# The impact term structure of central bank crisis interventions *

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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 come to see 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 from option prices on the SP-500 with maturities ranging from two weeks to ten years. To quantify the impact of Fed crisis interventions on market fear, 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 crisis announcements. These three PCs summarize 65% of the price variation around Fed announcements and should thus capture the majority of their information content.

We run separate regressions of announcement shocks on horizon-specific market fear. This allows us to obtain separate impact term structures for each PC thus capturing distinct channels via which the information revealed by Fed announcements impact risk perceptions. 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 intervention policy tools, such as asset purchases, the markets did calm down. However, that action also caused the private cost of disaster insurance to fall, as seen by the priced long-term impact in options markets, giving scope for moral hazard.

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 SP-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 SP-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 the spring of 2020, 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.

We group the Fed's interventions into five categories designed to capture the primary economic aspects and use the content of the accompanying Fed press release to classify each intervention. The first category includes policies related to interest rate decisions, including forward guidance. We refer to this category as IR. The second is LEN and involves lender of last resort actions that provide liquidity to market participants. The third is AP, asset purchases, primarily bonds, including a new corporate bond facility. Foreign exchange interventions, FX, is the fourth category, encompassing the Fed's dollar liquidity support for foreign central banks to be intermediated to their local financial institutions. Last is macroprudential regulation, MPR, where the Fed eases macroprudential constraints.

We concentrate on the surprise component of the Fed's interventions when inves-

[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 also closer 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).

tigating their impact on market fear. Pragmatically, our causal strategy requires unexpected Fed actions; option prices already factor in Fed actions that follow an established and well-understood crisis rule book. But, more importantly, from a conceptual perspective, we expect discretionary crisis actions to be particularly powerful and costly; very effective in breaking destabilizing dynamics as surprises lead market participants to update their beliefs about the likelihood of extreme market outcomes, but also costly as market participants will revise their beliefs about the central bank's reaction function in future crises, potentially giving rise to moral hazard.

Empirically, we face two challenges. First, crises are fast-moving, and market conditions can change rapidly. Using high-frequency CBOE options data, we extract minute-by-minute fear measures for horizons of up to 6 months. However, to gauge changes in market fear for terms beyond 6 months, we rely on OTC options data of daily frequency. When working with daily data, we need an empirical framework that separates the impact of the Fed's announcements from other factors that move market fears on a given day. Also, there can be multiple Fed announcements on a given day and we want to isolate the effects of individual announcements. This is particularly important when comparing the effectiveness of different policy categories. The second empirical challenge is that Fed announcements surprises can impact market fears via various channels and we need a measurement approach that acknowledges the multidimensional character of the generated shocks.

To address these empirical challenges, we adapt an identification strategy developed to identify monetary policy shocks using high-frequency asset price moves around regular FOMC announcements (see, e.g., Bernanke and Kuttner, 2005; Gurkaynak et al., 2005; Swanson, 2020) to the crisis intervention context. To capture the broad transmission channels of Fed crisis policies, we use a wide range of futures contracts covering fixed income, foreign exchange, and equity markets, as well as an ETF tracking equity market volatility. We then measure how each announcement changes the prices of these securities in a narrow window around Fed crisis announcements. Finally, we apply a principal component analysis to the panel of price changes to obtain a low-dimensional representation of the Fed's announcement surprises. We use the first three PCs as our measures of Fed surprises capturing about two-thirds of the overall price variation around Fed announcements. The first three PCs load naturally on announcement surprises in particular assets, and we refer to them as the (interest rate) level, market, and (interest rate) slope factors, respectively.

To measure the impact of Fed announcements on market fear, we regress daily changes in market fear on Fed announcement surprises as captured by our three factors. As the timing of Fed interventions can depend on market conditions, we control for market volatility, macroeconomic uncertainty, and measures of pandemic severity. Our main object of interest is the regression coefficients for the respective factors. We run these regressions for each fear horizon separately, giving us three impact coefficients, one per factor, where horizons go from two weeks to ten years ahead. We refer to the collection of regression coefficients for a given factor as the factor's *impact term structure*. The three impact term structures reflect the impact of Fed announcement surprises on market fear across different factors and horizons.

To identify the heterogeneity in how different policy types affect fear through the three factors, we regress each of the three factors on *policy type* dummies capturing the five policy categories (IR, LEN, AP, FX, MPR). For a given factor regression, the coefficient estimate for a given policy type summarizes the average impact an announcement involving this policy type has operating through the given factor. We refer to the regression coefficients for the policy dummies as *policy attributions*, as they measure how the composition of the surprise caused by a Fed announcement, level, market, or slope, differs across policy types.

We obtain three sets of results. First, crisis times are different. When we compare impact term structures of announcement surprises 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 disaster insurance. The market factor has a hump-shaped impact pattern, with the most substantial impact at shorter terms.

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 is asset purchases. Asset purchases primarily work through the second PC, impacting fear via the market factor, while liquidity interventions increase fear through the first PC, the level factor. Finally, FX adds fear via the third PC, the slope factor. This suggests that IR and FX's impact on fear primarily works 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, potentially distorting risk-taking incentives. A key message of this paper is that the central banks should pay attention to the impact of their discretionary crisis actions on insurance premia in long-term financial contracts to gauge distortions in the private sector's incentives to take on risk.

This papers intends 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. 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 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, the impact term structures in Section 3 and the contribution of individual Fed policies to fear in Section 4. Section 5 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 $\tau$ (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 $\gamma_\tau$, measuring how a Fed action impacts fear over horizon $\tau$. We thus obtain a collection of impact coefficients, which we refer to as the *impact term structure*. 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 $\gamma_\tau$ shocked by the different policy categories. 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 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 SP-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.,

[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 risk-neutral densities.

2017).[4] We concentrate on the consensus prices of options written on the SP-500 index, for which the Totem consensus pricing service features a notably higher number of submitters compared to other assets. The contracts with a 10 year horizon have on average 15 of the main broker-dealers for this market submitting their best market going price.[5]

Our primary notion of fear over a particular time horizon $\tau$ is the negative of the 10% quantile of the risk-neutral excess log-return distribution of the SP-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-maturity $\tau$ 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 risk-neutral distribution of excess-log-returns, fear for a given horizon $\tau$ 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 risk-neutral distribution of excess log-returns obtained from option prices. The risk-neutral measures capture exactly the most important quantities as they weigh the markets' objective expectations about future events by the pricing kernel that adjusts those probabilities of future events by an appropriate amount corresponding to the aversion to these events. Risk-neutral quantiles and VIX-type measures capture the markets' fears of those events.

Figure 1 provides an example of fear in the SP-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:

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

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 SP-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.

[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 depicts the transaction volume in long-dated (maturities exceeding 500 days) contracts on exchanges. It shows that liquidity in long-dated options is highest during crisis times.

Figure 1: One-year SP-500 fear at the height of the financial turmoil

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

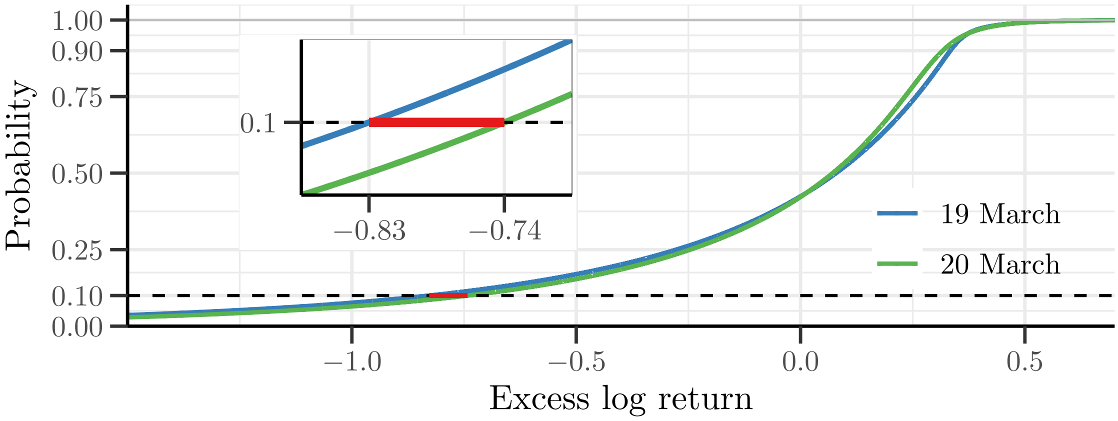



Figure 2: The term structure of fear before and during the 2020 crisis

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

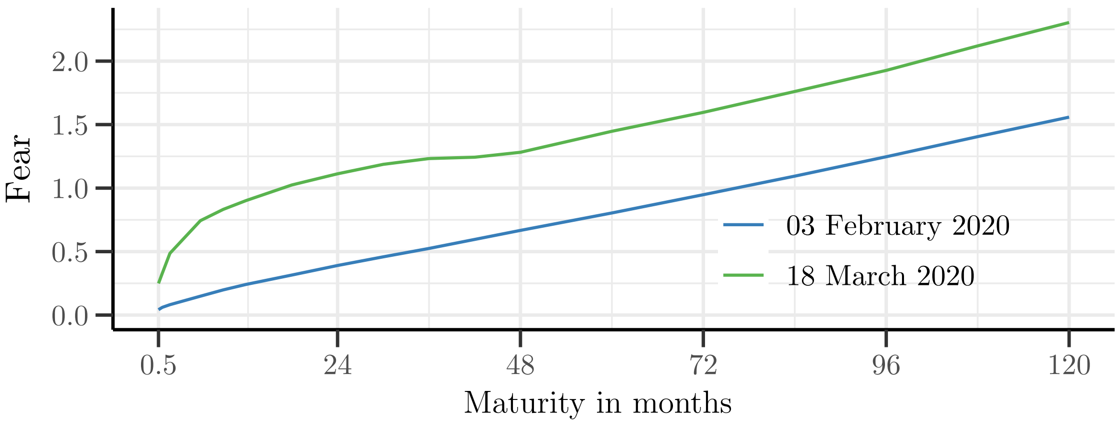



Figure 3 shows fear in the SP-500 from 2005 until the end of 2021, monthly until 2018, and daily after that. The figure covers two crisis episodes, 2008 and 2020, and three maturities, one month, one year, and a decade. The two crises are visibly different from regular times, as fear shoots up sharply 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[6] — and since the main Fed crisis-fighting tools only became available after the peak crisis of 2008 had passed.

Figure 3: SP-500 term structure of fear, 2005-2021

The time series of SP-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 the early spring of 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, it announced the Primary Dealer Credit Facility. 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 against 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 Fed announcements days, fear moved almost twice as much as on days without announcements.

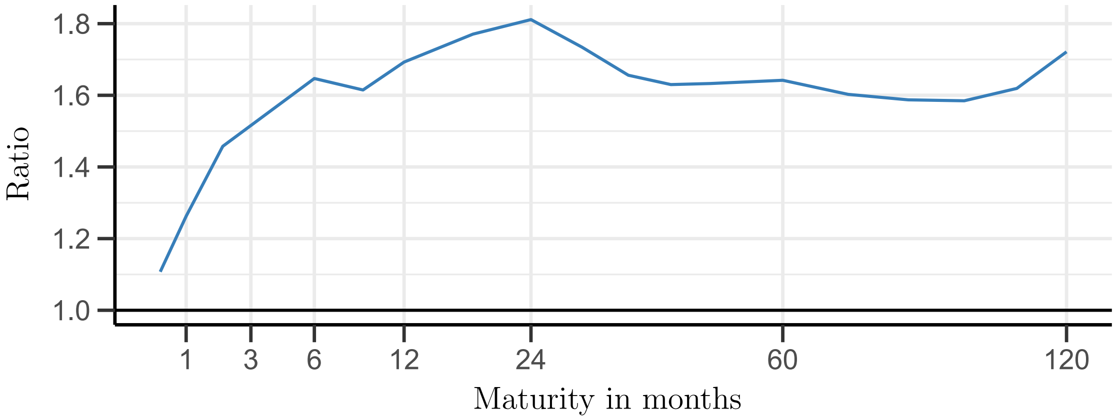
The Fed intervened using a wide range of instruments. We collect all announcements of the Fed's economic and financial crisis policies from 3 February 2020 to 29 July 2020, including precise time stamps of when an announcement was made, from the press releases section of the Fed's website.[7] See Appendix 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

[6]The Totem service has been providing SP-500 daily option price data only since 2018.
[7]See https://www.federalreserve.gov/newsevents/pressreleases.htm for more information.

Figure 4: Change in SP-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.




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 impacting 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 for identifying 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.[8] 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).[9] As an illustration, consider Figure 5, where we highlight the reaction of VIX ETF (VIXY) prices to different announcements of the Fed. In each

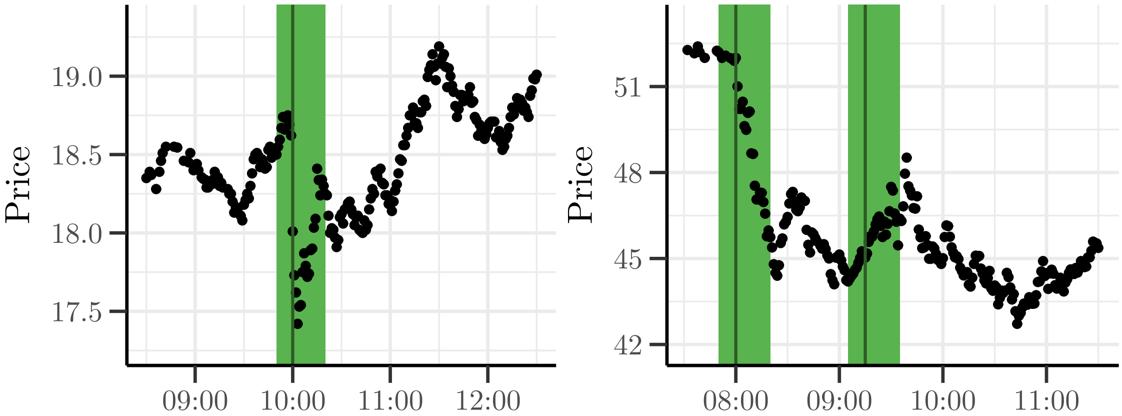
[8]Our sample of financial assets consists of the VIXY ETF contract and the E-Mini, 1st Fed fund, 3rd Fed fund, 1st Eurodollar, 3rd Eurodollar, 2-year T-Note, 5-year T-Note, 10-year T-Note, USD/EUR, USD/Yen and USD/GBP futures contracts. Table B1 in Appendix B provides the pairwise correlations for the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

[9]For robustness, we repeated the analysis with other window sizes, and our main results are robust to such changes, see Figure B1 in Appendix B. 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.

panel, the black dots correspond to the intraday minute-by-minute aggregates of VIXY prices.

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

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

Although principal components 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 for $PC_1$ 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 $PC_3$ corresponding 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 $\widetilde{\mathrm{PC}}_1$; (ii) the VIXY ETF (VIX; in vol points) on $\widetilde{\mathrm{PC}}_2$; 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 $\widetilde{\mathrm{PC}}_3$. 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.

# 3 Impact of policy announcements on fear

Our empirical investigation is based on regressing daily changes in fear, $\Delta\mathrm{Fear}_{t,\tau}$, 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 Fed announcement surprise factors and the three controls,

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

Three points merit attention here. First, as we regress daily changes in market fear on policy shocks, we must be mindful that factors other than the policy shock can cause changes in fear, especially during a fast-moving crisis. A second identification problem is the potential endogeneity of the timing of Fed crisis actions. The Fed could intervene after extreme days in financial markets, hence days with high market fear. To address both concerns, the regressions control for the contemporaneous severity of the pandemic, news about the US macro economy, and first difference in realized stock market variance, from $t-1$ to $t$.[10] The final challenge is using futures prices to indirectly measure the surprise in Fed crisis actions, implying we measure surprises with noise. A priori, this measurement error would lead us to underestimate the effects of Fed interventions. We use a wide range of futures contracts spanning fixed-income, foreign exchange, and equity markets to address this concern. This guarantees that we span a large space of market surprise, capturing broad transmission channels of the various Fed policies into financial markets.

[10] 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 SP-500 obtained from Oxford-Man's realized variance library according to their measure of quadratic price variations over 10-minute intervals, see `https://realized.oxford-man.ox.ac.uk/documentation/econometric-methods`.

In the regression, we normalize the PCs of 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 longer-term consequences of such crisis interventions. To that end, we use regressions of the form (3) that relate daily changes in market fear in the SP-500 to Fed announcement surprises for a range of time horizons (two weeks up 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.

## 3.1 The impact term structure of Fed announcements

We start by running regression (3) for varying horizons and refer to the resulting collection of regression coefficients as the *impact term structure* 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 any of the Fed announcements on the fear term structure in this section and show the impact by policy type in Section 4.

As the three factors, level, market, and slope are principal components, their units are not directly interpretable as they are linear combinations of the announcement surprises in the underlying assets. To give an economic sense of what a one unit increase in a (normalized) PC means, we choose a financial variable that captures our economic interpretation of a given factor and regress it on its corresponding PC. We find that a one-standard deviation increase in $\mathrm{PC}_1$ corresponds to a five basis point surprise decrease in the interest rate of the 1st Eurodollar futures contract. A one-standard deviation increase in $\mathrm{PC}_2$ corresponds to a 1.5 volatility point surprise decrease in the one-month VIX, and a one-standard deviation increase in $\mathrm{PC}_3$ corresponds to a three basis point surprise flattening of the interest rate term structure as captured by the yield spread between 10-year T-Note futures and the 1st Fed Fund futures contract. This helps to provide a sense of the economic size of the Fed's impact as measured by the coefficients of the impact term structure. For example, $\gamma_{36}^{\text{level}}$ gives the change in the three-year ahead fear caused by a one-standard deviation increase in the level factor. This increase corresponds to a surprise decrease of 1.5 volatility points in the one-month VIX at a Fed announcement. As fear is measured by the negative of the 10% log return quantile, this change is thus measured in units of (non-annualized) log returns over the next three years. A positive value implies an increase in fear.[11]

[11] 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 coeffi-

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 $\tau$. Rows $\widetilde{\mathrm{PC}}_1 - \widetilde{\mathrm{PC}}_3$ 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 ($\tau$) 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.

| | $\tau = 1$ | $\tau = 12$ | $\tau = 36$ | $\tau = 60$ | $\tau = 96$ |
|---|---|---|---|---|---|
| $\widetilde{\mathrm{PC}}_1$ | 0.008*** | 0.011* | 0.010 | 0.012** | 0.022*** |
| | (0.003) | (0.006) | (0.006) | (0.006) | (0.005) |
| $\widetilde{\mathrm{PC}}_2$ | −0.015*** | −0.036** | −0.029** | −0.021* | −0.017* |
| | (0.005) | (0.016) | (0.012) | (0.012) | (0.010) |
| $\widetilde{\mathrm{PC}}_3$ | 0.007*** | 0.017*** | 0.018*** | 0.019*** | 0.026*** |
| | (0.001) | (0.003) | (0.002) | (0.002) | (0.002) |
| $C_{\text{covid}}$ | −0.001 | 0.028 | 0.042 | 0.037 | 0.037 |
| | (0.018) | (0.029) | (0.037) | (0.034) | (0.033) |
| $C_{\text{ECSU}}$ | 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 |

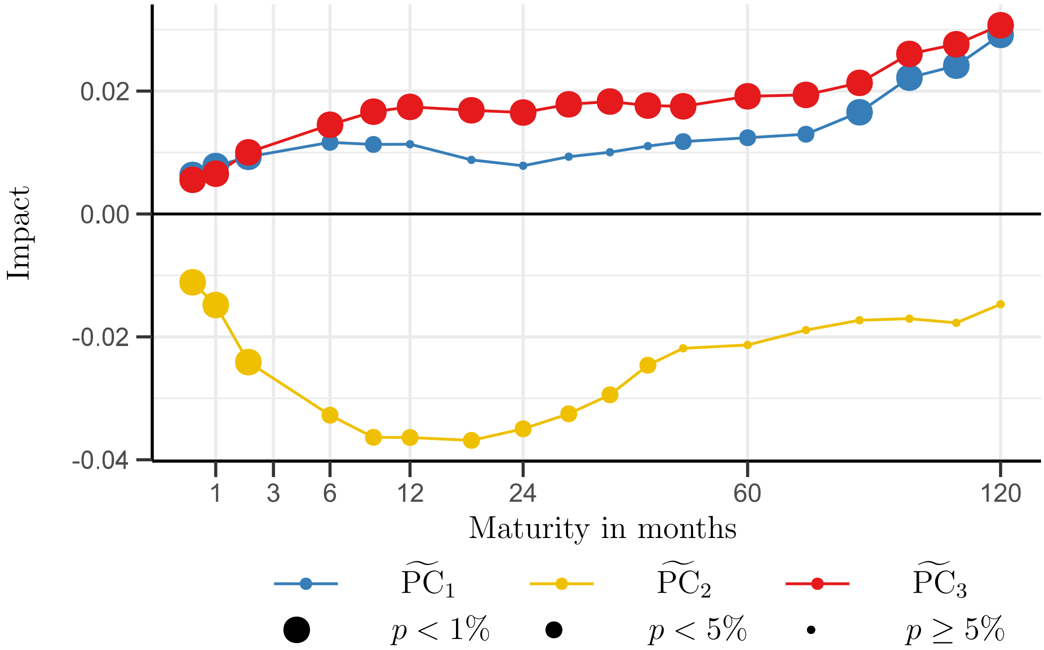
We present summary results for these regressions in Table 1, while Figure 6 displays the impact term structures for level (blue), market (yellow), and slope (red) factors. The sign of the impact coefficient for the market factor, $\gamma_\tau^{\text{market}}$, is negative for all $\tau$, i.e., reduces fear at all terms. This calming effect peaks at 18 months and slowly weakens over longer horizons. This pattern of the impact term structure indicates that Fed surprises that work via the market factor are mostly for the short to medium terms. Yet, they impact market fear well beyond the immediate crisis horizon.

The sign of the impact coefficient for the level factor $\gamma_\tau^{\text{level}}$ is positive for all horizons and increases with 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

cients would increase with the square root of maturity. A temporary impact of Fed announcement surprises induces a decreasing or hump-shaped impact term structure that converges to 0 for sufficiently long maturities. Appendix C provides more details on how to interpret the impact term structures.

Figure 6: Impact term structure of the SP-500

This figure displays the impact term structures for thelevel (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).




to a surprise five basis points interest level easing increases market fear by 0.03.[12]

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 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.

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 the impact is consistent with an information channel of Fed surprises: market participants infer information 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 indicates that market participants' information extraction is mainly about the probability of a protracted crisis.

When considering the temporal impact of the level and slope factors, neither points

[12]Table B4 in Appendix E displays coefficient estimates for regression (3) augmented by including the (normalized) fourth PC of the announcement surprises ($\widetilde{\mathrm{PC}}_4$).

to a trade-off between calming shorter market fear at the expense of distorting long-run risk-taking incentives. On the contrary, for both factors, an unexpected easing either via a lower level of interest rates or a flatter interest rate term structure causes an increase in fear at all horizons. What appear to be more accommodative Fed policies increase the cost of private disaster insurance. 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 Fed information effects 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. Unlike the level and slope factors, the impact of Fed announcements via the market factor raises the scope for moral hazard. The Fed likely intended to reduce short-term risk premia. However, the cheapening of private disaster risk insurance for longer-term horizons points to the potential costs of such relaxation by distorting risk-taking incentives.

#### High-frequency fear

In Table E1 in Appendix E, we also present additional findings using SP-500 high-frequency options data collected from CBOE TickHistory. This circumvents some of the identification concerns in previously employed frameworks with daily impact measures (Bekaert et al., 2013; Hattori et al., 2016; Haddad et al., 2021). We repeat the estimation by running regression (3), replacing the daily $\Delta Fear_{t,\tau}$ with high-frequency fear measures extracted from minute-by-minute quote data. We extract the risk-neutral quantiles for maturities of up to 6 months. We utilize the same time window for the high-frequency fear measure as we have employed for the future contracts. The control variables are excluded from this setup due to the lack of corresponding intra-daily variables. However, including the daily controls does not change the results, as one would expect when narrowing the event window to measure the change in fear. We mostly confirm the results presented in Table 1. As the high frequency approach reduces the noise in the daily fear measure, the significance level is raised below 1% across the board.

#### Fear decomposition

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,

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

Keeping in mind that $\mathrm{VIX}^2_{t,\tau} = -\frac{2}{\tau}\mathbb{E}^{\mathbb{Q}}_t(r_{t,\tau})$, 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, $\mathbb{E}_t^{\mathbb{Q}}(r_{t,\tau})$, upwards, reducing the dispersion of the log-returns, $\text{std}_t^{\mathbb{Q}}(r_{t,\tau})$, and changing the quantile of the standardized distribution, $F_{t,\tau}^{-1}(0.1)$. In unreported results we replace our fear measure with the change in the difference between the 10% and 20% quantiles (inter-quantile range). The results are very similar to using risk-neutral standard deviation. This further shows that the results are not caused by just a shift in the risk-neutral distribution. See Appendix D for more discussion and results.

### 3.2 Crisis times are different: Pre-crisis analysis

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[13] 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 term structure 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.

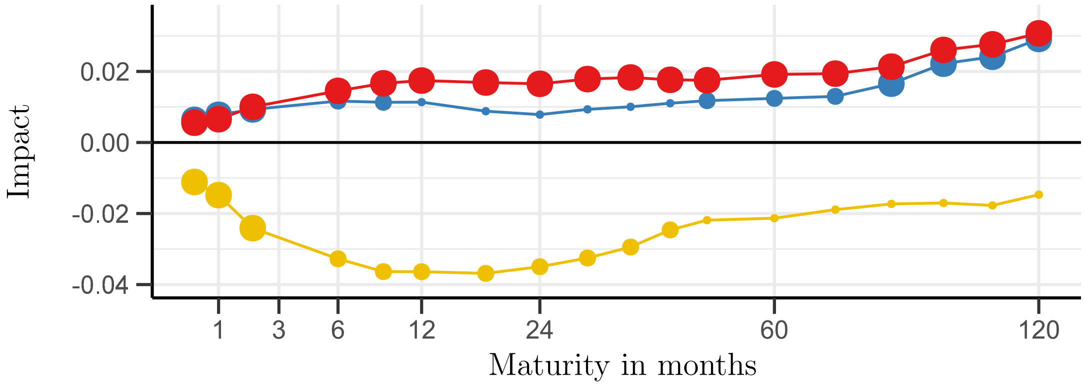
## 4 Announcement effects by policy type

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

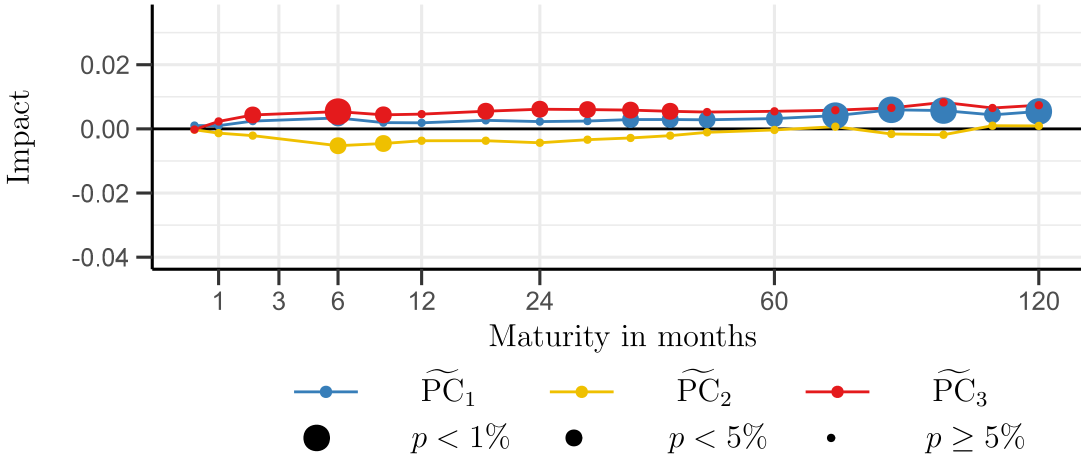
[13] For the pre-2020 period we do not have access to FX futures prices.

Figure 7: Crisis and pre-crisis impact term structures

The figure displays the impact term structure of announcement surprises at regular FOMC meetings for the period January 2018 to December 2019 (bottom panel) and reproduces the baseline impact term structure from the crisis period for comparison (top panel).




(a) Crisis




(b) Pre-crisis

interventions proved insufficient in that crisis, the Fed has since developed a wide range of unconventional policies, and 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 crisis announcements into five policy categories.[14] IR captures conventional interest rate decisions, including forward guidance. Second, LEN is 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 Cor-

[14] 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.

porate Credit Facilities. Fourth, FX is interventions that provide 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).

## 4.1 Identifying policy attributions

The Fed's impact on fear differs across policy types because different policies transmit through different economic factors as picked up by the three PCs of announcement surprises, level, market, and slope.[15] 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 $n^{\text{th}}$ Fed announcement, and $\delta_n^p$ is a dummy variable for policy $p$, i.e. it is equal to 1 if the $n^{\text{th}}$ announcement involved a policy of type $p \in \{\mathrm{IR}, \mathrm{LEN}, \mathrm{AP}, \mathrm{FX}, \mathrm{MPR}\}$ and 0 otherwise. The regression coefficient $\beta_i^p$ 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 $p$ 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 E3 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 large 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 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 $\mathrm{PC}_3$.

[15] In Table E2 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 term structure, 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 $\beta_i^p$ 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.

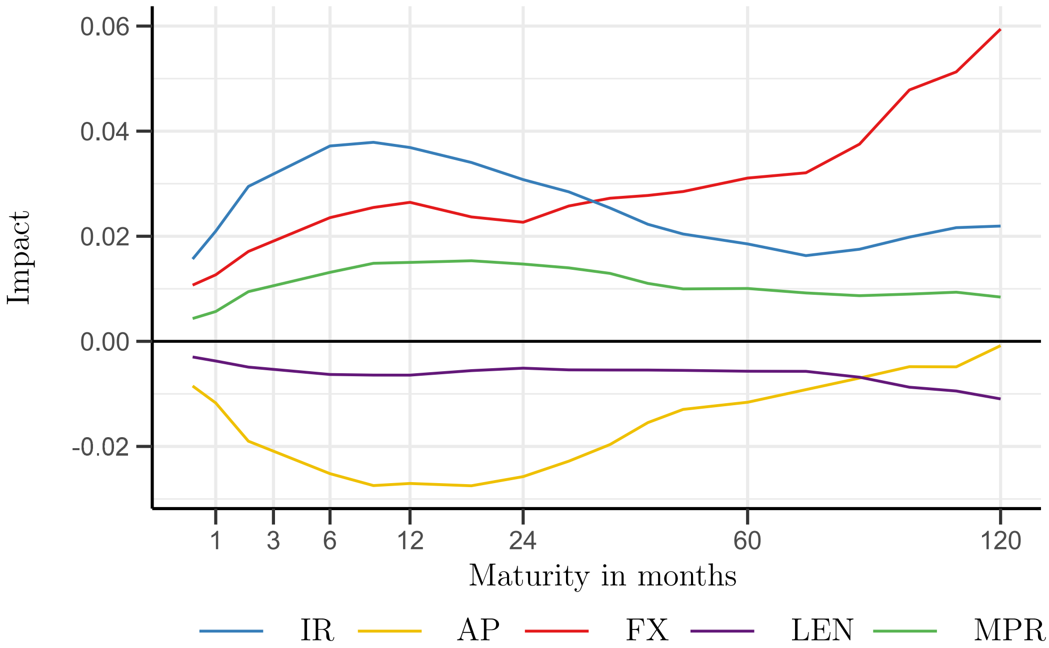



Figure 8 shows the expected impact of a Fed intervention of a given policy type on fear. We obtain these policy specific impacts by multiplying the average surprise caused by the policy of type $p$ in $\text{PC}_i$ as given in Table 8 by the impact coefficient of $\text{PC}_i$ for a corresponding horizon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

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

Overall, we see that asset purchases are most effective in calming fears. On average, they decreased fear by up to 0.03 log return units at the one-year horizon. Its impact term structure is an inverted hump shape 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 relax fear via the market factor, where its impact term structure inherits the shape of the market factor impact term structure. Liquidity interventions (IR and FX) increase fear through the level factor via an unexpected easing of interest rates. But FX adds 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 works 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 create moral hazard by reducing the private cost of disaster risk insurance, 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.

# 5 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 scaring 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 the central banks should pay attention to the impact of their discretionary crisis actions on insurance premia in long-term financial contracts to gauge distortions in the private sector's incentives to take on risk.

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# 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. |

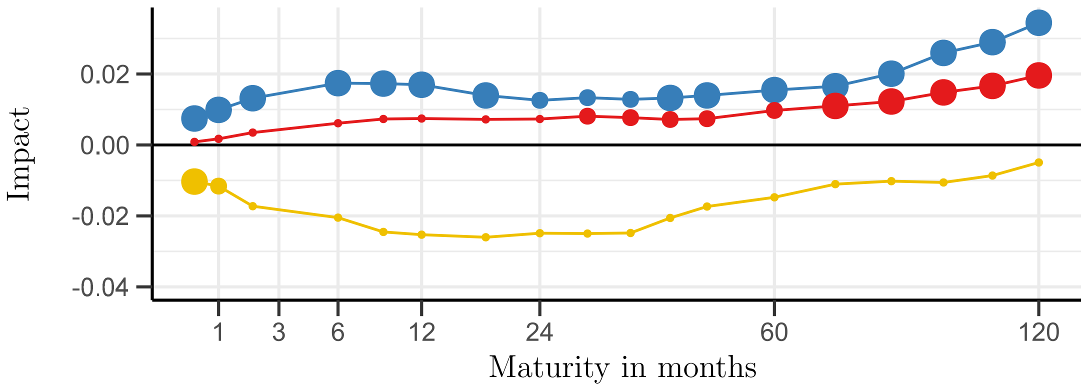
# B Announcement shocks and principal components analysis

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 SP-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.

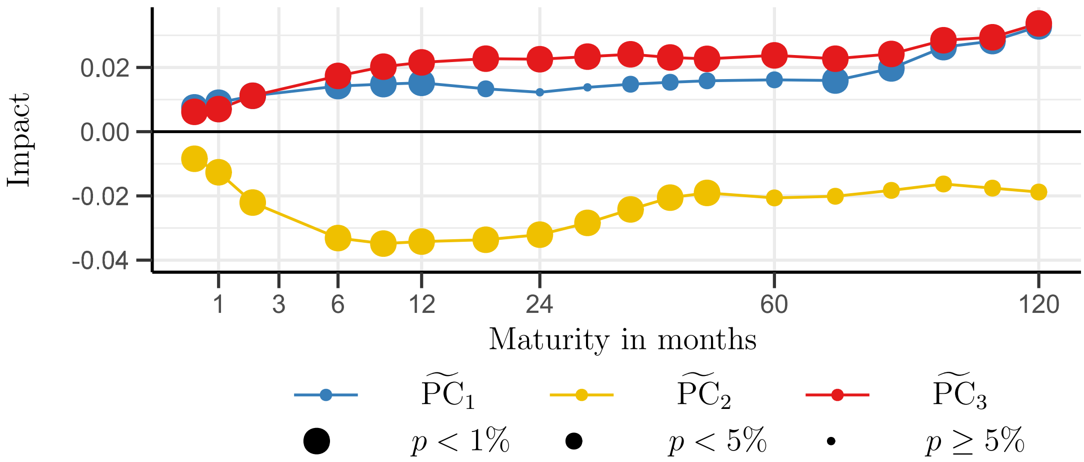
In the baseline analysis announcement surprises are based on price movements 10 minutes before to 20 minutes after the announcement. Here we show impact term structures obtained from regression (3) using two alternative window sizes. Figure B1a shows the impact term structures obtained for a narrower event window of 5 minutes before to 10 minutes after the announcement. Figure B1b shows the impact term structures for a wider event window of 15 minutes before to 60 minutes after the announcement.

Table B2 report the PCA factor loadings. Table E3 reports the p-values for the hypothesis tests that the mean of a given principal component does not differ across the two listed policies. That is, based on regression (4) in Section 4, the null hypothesis of the test for principal component $i$ and policies $p$ and $q$ is $H0 : \beta_i^p = \beta_i^q$. Table B3 shows the regression for the PCs.

Figure B1: Alternative event windows.




(a) 5 minutes before to 10 minutes after




(b) 15 minutes before to 60 minutes after

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).

| | *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 |
| *Note:* | | | $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ |

Table B4: Impact term structures with additional factor.

This table displays coefficient estimates for regression (3) augmented by including the (normalized) fourth PC of the announcement surprises ($\widetilde{\mathrm{PC}}_4$).

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

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

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 impact term structure

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 term structures we obtain from regression (3) and display in Figure 6.

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

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

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

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

The $\tau$ 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

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

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

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

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 risk-neutral 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 term structures, 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 $\tau$ 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 $\Delta$ 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 $\mu_i$. 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 term structure 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 $\tau$. A permanent increase in the mean of the per-period return distribution implies an impact term structure 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 $\sigma_i^2$. Again all other moments are assumed to be unaffected by the announcement. The corresponding impact term structure 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 $\tau$ up to $n$ periods ahead from where onwards it begins to decrease and, as $\tau$ grows large, the impact eventually reverts to 0. A permanent increase in the variance of the per-period return distribution implies an impact term structure that increases with the square root of the return horizon.

# D Decomposition of impact term structure

Equation (6) in Appendix C shows how to decompose changes in the quantile of the risk-neutral 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 risk-neutral 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

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

We obtain the impact term structure of the three principal component of announcement shocks, level, market and slope, for the mean and standard deviation of the risk-neutral distribution.

Figure D1a shows the impact term structures for the risk-neutral 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 risk-neutral distribution of excess log returns,

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

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 term structures for the risk-neutral standard deviation $s_{t,\tau}$ for the three announcement shock factors. Again, the impact of the market factor on the risk-neutral 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 risk-neutral mean and the risk-neutral 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 risk-neutral log return distribution. To analyze this impact, we define

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

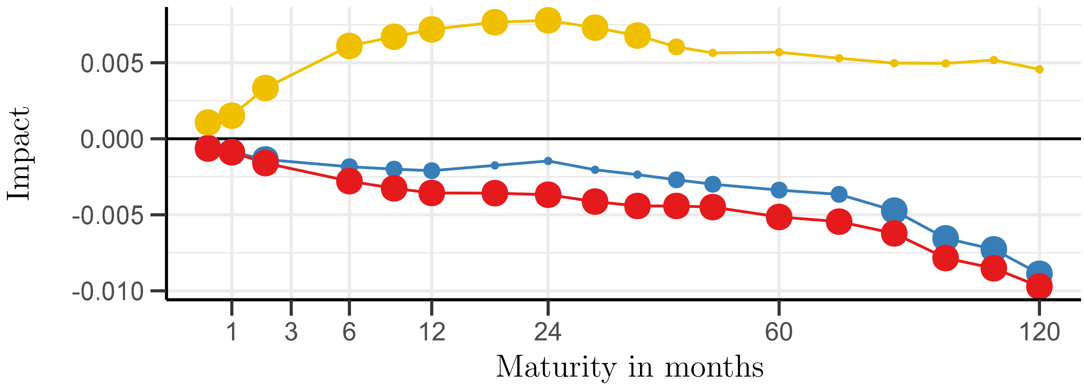
which is the negative of the 10% quantile of the normalized risk-neutral distribution of excess log returns. If log returns are normal, $x_{t,\tau}$ is the 10% quantile of the standard normal distribution, i.e. constant for all $t$ and $\tau$. Figure D1c displays the impact term structure for the regressions

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

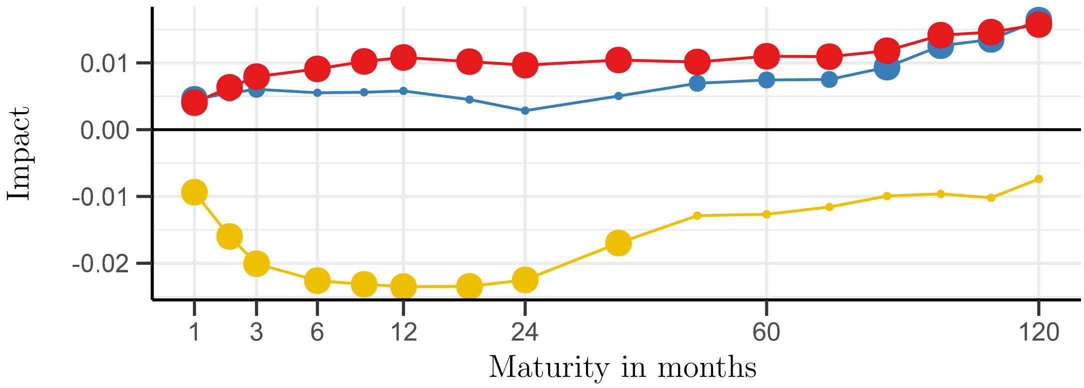
While we see some statistically significant impacts on higher moments of the return distribution at longer horizons, particularly so for the level factor, overall the

Figure D1: Decomposition of impact term structure

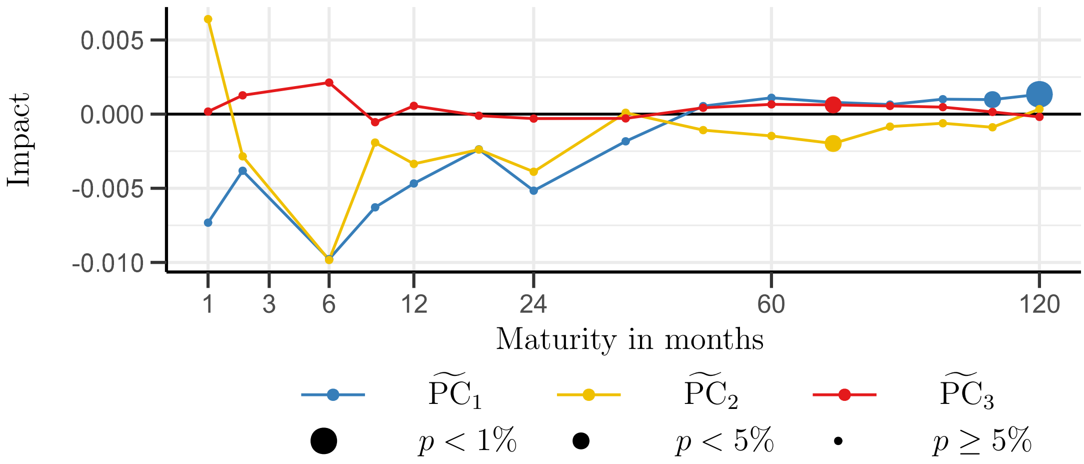
These figures show the impact term structures of Fed announcement surprises, i.e. the level (blue), market (yellow), and slope (red) factors, on the mean (top panel), standard deviation (middle panel), and the standardized 10% quantile (bottom panel) of the risk-neutral distribution of excess log returns.




(a) Risk-neutral mean




(b) Risk-neutral standard deviation




(c) Risk-neutral standardized quantile

majority of the impact of Fed announcement surprises on fear appears to work via the mean and standard deviation of the risk-neutral distribution of excess log returns.

# E Additional results and robustness checks

Table E1: Impact term structures 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.

| | Maturities | | | | |
|---|---|---|---|---|---|
| | $\tau = 1$ | $\tau = 2$ | $\tau = 3$ | $\tau = 4$ | $\tau = 6$ |
| $\widetilde{\mathrm{PC}}_1$ | 0.014*** | 0.015*** | 0.016*** | 0.018*** | 0.020*** |
| | (0.0002) | (0.0003) | (0.0003) | (0.0003) | (0.0004) |
| $\widetilde{\mathrm{PC}}_2$ | −0.004*** | −0.005*** | −0.006*** | −0.006*** | −0.007*** |
| | (0.0004) | (0.0004) | (0.0005) | (0.0005) | (0.001) |
| $\widetilde{\mathrm{PC}}_3$ | 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 E2: 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.

| | $\tau = 1$ | $\tau = 12$ | $\tau = 36$ | $\tau = 60$ | $\tau = 96$ |
|---|---|---|---|---|---|
| $\widetilde{\mathrm{PC}}_1$ | 0.009*** | 0.011** | 0.014** | 0.016*** | 0.025*** |
| | (0.003) | (0.006) | (0.006) | (0.006) | (0.006) |
| $\widetilde{\mathrm{PC}}_2$ | −0.018*** | −0.041*** | −0.034*** | −0.028** | −0.025** |
| | (0.004) | (0.014) | (0.012) | (0.011) | (0.010) |
| $\widetilde{\mathrm{PC}}_3$ | 0.009*** | 0.025*** | 0.026*** | 0.026*** | 0.032*** |
| | (0.002) | (0.004) | (0.005) | (0.005) | (0.005) |
| $I^{\mathrm{IR}}$ | 0.001 | 0.014 | 0.007 | 0.001 | 0.002 |
| | (0.007) | (0.016) | (0.020) | (0.020) | (0.025) |
| $I^{\mathrm{AP}}$ | 0.001 | 0.001 | 0.002 | 0.003 | 0.006 |
| | (0.005) | (0.013) | (0.011) | (0.011) | (0.012) |
| $I^{\mathrm{FX}}$ | −0.021*** | −0.051** | −0.072** | −0.065* | −0.063* |
| | (0.005) | (0.026) | (0.034) | (0.035) | (0.036) |
| $I^{\mathrm{LEN}}$ | 0.005 | 0.008 | 0.014 | 0.018 | 0.020 |
| | (0.004) | (0.010) | (0.013) | (0.014) | (0.014) |
| $I^{\mathrm{MPR}}$ | −0.009 | −0.019 | −0.011 | −0.017 | −0.017 |
| | (0.006) | (0.014) | (0.012) | (0.012) | (0.012) |
| $C_{\mathrm{covid}}$ | 0.007 | 0.051** | 0.060* | 0.053* | 0.052* |
| | (0.020) | (0.024) | (0.031) | (0.031) | (0.031) |
| $C_{\mathrm{ECSU}}$ | 0.003 | 0.002 | 0.001 | −0.002 | −0.007 |
| | (0.006) | (0.013) | (0.014) | (0.014) | (0.014) |
| $C_{\Delta\mathrm{RV}}$ | 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 |
| $\mathrm{R}^2$ | 0.570 | 0.516 | 0.477 | 0.524 | 0.582 |
| Adjusted $\mathrm{R}^2$ | 0.529 | 0.469 | 0.426 | 0.477 | 0.541 |
| *Note:* | | | | | *p<0.1; **p<0.05; ***p<0.01 |

Table E3: 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 $\widetilde{\mathrm{PC}}_i$ (column) where coefficient estimates derive from regression (5).

| Restriction | $\widetilde{\mathrm{PC}}_1 - \text{level}$ | $\widetilde{\mathrm{PC}}_2 - \text{market}$ | $\widetilde{\mathrm{PC}}_3 - \text{slope}$ |
|---|---|---|---|
| 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 |

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.