t^{\mathbb{Q}}(r_{t,\tau}) = s_{t,\tau}^2 = \sum_{j=0}^{\tau} \sigma_{t+j}^2.$$

Fear at t for horizon τ is then given by the negative of the 10% quantile of this distribution, that is

$$\text{Fear}_{t,\tau} = -q_{t,\tau}^* \quad \text{where} \quad \Phi\left(\frac{q_{t,\tau}^* - m_{t,\tau}}{s_{t,\tau}}\right) = 0.1,$$

from which directly follows that, for the case of normally distributed returns, fear can be expressed as,

$$\text{Fear}_{t,\tau} = -m_{t,\tau} - s_{t,\tau}\, \Phi^{-1}(0.1). \tag{6}$$

In the context of this paper, we think of the three principal components of announcement shocks as picking up shocks to the RN distribution of the factors that drive per-period returns, that is shocks to either $\mu_{i,t}$, $\sigma_{i,t}^2$ or both. Thus, to form an intuition for the impact across horizons, we simply need to understand how changes to $\mu_{i,t}$ and $\sigma_{i,t}^2$ translate into changes of the mean and standard deviation of the τ period returns, that is $m_{t,\tau}$ and $s_{t,\tau}$, i.e.

$$\Delta\text{Fear}_{t,\tau} = -\Delta m_{t,\tau} - \Delta s_{t,\tau}\, \Phi^{-1}(0.1),$$

where Δ refers to a change in fear induced by changes to the per-period return distributions caused by a Fed announcement.

Consider a Fed announcement that shifts the mean of factor i up by $k\%$ for n periods and then the mean reverts back to its (constant) pre-announcement level μ_i. We assume that the variance of factor i as well as all moments of the other two factors are unaffected by the announcement. The impact across horizons of such a temporary shift in the mean of a single factor is

$$\Delta \text{Fear}_{t,\tau} = \begin{cases} -(k\mu_i)\,\tau & \text{for } \tau \leq n \\ -(k\mu_i)\,n & \text{for } \tau > n. \end{cases}$$

This temporary shift in the mean of the per-period return distribution then implies a linear decrease in fear up to n periods ahead after which the decrease stays constant in the horizon τ. A permanent increase in the mean of the per-period return distribution implies an impact that decreases linearly in the return horizon.

Similarly, consider the impact of a Fed announcement that leads to a temporary $k\%$ increase in the variance of the per-period return distribution of factor i for n period after which it drops back to its (constant) pre-announcement level of σ_i^2. Again all other moments are assumed to be unaffected by the announcement. The corresponding impact across horizons is

$$\Delta \text{Fear}_{t,\tau} = \begin{cases} \sigma_i\, \Phi^{-1}(0.1)(\sqrt{1+k}-1)\sqrt{\tau} & \text{for } \tau \leq n \\ \sigma_i\, \Phi^{-1}(0.1)\left(\sqrt{1+\frac{nk}{\tau}}-1\right)\sqrt{\tau} & \text{for } \tau > n. \end{cases}$$

Fear increases with the square root of the return horizon τ up to n periods ahead from where onwards it begins to decrease and, as τ grows large, the impact eventually reverts to 0. A permanent increase in the variance of the per-period return distribution implies an impact that increases with the square root of the return horizon.

D Decomposition of the impact across horizons

Equation (6) in Appendix C shows how to decompose changes in the quantile of the RN distribution of excess log returns into changes in the mean and standard deviation of this distribution under the assumption that return are normally distributed.

Here, we repeat the analysis of Section 3 using daily changes in the RN mean $m_{t,\tau}$ and variance $s_{t,\tau}$ of the excess log return $r_{t,\tau}$ as the dependent variable in regression (3), that is

$$\Delta m_{t,\tau} = \alpha_\tau^m + \gamma_\tau^{m,\text{level}}\,\widetilde{\text{PC}}_{1,t} + \gamma_\tau^{m,\text{market}}\,\widetilde{\text{PC}}_{2,t} + \gamma_\tau^{m,\text{slope}}\,\widetilde{\text{PC}}_{3,t} + \sum_{j=1}^{3} \xi_\tau^{m,j}\,\text{Controls}_t^j + \epsilon_{t,\tau}^m,$$

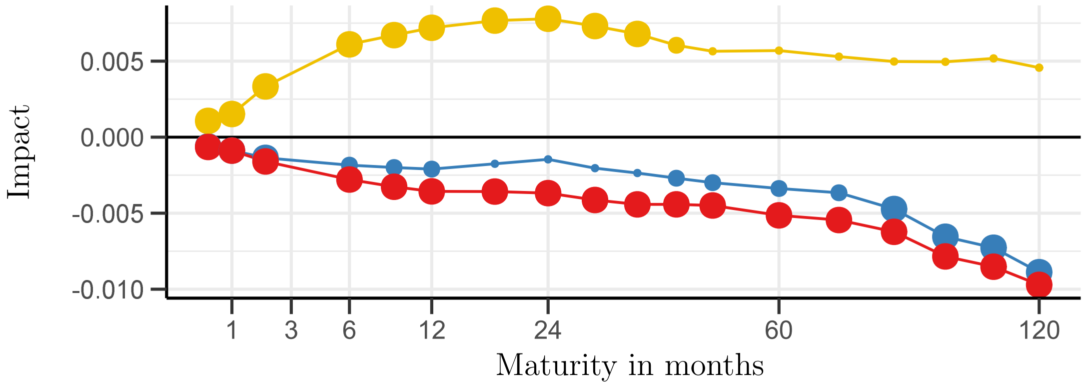
and

$$\Delta s_{t,\tau} = \alpha^s_\tau + \gamma^{s,\text{level}}_\tau \widetilde{\text{PC}}_{1,t} + \gamma^{s,\text{market}}_\tau \widetilde{\text{PC}}_{2,t} + \gamma^{s,\text{slope}}_\tau \widetilde{\text{PC}}_{3,t} + \sum_{j=1}^{3} \xi^{s,j}_\tau \,\text{Controls}^j_t + \epsilon^s_{t,\tau}.$$

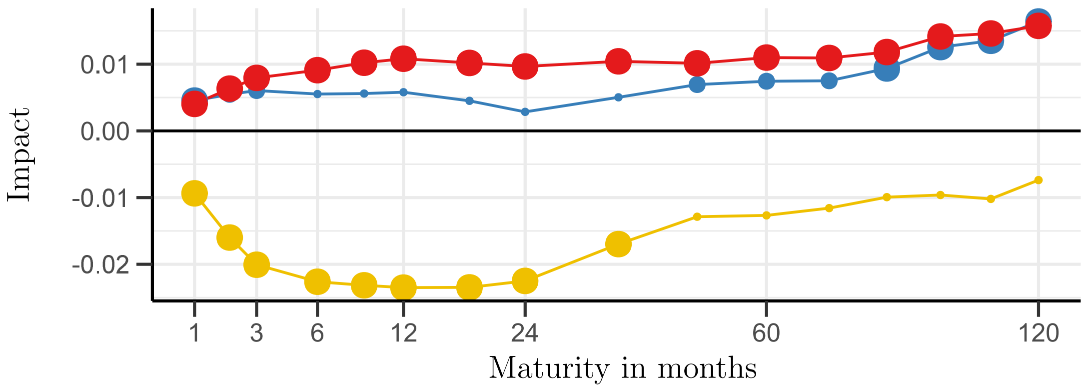
We obtain the impact across horizons of the three principal components of announcement shocks, level, market and slope, for the mean and standard deviation of the RN distribution.

Figure D1: Decomposition of the impact across horizons

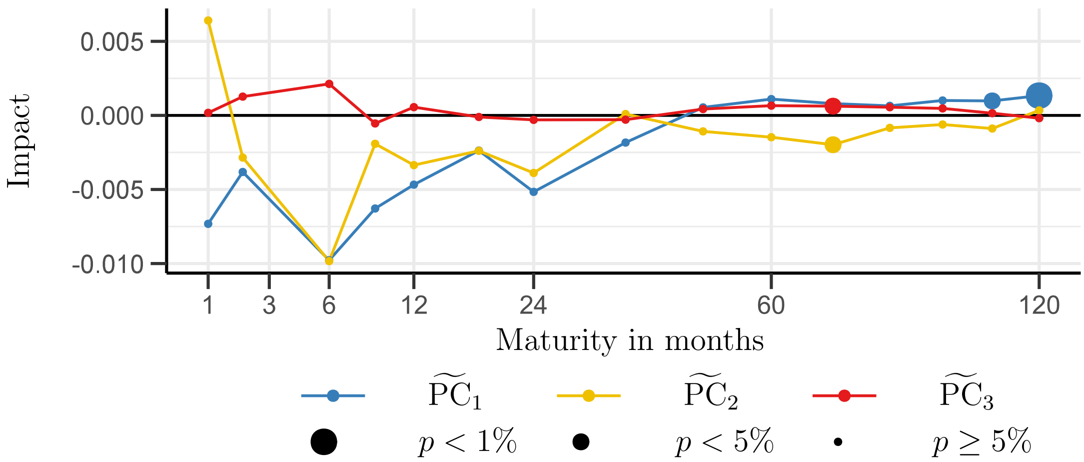
These figures show the impact of Fed announcement surprises across horizons, i.e. the level (blue), market (yellow), and slope (red) factors, on the mean (top panel), standard deviation (middle panel), and the standardized 10% quantile (bottom panel) of the RN distribution of excess log returns.



(a) Risk-neutral mean



(b) Risk-neutral standard deviation



(c) Risk-neutral standardized quantile

Figure D1a shows the impact across horizons for the RN mean $m_{t,\tau}$ for the three announcement shock factors. As the square of the VIX is a linear transformation of the mean of the RN distribution of excess log returns,

$$\text{VIX}^2_{t,\tau} = -\left(\frac{2}{\tau}\right)\mathbb{E}^{\mathbb{Q}}\left(r_{t,\tau}\right) = -\left(\frac{2}{\tau}\right)m_{t,\tau},$$

it can also be read as the impact of Fed announcement surprises on the term structure of the VIX. We see that while the impact of the market factor ($\widetilde{\text{PC}}_2$) has a horizon of two years, the impact of the level level ($\widetilde{\text{PC}}_1$) and the slope factor ($\widetilde{\text{PC}}_3$) is consistent with a long horizon impact on the risk neutral mean.

Figure D1b shows the impact across horizons for the RN standard deviation $s_{t,\tau}$ for the three announcement shock factors. Again, the impact of the market factor on the RN standard deviation on the horizons up to a year ahead, whereas level and slope factors appear to have long horizon impacts.

In terms of their overall impact on fear, we see that the factors' impacts work both through the RN mean and the RN standard deviation, in all cases reinforcing the effect. For the market factor, positive shocks both increase the mean and reduce the dispersion of the return distribution. For the level and slope factors, shocks that imply unexpected easing both negatively impact the mean and increase the dispersion of the return distribution, overall increasing fear.

If returns are not normally distributed, the quantiles can also change because Fed announcements affect the higher moments of the RN log return distribution. To analyze this impact, we define

$$x_{t,\tau} \equiv \frac{-\text{Fear}_{t,\tau} - m_{t,\tau}}{s_{t,\tau}} = -F^{-1}_{t,\tau}(0.1),$$

which is the negative of the 10% quantile of the normalized RN distribution of excess log returns. If log returns are normal, $x_{t,\tau}$ is the 10% quantile of the standard normal distribution, i.e. constant for all t and τ. Figure D1c displays the impact across horizons for the regressions

$$\Delta x_{t,\tau} = \alpha^x_\tau + \gamma^{x,\text{level}}_\tau \widetilde{\text{PC}}_{1,t} + \gamma^{x,\text{market}}_\tau \widetilde{\text{PC}}_{2,t} + \gamma^{x,\text{slope}}_\tau \widetilde{\text{PC}}_{3,t} + \sum_{j=1}^{3} \xi^{x,j}_\tau \,\text{Controls}^j_t + \epsilon^x_{t,\tau}.$$

While we see some statistically significant impacts on higher moments of the return distribution at longer horizons, particularly so for the level factor, overall the majority of the impact of Fed announcement surprises on fear appears to work via the mean and standard deviation of the RN distribution of excess log returns.

E Additional results and robustness checks

Figure E1: Liquidity of long dated options

In this figure, we plot the daily contract volume for options with a maturity of more than 500 days. This is the mean volume over a 10 day rolling window.

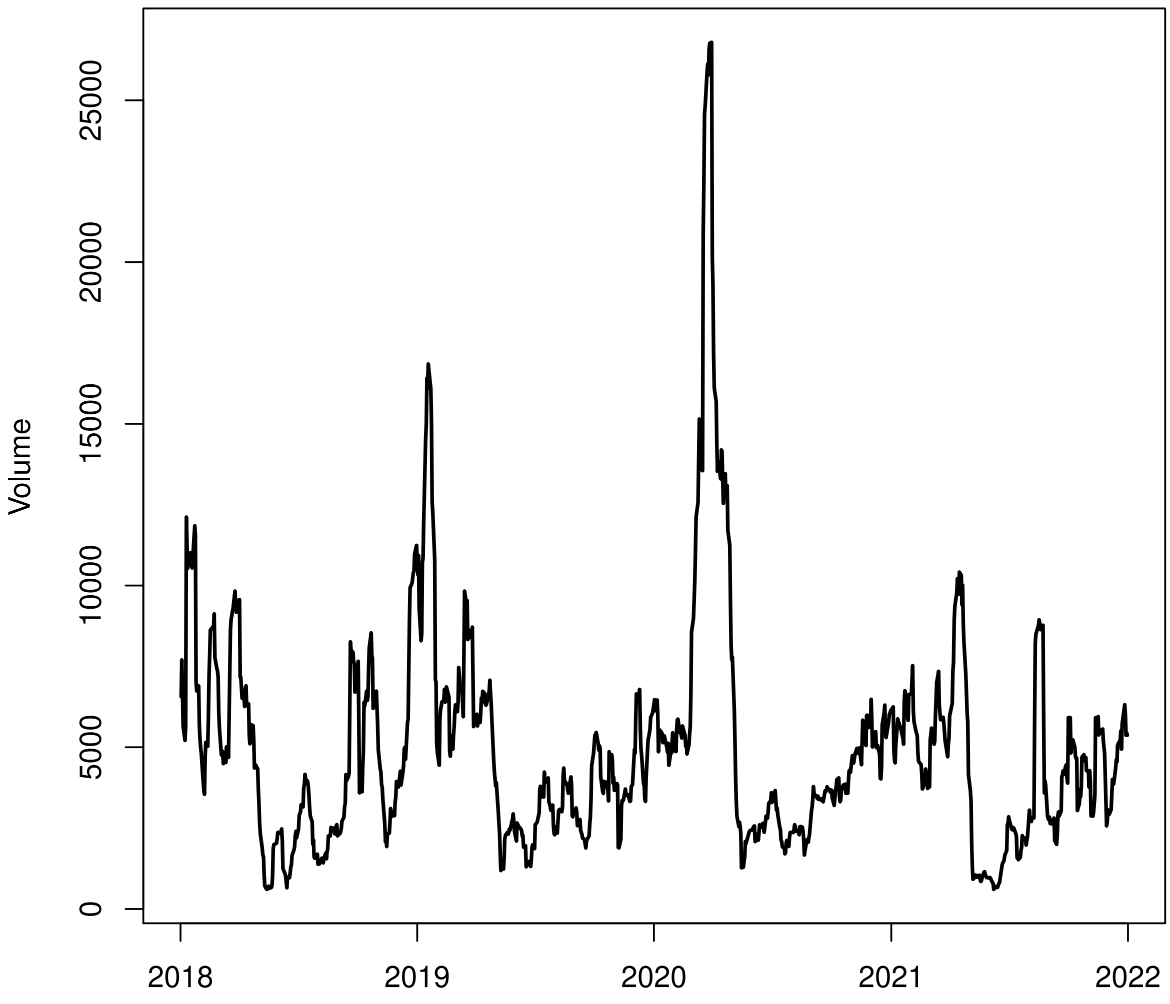


Table E1: Intervention impacts on market fear - FF shocks

The table reports the coefficient estimates of the announcement effects of Fed crisis actions on market fear over horizon τ. Instead of the three principal component shocks used in the baseline specification, the regression uses the monetary policy shock measured as the change in the third Fed funds futures contract around the announcement window. Rows report the impact coefficients from regression (3). The same control variables as in the baseline specification are included in the regressions; however, for brevity the coefficients on the controls and the constant are not reported in the table. The dependent variable is $\Delta \text{Fear}_{t,\tau}$ for maturities (τ) of 1, 12, 36, 60, and 96 months. Sample period: 3 February 2020 to 31 July 2020. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
FF	−0.144	−0.175	−0.110	−0.097	−0.187
	(0.174)	(0.380)	(0.347)	(0.335)	(0.473)
Observations	125	125	125	125	125
R^2	0.416	0.282	0.286	0.327	0.381
Adjusted R^2	0.397	0.258	0.262	0.305	0.360

Table E2: Intervention impacts on market fear - FF (level) and 10Y note - 2Y note (slope)

The table reports the coefficient estimates of the announcement effects of Fed crisis actions on market fear over horizon τ. The specification augments the baseline monetary policy shock with an additional slope shock, measured as the difference between the reaction of the 10-year Treasury note futures and the 2-year Treasury note futures around the announcement window. Rows report the impact coefficients from regression (3). The same control variables as in the baseline specification are included in the regressions; however, for brevity the coefficients on the controls and the constant are not reported in the table. The dependent variable is $\Delta \text{Fear}_{t,\tau}$ for maturities (τ) of 1, 12, 36, 60, and 96 months. Sample period: 3 February 2020 to 31 July 2020. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
FF	−0.032	0.042	0.173	0.204	0.263
	(0.144)	(0.356)	(0.280)	(0.257)	(0.313)
10Y-2Y	0.018	0.034	0.045*	0.048**	0.071**
	(0.017)	(0.039)	(0.025)	(0.023)	(0.029)
Observations	125	125	125	125	125
R^2	0.441	0.310	0.328	0.381	0.462
Adjusted R^2	0.418	0.281	0.300	0.355	0.440

Table E3: Intervention impacts on market fear - FF, 10Y note - 2Y note and SPX

The table reports the coefficient estimates of the announcement effects of Fed crisis actions on market fear over horizon τ. The specification extends the previous shock decomposition by including, in addition to the Fed funds futures shock and the yield-curve slope shock, an equity market shock measured as the reaction of the E-mini S&P 500 futures (SPX) around the announcement window. Rows report the impact coefficients from regression (3). The same control variables as in the baseline specification are included in the regressions; however, for brevity the coefficients on the controls and the constant are not reported in the table. The dependent variable is $\Delta \text{Fear}_{t,\tau}$ for maturities (τ) of 1, 12, 36, 60, and 96 months. Sample period: 3 February 2020 to 31 July 2020. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
FF	−0.037	0.031	0.165	0.197	0.255
	(0.098)	(0.240)	(0.200)	(0.181)	(0.237)
10Y-2Y	0.018	0.034	0.044***	0.047***	0.071***
	(0.012)	(0.026)	(0.017)	(0.015)	(0.021)
S&P	−0.001**	−0.001**	−0.001**	−0.001**	−0.001**
	(0.0002)	(0.001)	(0.0004)	(0.0005)	(0.001)
Observations	125	125	125	125	125
R^2	0.502	0.416	0.375	0.431	0.499
Adjusted R^2	0.476	0.386	0.344	0.402	0.474

Table E4: Intervention impacts on market fear - FF, 10Y note- 2Y, SPX and USD/Yen

The table reports the coefficient estimates of the announcement effects of Fed crisis actions on market fear over horizon τ. The specification further extends the shock decomposition by including, in addition to the Fed funds futures shock, the yield-curve slope shock, and the equity market shock measured using E-mini S&P 500 futures (SPX), an exchange rate shock measured as the reaction of the USD/Yen futures around the announcement window. Rows report the impact coefficients from regression (3). The same control variables as in the baseline specification are included in the regressions; however, for brevity the coefficients on the controls and the constant are not reported in the table. The dependent variable is $\Delta \text{Fear}_{t,\tau}$ for maturities (τ) of 1, 12, 36, 60, and 96 months. Sample period: 3 February 2020 to 31 July 2020. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
FF	−0.0002	0.179	0.336**	0.365***	0.492***
	(0.088)	(0.194)	(0.142)	(0.142)	(0.145)
10Y-2Y	0.011	0.006	0.012	0.015	0.026
	(0.011)	(0.026)	(0.025)	(0.025)	(0.025)
S&P	−0.001**	−0.001**	−0.001***	−0.001**	−0.001***
	(0.0002)	(0.001)	(0.0004)	(0.0004)	(0.0004)
USD/YEN	285.906	1,157.569*	1,339.081*	1,314.797*	1,850.674**
	(259.289)	(603.902)	(782.311)	(734.367)	(723.525)
Observations	125	125	125	125	125
R^2	0.508	0.446	0.412	0.471	0.553
Adjusted R^2	0.479	0.413	0.377	0.439	0.526

Table E5: Intervention impacts on market fear: excluding scheduled announcements

The table reports the coefficient estimates of the announcement effects of Fed crisis actions on market fear over horizon τ. The specification follows the baseline regression but excludes scheduled announcements that occurred during the sample period, focusing only on unanticipated policy actions. Rows $\widetilde{\text{PC}}_1 - \widetilde{\text{PC}}_3$ give the impact coefficients, $\gamma_\tau^{\text{level}}$, $\gamma_\tau^{\text{market}}$, and $\gamma_\tau^{\text{slope}}$, from regression (3). The same control variables as in the baseline specification are included in the regressions; however, for brevity the coefficients on the controls and the constant are not reported in the table. The dependent variable is $\Delta\text{Fear}_{t,\tau}$ for maturities (τ) of 1, 12, 36, 60, and 96 months. Sample period: 3 February 2020 to 31 July 2020. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
$\widetilde{\text{PC}}_1$	0.008***	0.011*	0.010	0.013*	0.023***
	(0.003)	(0.006)	(0.007)	(0.007)	(0.006)
$\widetilde{\text{PC}}_2$	−0.016***	−0.040**	−0.031**	−0.023*	−0.017
	(0.005)	(0.017)	(0.013)	(0.013)	(0.011)
$\widetilde{\text{PC}}_3$	0.007***	0.018***	0.019***	0.020***	0.027***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)
Observations	125	125	125	125	125
R^2	0.538	0.468	0.418	0.461	0.543
Adjusted R^2	0.515	0.441	0.388	0.433	0.519

Table E6: Intervention impacts on market fear - Placebo test (random shocks)

The table reports the coefficient estimates of the announcement effects of Fed crisis actions on market fear over horizon τ from a placebo test. Instead of using the actual announcement time stamps, a random time stamp is drawn on the same event date. If the event occurs when the futures market is closed, a random time stamp is drawn on the first subsequent trading day when the futures market is open. The fear measure is identical to that used in the baseline specification. Rows $\widetilde{\text{PC}}_1 - \widetilde{\text{PC}}_3$ give the impact coefficients, $\gamma_\tau^{\text{level}}$, $\gamma_\tau^{\text{market}}$, and $\gamma_\tau^{\text{slope}}$, from regression (3). The same control variables as in the baseline specification are included in the regressions; however, for brevity the coefficients on the controls and the constant are not reported in the table. The dependent variable is $\Delta\text{Fear}_{t,\tau}$ for maturities (τ) of 1, 12, 36, 60, and 96 months. Sample period: 3 February 2020 to 31 July 2020. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
$\widetilde{\text{PC}}_1$	0.001	0.001	0.001	0.003	0.009
	(0.002)	(0.007)	(0.006)	(0.006)	(0.006)
$\widetilde{\text{PC}}_2$	−0.005	−0.016	−0.016	−0.017*	−0.021*
	(0.005)	(0.012)	(0.010)	(0.010)	(0.011)
$\widetilde{\text{PC}}_3$	0.003	0.003	−0.005	−0.003	−0.0003
	(0.002)	(0.004)	(0.006)	(0.005)	(0.006)
Observations	125	125	125	125	125
R^2	0.436	0.351	0.349	0.406	0.472
Adjusted R^2	0.408	0.318	0.316	0.376	0.445

Figure E2: Intervention impacts on market fear: wider event window (pre 15 and post 60 min)

The figure reports the coefficient estimates of the announcement effects of Fed crisis actions on market fear over horizon τ. The specification follows the baseline regression but uses a wider event window around the policy announcements, starting 15 minutes before to 60 minutes after the announcement.

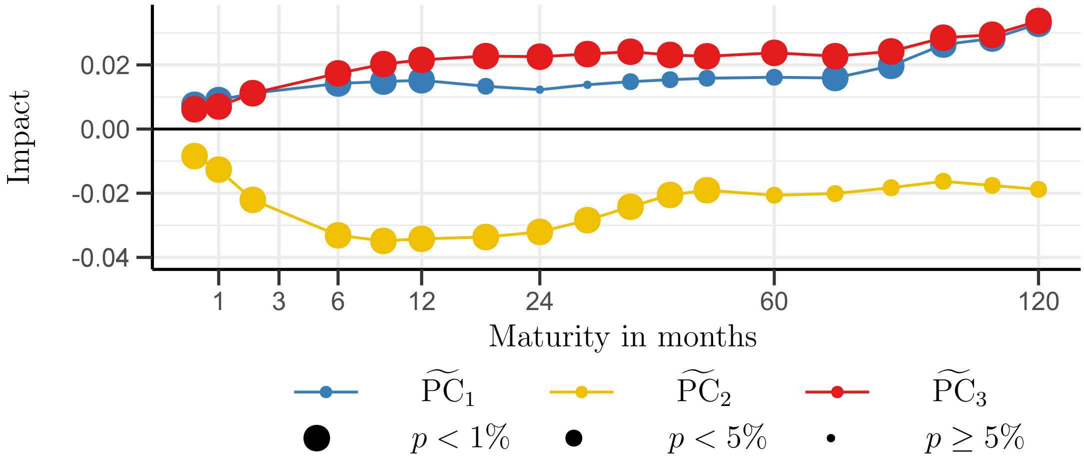


Table E7: Impact across horizons from HF option prices.

This table displays coefficient estimates for regression (3), where the daily $\Delta Fear_{t,\tau}$ is replaced by a high-frequency measure extracted from CBOE minute-by-minute quote data. We extract the risk-neutral quantiles for maturities of up to 6 months. The same 30-minute event window is applied to the fear measure as we use for the high-frequency shocks extracted from the futures contracts. *p<0.1; **p<0.05; ***p<0.01.

	Maturities				
	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 6$
$\widetilde{PC}_1$	0.014***	0.015***	0.016***	0.018***	0.020***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
$\widetilde{PC}_2$	−0.004***	−0.005***	−0.006***	−0.006***	−0.007***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.001)
$\widetilde{PC}_3$	0.018***	0.019***	0.021***	0.023***	0.026***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.014***	0.014***	0.015***	0.016***	0.020***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Observations	52	52	52	52	52
R^2	0.914	0.904	0.900	0.899	0.897
Adjusted R^2	0.909	0.898	0.893	0.893	0.890

Table E8: Intervention impacts on market fear: right tail (90%)

The table reports the coefficient estimates of the announcement effects of Fed crisis actions on market fear over horizon τ, using an alternative fear measure based on the right tail of the distribution. Specifically, market fear is constructed using the 90% quantile instead of the 10% quantile used in the baseline specification. Rows $\widetilde{PC}_1 - \widetilde{PC}_3$ give the impact coefficients, γ_τ^{level}, γ_τ^{market}, and γ_τ^{slope}, from regression (3). The same control variables as in the baseline specification are included in the regressions; however, for brevity the coefficients on the controls and the constant are not reported in the table. The dependent variable is $\Delta Fear_{t,\tau}$ for maturities (τ) of 1, 12, 36, 60, and 96 months. Sample period: 3 February 2020 to 31 July 2020. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
$\widetilde{PC}_1$	-0.006^{***}	-0.005^{**}	-0.004^{*}	-0.004^{**}	-0.005^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
$\widetilde{PC}_2$	0.005^{*}	0.010^{**}	0.008^{**}	0.004	0.003
	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
$\widetilde{PC}_3$	-0.004^{***}	-0.006^{***}	-0.005^{***}	-0.005^{***}	-0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	125	125	125	125	125
R^2	0.446	0.512	0.502	0.445	0.520
Adjusted R^2	0.418	0.487	0.476	0.417	0.495

Table E9: Intervention impacts on market fear: left tail (20%)

The table reports the coefficient estimates of the announcement effects of Fed crisis actions on market fear over horizon τ, using an alternative fear measure based on the left tail of the distribution. Specifically, market fear is constructed using the 20% quantile instead of the 10% quantile used in the baseline specification. Rows $\widetilde{PC}_1 - \widetilde{PC}_3$ give the impact coefficients, γ_τ^{level}, γ_τ^{market}, and γ_τ^{slope}, from regression (3). The same control variables as in the baseline specification are included in the regressions; however, for brevity the coefficients on the controls and the constant are not reported in the table. The dependent variable is $\Delta Fear_{t,\tau}$ for maturities (τ) of 1, 12, 36, 60, and 96 months. Sample period: 3 February 2020 to 31 July 2020. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
$\widetilde{PC}_1$	0.006^{***}	0.008^{**}	0.007^{*}	0.007^{*}	0.013^{***}
	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
$\widetilde{PC}_2$	-0.007^{**}	-0.018^{*}	-0.017^{*}	-0.012	-0.010
	(0.003)	(0.011)	(0.009)	(0.007)	(0.007)
$\widetilde{PC}_3$	0.005^{***}	0.010^{***}	0.011^{***}	0.011^{***}	0.016^{***}
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Observations	125	125	125	125	125
R^2	0.532	0.454	0.420	0.449	0.529
Adjusted R^2	0.509	0.427	0.391	0.421	0.505

Table E10: Intervention impacts on market fear: Interquantile 10% – 20%

The table reports the coefficient estimates of the announcement effects of Fed crisis actions on market fear over horizon τ, using an alternative fear measure based on an interquantile range of the left tail of the distribution. Specifically, market fear is constructed as the difference between the 10% quantile and the 20% quantile fear measures (10%–20% fear), instead of the 10% quantile used in the baseline specification. Rows $\widetilde{\text{PC}}_1 - \widetilde{\text{PC}}_3$ give the impact coefficients, $\gamma_\tau^{\text{level}}$, $\gamma_\tau^{\text{market}}$, and $\gamma_\tau^{\text{slope}}$, from regression (3). The same control variables as in the baseline specification are included in the regressions; however, for brevity the coefficients on the controls and the constant are not reported in the table. The dependent variable is $\Delta\text{Fear}_{t,\tau}$ for maturities (τ) of 1, 12, 36, 60, and 96 months. Sample period: 3 February 2020 to 31 July 2020. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
$\widetilde{\text{PC}}_1$	0.002*	0.004*	0.003	0.005**	0.009***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$\widetilde{\text{PC}}_2$	−0.008***	−0.018***	−0.012***	−0.010**	−0.007**
	(0.002)	(0.006)	(0.004)	(0.005)	(0.004)
$\widetilde{\text{PC}}_3$	0.002***	0.008***	0.007***	0.008***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	125	125	125	125	125
R^2	0.457	0.434	0.388	0.469	0.538
Adjusted R^2	0.429	0.405	0.357	0.442	0.514

Figure E3: Impact across horizons – International indexes

These figures show the impact of Fed announcement surprises across horizons for different national equity indexes. Each subplot reports the impact for one of the announcement factors: level (top panel), market (middle panel), and slope (bottom panel). The lines correspond to the estimated responses of the national indexes DAX30, FTSE, ASX200, KOSPI200, N225, and TSX60. For comparability across indexes, the horizon is truncated at 60 months due to data quality concerns for some of the series.

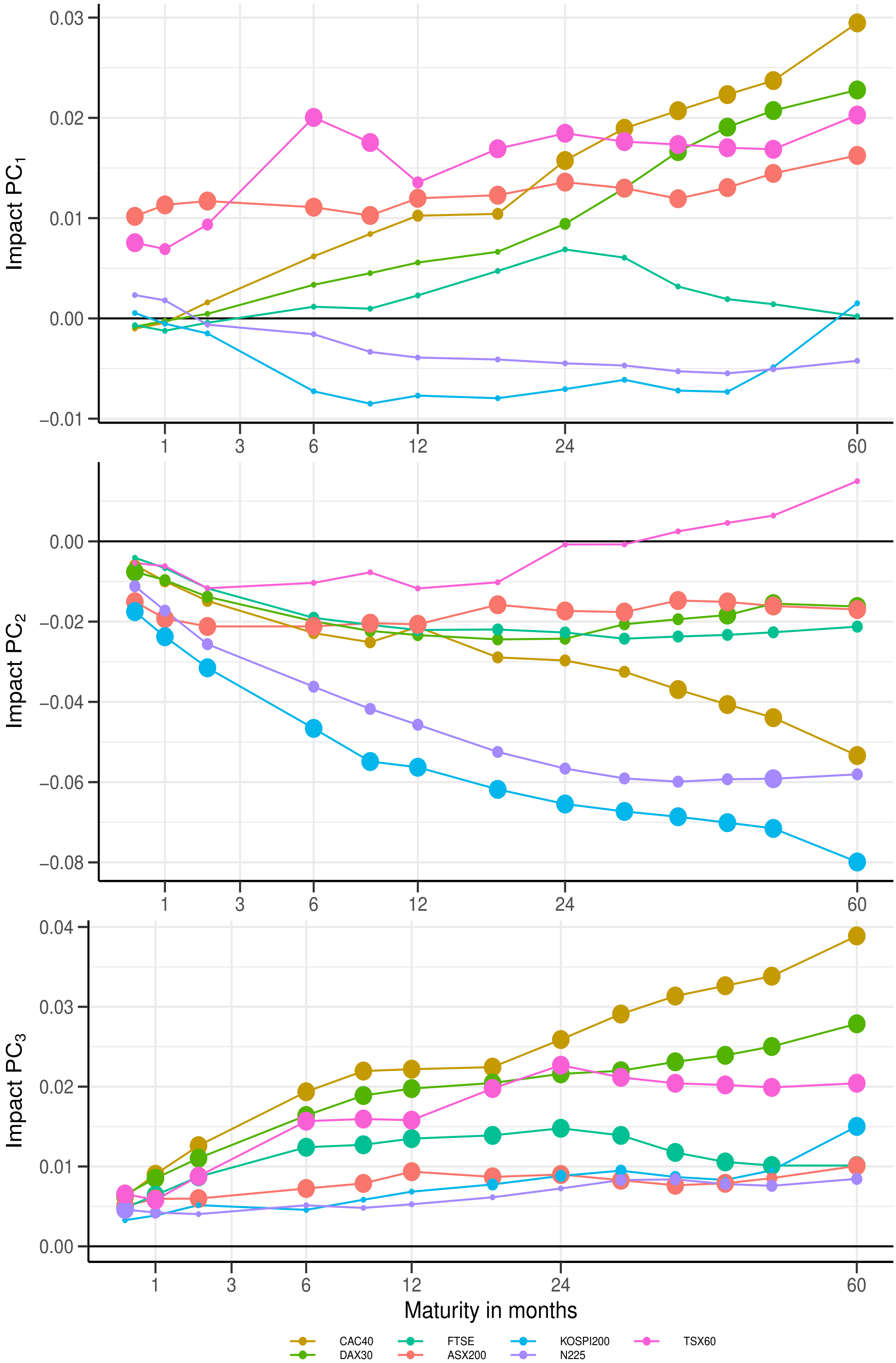


Figure E4: Impact across horizons – Sectoral indexes

These figures show the impact of Fed announcement surprises across horizons for different U.S. equity sectors. Each subplot reports the impact for one of the announcement factors: level (top panel), market (middle panel), and slope (bottom panel). The lines correspond to the estimated responses of the sector indexes Energy, Financials, Health Care, Information Technology, Real Estate, and Utilities. For comparability across sectors, the horizon is truncated at 12 months due to data quality concerns for some of the series.

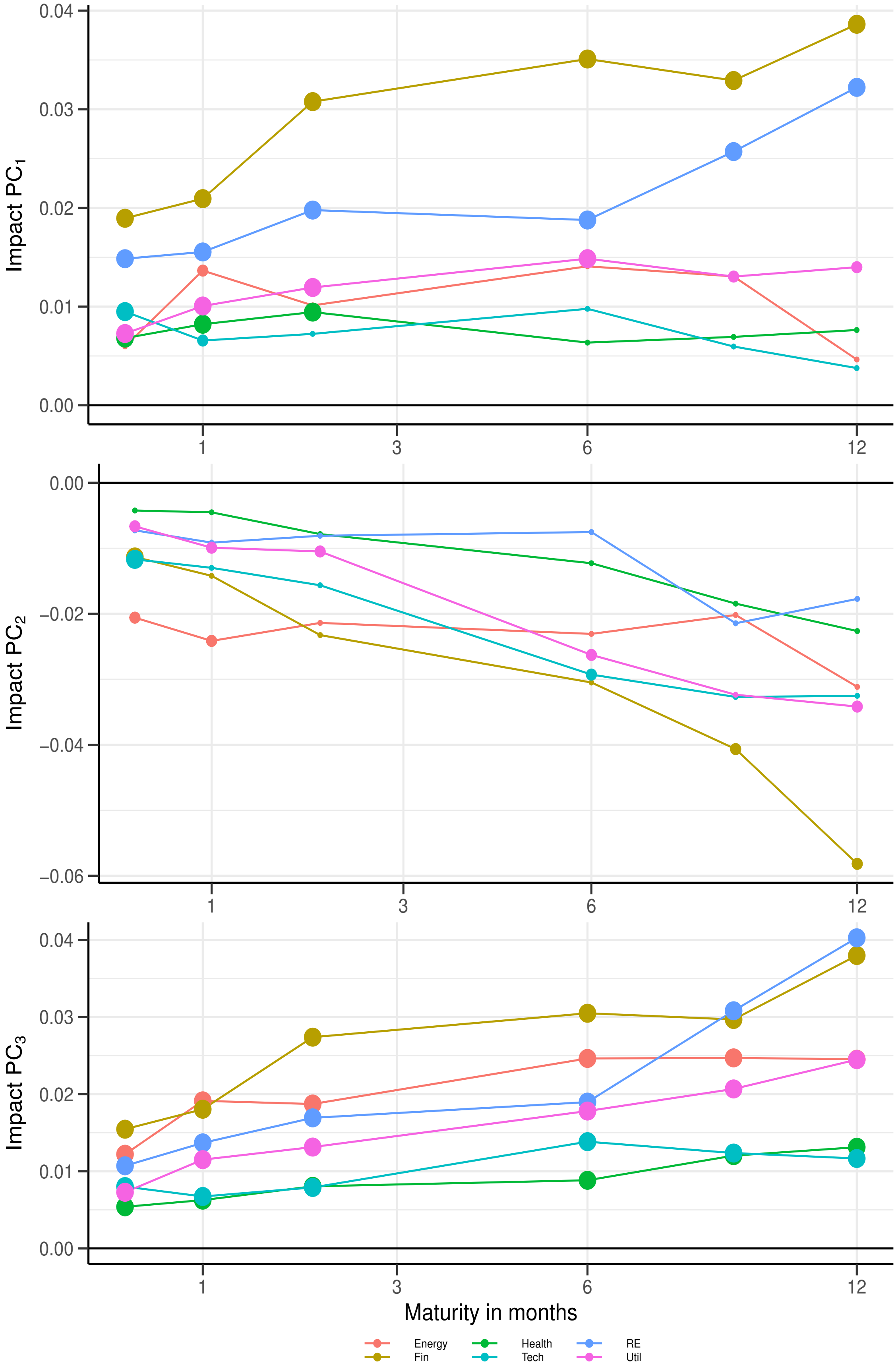


Table E11: Regression with policy dummies.

This table displays coefficient estimates for regression (3) augmented by including dummies for policy types, i.e. $I_t^p = 1$ if a Fed announcement on day t involved a policy of type p, $I_t^p = 0$ otherwise. *p<0.1; **p<0.05; ***p<0.01.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
$\widetilde{\text{PC}}_1$	0.009***	0.011**	0.014**	0.016***	0.025***
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
$\widetilde{\text{PC}}_2$	−0.018***	−0.041***	−0.034***	−0.028**	−0.025**
	(0.004)	(0.014)	(0.012)	(0.011)	(0.010)
$\widetilde{\text{PC}}_3$	0.009***	0.025***	0.026***	0.026***	0.032***
	(0.002)	(0.004)	(0.005)	(0.005)	(0.005)
I^{IR}	0.001	0.014	0.007	0.001	0.002
	(0.007)	(0.016)	(0.020)	(0.020)	(0.025)
I^{AP}	0.001	0.001	0.002	0.003	0.006
	(0.005)	(0.013)	(0.011)	(0.011)	(0.012)
I^{FX}	−0.021***	−0.051**	−0.072**	−0.065*	−0.063*
	(0.005)	(0.026)	(0.034)	(0.035)	(0.036)
I^{LEN}	0.005	0.008	0.014	0.018	0.020
	(0.004)	(0.010)	(0.013)	(0.014)	(0.014)
I^{MPR}	−0.009	−0.019	−0.011	−0.017	−0.017
	(0.006)	(0.014)	(0.012)	(0.012)	(0.012)
C_{covid}	0.007	0.051**	0.060*	0.053*	0.052*
	(0.020)	(0.024)	(0.031)	(0.031)	(0.031)
C_{ECSU}	0.003	0.002	0.001	−0.002	−0.007
	(0.006)	(0.013)	(0.014)	(0.014)	(0.014)
$C_{\Delta\text{RV}}$	0.107***	0.165***	0.172***	0.174***	0.220***
	(0.017)	(0.027)	(0.031)	(0.027)	(0.036)
Constant	−0.001	0.0002	−0.001	0.001	0.001
	(0.002)	(0.004)	(0.005)	(0.004)	(0.005)
Observations	125	125	125	125	125
R^2	0.570	0.516	0.477	0.524	0.582
Adjusted R^2	0.529	0.469	0.426	0.477	0.541

Table E12: Pairwise restriction tests on policy weights (p-values)

This table reports the p-values of pairwise hypothesis tests with $H0 : \beta_i^p = \beta_i^q$ for policies p and q (rows) and $\widetilde{\text{PC}}_i$ (column) where coefficient estimates derive from regression (5).

Restriction	$\widetilde{\text{PC}}_1$ − level	$\widetilde{\text{PC}}_2$ − market	$\widetilde{\text{PC}}_3$ − slope
AP=FX	0.0798	0.1492	0.2539
AP=LEN	0.6163	0.0739	0.2656
AP=MPR	0.9541	0.0033	0.4236
FX=LEN	0.0345	0.9513	0.0433
FX=MPR	0.0680	0.4146	0.0627
IR=AP	0.0109	0.0057	0.0098
IR=FX	0.2478	0.1105	0.0008
IR=LEN	0.0001	0.0330	0.0135
IR=MPR	0.0010	0.1612	0.0054
LEN=MPR	0.4033	0.2080	0.5463