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

Mattia Bevilacqua† Jon Danielsson† Lerby Ergun‡
Andreas Uthemann‡ Jean-Pierre Zigrand†

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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 market fear term structures from option markets covering event horizons from two weeks up to 10 years ahead. We identify the discretionary component of crisis interventions, grouped into five policy categories, using announcement surprises during the market turmoil of spring 2020. The Fed's liquidity provision for financial intermediation, especially via its FX swap lines, had a strong impact on fear, while interest rate changes and credit support to the wider economy support were less effective. The strong effects on long-run risk perceptions point to the risk of moral hazard of discretionary crisis interventions.

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†London School of Economics, Systemic Risk Centre

‡Bank of Canada

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 key part of their mission. The reason is obvious. Financial distress has real economic costs. Perceived high risk curtails real economy investments and sustained market stress can lead to 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, which led the government to force the Bank to develop a formal crisis response along the lines laid out in Bagehot's classic exposition of the "lender of last resort" function (Bagehot, 1873). However, calming market distress is not costless. The financial markets may perceive interventions as signalling future calming, and thus induced to take on more risk. The central banks face a dilemma. Quiet down immediate distress and risk moral hazard or let a crisis play out with potentially even costlier consequence.

The degree to which central bank interventions aimed at calming the markets create moral hazard is controversial, motivating our work here. A key problem in answering this question is measurement. To that end, we study the impact of Fed crisis interventions on the price of insurance against large financial losses over event horizons from one week up to ten years into the future. While the short term impact gauges the ability of crisis interventions to calm immediate market fears, the long term impact evaluates whether financial markets see the central bank intervention as a signal of its willingness to backstop future large losses as well. The latter reduces market participants' private cost of risk taking causing moral hazard.

Focusing on market fears during the extreme market turmoil in the spring of 2020, we find that the Federal Reserve (Fed) crisis interventions helped to significantly calm markets. The Fed's actions were not only effective in stemming immediate market fears, but also strongly reduced the likelihood the market attached to large losses over longer horizons. We show that some policies in the Fed's crisis toolkit are more effective than other. While we only find a weak impact of interest rate and credit policies, the Fed's liquidity facilities and macroprudential relaxations significantly impacted risk perceptions. The Fed's liquidity support via foreign exchange swap lines and repos are particularly effective, confirming the importance of the Fed as international lender of last resort. Finally, the strong flare up of market fears before the crisis interventions and big surprises around announcements raise the question of how well market participants understand the Fed's crisis rulebook.

In order to identify how financial markets perceive the impact of central bank interventions beyond the current crisis, it is necessary to use financial instruments that capture the market's risk perceptions over different event horizons, from the immediate to years into the future. And that is what the option markets do. Options encode information about the market's perception of large price moves over pre-specified time horizons and how much market participants are willing to pay to insure against them. We have access to a uniquely rich data set on the global option markets[1], allowing us to capture risk perceptions in main stock market indices and individual stocks, from one week ahead up to tens years into the future. We extract risk-neutral distribution of futures asset price moves from the option prices applying standard methods that build on the insights of Breeden and Litzenberger (1978). Our primary focus is on the 10% quantile of an asset's risk neutral log return distribution for a given investment horizon. We refer to these risk-neutral tail risk perceptions as the asset's *market fear* for the given horizon. The rich nature of our data allows us to construct daily market fear term structures across a large range of assets and time horizons.[2]

Our empirical analysis concentrates on the impact of the Fed's reactions to the financial turmoil in the spring of 2020. This focus on the spring of 2020 is motivated by two considerations. First, to study the impact of Fed crisis interventions, we need a crisis. Certain central bank tools, especially broadly targeted lender of last resort interventions, are only deployed in crisis situations. Market reactions to regular Fed actions, such as interest rate decision taken at pre-announced FOMC meetings, do not allow us to gauge how effective Fed interventions are in calming market fears about worst case scenarios at the peak of a crisis.[3] Second, a range of Fed crisis tools, such as the Fed's FX swap lines and certain macroprudential levers, were only introduced after the peak of the Great Financial Crisis. The 2020 market turmoil is the first crisis where this broad range of crisis tools was fully available to the Fed. This gives us the opportunity to provide a first evaluation of the effectiveness of these tools in calming financial markets.

To compare the effect of Fed crisis actions on market fear across crisis tools, we categorize all Fed announcements of crisis actions at the height of the crisis

[1]The options data has been provided by IHS Markit's Totem service, the main consensus pricing service for the over-the-counter (OTC) derivatives market. The option prices are the mid-quote estimates of the main market makers, mostly large international banks. The data include prices for options with very distant times-to-expiration, in some cases up to 30 years, 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.

[2]We also repeat our analysis in terms of daily term structure of the VIX, a standard measure of market-expected stock market volatility that can be obtained from the risk-neutral distributions. We occasionally refer to the VIX as the market fear of volatility while our primary notion of market fear relates to the fear of losses.

[3]Indeed, for robustness, we repeat our analysis in the immediate pre-Covid period, and find that market fears do not significantly react to regular FOMC announcements.

in financial markets, from the beginning of February to the end of July, into five policy classes: (1) credit to households, businesses, and the public sector, (2) interest rate decisions, including forward guidance, (3) liquidity support for financial intermediation and market functioning, (4) macroprudential regulations, and (5) foreign exchange intervention via US dollar swap lines and the FIMA repo facility.In total, there were 44 crisis announcements containing 51 distinct actions.

To study the impact of Fed interventions on market fears, we concentrate on the surprise component of these Fed crisis actions. The focus on market surprises has pragmatic and conceptual reasons. 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. More importantly, from a conceptual perspective, we expect discretionary crisis actions to be particularly powerful, yet also potentially 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 they might update their beliefs about the central bank's reaction function in futures crises creating the potential for moral hazard.

We measure market surprises using price movements of futures contracts in narrow windows around Fed announcements of crisis actions. Our main analysis concentrates on surprises in SP-500 futures contracts, but we also show that the results are robust to combining shocks extracted from a wider set of futures contracts including fed funds, eurodollars, longer maturity US Treasuries and exchange rates. This approach has several advantages over more conventional methods such as employing dummy variables for policy actions. First, we can pinpoint the exact moment when the Fed actions impacts the market. Second, the size of the shock provides a natural weight for the importance of individual Fed actions within a given policy category. This is particularly important given the fast moving nature of the crisis and the multitude of actions taken at different points during the crisis.

To measure the impact of Fed actions on market fears, we regress daily changes in market fear at different horizons on Fed policy shocks and a set of control variables. Our main focus is on market fears for the SP-500 index, capturing broad transmission channels of Fed policies, and fear for global systemically important banks (G-SIBs) as direct counterparties of Fed crisis interventions. We separate out the impact on US and non-US G-SIBs. For the analysis of G-SIBs' responses, we perform a panel regression with bank fixed effects.

Our main object of interest is the regression coefficient on the policy shock. As we categorize shocks into five policy categories and consider market fears in a given asset for different horizons, we have separate measures of the Fed's impact on market fear by policy category and event horizon. The analysis groups these regression coefficients by policy category and studies their variation from the very short term, the immediate crisis, to the long term up to 10 years ahead. We refer to the collection of regression coefficients for a given policy across time horizons as the *impact term structure* of the policy for a given asset.

We face three identification challenges in our empirical work. The first is to be mindful of other factors besides that announcements that impact on fear, which we address by weighing interventions by their high-frequency impact in futures markets. The second is endogeneity in the timing of interventions, which we control for by including measures of market volatility, macroeconomic uncertainty and pandemic severity into our regressions. Our final challenge arises from the use of futures prices as an indirect measure of Fed policy surprises, which we address by considering the high-frequency reaction of a broad range of futures prices, spanning equities, interest rates and exchange rates, to Fed announcement.

We first consider the overall impact of Fed shocks, that is pooled across all policies, on market fears in the SP-500 during the 2020 market crisis. We find that unexpected Fed crisis actions, on average, managed to calm the US stock market; positive surprises reduced market fears at all horizons and the average Fed policy shock during the crisis was indeed positive. The average Fed policy shock increased the 10% risk-neutral return quantile for the month ahead by one percent of its pre-announcement value. Fed crisis interventions were not only effective in calming immediate market fears, but they also strongly influence risk perceptions at longer term horizons beyond the immediate market dislocations. The average policy shock increase the 10% risk-neutral returns quantiles for horizons between one year and eight years ahead by approximately three percent. The effect sizes are statistically and economically significant for all horizons. The Fed's impact corresponds to roughly 50% of the daily standard deviation in markets fears at the respective horizons.

When we repeat the same regression for regular, pre-announced FOMC meeting , we find that Fed policy shocks have a statistically and economically insignificant impact on market fears. This confirms that market fears react differently to Fed actions during crisis times and justifies our focus on the 2020 crisis period. This is not surprising. Different policy tools are used during a crisis. Furthermore, financial markets will be more sensitive to the implications of Fed actions for tail events. Similarly, when we use random timestamp during the 2020 crisis to create placebo policy shocks from futures prices around these placebo events, we do not find any significant effect of these shocks on market fears.

We find considerable heterogeneity across policy instruments. Announcements of policies providing credit to households, businesses and the public sector had little discernible impact on market fears. Interest rate decisions also had little impact on fear, none on market fears in the SP-500 and a small, if persistent, impact on fears in G-SIBs. This obviously does not mean that interest and credit policies were overall ineffective as a crisis response. Not only are we only evaluating their impact on market fears in stock markets, our empirical strategy only identifies the impact of Fed policy surprises. Fed crisis actions that the market expected, i.e. that agreed with the market's expected Fed crisis response function, would have already been factored into option prices and, hence, market fears. The other three policies, liquidity support for financial intermediation and market functioning, changes to macroprudential regulations and the Fed's foreign exchange support, all had a strong impact on fear, with the foreign exchange interventions via the Fed's FX swaps lines and FIMA repo facility being particularly powerful, especially on banks.

We expect market fears in US banks to be particularly sensitive to Fed actions. US banks have direct access to Fed lender-of-last-resort type crisis support. The Fed is also the regulator of large US bank holding companies and thus able to change marcoprudential regulations that apply to them. It is, by now, well established that the stock prices of big US banks contain a large premium related to their privileged access to public crisis support (e.g. Gandhi and Lustig, 2015; Kelly et al., 2016). While we see a significant build up in market fears in US G-SIBs in the run up to Fed action even when compared to non-US GSIBs, we do indeed see that, on average, Fed policy shocks had a particularly strong impact on calming fears in US G-SIBs. As expected, we find actions targeted as liquidity support and unexpected relaxations of macroprudential regulations to be especially impactful. For these two policy types, the impacts are very strong at long horizons showing that the Fed's policy actions not only reduced fears concerning the immediate crisis but also had a lasting impact on the price of financial disaster risk insurance as embedded in US G-SIBs' option prices. We find that market fears in non-US G-SIBs reacted less strongly to Fed actions. Here, the Fed's FX actions were, unsurprisingly, particularly powerful; by channelling short term USD funding to international banks via their local central, the Fed essentially acted as an international lender-of-last-resort for the off-shore US dollar market. Another lesson from the heterogeneity in impact across G-SIBs is that movements in market fears triggered by Fed actions do not simply reflect uniform movements in risk premia in the options markets, e.g. caused by tightening risk constraints of market participants.

We see this paper as making both methodological contributions and broader suggestions for policymakers on the effectiveness and consequences of their interventions.

First, we focus on the term structure of the impact to capture both immediate benefits and long term consequences of crisis actions. To do so, we we develop the notion of a term structure of market fears and implement it empirically. This requires data on the market's risk perceptions of extreme events for event horizons that not only cover the immediate crisis but also potential future crises. 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. Previous work has shown a strong impact of monetary policy on market risk perceptions extracted from option prices (Bekaert et al., 2013; Hattori et al., 2016; Hu et al., 2019). Kelly et al. (2016) have documented large 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). Our focus here is on the impact of Fed actions at peak crisis time on the term structure of risk perceptions to gauge the trade-off between immediate benefits and potentially delayed costs of interventions.

Second, we analyze how unexpected central bank interventions, that is actions that deviate from what markets understood to be the central bank's crisis rulebook, impact risk perceptions. We see these surprises to be of particular importance here; surprises are, by definition, new information on which market participants update their beliefs about extreme events. This can be very effective in breaking destabilizing dynamics. But it can also lead them to update their beliefs about the central bank's reaction function in any future crisis potentially creating moral hazard. To construct surprises, we use methods developed to extract monetary policy shocks from futures prices (Bernanke and Kuttner, 2005; Gürkaynak et al., 2005). However, our aim is not to identify the effects of conventional monetary policy. Instead, we study how effective discretionary, in the sense of unexpected, crisis interventions are in calming financial markets. In using future contracts other than the fed funds futures to capture broader transmission channels of Fed policy we follow Jarociński and Karadi (2020) and Swanson (2020).

Our final methodological contribution is to evaluate the relative efficacy of the tools in the Fed's crisis toolkit in calming market fears by creating policy-specific shocks. To do so, we classify Fed announcements into distinct policy categories and interact this classification with high-frequency price movements around these announcements. It also enables us to compare these tools in terms of their long term impact of the cost of private sector disaster insurance. 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, 2020b) and the 2020 market crisis (e.g. Bahaj and Reis, 2020a; O'Hara and Zhou, 2021; Haddad et al., 2021; Boyarchenko et al., 2021; Fleming et al., 2021).[4]

[4]More broadly, a number of recent papers have analyzed the impact of the Covid-19 shock had on US equity markets (e.g. Alfaro et al., 2020; Croce et al., 2020; Ramelli and Wagner, 2020; Baker et al., 2020; Gormsen and Koijen, 2020; Landier and Thesmar, 2020; Cox et al., 2020).

We further contribute more directly to discussions on the effectiveness of financial policymaking. First, we document a strong flare up of market fear in the run-up to Fed interventions, particularly in US G-SIBs, and an immediate calming upon announcement. This raises the question to which extent policy uncertainty contributed to this flare up and whether the Fed's crisis policies, especially regarding the Fed's new crisis facilities, are well-understood by the market. It also points to the potentially benefit of standing facilities with clear trigger points. However, we also document a strong impact of crisis interventions on long term risk perceptions. These long term impacts could serve as a measurement tool to gauge the cost of discretionary crisis interventions and to compare different crisis tools in this regard.

Lastly, we document strong spillovers of Fed crisis interventions into risk perceptions in international equity markets. Especially the Fed FX interventions via swap lines and repo facilities significantly reduces fears in non-US G-SIBs. This points to the importance of the Fed as lender-of-last resort and US monetary policy as a key driver of risk premia in international asset prices.

The remainder of the paper is organized as follows. Section 2 introduces the risk terms structures we construct and the Fed policy announcements and the identification strategy. The empirical results are discussed in section 3. The broader implications are discussed in Section **??**. We show robustness checks in Section **??** Section 5 concludes the paper. A set of additional results, robustness checks, and information on the Fed policies are relegated to the paper Appendix.

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 Fed crisis actions on day t on contemporaneous daily changes in market fears over varying time horizons τ. The coefficient γ_τ that measure the impact of the Fed's action on fear is our main object of interest. We estimate these regression for different event horizons τ and Fed policy actions. We thus obtain a collection of impact coefficients for a given Fed policy instrument, which we refer to as the *impact term structure* of the policy instrument.

To implement this approach, we need empirical measures of "market fear" and "Fed crisis action". We derive the former from option prices and the latter from Fed crisis announcement that we weigh by importance using contemperaneous movements in high-frequency futures prices. These Fed actions, grouped by policy type, together with control variables that account for confounding factor moving market fears allow us to identify the impact term structures.

2.1 Measuring market fear

We obtain our fear measure from the options markets. As an option insures its owner against price moves, the option's price contains information both on how likely the market deems the price move 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 prices moves of the asset over the corresponding horizon, using Breeden and Litzenberger's (1978) technique. As option prices include risk premia, adverse events receive higher weight than under the empirical distribution. For the technical details, see Appendix C.

While there are several sources of option data, we opt for a database provided by IHS Markit's Totem service, the internal model validation facility used by the largest banks to validate their option pricing models. This data is exceptionally rich in both the cross section and time dimension, spanning options with maturity from one week up to 30 years, globally for 242 indices and 3,334 stocks, measured at the close of the trading day in each country. The data contains assets, moneyness, and maturities not available from other databases derived from traded options. We only use a subset here, focusing on the most representative financial markets and limiting the maturity because not all assets have options with 30 year maturities.

Our primary notion of fear is the negative of the 10% quantiles of excess log returns of the risk-neutral distribution of a given asse for a given event horizon τ, $\text{Fear}_{t,\tau}$. Specifically, the return from capital gains over the period plus the dividend yield $\delta_{t,\tau}$ over the period minus the opportunity cost of money over the term (with current futures price for time-to-maturity (ttm) τ given by $f_{t,t+\tau}$):

$$R_{t,\tau} := \ln \frac{S_{t+\tau}}{f_{t,t+\tau}} = \ln \left(\frac{S_{t+\tau}}{S_t \exp((r_{t,\tau} - \delta_{t,\tau})\tau)} \right) = \ln \frac{S_{t+\tau}}{S_t} + \delta_{t,\tau}\tau - r_{t,\tau}\tau.$$

For a asset, the risk neutral probabilities (RNP) $\mathbb{Q}$ of large market movements and the quantiles for specific risk neutral probabilities are then defined respectively as

$$F_{t,\tau}(R^*) := \mathbb{Q}_t\left(R_{t,\tau} \leq R^*\right) \tag{2}$$

and

$$\text{Fear}_{t,\tau}(x) := -R^*. \tag{3}$$

Here $F_{t,\tau}(R^*)$ is the risk neutral distribution whose value equals the RNP that the return of the asset is below R^* at time $t+\tau$, and its inverse $\text{Fear}_{t,\tau}(x)$ is the negative (so that a larger number means a larger fear of losses) of the excess log return R^* such that the RNP equals x (x% quantile). These quantiles correspond to large drops in asset prices, yet are sufficiently likely to influence investors' decisions, e.g by increasing margins or triggering internal risk limits. We do not decompose the risk-neutral distribution into risk premia and empirical probabilities, as we see the risk-neutral distribution as the decision-relevant object for market participants.

The dependent variable in our regressions is the one day change in fear for horizon τ, that is, $\Delta\text{Fear}_{t,\tau}$. Figure 1 provides a representative example of this empirical measure . It shows the risk-neutral cumulative distribution function (CDF) for the US SP-500 stock market index, at maturity one year on two consecutive days at the height of the crisis March 19 and 20 2020. The x-axis shows returns while the y-axis shows the probability of these outcomes. The plot shows two consecutive days at the height of the crisis. The dotted line highlights the 20% probability. Our variable of interest, $\Delta\text{Fear}^{a}_{t,\tau}$, is the change in fear from one day to the next, in this particular case:

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

Figure 1: SP-500 Fear at height of the 2020 financial turmoil

The derived risk-neutral cumulative distribution from the SVI fit in equation (7) (Appendix C) on 19 and 20 March 2020 with a maturity of one year. The red line highlights what we define as change in market fear: the daily change in the risk-neutral negative 10% quantile.

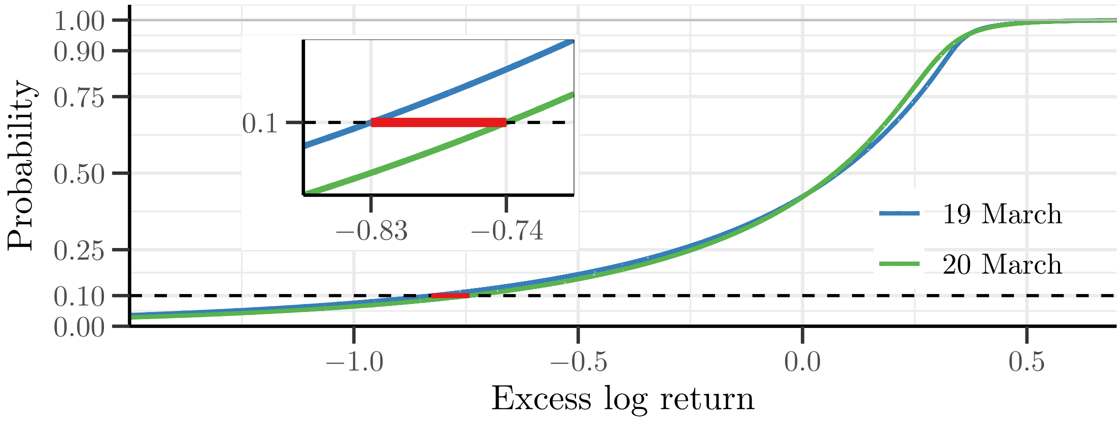
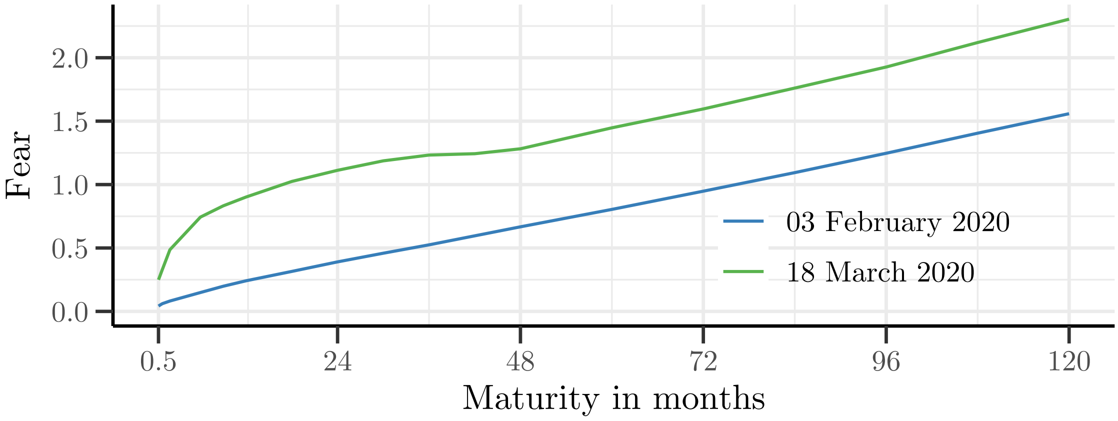


Figure 2 shows how the 2020 crisis manifested in the term structure of fear for the SP-500. We clearly see how different the main crisis days, here March 18, are from calmer days, such as February 3. On the "normal day", fear increases linearly, approximately at the rate of square root of time. As expected, fear increases across the maturity structure on the crisis day, but what stands out is the relative the higher increase at shorter immediate maturities, one month to three years.

Figure 3 shows fear in the SP-500 from 2005 until the end of 2021. It covers two crisis episodes, 2008 and 2020, and three maturities, one month, one year, and a decade. The two crises are visibly different from normal times, fear shoots up sharply and only reverts slowly. There are important differences between the 2008

Figure 2: SP-500 term structure of fear before and during the crisis 10%

The SP-500 term structure of fear on 3 February 2020 and 18 March 2020. The risk-neutral quantiles are extracted from options provided by IHS Markit's Totem service.



and 2020 crisis. In the 2020 crisis short-term fear is more pronounced, while the in 2008 the relatively strongest reactions were in long-term fears. Furthermore, while the flare-up of fear happens more quickly in 2020, it also reverts more quickly. These differences reflect the different nature of these two crises: one is a banking crisis, the other a crisis triggered by an large liquidity demand shock. It might also reflect differences in the financial authorities' crisis interventions. In this paper, we do not compare the two episodes and exclusively focus on the 2020 crisis. This is both due to data limitations for the 2008 crisis – daily option price data for long=dated maturities are not available for that time period – and the fact that a range of Fed crisis policy tools have only come 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 fears for 1 month, 1 year and 10 years from 2005 to 2021. The risk-neutral quantiles are extracted from options provided by IHS Markit's Totem service. The sampling frequency is monthly until 2018 after which it is daily.

2.2 Fed announcements

Once it became clear that the early spring of 2020 was bringing considerable market turmoil, the central banks quickly reacted and the Fed commenced a series of actions and policies aiming to contain the economic contraction and market distress. As an example of this, in the morning of 17 March, the Fed established a Commercial Paper Funding Facility, and in the afternoon of the same day, announced a Primary Dealer Credit Facility.

The Fed intervened using a wide range of instrument and a key aim of this work is to study relative effectiveness of its crisis tools. Hence need to categorizethe Fed' policy actions before quantifying their impact in the empirical analysis. To do so, we analyzed all Fed crisis policy announcements during the crisis and identified five broad policy categories. First are policies related to the most traditional central bank tool, interest rate decisions including forward guidance. Second are lender-of-last resort type actions that are aimed at providing liquidity to stressed financial market participants, especially banks and primary dealers. An example is the aforementioned Primary Dealer Credit Facility and asset purchases aimed at guaranteeing the market liquidity of US Treasuries. Third, and closely related to domestic liquidity support, are foreign exchange interventions that provide dollar liquidity to foreign central banks and international organizations via the Fed's FX swap lines and its FIMA repo facility. Fourth are actions intended to help households, firms and the public sector obtain affordable financing such as the Main Street Lending Program. Lastly, as the regulator of US bank holding companies, the Fed has important macroprudential levers under its control. In this category, an action that has received a lot of attention is the Fed's decision to exclude reserves and US Treasuries from banks' supplementary leverage ratio calculations.

To summarize, we classify Fed policy actions into the following five categories in accordance with the channels through which they affected the economy:

IR Interest rate changes and forward guidance;

LFI Liquidity for financial intermediation programs, ensuring intermediaries can roll over their short term liabilities;

FX US dollar swap lines and FIMA Repo programs focusing on alleviating the demand pressure from foreign entities on the US money market, similar to the LFI category.

CHBP Credit to households, businesses, and public sector;

MPR Macroprudential regulations relaxing some of the regulatory restrictions of regulated financial entities.

To create our dataset on individual Fed crisis actions, we collect observations on the economic and financial policies from the press releases section of the Fed's website,[5] in particular, dates and timestamps of press releases regarding announcements and meetings spanning from the 3 February 2020 to 29 July 2020.[6] We classify the Fed policies into five categories in accordance with the channels through which they affected the economy.

For the full list of the announcements and category assignments and more details see Table 4 in Appendix B. Altogether, there are 44 unique press releases and 51 (N) policy events subdivided into $N_{\text{CHBP}} = 16$, $N_{\text{FX}} = 5$, $N_{\text{IR}} = 6$, $N_{LFI} = 11$, $N_{\text{MPR}} = 13$. Some press releases are counted in multiple categories as they announce more than one policy. The database of announcements can be downloaded from our web Appendix, modelsandrisk.org/appendix/fearcovid.

We cannot use an announcement directly in the regression (1) because at the height of the crisis the Fed made multiple interventions on the same day, and the fear observations are only available at the daily frequency. Therefore, some of the

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

[6] Our selection is similar to Cox et al. (2020), but we additionally include macroprudential policies and extend the date set until the end of July. We also add the following policies which are not included in Cox et al. (2020): policies announced at 16:30 on 16 March 2020, at 08:30 on 19 March 2020, at 11:00 on 20 March 2020, at 17:30 on 23 April 2020 in our category LFI and the policy announced at 11:00 on 20 March 2020 in our category CHBP. We do not include the policy announced at 17:45 on 23 April 2020 since it is considered proposal only rather than an implementation. For robustness, we also consider the aggregate of interventions and other intervention schemes.

Fed policy announcements are likely to have happened on days with other news about the pandemic and the economy that could also have affected the financial market. This necessitates identifying the impact of each policy. We are only interested in identifying the discretionary part of Fed interventions for pragmatic and conceptual reason. Hence, we focus on high-frequency price shocks around Fed announcements, measuring the change in values of these assets in a window beginning 10 minutes prior to and ending 20 minutes after the announcement of a policy (see also Gürkaynak et al., 2005; Jarociński and Karadi, 2020). For robustness we also try other window sizes (15, 60, and 90 minutes) and find that the impact of the policies is, overall, robust to the choice of the window length around the policy announcements (see Appendix D). Market surprises can be multidimensional and different surprise components can affect market fears via different transmission channels, why we initially use a broad set of financial asset prices (list 12 assets) to identify Fed surprises. Of those surprises, we found e-mini futures to be the main channel via which Fed surprises affects market fear. Hence, we the paper concentrates on e-mini shocks.

As an illustration, consider Figure 4, where we highlight the reaction of the SP-500 E-mini futures to different announcements of the Fed. In each panel, the black dots correspond to the intraday aggregates of SP-500 E-mini futures prices. The vertical black line indicates the timing of a press release of the Fed, and the green area highlights the window starting 10 minutes prior and ending 20 minutes after it. The unscheduled meetings on 3 March at 10:00 (panel (a)) and on 23 March at 08:00 (panel (b)), were well received by the market. While the 9:15 Announcement on 23 March appears to have been negatively received.

The announcements made after trading hours are aggregated and carried over to the next trading day. Given that assets traded in different exchanges are subject to different closure times as well as time zones, the effects of an announcement shock are not necessarily realized on the same date for all assets. So, the value of news contained in all Fed announcements belonging to each category i, Fed surprise$_t^i$ is:

$$\text{Fed surprise}_t^c = \frac{1}{\overline{\overline{\text{Fed surprise}}}} \sum_{\pi \in \Pi_t^c} \beta_{t,\pi}^c \left(F_{t,\pi+20} - F_{t,\pi-10}\right), \tag{4}$$

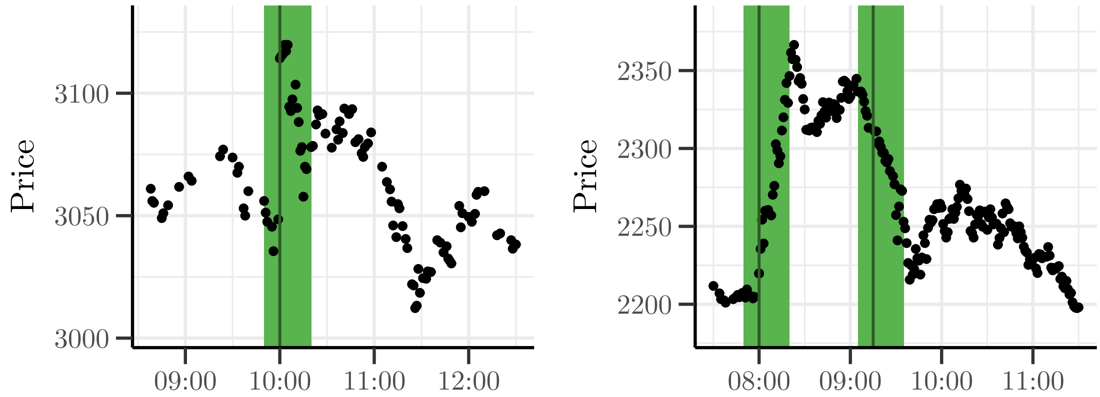
$$\text{where } \overline{\text{Fed surprise}} := \frac{1}{N} \sum_{t \in T} \sum_{c \in I} \sum_{\pi \in \Pi_t^c} \beta_{t,\pi}^c |F_{t,\pi+20}^c - F_{t,\pi-10}^c|$$

$$I = \{\text{CHBP}, \text{FX}, \text{IR}, \text{LFI}, \text{MPR}\}$$

where $F_{t,\pi}$ is the price of the SP-500 E-mini futures on trading day t and minute π. Π_t^c is the set of timestamps for all policies in category c on day t and T is the

Figure 4: Change in SP-500 E-mini futures prices around Fed announcements

These figures illustrate the intraday changes in the SP-500 E-mini futures around Fed policy announcements. We show the intrayday one-minute aggregates of the SP-500 E-mini futures prices (black dots) around the Fed announcements timestamps. To highlight the reaction of the SP-500 E-mini futures to the Fed announcements, the event window starting 10 minutes prior to and ending 20 minutes after the announcement is displayed in green. The two events are: (a) unscheduled FOMC meeting at 10:00 on 3 March (IR) and (b) unscheduled FOMC meeting at 08:00 (LFI, unlimited purchases, "all it takes" moment), and two press releases regarding CHBP at 08:00 as well as regarding MPR at 09:15 on 23 March. The timestamps of the announcements are retrieved from the website of the Federal Reserve: https://www.federalreserve.gov/newsevents/pressreleases.htm.



(a) 3 March 2020 (b) 23 March 2020

set of days with Fed policy announcements. T is all trading days between 3 Feb and 31 July, on days without Fed policies Fed surprise is 0. We sum over all the events of category c during $(t-1, t]$.[7] The coefficient $\beta^c_{t,\pi}$ measures the fraction of the market move at time π due to policy c being announced.

If the Fed only announces policies that fall into a single policy category, $\beta^c_{t,\pi} = 1$. Occasionally, the Fed announces policies in multiple categories at the same time, and therefore the change in the SP-500 E-mini futures shows the market response to this whole set of policies. We disaggregate that market movement into the components corresponding to the policies announced at that press release by using the information from all the press releases which only announce a policy in a single category. For the set of all such single category press releases Λ, we define $\beta_c > 0$ to be the mean surprise (in absolute value) in windows around pure policy c announcements. For instance, for a press release involving policies LFI and CHBP at time π on day t, we then use as weight $\beta^{\text{LFI}}_{t,\pi} := \beta_{\text{LFI}}/(\beta_{\text{LFI}} + \beta_{\text{CHBP}})$.[8]

[7] Though only one day, 30 April, had two press releases on the same policy, CHBP, at 10:00 and 17:15.

[8] For robustness, we have also equally allocated the market move to each policy announced. For example, the Fed released two press statements at 08:00 on 23 March 2020. We categorize the first one as CHBP and the second one as LFI. Therefore, in the robustness check, we allocate one half of the E-mini futures' price increase by \$141.5 to the category CHBP and the other half to the category LFI for that day. As expected, results are similar, with effects slightly less

In addition, to test whether our results are driven by our definition of $\beta^c_{t,\pi}$ used to disentangle announcements of policies in multiple categories at the same time, we repeat our analysis by only classifying press releases for which we have a single policy announcement into single policy categories. All the other press releases featuring multiple policy announcements are aggregated into an additional control variable. We find that the results remain comparable, both in terms of magnitude and significance. This further supports our adopted identification approach.

As a sanity check of our identification strategy, we create pseudo events, by selecting random time stamps on policy announcement days. When we use these in place of the actual policy announcements in our analysis, we find that these pseudo events have no significant impact on fear.

2.3 Identifying the impact of Fed crisis interventions

Our empirical investigation is based on regressing daily changes in fear in a given asset a, $\Delta\text{Fear}^a_{t,\tau}$, on Fed announcement surprises and a set of controls. We start by modifying (1) to incorporate the five categories of Fed announcements and the two controls[9]

$$\Delta\text{Fear}^a_{t+r,\tau} = \alpha^a_\tau + \sum_{c\in\text{categories}} \gamma^{c,a}_\tau \,\text{Fed surprise}^c_t + \sum_{j=1}^{2} \xi^{j,a}_\tau \,\text{Controls}^j_t + \epsilon^a_{t,\tau} \;;\; t \in T. \quad (5)$$

The control variables include proxies for severity of the pandemic, for macroeconomic uncertainty and stock market volatility.[10] We also run panel regressions with several assets to study the differential impact of Fed crisis policies across sectors and institutions. Our panel regressions include asset fixed effects, allow for asset-specific policy impacts but restrict the effect of control variables to be the

pronounced in equally weighted approach.

[9]In order to control for residual serial correlation and heteroskedasticity, we use the Newey West approach to calculate all standard errors.

[10]We use the log of the 7-day rolling mean of new Covid-19 cases. Daily data on the cumulative number of Covid-19 confirmed cases in the United States is collected from the Johns Hopkins Coronavirus Resource Center. The data can be downloaded from https://github.com/CSSEGISandData/COVID-19 and visualized at https://coronavirus.jhu.edu/map.html. We calculate the daily number of new confirmed cases and the rolling mean over the past seven days (see Figure **??** in Appendix **??**). We proxy macroeconomic uncertainty using Bloomberg's economic surprise index (ECSU). To capture stock market we use first-difference daily 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. For a summary of their methodology: https://realized.oxford-man.ox.ac.uk/documentation/econometric-methods.

same across assets,

$$\Delta\text{Fear}^a_{t+r,\tau} = \alpha^a_\tau + \sum_{c \in \text{categories}} \gamma^{c,a}_\tau \,\text{Fed surprise}^c_t + \sum_{j=1}^{2} \xi^j_\tau \,\text{Controls}^j_t + \epsilon^a_{t,\tau} \;;\; t \in T \,\text{and}\, a \in A, \quad (6)$$

where A is the set of assets included in the panel.

Our main focus is on $\gamma^{c,a}_\tau$, the impact of Fed crisis policy c on market fear in asset a measured over horizon τ. A negative $\gamma^{a,c}_\tau$ implies that a positive policy shock in category c reduced fear. As fear is measured in units of log returns and policy shocks are normalized by the average absolute size of policy shocks, the size of the impact coefficient is in log return units for a "typical shock size". We display our results in terms of *impact term structures*, that is for a fixed policy category c across time horizons τ: $\{\gamma^{c,a}_\tau\}_{\tau \in \{1,\ldots,\bar{\tau}\}}$.

We face three major threats to identifying the causal effect of Fed policy shocks on market fears. First, as we regress daily changes in market fear on policy shocks, we need to be mindful that factors other than the policy shock can cause changes in fear, especially during a fast moving crisis. If we could use high-frequency movements in market fears around Fed announcements, we would not face this problem. But option price data for the extreme events considered in this paper are not available at intraday frequencies. A second identification problem is the potential endogeneity of the timing of Fed crisis actions. The Fed could intervene after particularly extreme days in financial markets, that is days with high market fears. If we find that Fed policy shocks reduce market fears in our regression framework, we might pick up mean-reversion in market fears after extreme days rather than a causal effect of the Fed action. To address both concerns, the regressions control for the contemporaneous severity of the pandemic, news about the US macroeconomy, and realized stock market variance on the day of the Fed actions and the previous day. This is a conservative approach, as realized variance on the day of the Fed action can be influenced by the Fed action itself. A third threat to identifying policy shocks lies in our use of futures prices as an indirect measure of the surprise in Fed crisis actions. This means that we measure surprises with noise. A priori, this measurement error would lead us to underestimate effects working in our favour. However, we also compare effects across policies. Futures prices may react more or less strongly to surprises in different policy categories. To address this concern, we use a wide range of futures contracts spanning fixed income, foreign exchange and equity markets. This guarantees that we consider a broad concept of market surprise capturing broad transmission channels of the various Fed policies into financial markets.

3 Results

Our interest is in the effectiveness of discretionary central bank crisis interventions in alleviating short term market turmoil but also measuring the longer term consequences of these actions. The primary empirical device is equations of the form shown in (5) and (6) where we regress daily changes in market fear for different time horizons, two weeks to up to 10 years, and across a range of assets, on Fed announcement surprises and controls. Our main sample is daily data for the period February to July 2020, as that is when the Fed directly intervened to contain the extreme market turmoil at that time. We expect standard monetary policy actions in calm times to have little or no impact on fear while interventions at the height of the crisis to be very effective in alleviating fear, and that is precisely what we find when we compare crisis impacts to the effect of announcement surprises at regular, pre-scheduled FOMC meetings before January 2020. The crises interventions of central banks in peak crisis times are different, and we data during a crisis to judge the effectiveness and impact of such interventions.

For crisis interventions that are explicitly directed at calming short term financial market turmoil, most longer term reduction in fear would is likely unintended. It is also undesirable, if the market perceives the interventions as the central bank underwriting private insurance against future tail risks. The reduction in market fears is the outward manifestation of the cheapening of private insurance against tail losses signals the risk of incentive distortions for market participants; as they update their beliefs about the Fed's willingness to tolerate large asset price drops, they may discount tail scenarios in their investment decisions counting on the public sector to protect them from these events. As future Fed crisis interventions are most likely to coincide with financial sector stress, any Fed policy that enforces a lower bound on asset prices should hence have the strongest effect on fear in financial stocks.

We disentangle various consequences of Fed interventions by contrasting their impact on the main stock market index of the United States, the SP-500 with the impact on key sectors, including the financial sector. Here, banks as most direct beneficiaries of central bank support, are of particular interest and we conclude our empirical analysis by measuring the impact of Fed crisis interventions on fears in globally systemically important banks, G-SIBs, both in the US and elsewhere. That ultimately allows us to further gauge the importance of the Fed as the international lender of last resort.

3.1 Impact on the SP-500 index

We start our empirical investigation by running regression (5) on daily changes in fear in the SP-500, across maturities from two weeks to 10 years, over the main crisis period, February through July 2020, and present the results both in Table 1 and Figure 5. We see that most of the policy interventions are significant, with two of the controls, macroeconomic uncertainty and the state of infections, significant from one year, while realized variance of the SP-500 is always significant. The table implies a considerable heterogeneity in the impact of the various Fed policies, and a Wald test (reported in Table 3 in the Appendix) strongly rejects a constraint imposing the equality of all policy coefficients.

As we are interested in seeing the impact across the entire maturity structure, we also plot the regression coefficients in Figure 5 for each maturity date, where

Table 1: Policy impacts for the SP-500

*p<0.1; **p<0.05; ***p<0.01. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. Sample period: daily, 3 February 2020 to 31 July 2020. $\gamma_\tau^{c,SP}$ are the policy impact coefficients from running (5). The dependent variable is $\Delta\text{Fear}_{t,\tau}^{SP}$ for maturities $\tau=1$, $\tau=12$, $\tau=36$, $\tau=60$, and $\tau=120$ months.

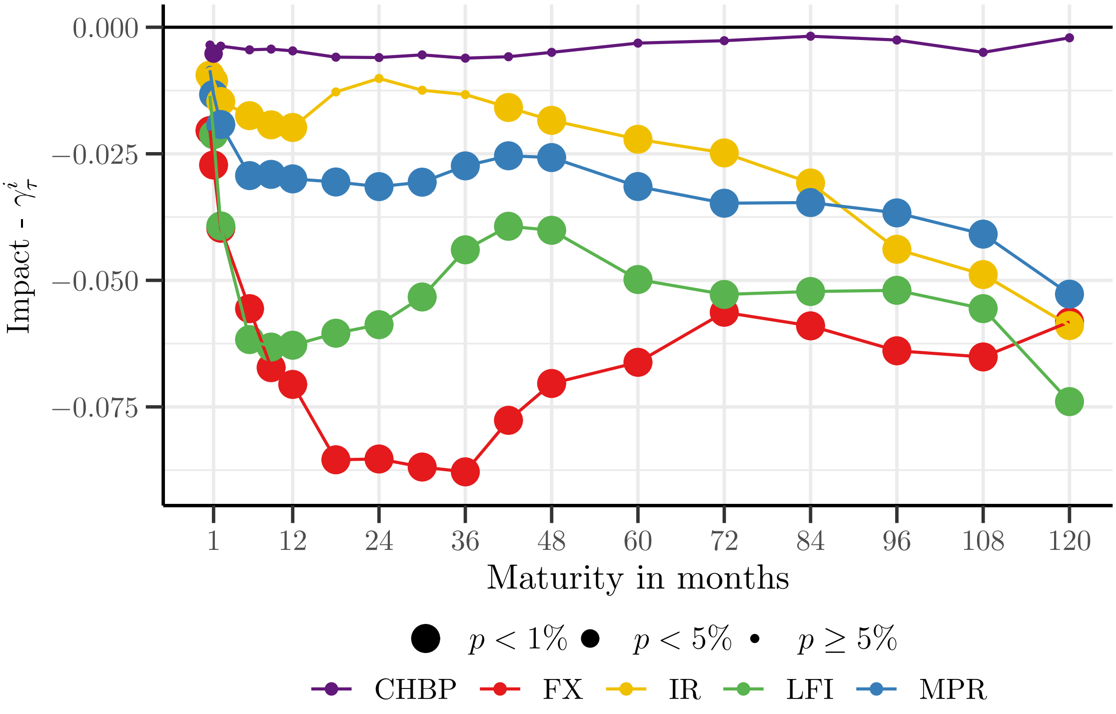
	Maturities				
Intervenion	$\tau=1$	$\tau=12$	$\tau=36$	$\tau=60$	$\tau=120$
$\gamma_\tau^{CHBP,SP}$	-0.005^{**}	-0.005	-0.006	-0.003	-0.002
	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
$\gamma_\tau^{FX,SP}$	-0.027^{***}	-0.071^{***}	-0.088^{***}	-0.066^{***}	-0.058^{***}
	(0.005)	(0.006)	(0.015)	(0.014)	(0.010)
$\gamma_\tau^{IR,SP}$	-0.011^{***}	-0.020^{***}	-0.013^{*}	-0.022^{***}	-0.059^{***}
	(0.004)	(0.006)	(0.007)	(0.007)	(0.017)
$\gamma_\tau^{LFI,SP}$	-0.021^{***}	-0.063^{***}	-0.044^{***}	-0.050^{***}	-0.074^{***}
	(0.005)	(0.006)	(0.009)	(0.009)	(0.010)
$\gamma_\tau^{MPR,SP}$	-0.013^{***}	-0.030^{***}	-0.027^{***}	-0.031^{***}	-0.053^{***}
	(0.005)	(0.007)	(0.007)	(0.007)	(0.008)
$C_{t,\text{covid}}$	0.013	0.053^{***}	0.062^{**}	0.054^{**}	0.067^{**}
	(0.016)	(0.017)	(0.025)	(0.024)	(0.027)
$C_{t,\Delta\text{ECSU}}$	-0.039	-0.151^{***}	-0.243^{**}	-0.210^{**}	-0.146^{*}
	(0.036)	(0.058)	(0.099)	(0.085)	(0.085)
$C_{t,\Delta\text{RV}}$	0.117^{***}	0.184^{***}	0.184^{***}	0.188^{***}	0.294^{***}
	(0.016)	(0.024)	(0.030)	(0.026)	(0.040)
Constant	0.001	0.002	0.002	0.002	0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Observations	119	119	119	119	117
R^2	0.564	0.613	0.572	0.629	0.643
Adjusted R^2	0.532	0.585	0.541	0.603	0.617

the size of the dot indicates statistical significance. We use the phrase *impact term structure* to indicate the magnitude and significance of its policy intervention across all maturities.

Credit to households, businesses, and the public sector (CHBP) has little impact, in magnitude and significance, except at the very short end. A reason for this small magnitude could be a leakage of information before the announcement as these measures required fiscal backing and hence involved a more complex political process than more standard central bank policies. Hence, these action might have already been priced into options at the time of announcement. However, we see large announcement effects in futures prices for these measures and, hence, big policy shocks according to our methodology. For example, the Fed's March 23 announcement of the Primary and Secondary Market Corporate Credit Facility, a CHBP action under our classification, is the second largest policy shock in our sample. Furthermore, Haddad et al. (2021) and O'Hara and Zhou (2021) show

Figure 5: Impact term structure of the SP-500

Impact of different policy categories on fear for different terms τ (x-axis). The effect of a policy on the change in the excess log return for the tail probability 10%. In red, green, blue, yellow, and purple are the effects of the FX, LFI, MPR, IR and CHBP policies, respectively. The sizes of the dots give the different levels of significance, · p≥0.05; • p<0.05; ● p<0.01, calculated using robust standard errors based on Newey and West (1987).



that this action had a very large effect on corporate bond market spreads. Our result shows that the impact of the Fed's credit policies directed at the non-financial sector of the US economy were significantly less impactful when considering market fears in the SP-500.

Maybe surprisingly, interest policies (IR), the Fed's main and most immediate policy tool, have relatively small effects on short-run fears. Given the importance of the importance of short-term rates for money markets, a key source for worst-case outcomes in financial markets, a likely explanation for the magnitude of these effects is that markets expected the lowering of the policy rate and strong forward guidance in the given scenario. These are well-understood crisis reactions by a central bank and are largely priced into options at the time of the announcements. Indeed, announcement surprises around interest rate decisions during the crisis are significantly smaller than surprises of less conventional liquidity and credit support actions.

The Fed's marcoprudential policy actions (MPR) appear to have been effective in addressing market fears at all horizons. However, the impact coefficient plots hide that the average marcoprudential policy shocks is negative. Indeed, the largest policy shock in our sample is the Fed's March 23 announcement to relax banks' capital buffer (TLAC) requirements which negatively surprised markets. On average, macroprudential actions increased market fears. These negative reactions could be linked to markets making inferences about the Fed's assessment of the state of the economy rather than the effectiveness of these actions. However, the large announcement surprises around marcoprudential announcements also suggest that markets do not seem to have a good understanding of the how the Fed uses its new macroprudential tools in a crisis. This policy uncertainty appears to have contributed to market fears.

Liquidity support for financial intermediation (LFI) has a similar but stronger impact on market fears than interest rate and macroprudential policies, especially at the short to medium term up to two years ahead. This is unsurprising given the import role of lender-of-last resort liquidity support for by providing emergency funding that can prevent stress asset sales into falling markets. It also reflects the stronger discretionary component of such emergency support, i.e. the less predictable nature of interventions for market participants, when compared to liquidity support via low interest rate policies. Central banks tend to be reluctant to spell out precise parameters for interventions as such strategic ambiguity is seen as a way to reduce moral hazard.

The strongest policies are the US dollar swap lines and FIMA repo facility (FX), emergency liquidity support that is directed at international investors without direct Fed access. At first thought, this might be unexpected as these interventions are targeted at non-US entities, and here we are measuring the impact on US market fears. However, the FX swaps give foreign central banks access to USD liquidity which they can intermediate to their own institutions, and the effectiveness of this policy confirms that there were severe USD liquidity shortages throughout the international financial system (Bahaj and Reis, 2020a).

To illustrate that we need to look at crisis to understand the effectiveness of the Fed's policy toolkit to alleviate market fears, we contrast the Fed impact term structure at the height of the crisis to the pre-crisis impact structure using announcement surprise around regular FOMC meeting before January 2020. Figure 5 shows both impact term structures. We see that regular FOMC policy surprises do not impact the market fear. Clearly, regular, pre-scheduled meeting involves different policy levers than crisis actions, typically interest rate and asset purchase decision that have been carefully prepared and communicated. Surprises in this announcements do not appear to move market participants' beliefs about the likelihood of extreme market events.

3.2 Sectoral and GSIB impacts

The aggregate SP-500 results above show how the market perceived the impact on the main US stock market index which captures broad transmission channels of Fed policies to the US economy. While significant, that by itself does not imply the Fed is subsidizing insurance against large losses. To provide further evidence on this channel, we now contrast the impact of Fed policies on the financial sector with that of other sectors. As future Fed crisis interventions are most likely to coincide with financial sector stress, any Fed policy that enforces a lower bound on asset prices should hence have the strongest effect on fear in financial stocks. To check that Fed crisis policies had a comparatively stronger impact on the financial sector than on other sectors of the US economy, we study fear in sectoral ETFs that jointly make up the SP-500 index. In particular, we SPDR's sector ETFs that decompose the SP-500 into 11 sectors.[11]. We then zoom in on fear in banks classified by the Financial Stability Board as globally systemically important (GSIBs). The aim of this exercise is to check for stronger effects of Fed actions on US banks that have both direct access to Fed crisis facilities and are regulated by the Fed as BHC, when compared to non-US GSIBs that we classify into two separate groups: Chinese and Japanese banks, and others.[12]

[11]These 11 sectoral ETFs are (ticker symbol in parentheses): Technology (XLK), Financial (XLF), Health Care (XLV), Consumer Discretionary (XLY), Industrial (XLI), Energy (XLE), Consumer Staples (XLP), Communication Services (XLC), Utilities (XLU), Materials (XLB), Real Estate (XLRE).

[12]The 2020 list of global systemically important banks (GSIBs) includes Citigroup, J.P. Morgan Chase, Bank of America, Bank of New York Mellon, Goldman Sachs, Morgan Stanley, State Street, and Wells Fargo for the US and outside of the US HSBC, Bank of China,

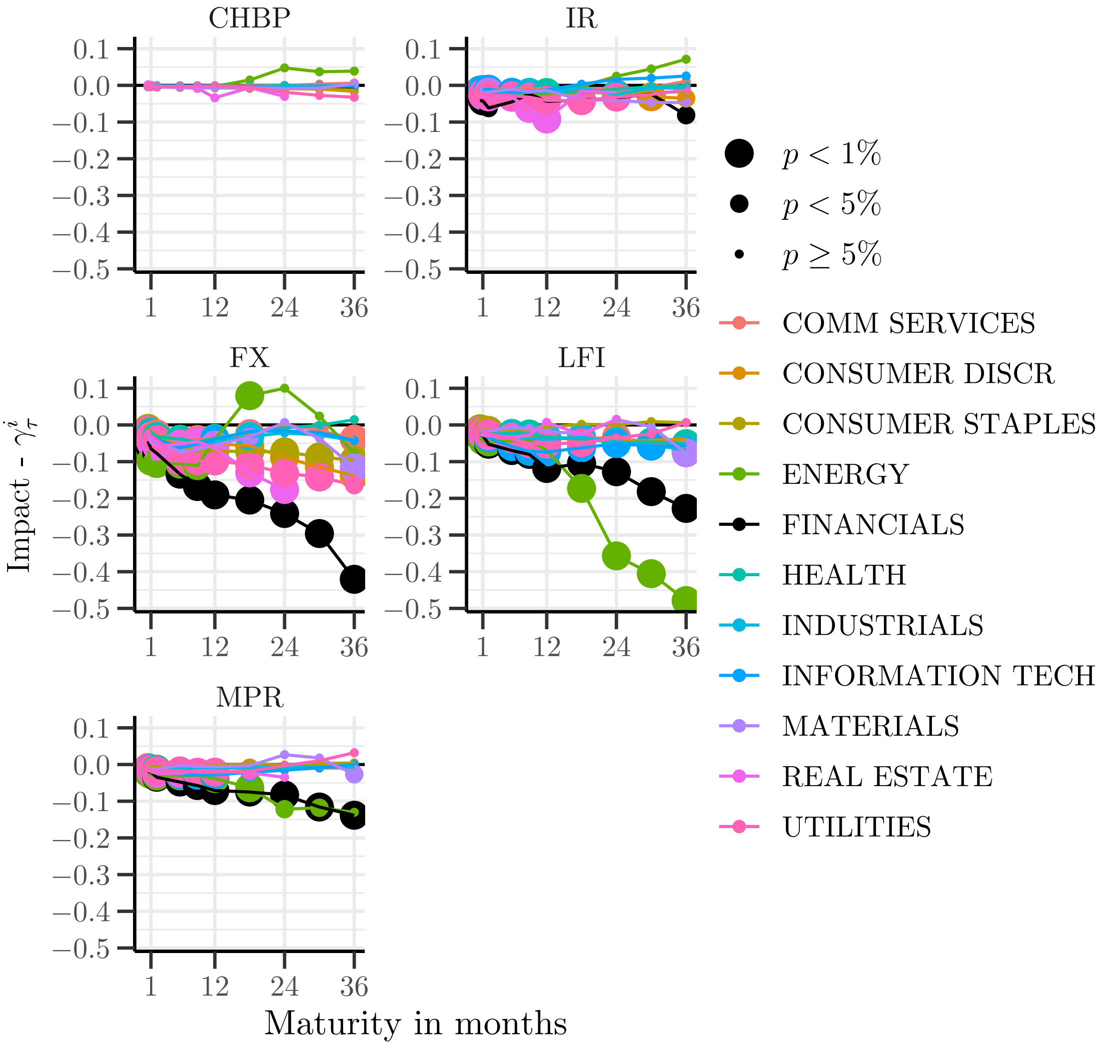
Table 2: Sectoral ETF and GSIB impacts

Impact of different policy categories on fear for different sectors averaged across the maturities of 0.5, 1, 2, 6, 9, 12, 18, 24, 30 and 36 months.

	Coefficient averages				
Asset	CHBP	FX	IR	LFI	MPR
SP-500	-0.0049	-0.0626	-0.0140	-0.0478	-0.0249
Financials	-0.0036	-0.1766	-0.0426	-0.1039	-0.0630
Communication Services	-0.0016	-0.0273	-0.0069	-0.0319	-0.0110
Consumer Discretionary	-0.0060	-0.0664	-0.0246	-0.0329	-0.0073
Consumer Staples	-0.0064	-0.0660	-0.0209	-0.0016	-0.0022
Energy	0.0133	-0.0286	0.0045	-0.1759	-0.0590
Health	-0.0027	-0.0243	-0.0126	-0.0312	-0.0126
Industrials	-0.0022	-0.0407	-0.0164	-0.0374	-0.0112
Information Tech	-0.0036	-0.0370	-0.0027	-0.0511	-0.0204
Materials	-0.0048	-0.0440	-0.0233	-0.0156	-0.0033
Real Estate	-0.0085	-0.0768	-0.0498	-0.0372	-0.0312
Utilities	-0.0096	-0.0957	-0.0292	-0.0266	-0.0038
US GSIB	0.0038	-0.0831	-0.0111	-0.1359	-0.0803
China+Japan GSIB	-0.0090	-0.0055	0.0020	-0.0254	-0.0083
non-US, China, Japan GSIB	-0.0048	-0.0953	-0.0367	-0.0468	-0.0314

Figure 6: Impact term structure for sectoral ETFs of the SP-500

Impact of different policy categories on fear for different terms τ (x-axis). The effect of a policy on the change in the excess log return for the tail probability 10%. In red, green, blue, yellow, and purple are the effects of the FX, LFI, MPR, IR and CHBP policies, respectively. The sizes of the dots give the different levels of significance, · p≥0.05; • p<0.05; ● p<0.01, calculated using robust standard errors based on Newey and West (1987).



Both for the sectoral ETF analysis and the G-SIB analysis we run panel regressions of the form (6) with asset fixed effects and allowing for asset specific policy impacts. We present the individual impact term structures by policy category in Figure 6 for the ETF panel and in Figure 10 for the GSIB panel. We show average impacts for all maturities up to three years in Table 2. We indeed find that, with the exception of the energy sector, the US financial sector shows the strongest reactions to discretionary Fed crisis interventions. When zooming in on G-SIBs, we find that fears in US G-SIBs are more sensitive to Fed domestic liquidity support for financial intermediation (LFI) and to macroprudential actions than their international counterparts, especially at the long end. Fear in international G-SIBs is most responsive to the Fed's FX policies, pointing to their importance for stabilizing the international financial system.

4 Discussion

The results above cast light on how the financial markets perceive the Fed crisis interventions. The strong reactions in market fears beyond the current crisis, and the fact that the impacts on financial institutions stand out, clearly point to the risk of increased moral hazard. The substantial reduction of long-term fear means that the interventions lowered the cost of insurance against future tail events. Whether that implies moral hazard, depends on how the financial markets perceived the chain of events. If the lesson the markets drew from the crisis is that the central bank is forced to bound the worst market losses, provided the crisis is bad enough to apply sufficient pressure on the Fed, the danger is that such expectations become embedded in the market's understanding of the central bank's crisis reaction function. Because the markets come to expect the underwriting of extreme losses, they will take on more risk, so that when the next extreme turmoil comes around, they are particularly vulnerable, and the central bank has no choice but further support the market — moral hazard. We consequently provide three sets of lessons for the design of future central bank interventions.

The first is that the central banks should monitor the reactions of the term structure of fear to its actions, as that gives them near real-time indication of market participants' view on the implications for worst-case outcomes. Here the long term is particularly important. Daily market volatility, the monthly VIX index, CDS spreads, and the various market risk measures, such as Value-at-Risk

Barclays, BNP Paribas, China Construction Bank, Deutsche Bank, Industrial and Commercial Bank of China, Mitsubishi UFJ FG, Agricultural Bank of China, Credit Suisse, Groupe Crdit Agricole, ING Bank, Mizuho FG, Royal Bank of Canada, Santander, Socit Gnrale, Standard Chartered, Sumitomo Mitsui FG, Toronto Dominion, UBS, and UniCredit (see https://www.fsb.org/wp-content/uploads/P111120.pdf) and expected shortfall are all short-term measures. Significant reactions at distant horizons can indicate changes in market participants' beliefs of the central bank's crisis reaction function, providing policymakers valuable real-time feedback on the risk of incentive distortions caused by their actions.

The second lesson is that central bank communication could be improved. Our data reveal a strong flare-up in short and long term market fear weeks before the Fed intervened, fear that immediately subsided once the Fed intervened, suggesting that fear increased, in part, because of policy uncertainty, raising the question of how well market participants understand the Fed's crisis policy function. The large market surprises around Fed crisis announcements point in the same direction. We suspect that standing facilities, and/or clearly communicated crisis intervention parameters, could have prevented some of the observed market dislocations. That lesson, seems in part, to have been absorbed by the Fed, as it now has turned its domestic and foreign repo facilities into standing facilities. However, such clarity undermines strategic ambiguity as a key tool to control the moral hazard of crisis interventions. As the markets seem to have learned from the crisis episode that the central bank bounds the worst market losses, better communication, clarity, and a firm commitment to what the central bank will do in future crises would benefit.

There are further international consequences of the crisis interventions. The Fed's consistently most impactful type of interventions were currency swap facilities provided to key international central banks. This illustrates the role of the Fed as the international lender-of-last-resort and the importance of international investors to US financial markets. Typically, the privilege of crisis liquidity assistance comes with the quid pro quo of ex-ante regulation. But while the Fed is the regulator of US bank holding companies, any moral hazard caused by its international facilities would require international cooperation with other regulators. If not, the Fed might be forced into the position where it indirectly imposes regulatory standards via eligibility criteria for its foreign exchange facilities. Such standards risk being narrowly focused on the risks for US financial markets. The relative power of the FX facilities to calm markets throughout the world, therefore, reinforces results in the nexus literature on the primacy of the US financial markets and points to weaknesses due to the inability of global regulatory oversight, reinforcing the importance of global coordination in financial policymaking.

5 Conclusion

We study the impact of the Federal Reserve's policy interventions on fear in the US stock market. 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. We then classify these actions into five broad policy categories: credit, market liquidity, interest rate policies, foreign exchange policies and macroprudential policies, and study their effects on the risk term structure.

The Fed's liquidity provision for financial intermediation, especially via its FX swap lines, had a strong impact on fear, while interest rate changes and credit support to the wider economy support were less effective in calming markets. The strong effects on long-run risk perceptions and financial sector fears point to the moral hazard of crisis interventions. 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 Additional futures contracts

Given the heterogeneity in the intended beneficiaries and goals of the policies and programs announced by the Fed, we opt for a wider net of instruments. S&P 500 E-Mini Futures represent a broad spectrum of companies that are affected by Fed actions through different channels. Furthermore, stock prices are affected by discount rate changes and changes in expected future cash flows. It is in the latter that news on extreme outcomes is manifested. Moreover, related studies have used federal funds futures, Eurodollar futures, and Treasury bond yields to measure the impact of policy surprises and monetary shocks on the real economy and economic activity (e.g. Gürkaynak et al., 2005; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018). However, we extend these studies in the spirit of Swanson (2020), by including also the exchange rates and by estimating a factor model of these data. By adopting this range of assets we can measure the reaction of the market fears about the short, medium and long run as well as the international spillovers of the market fears.

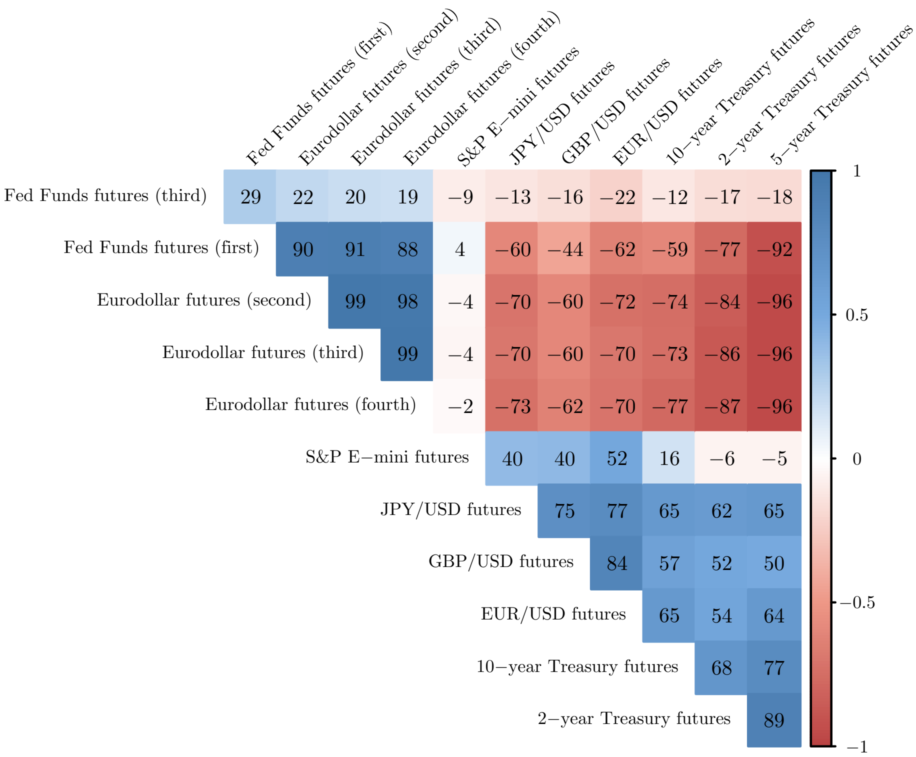
However, rather than including several assets and relying on principal components analysis as in (Gürkaynak et al., 2005; Swanson, 2020), we take a different approach.[13]

The first and third federal funds futures contracts provide good estimates of the market expectation of the federal funds rate about the next 1 to 3 months. The second through fourth Eurodollar futures contracts provide information about the market expectation of the path of the federal funds rate over a horizon from about 5 to 14 months ahead. The 2-, 5-, and 10-year Treasury yields provide information about interest rate expectations and risk premia over longer horizons, out to 10 years. In addition to these assets we also include the S&P 500 E-Mini Futures contract and the exchange rate futures contracts. The S&P 500 E-Mini Futures provide an overview of the change in market expectations over a continuous span of time, and the exchange rate futures provide information about a possible international spillover effect from the US financial market to the other economies.

We focus on some rather than all twelve assets since they (and the resulting surprises around Fed announcements) are highly correlated.[14] From Figure 7, we can see that contracts in the same asset group are highly correlated (e.g.

[13] They include the first and third federal funds futures contracts, the second, third, and fourth Eurodollar futures contracts, the 2-, 5-, and 10-year Treasury yields.

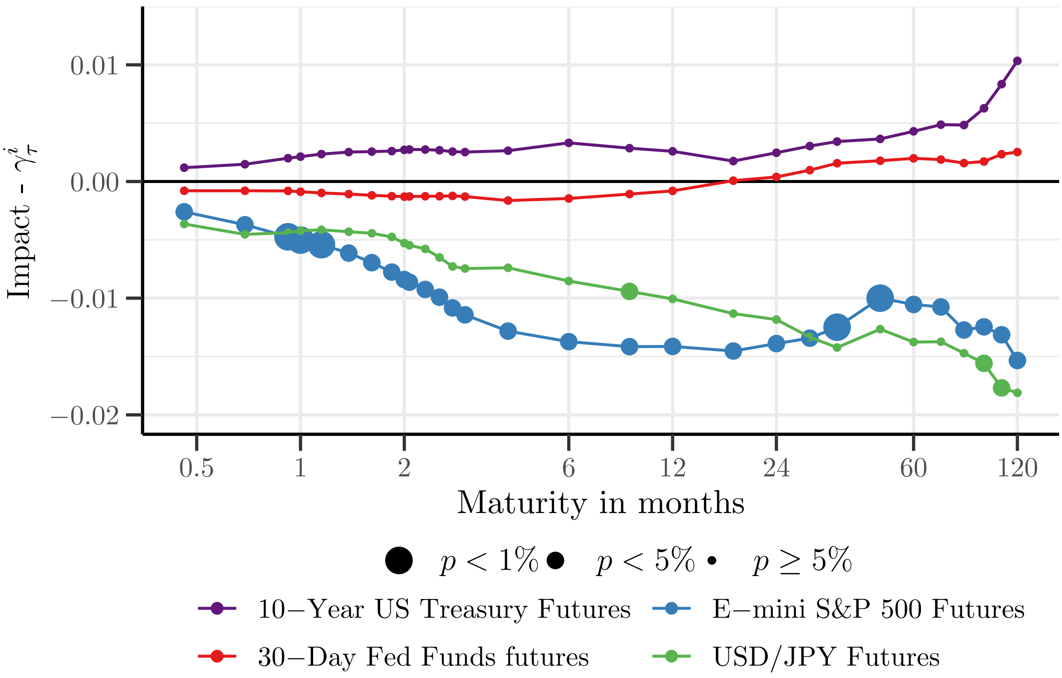
[14] The Fed funds futures contracts are scaled by the number of days remaining in the month to provide the best estimate of the surprise change in the federal funds rate at the FOMC meeting (see Gürkaynak et al., 2005; Kuttner, 2001). For all the other assets, we take the June contract as the first contract in March, April and May, and the September contract as the first contract in June and July. To rule out liquidity concerns, we rollover to the next contract before the previous contract expires.



We show the results of this regression in Figure 8. We observe that among the four different channels, the S&P 500 E-Mini Futures is the one that reacts more to the Fed unexpected interventions reducing the stock market fear.

Figure 8: Impact of different components of Fed policy announcements on market fear

[match colour and indices -]In this figure, the impact of the different components of Fed policies on market fear for different terms τ (x-axis) is shown. The red, blue, green, and purple dots correspond to the effects measured through the 10-year US Treasury futures, the 30-day Fed Funds futures, the S&P 500 E-mini futures, and the USD/JPY futures from running equation (??) with sample period 3 February 2020 to 31 July 2020. The sizes of the dots give the different levels of significance, · p≥0.05; • p<0.05; ● p<0.01, calculated using robust standard errors based on Newey and West (1987).



B Additional Tables and Figures

Table 3: Testing equality restrictions on the policy impacts of the SP-500

A series of constraints on the coefficients of (5) are subjected to a Wald test. The constraints impose equality between all policy impacts as well as between all combinations of policy impact pairs. P-values

Restriction	$\tau = 1$	$\tau = 2$	$\tau = 6$	$\tau = 12$	$\tau = 36$	$\tau = 60$
$\gamma_\tau^{CHBP} = \gamma_\tau^{FX}$	0.000	0.000	0.000	0.000	0.000	0.000
$\gamma_\tau^{CHBP} = \gamma_\tau^{IR}$	0.248	0.033	0.105	0.032	0.333	0.004
$\gamma_\tau^{CHBP} = \gamma_\tau^{LFI}$	0.006	0.000	0.000	0.000	0.000	0.000
$\gamma_\tau^{CHBP} = \gamma_\tau^{MPR}$	0.113	0.000	0.000	0.000	0.000	0.000
$\gamma_\tau^{FX} = \gamma_\tau^{IR}$	0.000	0.000	0.000	0.000	0.000	0.001
$\gamma_\tau^{FX} = \gamma_\tau^{LFI}$	0.399	0.957	0.525	0.402	0.000	0.291
$\gamma_\tau^{FX} = \gamma_\tau^{MPR}$	0.054	0.009	0.001	0.000	0.000	0.013
$\gamma_\tau^{IR} = \gamma_\tau^{LFI}$	0.062	0.000	0.000	0.000	0.000	0.000
$\gamma_\tau^{IR} = \gamma_\tau^{MPR}$	0.666	0.431	0.089	0.141	0.063	0.194
$\gamma_\tau^{LFI} = \gamma_\tau^{MPR}$	0.001	0.000	0.000	0.000	0.000	0.000
$\gamma_\tau^{CHBP} = \gamma_\tau^{FX} = \gamma_\tau^{IR} = \gamma_\tau^{LFI} = \gamma_\tau^{MPR}$	0.000	0.000	0.000	0.000	0.000	0.000

Figure 9: Crises are Different

Impact of policies combined into a single category during the COVID crisis and also during an earlier sample comprising the period between June 2018 and December 2019. The sizes of the dots give the different levels of significance, calculated using robust standard errors based on Newey and West (1987).

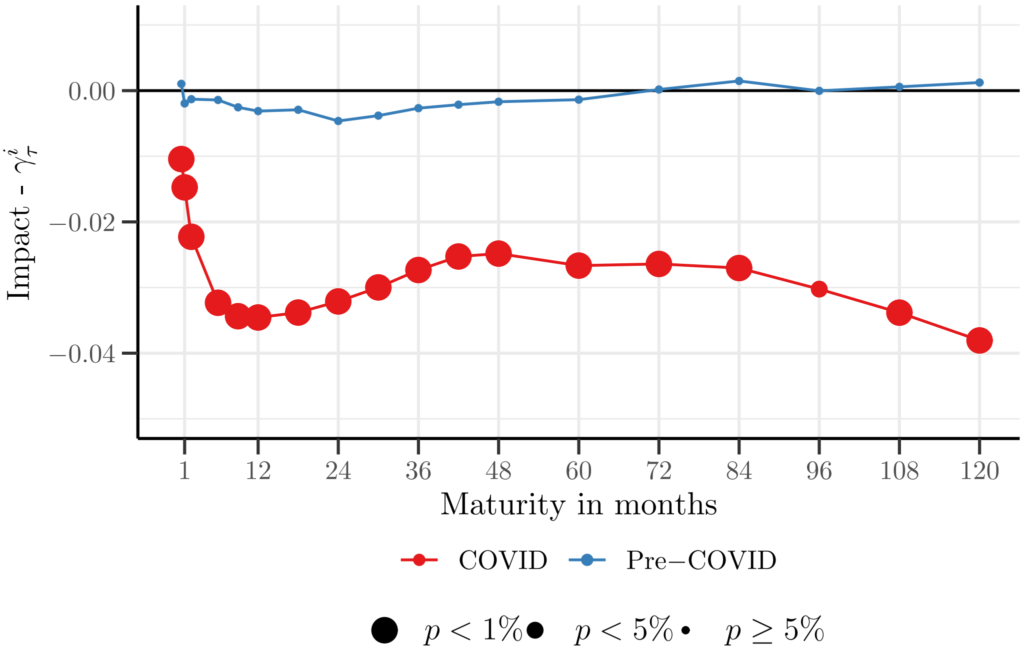
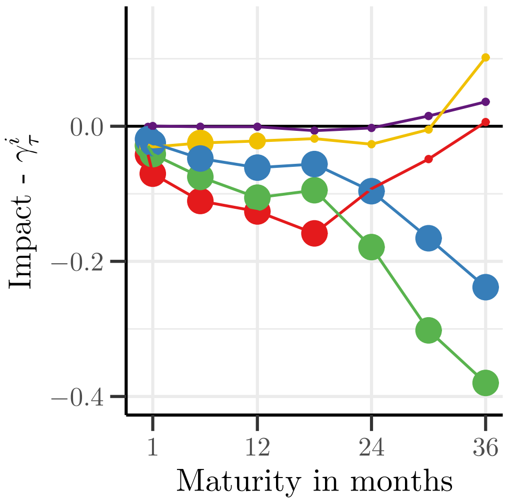
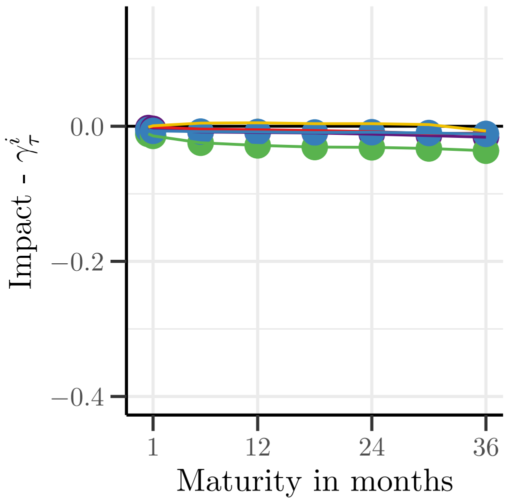


Figure 10: Impact response term structure of the GSIBs

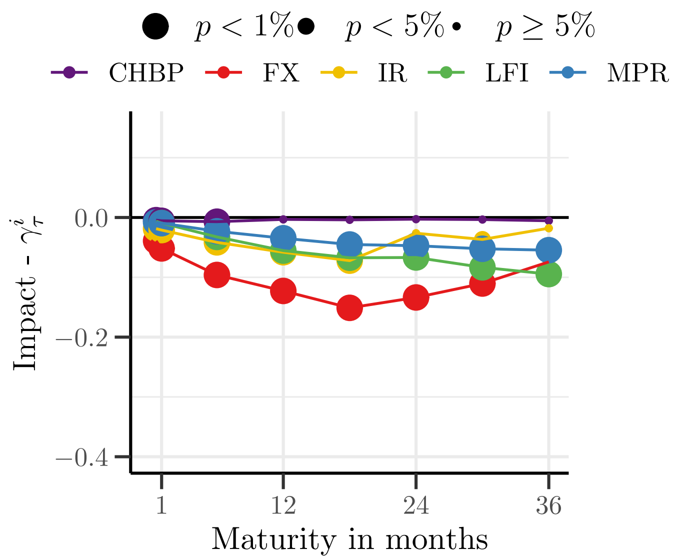
The impact of different policy categories on fear for different terms τ (x-axis) on US GSIBs (panel (a)), Chinese and Japanese GSIBs (panel (b)), and the remaining GSIBs (panel (c)). We show the effect of a policy on the change in the excess log return for the tail probability 10%. In red, green, blue, yellow, and purple are the effects of the FX, LFI, MPR, IR and CHBP policies, respectively. The sizes of the dots give the different levels of significance, $\cdot$ p≥0.05; $\bullet$ p<0.05; ⬤ p<0.01, calculated using robust standard errors based on Newey and West (1987).



(a) US-GSIBs



(b) Chinese and Japanese-GSIBs



(c) Other-GSIBs

Table 4: Federal Reserve announcements March-July 2020

Date and Time Stamp	Category	Policy Description	△ SPX E-mini Futures
03/03/2020 10:00	IR	FOMC lowered the target range for the federal funds rate by 1/2 percentage point, to 1 to 11/4 percent.	22
15/03/2020 17:00	IR	FOMC lowered the target range for the federal funds rate by 1 percentage point, to 0 to 1/4 percent.	-20.08
15/03/2020 17:00	LFI	FOMC will increase its holdings of Treasury securities by at least $500 billion and its holdings of agency mortgage-backed securities by at least $200 billion.	-11.76
15/03/2020 17:00	MPR	The Fed is encouraging banks to use their capital and liquidity buffers as they lend to households and businesses.	-13.34
15/03/2020 17:00	FX	The Fed announced measures related to the U.S. dollar liquidity swap line arrangements.	-10.82
16/03/2020 16:30	IR	The Fed approved decreased the discount rate (the primary credit rate) from 1-3/4 percent to 1/4 percent.	27.5
17/03/2020 09:15	MPR	Banks allowed to continue lending to households and businesses easing the use of firms' capital buffers.	-33.75
17/03/2020 10:45	CHBP	The Fed announced that it will establish a Commercial Paper Funding Facility (CPFF) to support the flow of credit to households and businesses.	27
17/03/2020 18:00	LFI	The Fed announced that it will establish a Primary Dealer Credit Facility (PDCF) to support the credit of households and businesses. The Boston Fed will make loans available to eligible financial institutions.	-13.25
18/03/2020 23:30	LFI CHBP	The Fed established a Money Market Mutual Fund Liquidity Facility (MMLF) to support the flow of credit to households and businesses by taking steps to enhance the liquidity and functioning of crucial money markets.	-9.86 -9.89
19/03/2020 08:30	LFI	Interim final rule to ensure that financial institutions will be able to effectively use a liquidity facility, the MMLF.	21
19/03/2020 09:00	FX	The Fed announced temporary U.S. dollar liquidity arrangements (swap lines) with several international central banks.	11.5
20/03/2020 10:00	FX	The BoC, the BoE, the BoJ, the ECB, the Fed, and the SNB announced a coordinated action to enhance the provision of liquidity via the standing U.S. dollar liquidity swap line arrangements.	24.75
20/03/2020 11:00	LFI CHBP	The Fed expanded its program of support for the flow of credit to the economy by enhancing the liquidity and functioning of money markets. The Boston Fed will make loans available to eligible financial institutions.	-9.61 -9.64
23/03/2020 08:00	LFI	The Fed will continue to purchase Treasury securities and agency mortgage-backed securities *in the amounts needed* to support smooth market functioning and effective transmission of monetary policy.	70.65
23/03/2020 08:00	CHBP	The FOMC is taking further actions to support the flow of credit to households and businesses by addressing strains in the markets for Treasury securities and agency mortgage-backed securities. The Fed announces the Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF).	70.85

Date and Time Stamp	Category	Policy Description	△ SPX E-mini Futures
23/03/2020 09:15	MPR	The Fed announced a change to automatic restrictions associated with a firm's "total loss-absorbing capacity", or TLAC, buffer requirements, to support the U.S. economy and allow banks to continue lending to households and businesses.	-83.5
27/03/2020 12:00	MPR	Announced actions to support the U.S. economy and allow banks to continue lending to households and businesses.	1.25
31/03/2020 08:30	FX	The Fed announced a temporary repurchase agreement facility for foreign and international monetary authorities (FIMA Repo Facility) to help support the smooth functioning of financial markets, including the U.S. Treasury market.	3.75
01/04/2020 16:45	MPR	The Fed announced a temporary change to its supplementary leverage ratio rule to ease strains in the Treasury market and increase banking organizations' ability to provide credit to households and businesses.	13.25
03/04/2020 18:30	MPR	Issued a policy statement providing regulatory flexibility to enable mortgage servicers to work with struggling consumers.	29.5
06/04/2020 09:00	MPR	Issued two interim final rules to provide temporary relief to community banking organizations which require the agencies to temporarily lower the community bank leverage ratio to 8 percent.	0
06/04/2020 14:00	CHBP	The Fed will ease lending to small businesses via the Small Business Administration's Paycheck Protection Program (PPP).	-12.5
07/04/2020 15:00	MPR	Issued a revised interagency statement encouraging financial institutions to work constructively with borrowers affected by COVID-19.	-6.5
09/04/2020 08:30	CHBP	The Fed took additional actions to provide up to $2.3 trillion in loans to support the economy.	47.5
09/04/2020 09:30	MPR	Announced an interim final rule to encourage lending to small businesses through the Small Business Administration's Paycheck Protection Program, or PPP.	6.75
14/04/2020 18:00	MPR	Issued an interim final rule to temporarily defer real estate-related appraisals and evaluations to allow regulated institutions to extend financing to creditworthy households and businesses quickly.	-4.25
23/04/2020 17:30	LFI	The Fed outlined the extensive public information regarding its programs to support the flow of credit to households and businesses.	-9.25
24/04/2020 10:00	MPR	The Fed announced an interim final rule to amend Regulation D (Reserve Requirements of Depository Institutions) to delete the six-per-month limit on convenient transfers from the "savings deposit" definition.	6
27/04/2020 16:30	CHBP	The Fed announced an expansion offering up to $500 billion in lending to states and municipalities.	2
29/04/2020 14:00	IR	The Fed decided to maintain the target range for the federal funds rate at 0 to 1/4 percent.	-2.21
29/04/2020 14:00	LFI	To support the flow of credit to households and businesses, and market functioning, the Fed will continue to purchase Treasury securities and agency residential and commercial mortgage-backed securities	-1.29

Date and Time Stamp	Category	Policy Description	△ SPX E-mini Futures
30/04/2020 10:00	CHBP	The Fed announced an expansion with respect to loan options available to businesses.	7.25
30/04/2020 17:15	CHBP	The Fed expanded access to its Paycheck Protection Program Liquidity Facility (PPPLF) to additional lenders.	-11.25
05/05/2020 15:30	MPR	The Fed announced an interim final rule that modifies the agencies' Liquidity Coverage Ratio (LCR) rule to support banking organizations' participation in the Fed's Money Market Mutual Fund Liquidity Facility.	-8
15/05/2020 17:45	MPR	The federal bank regulatory agencies announced temporary changes to their supplementary leverage ratio rule to provide flexibility to depository institutions to expand their balance sheets as to provide credit to households and businesses.	4.5
03/06/2020 13:00	CHBP	The Fed announced an expansion in the number and type of entities eligible to directly use its Municipal Liquidity Facility (MLF).	1
08/06/2020 15:30	CHBP	The Fed expanded its Main Street Lending Program to allow more small and medium-sized businesses to be able to receive support.	10
10/06/2020 14:00	IR	The Fed decided to maintain the target range for the federal funds rate at 0 to 1/4 percent.	12.45
10/06/2020 14:00	LFI	The Fed will increase its holdings of Treasury securities and agency residential and commercial mortgage-backed securities to sustain smooth market functioning, thereby fostering effective transmission of monetary policy to broader financial conditions.	7.3
15/06/2020 14:00	CHBP	The Fed announced updates to the Secondary Market Corporate Credit Facility (SMCCF), which will begin buying a broad and diversified portfolio of corporate bonds to support market liquidity and the availability of credit for large employers.	39
15/07/2020 16:30	CHBP	The Fed announced an extension to bolster the Small Business Administration's (SBA) Paycheck Protection Program (PPP)	2
17/07/2020 10:00	CHBP	The Fed modified the Main Street Lending Program to provide greater access to credit.	-6.5
23/07/2020 14:30	CHBP	The Fed broadened the set of firms eligible to transact with and provide services in three emergency lending facilities.	8.5
28/07/2020 09:30	LFI CHBP	The Fed announced a three-month extension of its lending facilities that will ease planning by potential facility participants and provide certainty that the facilities will continue to be available.	-2.25 -2.25
29/07/2020 14:00	IR	The Fed decided to maintain the target range for the federal funds rate at 0 to 1/4 percent.	0.47
29/07/2020 14:00	LFI	The Fed will increase its holdings of Treasury securities and agency residential and commercial mortgage-backed securities to sustain smooth market functioning, fostering effective transmission of monetary policy to broader financial conditions.	0.28
29/07/2020 14:00	FX	The Open Market Desk will continue to offer large-scale overnight and term repurchase agreement operations.	0.25

Notes: In this table, the Federal Reserve (Fed) announcements that we collect between March and July 2020 are reported. The announcements dates and time stamps are collected from the press release section of the Federal Reserve website at https://www.federalreserve.gov/newsevents/pressreleases.htm. In the second column, the category of the policy, namely "Credit to households, businesses, and public sector" (CHBP), "Foreign Exchange" (FX), "Interest rate" (IR), "Liquidity for financial intermediation" (LFI), and "Macroprudential regulations" (MPR) is reported. In the third column, we briefly describe the policy. For a more extensive description of the policy and more details see the Federal Reserve website above. In the last column, the intraday S&P 500 changes around the 30-minute policy announcement window are reported.

C From IVs to risk-neutral distributions (RNDs)

In this section, we describe how we take implied volatilities from option, fit a curve through the implied volatilities and subsequently use the Breeden and Litzenberger (1978) approach extract the risk-neutral densities.

Here we discuss in more details the stochastic volatility inspired (SVI) curve fit to the consensus IVs for strike prices in $[\underline{K}, \overline{K}]$ under a constraint of no-arbitrage. For a given parameter set $P = a; b; m; \rho; \sigma$ the raw SVI parameterization of the consensus implied volatility reads:

$$w^{\mathrm{SVI}}_{\mathrm{imp}}(x) = a + b(\rho(x-m) + \sqrt{(x-m)^2\sigma^2}) \tag{7}$$

where $a \in R$, $b \geq 0$, $|\rho| \leq 1$, $m \in R$, and $\sigma > 0$, in addition to the obvious condition $a + b\sigma\sqrt{1-\rho^2} \geq 0$, which ensures that $w^{\mathrm{SVI}}_{\mathrm{imp}}(x) \geq 0$ for all $x \in R$. This ensures that the minimum of the function $w^{\mathrm{SVI}}_{\mathrm{imp}}(x)$ is not negative. Increasing a increases the general level of variance with a vertical translation of the smile; increasing b increases the slopes of both call and put wings tightening the smile; increasing ρ decreases (increases) the slope of the left (right) wing, a counter-clockwise rotation of the smile; increasing m translates the smile to the right; increasing σ reduces the at-the-money (ATM) curvature of the smile. We ensure the consistency of the SVI parameterization by fixing arbitrage bounds for extreme strikes. More specifically, we ensure static arbitrage for a given volatility surface (or for call options) by satisfying the following conditions: (a) it is free of calendar spread arbitrage; (b) each time slice is free of butterfly arbitrage. For more details see also previous work by Gatheral and Jacquier (2013).

With the SVI fits in hand, we convert them into volatilities. For each term τ and submission date t, we calculate European call prices using the well known Black and Scholes (1973) model for a fine grid of strike prices $\underline{K} < K_2 < ... < \overline{K}$. The payoff at maturity of a European call option maturing at a generic time T, with an exercise price K, is $\max(F_T - K, 0)$, with F_T representing the final underlying price being this in our case equal to the forward price as provided in our Totem data set. We denote the observed time t market value of a European call with strike equal to K and with a tenor of $\tau = T - t$ by $\mathbb{C}(t, K, \tau)$. Absent arbitrage, therefore, the option value is equal to the present expected value of the terminal payoff under the risk-neutral distribution:

$$\mathbb{C}(t, K, \tau) = \exp^{-r_{t,\tau}\tau} \mathbb{E}_t[\max(F_{t,\tau} - K, 0] = \exp^{-r_{t,\tau}\tau} \int_K^\infty (s-K)\pi_t(s)ds,$$

where $F_{t,\tau}$ is the time t underlying price, $r_{t,\tau}$ is the time-t continuously compounded risk rate, $\mathbb{E}_t$ is the expectation operator taken under the time-t risk-neutral probability measure, and π_t is the time-t risk-neutral probability density of the underlying price $F_{t,\tau}$. Following the approach by Breeden and Litzenberger (1978), we then calculate the 1st and 2nd derivative of call price function. We differentiate the market call price with respect to the exercise price K to get the exercise price delta as:[15]

$$\frac{\delta}{\delta K}\mathbb{C}(t,K,\tau) = \exp^{-r_{t,\tau}\tau}[\int_0^K \pi_t(s)ds - 1].$$

The time-t risk-neutral cumulative distribution function $\Pi_t(K)$ of the future asset price (the probability that the final underlying price $F_{t,\tau}$ will be K or lower) is equal to 1 plus the future value of the exercise price delta of the European call with strike K:

$$\Pi_t(K) = \int_0^K \pi_t(s)ds = 1 + \exp^{-r_{t,\tau}\tau}\frac{\delta}{\delta K}\mathbb{C}(t,K,\tau).$$

We differentiate again with respect to K as follows:

$$\pi_t(K) = \exp^{-r_{t,\tau}\tau}\frac{\delta^2}{\delta K^2}\mathbb{C}(t,K,\tau).$$

We observe that the time t risk-neutral probability function is the future value of the second derivative of the call price with respect to the exercise price. Finally, we calculate the corresponding implied cumulative density function (CDF) and probability density function (PDF) by taking finite differences in exercise prices of the call valuation functions, hence we report discretized versions of the implied estimate of the risk-neutral CDF and PDF as follows:

$$\Pi_t(K) \approx 1 + \exp^{-r_{t,\tau}\tau}\frac{1}{\triangle}[\mathbb{C}(t,K+\frac{\triangle}{2},\tau) - \mathbb{C}(t,K-\frac{\triangle}{2},\tau)].$$

and

$$\begin{aligned}\pi_t(K) &\approx \frac{1}{\triangle}[\Pi_t(K+\frac{\triangle}{2}) - \Pi_t(K-\frac{\triangle}{2})]\\ &\approx \exp^{-r_{t,\tau}\tau}\frac{1}{\triangle^2}[\mathbb{C}(t,K+\triangle,\tau) + \mathbb{C}(t,K-\triangle,\tau) - 2\mathbb{C}(t,K,\tau)].\end{aligned}$$

when $\triangle \to 0$ the expressions converge to the risk-neutral distributions.

[15] In the absence of arbitrage, the mathematical derivative of the call option value with respect to the exercise price is closely related to the risk-neutral probability that the future asset price will be no higher than the exercise price at option maturity.

D Additional results and robustness checks

We check the robustness of our results by controlling for other variables in addition to the set of controls, $C_{t,o}$, which includes the 7-day rolling mean of new Covid-19 cases, and the Bloomberg Economic Surprise Index.[16] First, we control for days with scheduled FOMC meetings by including a dummy which takes value 1 on days with scheduled FOMC meetings and 0 otherwise. The scheduled meetings during our sample period (from 3 February to 31 July 2020) took place on 29 April, 10 June, and 29 July. We show the results in Figure 11 in Appendix D and these appear to be robust. Lucca and Moench (2015) document how US equities might actually anticipate monetary policy decisions at scheduled FOMC meetings, what they call the pre-FOMC announcement drift. By controlling for the scheduled FOMC announcements we show that the high-frequency identification is robust and the possible reactions in the risk-neutral distribution are not due to the effect of the pre-announcement drift risk premia being monetized. What we rather capture in our results is the effect of the set of unprecedented Fed policies that the market, and so the fear measures we construct, may not have anticipated yet.

Next, the VIX has strong mean-reverting properties, likely to be also present in the fear of loss measures. It is possible that the mean reversion is driving the significance of the results. When financial markets' fear is high, the Fed might react by introducing policies in order to calm the market, which would have reverted to normal levels anyway. To address this possible argument, we control for the previous changes in fears in our regressions. We include the lagged dependent variables, namely $\Delta F^{a\leftarrow}_{t-1,\tau}(x)$ and $\Delta \mathrm{VIX}^{a}_{t-1,\tau}$ in (5) and (**??**), respectively. Interestingly, we find that our results are robust to the inclusion of the dependent variables' lags. This corroborates the main message of this section, namely that policies in categories such as FX, LFI and MPR are effective in reducing fears, even when controlling for mean reversion.

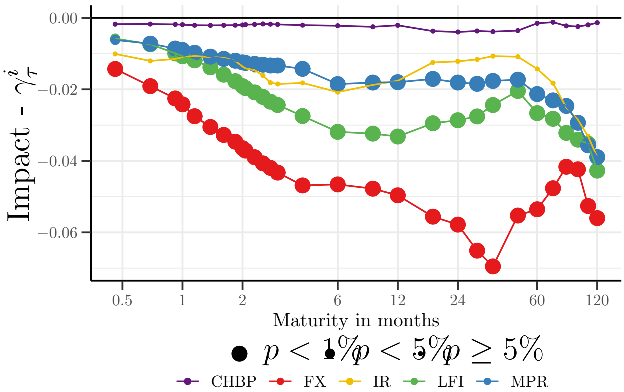
In the onset of the Covid-19 crisis, options trading volume in tech companies has seen a significant increase. It is possible that the trading volume could be correlated with days of Fed announcements and subsequently bias our results. To control for changes for in trading volume the total option volume on the shares of the big technological companies, Alphabet (GOOGL), Amazon (AMZN), Facebook (FB), Apple (AAPL), and Microsoft (MSFT), which we collected from Bloomberg, is included as control. The corresponding results are shown in Figure 13 in Appendix D and again are robust.

Besides that, we also repeat the analysis by looking at the effect on excess

[16] We repeated the exact same robustness checks with respect to the US individual stocks and sector indices. The results still hold robust after the inclusion of other controls and are available upon request from the authors.

Figure 11: Impact of announcements of the Fed, controlling for FOMC meetings

In this figure, the impact of different policy categories on fear for different terms τ (x-axis) is shown. We show the effect of a policy on the change in the excess log return for the tail probability 20%, when additionally including a dummy for the three days in our sample period (29 April, 10 June, and 29 July 2020) with scheduled FOMC meetings. In red, green, blue, yellow, and purple are the effects of the FX, LFI, MPR, IR and CHBP policies, respectively. The sizes of the dots give the different levels of significance, · p≥0.05; • p<0.05; ⬤ p<0.01, calculated using robust standard errors based on Newey and West (1987).



log returns for different tail probabilities and VIXs of the Russell 2000 Index and S&P 500 sectoral indices, namely the energy and financial sectors.[17] This shows whether the impact on fear is different for small- and mid-cap companies versus the large ones represented in the S&P 500 and give further insights into potential heterogeneities across industries. We find that this analysis confirms the somewhat larger magnitudes for the financial sector as a whole and that and that again FX, LFI, and MPR have the strongest effects.

Finally, we control for the effect of announcements of five important fiscal policy responses (see also Alfaro et al., 2020). In particular, we add a dummy to $C_{t,o}$ which takes value 1 on days when one of the five acts we include either passed the House of Representatives or the Senate, or became law. The five acts with the corresponding dates of the stages in the legislative process are listed in Table 5 in Appendix D, and the results are reported in Figure 12 in Appendix D. Once again, our results are robust.

[17]Due to data availability the impact on sectoral indices is only reported up to the one-year maturity.

Table 5: Fiscal policy responses to Covid-19

In this table, the key fiscal policy responses in the US to the Covid-19 pandemic are reported. The policy dates are collected from the online database of US Congress legislative information at https://www.congress.gov/. The dates correspond to the days on which the dummy for important fiscal policy responses takes value 1. Exceptions are that the dummy takes value 1 on 15 instead of 14 March because this is a Sunday. Moreover, the dummy also takes value 1 on the 18 and 27 March on which multiple stages of the legislative process were passed.

Date	Act	Stage in legislative process
04 March	Coronavirus Preparedness and Response Supplemental Appropriations Act	Passed House of Representatives
05 March	Coronavirus Preparedness and Response Supplemental Appropriations Act	Passed Senate
06 March	Coronavirus Preparedness and Response Supplemental Appropriations Act	Became Law
14 March	Families First Coronavirus Response Act	Passed House of Representatives
18 March	Families First Coronavirus Response Act	Passed Senate
18 March	Families First Coronavirus Response Act	Became Law
25 March	Coronavirus Aid, Relief, and Economic Security Act	Passed Senate
27 March	Coronavirus Aid, Relief, and Economic Security Act	Passed House of Representatives
27 March	Coronavirus Aid, Relief, and Economic Security Act	Became Law
21 April	Paycheck Protection Program and Health Care Enhancement Act	Passed Senate
23 April	Paycheck Protection Program and Health Care Enhancement Act	Passed House of Representatives
24 April	Paycheck Protection Program and Health Care Enhancement Act	Became Law
28 May	Paycheck Protection Program Flexibility Act	Passed House of Representatives
03 June	Paycheck Protection Program Flexibility Act	Passed Senate
05 June	Paycheck Protection Program Flexibility Act	Became Law

Figure 12: Impact of announcements of the Fed, controlling for fiscal policies

In this figure, the impact of different policy categories on fear for different terms τ (x-axis) is shown. We show the effect of a policy on the change in the excess log return for the tail probability 20%, when additionally including a dummy for the days with important fiscal policy announcements (see Table 5). In red, green, blue, yellow, and purple are the effects of the FX, LFI, MPR, IR and CHBP policies, respectively. The sizes of the dots give the different levels of significance, · p≥0.05; • p<0.05; ● p<0.01, calculated using robust standard errors based on Newey and West (1987).

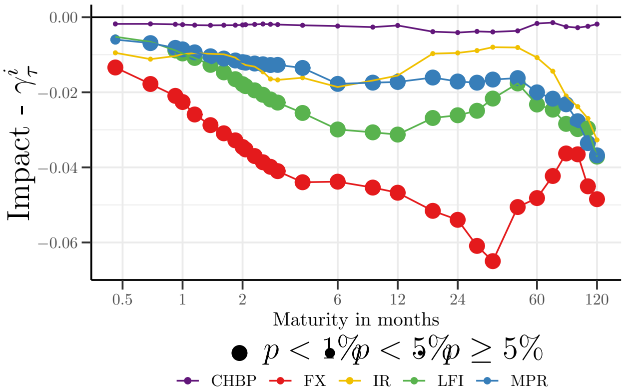


Figure 13: Impact of announcements of the Fed, controlling for the "GAFAM" option volume

In this figure, the impact of different policy categories on fear for different terms τ (x-axis) is shown. We show the effect of a policy on the change in the excess log return for the tail probability 20%, when additionally including a dummy for the change in logs of the total volume of options on the shares of the big technological companies. In red, green, blue, yellow, and purple are the effects of the FX, LFI, MPR, IR and CHBP policies, respectively. The sizes of the dots give the different levels of significance, · p≥0.05; • p<0.05; ● p<0.01, calculated using robust standard errors based on Newey and West (1987).

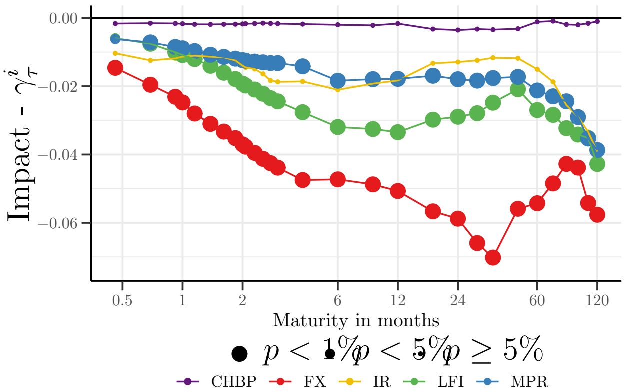
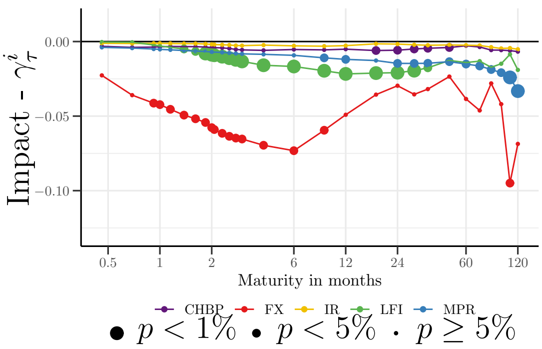
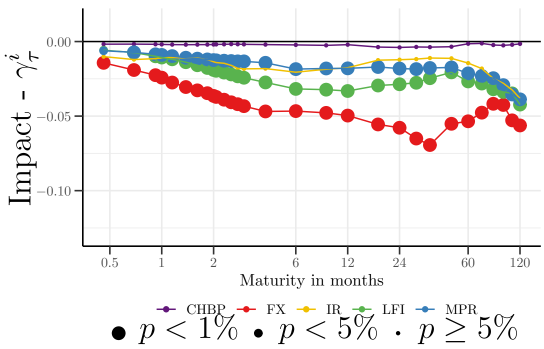


Figure 14: Impact of announcements of the Fed for different intraday window sizes around announcements' time stamps

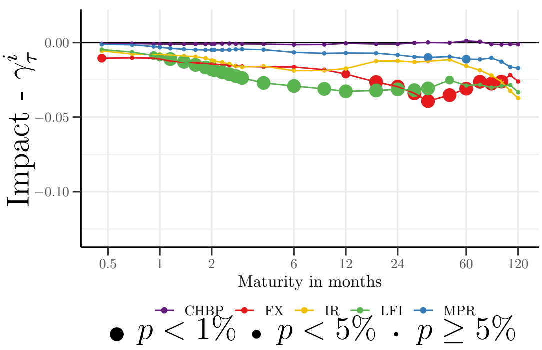
In this figure, the impact of different policy categories on fear for different terms τ (x-axis) is shown. In the four panels, we show the effect of a policy on the change in the excess log return for the tail probability 20%, with different choices of intraday window sizes,namely 15 minutes (-5, +10), 30 minutes (-10, +20) (default for main analysis), 60 minutes (-15, +45) and 90 minutes (-30, +60). In red, green, blue, yellow, and purple are the effects of the FX, LFI, MPR, IR and CHBP policies, respectively. The sizes of the dots give the different levels of significance, · p≥0.05; • p<0.05; ● p<0.01, calculated using robust standard errors based on Newey and West (1987).



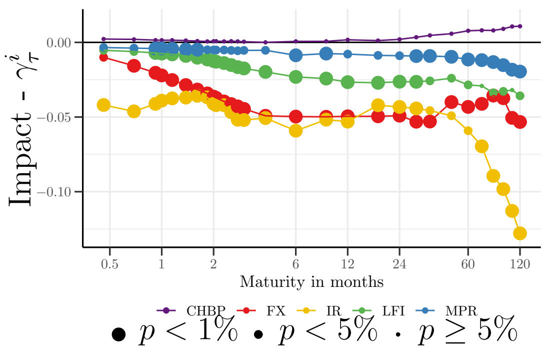
(a) 15min window



(b) 30min window



(c) 60min window



(d) 90min window