The calming of short-term market fear and its long-term consequences: The central banks' dilemma[*]

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Abstract

We study the short-term effects and long-term consequences of Fed crisis interventions on market fears — the risk perception of large asset price drops. We extract daily fear term structures from option markets covering event horizons from two weeks up to 10 years ahead and use announcement surprises in a broad set of futures contracts and ETFs, covering equity, fixed income, and FX markets, to identify the unexpected component of Fed interventions. Focusing on the 2020 market turmoil, we find that the Fed impacts market fear via risk sentiment and information channels. The risk sentiment channel is the dominant channel for asset purchases and operates at the short to medium term. In contrast, the information channel strongly impacts long-term fears and is the dominant channel for interest rate policies.

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1 Introduction

The 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 harms the real economy since the resulting high uncertainty reduces business investment and hiring and may 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 transportation 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.

Focusing on the extreme market turmoil in the spring of 2020, we find that the Federal Reserve, Fed, achieved its immediate goal of calming fear. However, while it wielded crisis tools that can put a floor under asset prices, thus preventing market participants from coordinating their expectations on worst-case scenarios, using such tools proved far from costless. Our results suggest the Fed faced two trade-offs when intervening. The first is that 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 policies, 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. Disentangling these two trade-offs motivates our work here.

When investigating how the market perceives the Fed 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 to coordinate their expectations.

In this paper, we use a uniquely rich data set on the over-the-counter options markets,[1] allowing us to capture tail risk perceptions from one week ahead up to ten years into the future. 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 on the 10% quantile of the SP-500 risk-neutral log return distribution for a given

[1] The data is provided by IHS Markit's Totem, 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%. Options with such extreme contract terms are exclusively traded in the OTC market and not available in standard option price datasets derived from exchange-based trading activity.

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*.

Our focus is 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 about worst-case scenarios 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 financial crisis in 2008. The 2020 market turmoil is the first episode where this broad range of crisis tools was fully available to it.

We classify the interventions into five categories designed to capture the primary economic aspects and use the accompanying Fed press releases to classify them; First is IR, policies related to interest rate decisions, including forward guidance. Second is LEN, or lender of last resort actions that provide liquidity to market participants. The third is asset purchases or AP, focused on bonds, including a new corporate bond facility. Foreign exchange, FX, is the fourth, a US dollar liquidity support that foreign central banks intermediate to their financial institutions. Last is macroprudential relaxing, MPR, where the Fed, the regulator of bank holding companies, relaxes macroprudential constraints.

We concentrate on the surprise component of interventions when investigating the impact of Fed interventions 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 update their beliefs about the central bank's reaction function in future crises, giving rise to moral hazard.

Empirically, we face three challenges. First, Fed crisis announcements can refer to a multitude of policy levers impacting financial markets through various transmission channels. This means announcement surprises are multidimensional, and we need a measurement approach that captures that. Second, crises are fast-moving, and market conditions can change rapidly. To identify the Fed's impact on fear, it, therefore, is important to pinpoint the exact moment an announcement surprise hits the market. Third, not all announcements create surprises of the same magnitude or direction, which is particularly important if we want to compare the relative effectiveness of different Fed policies, so we require a method to compare the size and sign of announcement surprises across policies.

To address these empirical challenges, we propose an identification strategy that adapts techniques developed for identifying monetary policy shocks from 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. First, with a wide range of futures contracts and ETFs that cover fixed income, foreign exchange, and equity markets to capture the broad transmission channels of Fed crisis policies. Then, measuring how each announcement changes prices in a narrow event window around Fed crisis announcements leaves us with a panel of Fed interventions and price moves, i.e., announcement surprises. And finally, by using a principal component analysis on the z-scored panel of price moves to obtain a low dimensional representation of the Fed's announcement surprises that captures a large fraction of the informational content of the individual series of price moves. We use the first three principal components (PCs) as our measure of Fed surprises.

The principal components load naturally on announcement surprises in particular assets. The first PC loads mainly on surprise shifts in the yield curve and USD depreciation against major currencies, and we hence refer to it as the "interest level" factor. Meanwhile, the second PC loads most strongly on equity market surprises, negatively on expected volatility, and positively on returns. It also loads positively on surprise depreciation of the US dollar against major currencies but does not co-move strongly with surprises in interest rate futures. These correlations are consistent with a broad easing of risk sentiment across asset markets, and we refer to the second PC as the "risk sentiment" factor. Finally, the third PC strongly loads on the surprise steepening of the interest rate term structure. It coincides with a surprise appreciation of the US dollar, a decrease in expected equity market volatility, and positive stock market returns. Taken together, these suggest the third PC picks up an information component of Fed announcement surprises, i.e., a higher value of it corresponds to a positive update of market participants' expectations for the longer-term economic outlook in response to a Fed announcement. We, therefore, refer to the third PC as the "information" factor.

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; interest level, risk sentiment, and information. As the timing of Fed interventions likely depends 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 across a range of time horizons, giving us three impact coefficients, one per factor, for each time horizon of fear, from two weeks to ten years ahead, and refer to the collection of regression coefficients for a given factor across time horizons as the factor's *impact term structure*. The three impact term structures encapsulate the impact of Fed announcement surprises on market fear across different transmission channels and time horizons.

The impact term structure captures how the principal components affect fear. To further identify the impact of each of the five policies, we regress individual PCs on policy type dummies, giving us the average size and direction of an announcement surprise in a particular policy via a given PC. We refer to the regression coefficients for these dummies as *policy attributions*, as they measure how announcement surprises in a given policy are reflected via the three factors and how this differs across policies.

We obtain three sets of results. The first is that the impact of Fed interventions on fear is much stronger during crises than in calmer times. When we compare impact term structures of announcement surprises at crisis interventions to that at regular FOMC meetings in normal market conditions, we find the former to dominate the latter in size. Crisis times are different. 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 calibrating crisis intervention tools, it is necessary to tune them on crisis data, not data generated in normal times.

Second, each of the three factors, interest level, risk sentiment, and information, exert a distinct impact on fear. While the interest level factor, the first principal component of the PCA, captures most of the Fed announcement surprises, accounting for 33% of the variance of price shocks, we still find that surprises picked up by the risk sentiment and information factors move fear significantly. The impact pattern of the level and information factors, both increasing with the maturity horizon, suggest that Fed surprises that operate via this factor are permanent. For both factors, an unexpected easing, either via a lower level of interest rates or a flatter interest rate term structure, cause an increase in fear at all horizons. What appears to be more accommodative Fed policies increase the cost of private disaster insurance. The sentiment factor has a transitory impact pattern, with the most substantial impact coming at the short horizon. Still, it does not die out rapidly, staying significant well beyond the immediate crisis horizon. An unexpected easing in risk sentiment coincides with lower fear when the announcement is made.

Third, when we identify policy attribution coefficients, we find that not only is a null hypothesis of the policies being collectively indistinguishable from each other firmly rejected, but the signs are also different, implying the transmission channels significantly differ across policies. 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. The reason relates to how the three PCs pick up announcement surprises in these policies. Asset purchases primarily work through the second PC, impacting fear via the risk sentiment factor, while liquidity interventions increase fear through the first PC, the interest level factor. Finally, FX adds fear via the third PC, the information factor. This suggests that IR and FX's impact on fear primarily works via Fed information type effects, signaling to market participants that the long-term economic outlook is worse than expected.

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 distorting long-term risk-taking incentives, thus creating moral hazard. 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.

We make three main contributions. First, we focus on the term structure of the impact to capture both the immediate benefits and long-term consequences of crisis interventions. To do so, we develop the notion of the term structure of market fear and implement it empirically. We profit from access to a unique dataset on OTC options with extreme contract terms that cover sufficiently extreme price drops over time horizons from several weeks up to ten years into the future. An increasing body of evidence finds that the Fed interventions affected the market perception of risk. Haddad et al. (2022), for example, focusing on the Fed's announcement of US corporate bond and bond ETF purchases during the 2020 crisis, find that this has led to significant revisions in market participants' perception of the Fed's willingness to support corporate bond prices in future market turmoils. Kelly et al. (2016) have documented significant premia in 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). Previous work has shown that monetary policy substantially impacts market risk perceptions extracted from option prices (Bekaert et al., 2013; Hattori et al., 2016; Hu et al., 2022).

Second, we analyze how unexpected central bank interventions — actions that deviate from what markets understood to be the central bank's crisis rulebook — impact risk perceptions. To construct announcement surprises, we use well-established methods developed to extract monetary policy shocks from futures prices (Bernanke and Kuttner, 2005; Gürkaynak et al., 2005). However, we do not aim to identify the effects of conventional monetary policy. Instead, we study how effective discretionary, unexpected crisis interventions are in calming financial markets. In using a broad set of future contracts to capture broader transmission channels of Fed policy, we follow Swanson (2020). Our results point to strong Fed information effects of crisis interventions, especially for conventional interest rate-based policies. We do not find such effects for regular FOMC announcements, complementing results in Jarociński and Karadi (2020) who show that announcement surprises contain a significant information effect component during stock market downturns but primarily reflect revisions about the future path of interest rates in regular times. The trade-off between relaxing funding costs and increasing market fear also 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.

Finally, we evaluate the relative efficacy of the Fed's crisis toolkit in calming market fear by studying how the transmission channels from Fed surprises to market fear differ across crisis tools. A range of papers have evaluated the effectiveness of individual Fed crisis facilities both after the 2008 financial crisis (e.g. Acharya et al., 2017; Carlson and Macchiavelli, 2020; Bahaj and Reis, 2022) and the 2020 market crisis (e.g. Bahaj and Reis, 2020; O'Hara and Zhou, 2021; Haddad et al., 2021; Boyarchenko et al., 2021; Fleming et al., 2021). More broadly, several recent papers have analyzed the impact of the Covid-19 shock on US equity markets (e.g. Ramelli and Wagner, 2020; Baker et al., 2020; Cox et al., 2020).

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 3and the contribution of individual Fed policies to fear in section 4. 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, $\Delta\text{Fear}_{t,\tau}$, across time horizons τ (measured in months) on Fed crisis actions and controls. 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 impact coefficients, which we refer to as the *impact term structure*. We need empirical measures of market fear and Fed crisis actions to implement this approach.

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 there are several sources of option data, we rely on data from the IHS Markit's Totem service, 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.[2] 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

[2]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.

crucial for capturing tail events but are not available in standard data sets derived from exchange-based trading activity.

Our primary notion of fear over a particular time horizon τ 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 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 risk-neutral 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 risk-neutral distribution of excess log-returns obtained from option prices.

We also use our risk-neutral distributions to construct alternative measures of fear, especially the CBOE VIX index, which we create for all points on our maturity structure, both for robustness and to study how the distribution of returns changes in response to policy announcements. See Appendix C for the technical details.

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.

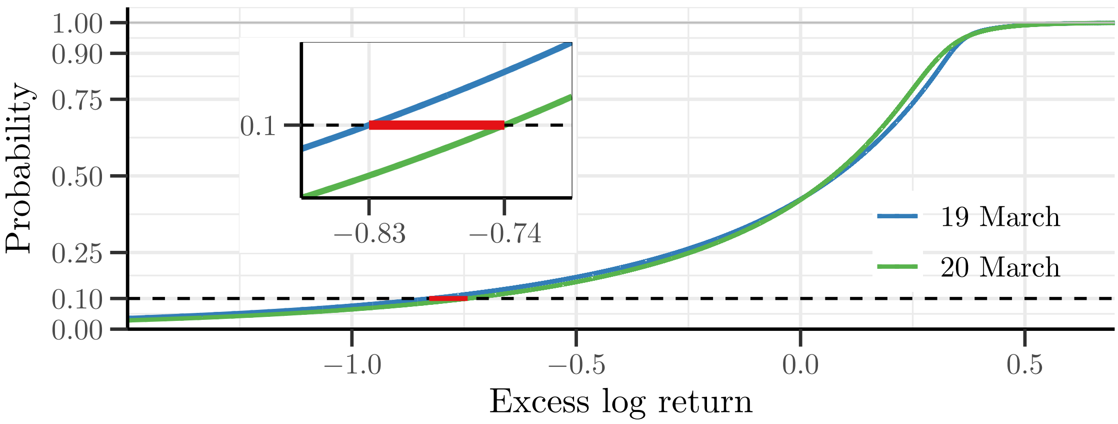


Figure 1 provides an example of fear in the SP-500 index over a one-year horizon on two consecutive days at the height of the crisis, March 19 and 20, 2020. $\Delta\text{Fear}_{t,\tau}$, the daily change in fear, in this particular case, was:

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

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.

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).

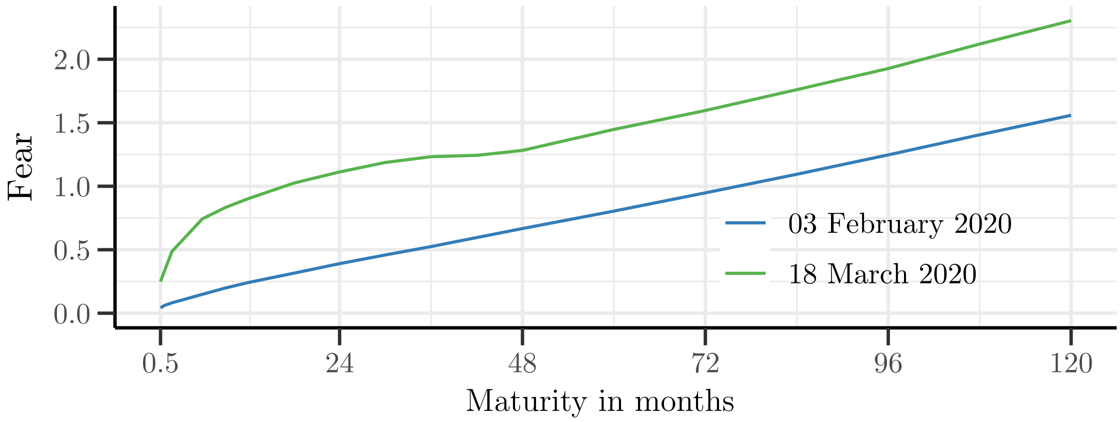


Figure 3 shows fear in the SP-500 from 2005 until the end of 2021, monthly until 2018, and daily after that. The figure covers two crisis episodes, 2008 and 2020, and three maturities, one month, one year, and a decade. The two crises are visibly different from regular times, as fear shoots up sharply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

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

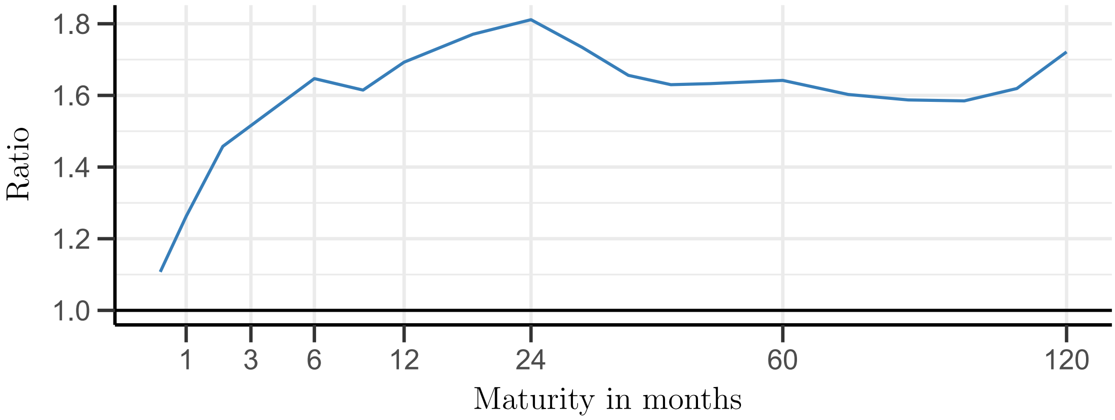
Figure 3: SP-500 term structure of fear, 2005-2021

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.

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.

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.



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.[3]

While the obvious way forward might be to directly use an announcement dummy in regression (1), 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 impacting financial markets through various transmission channels. This means that announcement surprises are multidimensional, and we need a measurement approach that captures this aspect.

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 (2020). 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.[4] 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).[5] 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 intraday minute-by-minute aggregates of VIXY prices.

2.3 Measuring announcement surprises

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 1 shows the factor loadings of the first three principal components (PCs). Together these PCs capture approximately 70% of the variation in the announcement surprises captured by the futures and ETF prices. More details can be found in Appendix A.

Although principal components analysis is a purely statistical technique for dimensionality reduction, the loadings in Table 1 show that the PCs have intuitive economic interpretations. PC_1 picks up surprise level shifts in the interest rate

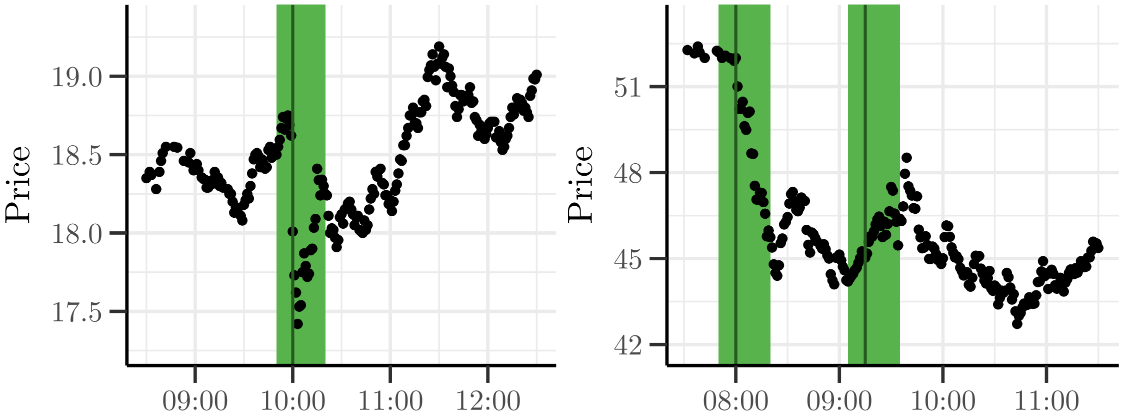
[3]See https://www.federalreserve.gov/newsevents/pressreleases.htm for more information and data.

[4]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.

[5]For robustness, we repeated the analysis with other window sizes, and our main results are robust to such changes, see Appendix F. 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

Table 1: 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

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 also coincides with a surprise depreciation of the US dollar against the euro, yen, and pound. The loadings of PC_1 on VIXY and E-Mini futures are positive but small. These cross-market correlations are consistent with a conventional easing channel via interest rate policies.[6] In what follows, we refer to PC_1 as the "interest level" factor.

PC_2 loads strongly on the equity markets, negatively on the VIXY ETF, and positively on the E-mini futures. An increase in PC_2 also leads to a depreciation of the US dollar against the three major currencies and a flattening of the interest rate term structure. An increase in PC_2 implies a surprise reduction in expected market volatility, positive stock market returns, a depreciation of the US dollar, and interest rate changes suggesting a reduction of the term premium in long-term rates. These correlations are consistent with a broad easing of risk sentiment across asset markets, and we refer to PC_2 as the "risk sentiment" 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. It also coincides with a surprise appreciation of the US dollar, a decrease in expected equity market volatility, and positive stock market returns. The coincidence of a steeper interest term structure, a USD appreciation, and a positive stock market reaction suggests that PC_3 picks up an information component of Fed announcement surprises, i.e., a higher value of PC_3 implies a positive update of market participants' expectations for the longer term economic outlook. We, therefore, refer to PC_3 as the "information" factor.

2.4 Identifying the impact of Fed crisis interventions

We face three main challenges in our empirical exercise. 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. 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.

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.[7] We modify (1) to incorporate the three Fed announcement surprise factors and the three con-

[6] Table 3 in Appendix A showing that movements in PC_1 are largest for Fed announcements that involve interest rate decisions, including forward guidance.

[7] Our results are robust to including additional principal components, see Appendix F.

trols,

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

In the regression, we normalize the PCs of announcement surprise by their standard deviation and denote these normalized PCs by $\widetilde{PC}$. We control for the severity of the pandemic, macroeconomic uncertainty, and stock market volatility.[8] To control for residual serial correlation and heteroskedasticity, we use the Newey-West (HAC) estimator to calculate all standard errors.

3 Impact of policy announcements on fear

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), controlling for possible confounders. The primary sample is daily observations from February to July 2020, when the Fed directly intervened to address significant financial market dislocations and support the wider economy.

The conventional Fed response to address market turmoil is to lower its target for the federal funds rate, perhaps coupled with strong forward guidance. And these were indeed the first two crisis actions of the Fed on 3 March and 15 March. However, as markets became more fearful by the middle of March, the Fed proceeded to deploy a broader set of tools, many developed in response to the 2008 crisis. These include asset purchases, macroprudential interventions, lending to financial and non-financial corporations, and foreign exchange interventions, clearly showing that different aspects of the crisis were targeted.

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.

[8] 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`.

As the three factors, interest level, sentiment, and information are principal components, their units are not directly interpretable as they are linear combinations of the z-scored 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 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 PC_2 corresponds to a 1.5 volatility point surprise decrease in the one-month VIX, and a one-standard deviation increase in 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, $\gamma_{36}^{\text{sentiment}}$ gives the change in the three-year ahead fear caused by a one-standard deviation increase in the risk sentiment 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.[9]

We present summary results for these regressions in Table 2, while Figure 6 displays the impact term structures for interest level (blue), risk sentiment (yellow), and information (red) factors. The sign of the impact coefficient for the risk sentiment factor, $\gamma_{\tau}^{\text{sentiment}}$, is negative for all τ, an announcement easing risk sentiment reduces fear at all horizons. This calming effect peaks at 18 months and slowly weaken over longer horizons. This temporal pattern of the impact term structure indicates that Fed surprises that work via the risk sentiment factor are mostly transitory. Yet, they impact market fear well beyond the immediate crisis horizon. For example, at the 18 months horizon, a Fed announcement that induces a one-standard deviation increase in the risk sentiment factor corresponding to a 1.5 volatility point drop in the one-month VIX reduces fear by 0.04, i.e., causes the 10% quantile of the log return distribution to drop by 0.04.

The sign of the impact coefficient for the interest 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 to a surprise five bps interest level easing increases market fear by 0.03.

[9] 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. Suppose a Fed announcement surprise was to permanently increase the variance of such a log return distribution. The impact coefficients would increase with the square root of maturity. A temporary impact of Fed announcement surprises would induce a decreasing or hump-shaped impact term structure that converges to 0 for sufficiently long maturities. Appendix B provides more guidance on interpreting the impact term structures.

Table 2: 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 $\widetilde{\mathrm{PC}}_1 - \widetilde{\mathrm{PC}}_3$ give the impact coefficients, γ_τ^{level}, $\gamma_\tau^{\mathrm{sentiment}}$, and $\gamma_\tau^{\mathrm{info}}$, from regression (3). Controls are $C_{t,\mathrm{covid}}$, the rolling 7-day mean of the confirmed covid cases in the US, $C_{t,\Delta\mathrm{ECSU}}$, the change in the Bloomberg economic surprise index, and $C_{t,\Delta\mathrm{RV}}$, the change in realized variance from $t-1$ to t. The dependent variable is $\Delta\mathrm{Fear}_{t,\tau}$ 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.

	$\tau = 1$	$\tau = 12$	$\tau = 36$	$\tau = 60$	$\tau = 96$
$\widetilde{\mathrm{PC}}_1$	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_{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)
$C_{\Delta\mathrm{RV}}$	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

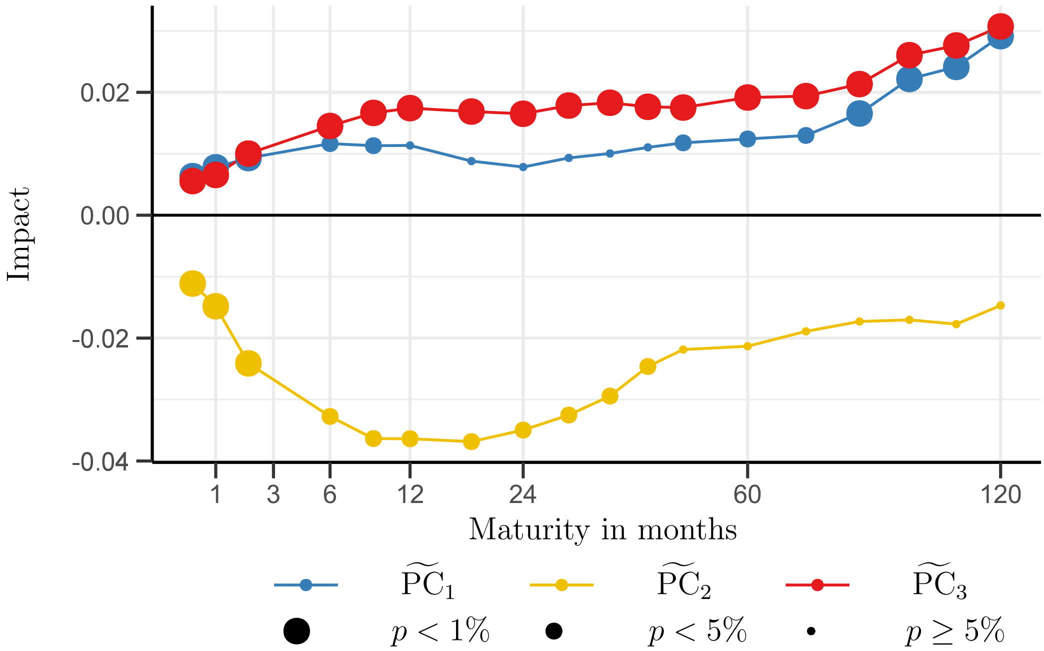
The impact of surprises captured through the information factor $\gamma_\tau^{\mathrm{info}}$ have a very similar term structure as that of the interest level factor, but the impacts are typically somewhat larger. For example, at the ten-year horizon, a one-standard deviation increase in the information factor corresponding to a three bps surprise flattening of the interest term structure also increases fear by 0.03.

When we run analogous regressions for the pre-crisis period from mid-2018 to January 2020, focusing on announcement surprises at regular FOMC meetings,[10] we find impact term structures that a much smaller in magnitude. Crisis times are different. In Appendix D, we provide more details and show that a PCA on pre-crisis announcement shocks yields very different factor loadings than in crisis time. 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.

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

Figure 6: Impact term structure of the SP-500

This figure displays the impact term structures for the interest level (blue), risk sentiment (yellow), and information (red) factors. The y-axis provides the value of point estimates of the coefficients, γ_τ^{level}, $\gamma_\tau^{\text{sentiment}}$, and $\gamma_\tau^{\text{info}}$. 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).



We further look in detail at which aspects of the risk-neutral distribution of excess log returns contribute to the changes in fear in response to Fed announcements (see Appendix C). The 10% quantile can be expressed in terms of the mean, the variance, and higher moments of the return distribution,

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

Figure 8 in the Appendix 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, $F_{t,\tau}^{-1}(0.1)$. The first two effects are large and reinforce each other. When Fed interventions ease fear, it is because the announcement's surprise component increases both the mean and reduces the variance of the return distribution. The effects via the changing shape of the standardized distribution are smaller.

3.2 Analysis

While the interest level factor capture most of the Fed announcement surprises — 33% of the standard deviation of announcement shocks compared to 19% and 12% for sentiment and information respectively (see Appendix A) — Fed announcements also strongly impact fear via sentiment and information factors. Sentiment has a transitory impact pattern, with the most substantial effects coming at the short to medium-term horizon. Information's impact pattern, increasing with the horizon, is consistent with a permanent effect of Fed surprises that operate via this factor.

Regarding the impact of the information factor, it is of particular interest to us 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. We want to stress that the label "information" for this PC was chosen based on the factor loadings of the PCA and did not use results from the regression analysis. In that sense, the impact term structure of the information factor provides additional justification for the label.

When considering the temporal impact of the interest level and information factors, neither points to a trade-off between calming shorter market fear at the expense of distorting long-run risk-taking incentives — moral hazard. 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 risk sentiment factor is to reduce fear. An unexpected easing in risk sentiment coincides with lower fear when the announcement is made. 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 interest rate and information factors, the impact of Fed announcements via the risk sentiment factor raises moral hazard concerns. 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.

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 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.[11] 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 Corporate 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 actions. 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. See Appendix E for the announcements and category assignments list. 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.

4.1 Identifying policy attributions

The Fed's impact on fear differs across policy types because different policies transmit through different economic channels as picked up by the three PCs of announcement surprises, level, sentiment, and information.[12] 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 captured by the given PCs.

Table 3 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

[11] 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.

[12] In Appendix F, 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.

the type of policy that was announced. We show in Appendix A 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 ($\text{PC}_1 > 0$) together with a steepening of the term structure ($\text{PC}_3 > 0$) while causing risk sentiment to worsen ($\text{PC}_2 < 0$). FX policies also lowered interest rate levels on average, but unlike IR, they flattened the interest rate term structure and improved risk sentiment. The strong effect of AP policies came through improving risk sentiment. 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. Table 4 in Appendix A reports the p-values for pairwise comparisons of conditional means across policies.

Table 3: 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.

	$\widetilde{\text{PC}}_1$ – Interest level	$\widetilde{\text{PC}}_2$ – Risk Sentiment	$\widetilde{\text{PC}}_3$ – Information
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 7 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 PC_i as given in Table 7 by the impact coefficient of PC_i for a corresponding horizon τ obtained in regression (4) and then summing across PCs, that is,

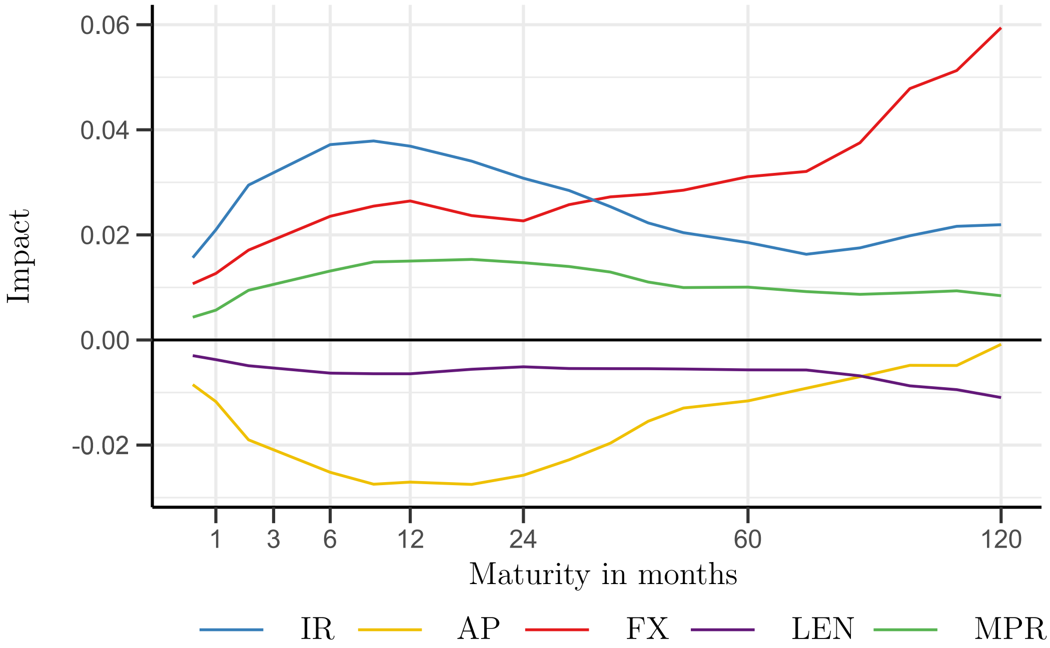
$$\mathbb{E}\left(\Delta\text{Fear}_\tau|\text{policy} = p\right) = \gamma_\tau^{\text{level}}\,\beta_1^p + \gamma_\tau^{\text{sentiment}}\,\beta_2^p + \gamma_\tau^{\text{info}}\,\beta_3^p \tag{5}$$

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 channels. Asset purchases mostly

Figure 7: 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.



relax fear via the sentiment factor, where its impact term structure inherits the shape of the sentiment 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 information factor, whereas IR lowers risk 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 3 shows that all the non-conventional policies (LEN, FX, AP, MPR) have negative coefficients for the information 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 interest level and information 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 risk sentiment channel. To the extent that this channel creates 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, thus creating moral hazard. 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 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 6 provides the pairwise correlations for the announcement shocks in these 12 contracts. Table 4 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 5 show the regression for the PCs.

Table 4: 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	$\widetilde{\mathrm{PC}}_1$ – Interest level	$\widetilde{\mathrm{PC}}_2$ – Risk Sentiment	$\widetilde{\mathrm{PC}}_3$ – Information
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

Table 5: 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 $\widetilde{\mathrm{PC}}_1$ (1st column), (ii) the VIXY ETF (VIX; in vol points) on $\widetilde{\mathrm{PC}}_2$ (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 $\widetilde{\mathrm{PC}}_3$ (3rd column).

	Dependent variable:		
	ED 1st	VIX	TN 10-yr - FF 1st
$\widetilde{\mathrm{PC}}_1$ – Interest level	-0.052^{***}		
	(0.003)		
$\widetilde{\mathrm{PC}}_2$ – Risk Sentiment		-1.421^{***}	
		(0.126)	
$\widetilde{\mathrm{PC}}_3$ – Information			-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 6: 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

B 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 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

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

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

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

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 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 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 τ. 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 σ_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 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 term structure that increases with the square root of the return horizon.

C Decomposition of impact term structure

Equation (6) in Appendix B 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

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

and

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

We obtain the impact term structure of the three principal component of announcement shocks, interest rate level, risk sentiment and Fed information, for the mean and standard deviation of the risk-neutral distribution.

Figure 8a 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. This may be of independent interest to the reader given the large literature that uses VIX as an uncertainty measure. We see that while the impact of the risk sentiment factor ($\widetilde{\text{PC}}_2$) has a horizon of two years, the impact of the interest rate level ($\widetilde{\text{PC}}_1$) and the information factor ($\widetilde{\text{PC}}_3$) is consistent with a permanent impact on the risk neutral mean.

Figure 8b 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 risk sentiment factor on the risk-neutral standard deviation is temporary with a horizon of one year ahead whereas interest rate level and information factor appear to have permanent 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 risk sentiment factors, positive shocks both increase the mean and reduce the dispersion of the return distribution. For the interest rate and information factor, 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

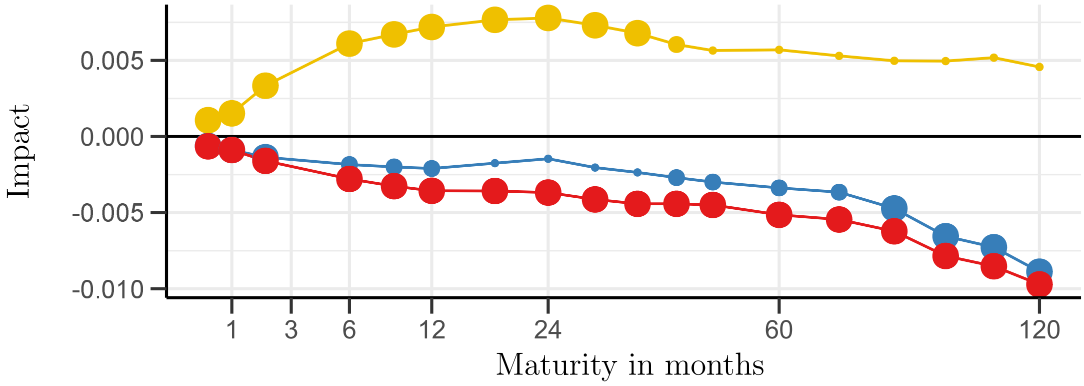
$$x_{t,\tau} \equiv \frac{-\text{Fear}_{t,\tau} - m_{t,\tau}}{s_{t,\tau}} = -F_{t,\tau}^{-1}(0.1),$$

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 τ. Figure 8c displays the impact term structure for the regressions

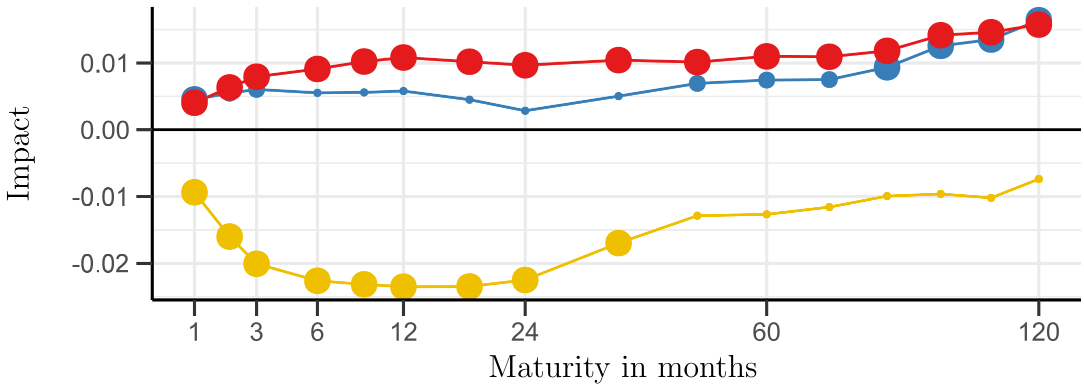
$$\Delta x_{t,\tau} = \alpha_\tau^x + \gamma_\tau^{x,\text{level}}\,\widetilde{\text{PC}}_{1,t} + \gamma_\tau^{x,\text{sentiment}}\,\widetilde{\text{PC}}_{2,t} + \gamma_\tau^{x,\text{info}}\,\widetilde{\text{PC}}_{3,t} + \sum_{j=1}^{3} \xi_\tau^{x,j}\,\text{Controls}_t^j + \epsilon_{t,\tau}^x.$$

Figure 8: Decomposition of impact term structure

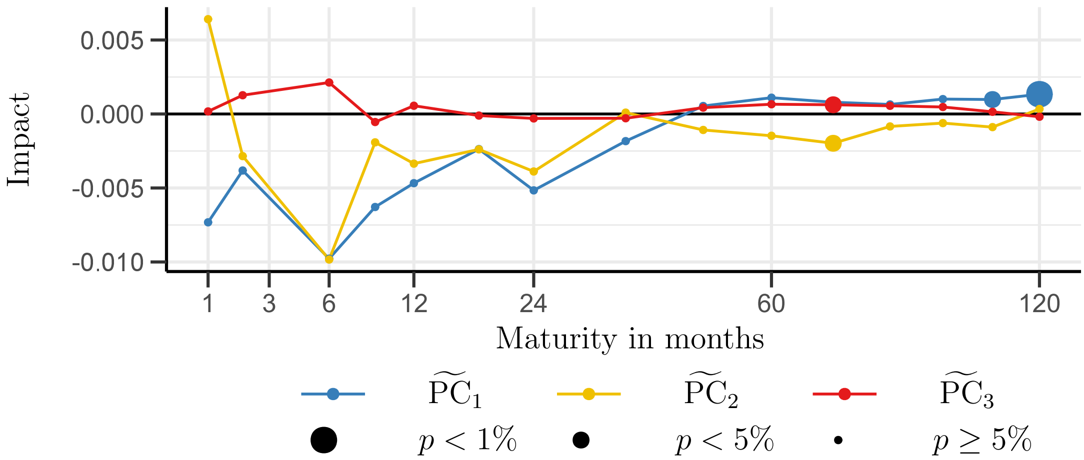
These figures show the impact term structures of Fed announcement surprises, i.e. the interest level (blue), risk sentiment (yellow), and information (red) factors, on the mean (top panel), standard deviation (middle panel), and the standardized 10% quantile (bottom panel) of the risk-neutral distribution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



(a) Risk-neutral mean



(b) Risk-neutral standard deviation



(c) Risk-neutral standardized quantile

While we see some statistically significant impacts on higher moments of the return distribution at longer horizons, particularly so for the interest 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 risk-neutral distribution of excess log returns.

D Crisis times are different: Pre-crisis analysis

We repeat the analysis for January 2018 to December 2019 focusing on the effect of announcement shocks of regular FOMC announcements on fear. The construction of the fear term structure is as described in section 2 of the main text and based on daily option pricing data provided by IHS Markit. 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 7. Note that this is a separate PCA from that conducted in the main analysis and thus allows for different factor loadings on the announcement shocks in the futures and ETF price shocks. This acknowledges the possibility that surprises at regular FOMC announcements contain very different information from that of Fed crisis policy announcement in stressed market conditions.

Table 7: 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

As in the main analysis, we regress daily changes in fear at varying time horizon on the first three principal components (PCs) of announcement shocks, that we normalize to have unit standard deviation. Thus, we have an analogue to regression

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

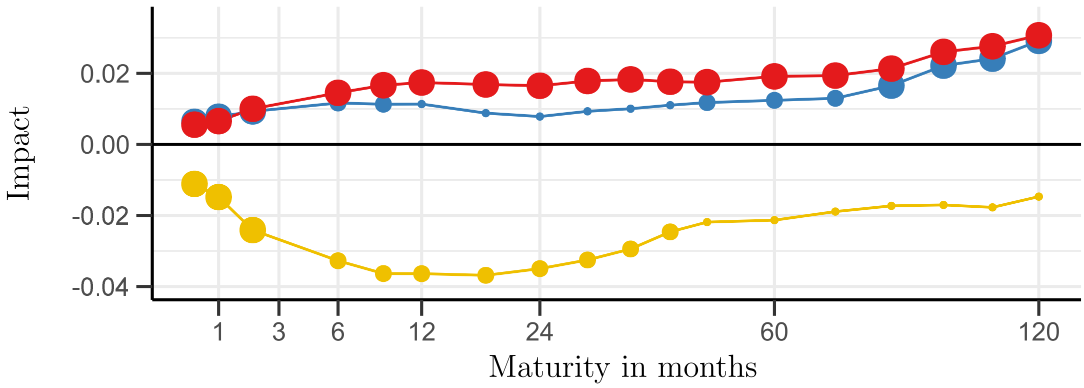
(3),

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

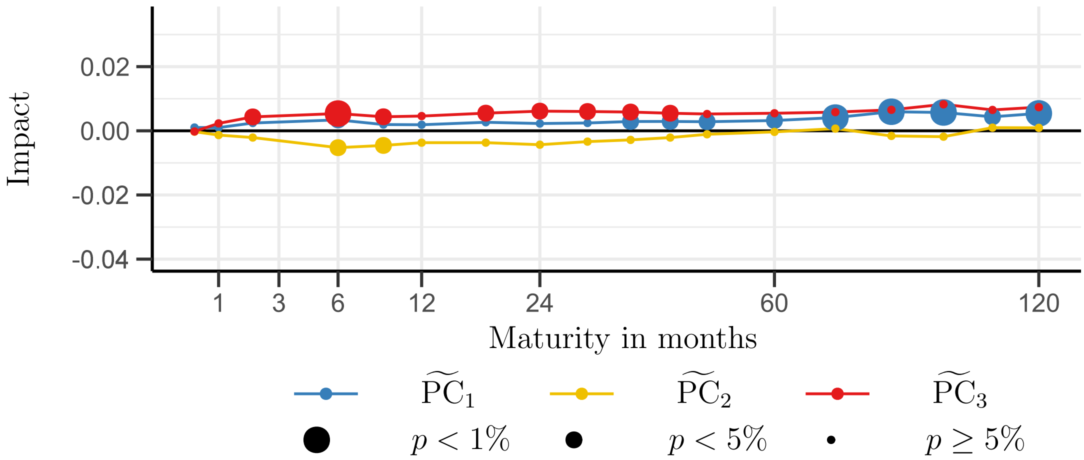
however the controls, for obvious reasons, do not include Covid cases. Figure 9 displays the impact term structure for both the crisis and pre-crisis period.

Figure 9: 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

E Announcements and classification

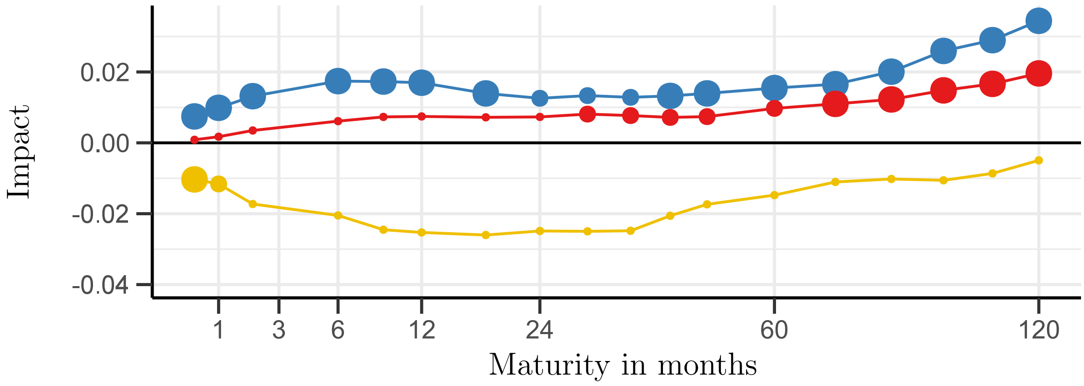
Table 8: Fed crisis announcements and policy classifications

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.

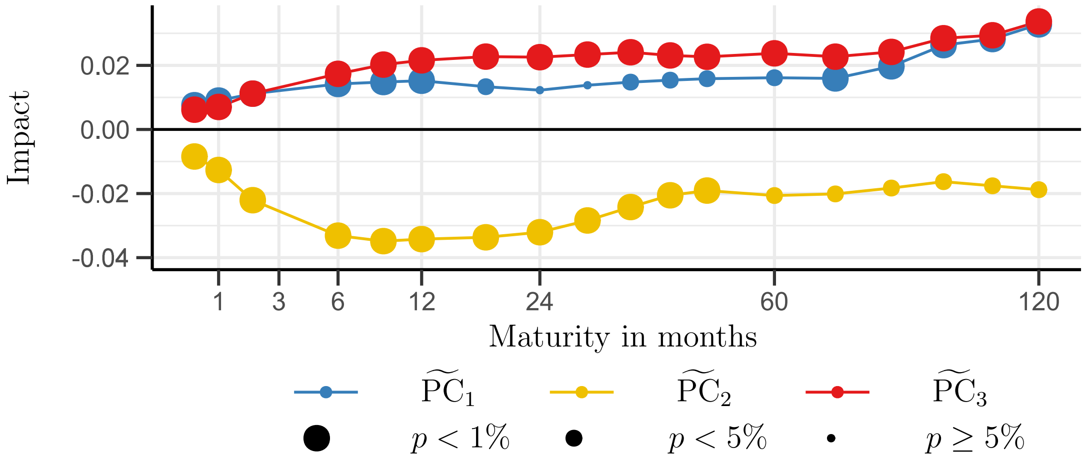
F Additional results and robustness checks

Figure 10: Alternative event windows.

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 10a shows the impact term structures obtained for a narrower event window of 5 minutes before to 10 minutes after the announcement. Figure 10b shows the impact term structures for a wider event window of 15 minutes before to 60 minutes after the announcement.



(a) 5 minutes before to 10 minutes after



(b) 15 minutes before to 60 minutes after

Table 9: 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_{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)
$C_{\Delta\mathrm{RV}}$	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
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
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 10: 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^{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)
$C_{\Delta\mathrm{RV}}$	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
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

Note: *p<0.1; **p<0.05; ***p<0.01