The Term Structure of Market Fear: Central Bank Responses to Covid-19*

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Abstract

We study the impact of five key Fed policy responses to the Covid-19 crisis on the stock market's fear of loss and variability. Using a unique global dataset of option prices to construct the term structures of fear, up to 10 years into the future, we find that FX swap lines have the most decisive impact on market fear, but only on the US and countries with access to the swaps. Liquidity support and macroprudential policies had a smaller but still significant impact, while policies aimed to support the wider economy did not affect fear. The critical importance of USD swap lines further lends support to the view that the USD is a global risk factor.

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1 Introduction

> "Crises feed uncertainty. And uncertainty affects behaviour, which feeds the crisis.[...] So what are policymakers to do? First and foremost, reduce uncertainty. Do so by removing tail risks, and the perception of tail risks."
>
> Olivier Blanchard (2009)

When Covid-19 first emerged as a threat in early 2020, the financial markets did not react, equity markets performed well, and perceived market fears of extreme outcomes were historically low. This all changed in the middle of February when prices started falling, and risk perceptions jumped upwards. The policy authorities eventually reacted by early March with a broad range of policy instruments, shaped by memories of the global crisis of 2008. Still, questions remain as to effectiveness of the various policy responses to Covid-19.

Our interest in this work is to identify how different Federal Reserve System (Fed) policy instruments directly impacted global market fears during the Covid-19 crisis, both the fear of loss (the left tail quantiles of the risk-neutral distribution) and the fear of variability (the VIX indices corresponding to the risk-neutral expectations of future realized variance). We refer to this impact of Fed policies on market fears as the *effectiveness* of Fed policies,[1] and obtain both our fear measures from the twin term structures of fear, loss and variability. Fear matters since it reflects how the market's perception of future adverse scenarios can hasten illiquidity driven feedback loops that not only threaten financial stability, but also immediately impact on financial asset prices and market functioning by affecting portfolio decisions and funding costs. The ultimate consequence is an adverse impact on real economy investment decisions.

Fed policy interventions can be very effective in calming market fears both domestically and globally, but may also trade off short term stability for longer term instability. Promoting financial stability is an explicit key element in meeting the Fed's dual mandate for monetary policy regarding full employment and stable prices. The Fed policy has been, certainly since Alan Greenspan's chairmanship, highly reactive to market fears, fears expressed both in the money and treasury markets as well as in the equity markets (Cieslak and Vissing-Jorgensen, 2020). Meanwhile, the US dollar money markets have become the nexus of financial imbalances and panics, the place where short-term obligations get tested and where

[1] While we see market fears in real time, the ultimate effects of the policies on other metrics of financial stability, unemployment and inflation are harder to identify and are beyond the scope of this paper.

flights to safety and dollar shortages can cause liquidity events that endanger the stability of the financial system.

Our empirical investigation is based on identifying the impact of Fed interventions on the term structures of market fear — loss and variability — constructed from the risk neutral distributions of market outcomes of daily options prices, supplied by IHS Markit.[2] This dataset contains 242 stock market indices (US based and international) and 3,334 individual stocks with maturity horizons ranging from one week up to 30 years. The subset studied in this work encompasses 4 US stock indices, 4 international stock indices and 15 individual stocks with maturity horizons spanning from two weeks to 10 years. We identify the Fed interventions from their press releases, constructing a database of five categories: 1) credit to households, businesses and public sector, 2) interest rate decisions (including forward guidance), 3) liquidity support for financial intermediation and market functioning support, 4) macroprudential regulations, and 5) foreign exchange intervention (swap lines and repos). The first two support the wider economy, the next two financial institutions, while the swaps aid USD creditors. We use the timestamps of Fed announcements to weigh the importance of Fed policies using intraday movements in the S&P 500 around the half hour of a policy's announcement (e.g. Gürkaynak et al., 2005; Jarociński and Karadi, 2020). This high-frequency identification scheme allows us to isolate the effects of individual policy actions.

Our empirical approach is based on regressing the changes in fear, either quantiles for a given probability and maturity or the changes in VIX for a given maturity, on market surprises due to Fed policy announcements and on a variety of controls, including Covid-19 new cases, the Bloomberg indicator of economic surprises and fiscal policies. The regression coefficient on the policy announcement, therefore, gives us a direct measurement of how a particular intervention type affected market fear. We start by market fear in the S&P 500, but also provide more colour by

[2]The risk-neutral measures capture exactly the most important quantities as they weigh the markets' objectives expectations about future events by the pricing kernel that adjusts those probabilities of future events by an appropriate amount corresponding to the aversion to these events. Probabilities get weighed upwards if the event is considered relatively painful, implying that agents are willing to pay relatively large amounts to insure against the event happening, and downwards if the event is considered less painful than average. Risk-neutral quantiles and VIX-type measures capture the markets' fears of those events. This usage of the term "fear" is also closer to how practitioners use it, in fact, the VIX measure is colloquially referred to as the "Fear Gauge," though other authors refer to the pricing kernel adjustment between the two measures as "fear", see, e.g. Bollerslev and Todorov (2011). If a market expects an event with high objective probability but does not place a high risk-neutral probability upon the event, the market signals that it is not fearful of the event. Likewise, suppose the market places a large risk-neutral probability on an event with low objective probability. In that case, it signals that it is afraid of the event through its relatively high willingness to pay and insure against the unlikely event.

repeating the analysis using fear in single stocks across various industries. We chose the individual stocks to represent sectoral differences, both companies that are as Covid 19 winners (such as internet retailers, certain health care companies) and loser (such as energy etc.). We finally use key international stock indexes, both for countries that enjoy the swap lines throughout (Germany, Japan, and UK), received them in the middle of the crisis (Korea), or never got them.

What is striking is that the wider economy support, credit to households, businesses and public sector, as well as interest rate decisions, have no impact on market fear. While these policies certainly provided much needed succour to households and companies, the market seems to either have expected those policies and priced them in or regarded them as a painkiller rather than giving material support for the economy.

Policies directed at financial institutions were much more impactful on fear, mostly in the short and medium run, with liquidity support reducing the one year 10% left-tail quantile by 7% while the macroprudential interventions reduce the same quantile by 5%. The impact on long-term fear of *loss* was smaller but remained significant while there was no discernible impact on long-term fear of *variability*. The market may have seen these policies foremost as helping banks through the most immediate difficulties, thus averting a banking crisis, but also enabling more real economy investment creating expectations of small but significant long-term positive benefits.

The strongest policy, measured by how it affected market fear, is the support for foreign creditors needing US dollars, the FX swap lines. The impact is not only twice as large as the financial institution support, it is also significant long term. These results are in line with the monetary view of finance (see, e.g. Mehrling, 2011; BIS, 2020). By way of example, the swap interventions reduced the one year 10% left-tail quantile of S&P 500 losses (i.e. those exceeded in only ten percent of cases) by 11% and the ten year 10% left-tail quantile by 10%. Meanwhile, the swap interventions cause the one month S&P 500 VIX to drop by nearly 9%, and the one year VIX by 4%. The swap lines are aimed at international USD creditors' need for USD liquidity. Some countries came into the crisis already with access to the Fed USD swap lines, like the UK, Germany, and Japan, and the fear in their leading stock indices reduced significantly, not the least at the longer maturities, in the case of the UK by 6% and 3% for Japan. By further sub-categorizing the FX swap announcements into standing and new swaps lines, and looking at Korea which got access with the new, we find that overall impact of the swap lines on Korea is moderate but highly significant once it got access, with over a 10% reduction in the 10% left-tail quantile.

The swap lines were so globally important because of both how market participants in the US scrambled for liquidity once a pandemic emerged but also because the global nature of the pandemic[3] created significant pressures for overseas USD creditors. We surmise that there are three reasons for why the US swap lines had such a long-term impact on global fear. The first one is the reduction of overall USD buying pressure in the *US* money markets themselves, a pressure initially exacerbated by the fact that absent swaps lines, both foreign and US players were fishing for dollar cash in the same pond. The second was to reassure foreign US dollar borrowers that they would not be starved of the dollars needed to fulfil their obligations. The market sees dry-ups in dollar liquidity as a significant concern, as noted by Bruno and Shin (2015). And thirdly they reaffirmed the commitment of the US to the global financial community, even when such commitments have come under increasing strain.

Our results on the importance of the FX swap lines are in line with recent literature, for example, Bahaj and Reis (2020b). This is consistent with the dominant role of the dollar in the international financial system and speaks to its importance as a driver of risk premia (Bruno and Shin, 2015). We add to the recent growing literature on the relationship between financial markets and the Covid-19 virus outbreak. Alfaro et al. (2020) show how surprises in reported Covid-19 infections can predict US stock returns in real time. Croce et al. (2020) and Ramelli and Wagner (2020) analyze of the Covid-19 contagion also increase financial contagion. Baker et al. (2020) investigate the near and medium term macroeconomic effects of the Covid induced uncertainties. Jordà et al. (2020) and Kozlowski et al. (2020), for instance, highlight the impact of Covid-19 on long term uncertainty. Gormsen and Koijen (2020) use dividend futures data (both for the US and the EU) to extract expectations about economic growth for up to seven years. In a similar analysis, Landier and Thesmar (2020) find, as we do, that the long horizon reaction is more muted. Giglio et al. (2020) use three separate surveys during the Covid-19 turmoil to poll among Vanguard investors expectations about short and long run stock market returns. Cox et al. (2020) find that the market's volatility during the early months of the Covid-19 pandemic is the pricing of stock market risk. More broadly, our paper contributes to understanding the impact of monetary policy and central bank announcements on stock market risk (see Bernanke and Kuttner, 2005; Jarociński and Karadi, 2020; Cieslak and Schrimpf, 2019). Our approach is closest to Bekaert et al. (2020) and Hattori et al. (2016), in that we use the options market to infer the contemporaneous reaction to Fed policies to risk perception.

The remainder of the paper is organized as follows. Section 2 introduces the risk terms structures we construct. Section 3 discussed the Fed policy announcements

[3] For a detailed study of the Fed's swap lines during Covid, see (see Bahaj and Reis, 2020a).

and the identification strategy. The results for the S&P 500, sectoral and individual stock reactions, and international indexes are discussed in section 4, 5 and 6 respectively. Section 7 concludes the paper. A set of additional results, robustness checks and information on the Fed policies are relegated to the paper Appendix.

2 The term structure of risk

There are various market data one can use to gauge the financial markets' fear, like realized volatility of stock prices, VIX, and variance swap contracts. While such data can provide a good indication of market risk, they are typically limited to a short to mid-term horizon and do not provide a detailed picture for market expectations of extreme market outcomes. We overcome this limitation using options prices from an OTC derivatives consensus pricing service, provided by the data vendor IHS Markit's Totem. This service provides large financial institutions with validation of their internal pricing models. As these institutions are called on to price derivatives in a large number of markets, maturities, and extremity of outcomes, we have a uniquely rich coverage of options on global equities.

The Totem data starts in late 1997, initially at the monthly frequency and with limited coverage, but it becomes richer over time and is daily from 2018. Our empirical work is focussed on maturities from one week to ten years. The institutions submit their data at the at the end of each trading day.

We use the option prices to recover the risk neutral distribution (RND), see Appendix A for a detailed discussion on how the risk neutral distributions are constructed. Denote the price of an asset, say the S&P 500, at time t by S_t. The risk neutral densities are in terms of excess log returns. The excess log return over term $[t, t+\tau]$ (not annualized) is defined as

$$R_{t,\tau} := \ln \frac{S_{t+\tau}}{S_t} + \delta_{t,\tau}\tau - r_{t,\tau}\tau,$$

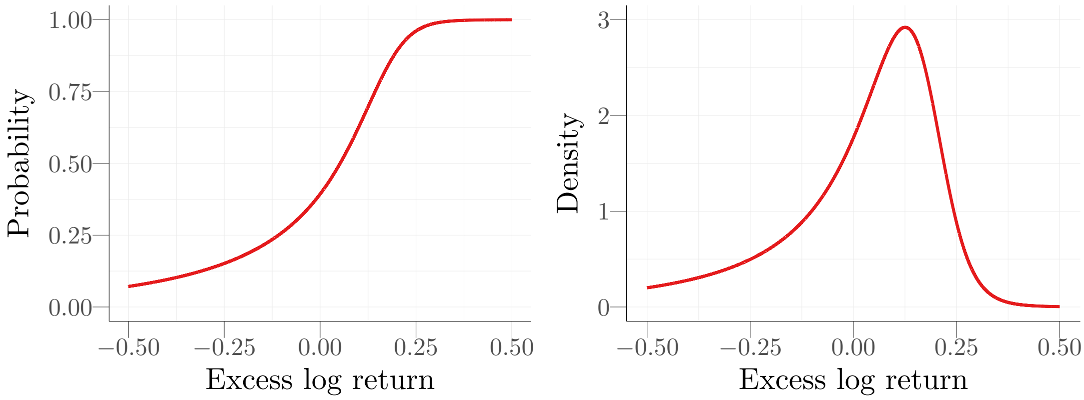
where $\delta_{t,\tau}$ is the dividend yield and $r_{t,\tau}$ is the risk-free rate for horizon τ, both continuously compounded. The risk-neutral mean of the annualised log excess return distribution is directly related to the VIX, namely

$$\mathrm{VIX}^2_{t,\tau} = -\frac{2}{\tau} E^{\mathbb{Q}}_t \left[R_{t,\tau} \right],$$

where we use $\mathbb{Q}$ to denote the risk-neutral measure.

As an example, Figure 1 displays the risk neutral pdf and cdf for excess log returns of the S&P 500 on 1 June 2020 over the year ahead.

Figure 1: S&P 500 risk neutral distribution



(a) Cumulative distribution function (b) Probability density function

These figures display the derived risk neutral probability density and cumulative distribution function from the SVI fit in equation (6) (Appendix) on 1 June 2020 with a maturity of one year. The left panel is the CDF corresponding to the risk neutral density in the right panel, derived by taking the first derivative of the European call price (generated by inserting the IVs into Black and Scholes (1973)) w.r.t. the strike price, as per Breeden and Litzenberger (1978). In the right panel, the risk neutral density function is displayed. The x-axis is in $R_{t,\tau}$. The data for the call options come from IHS Markit.

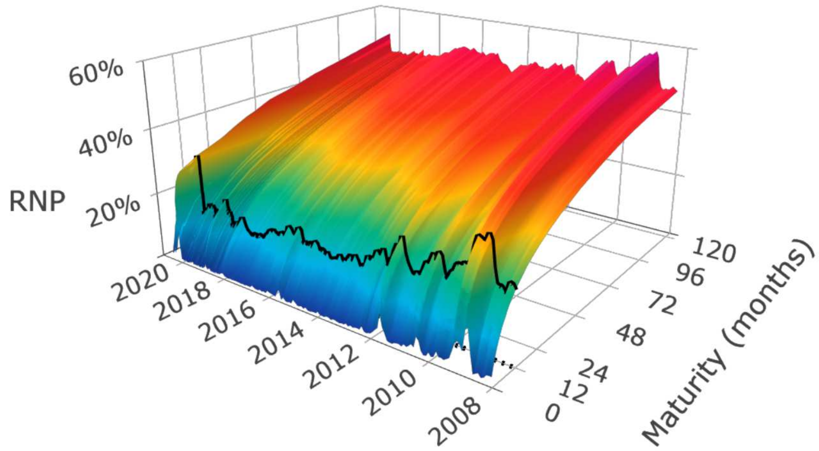
The RND takes us to the data we use for the subsequent analysis, the risk neutral probabilities (RNP) of large market movements and the quantiles for specific risk neutral probabilities.

$$F_{t,\tau}(R^*) := \mathbb{Q}\left(R_{t,\tau} \leq R^*\right) \tag{1}$$

$$F^{\leftarrow}_{t,\tau}(x) := R^*, \tag{2}$$

Here $F_{t,\tau}$ is the risk neutral distribution at time t for horizon τ and $F_{t,\tau}(R^*)$ is the RNP that the excess log return of the S&P 500 is below R^* at time $t+\tau$. $F^{\leftarrow}_{t,\tau}$ is its inverse and $F^{\leftarrow}_{t,\tau}(x)$ is the excess log return R^* such that the RNP equals x, that is the risk neutral $x\%$ quantile. Figure 2 visualises how the S&P 500 RNPs evolve over time for excess log returns smaller than $R^* = -20\%$ and $\tau \leq 120$ months, highlighting the trajectory for one year ($\tau = 12$). The figure shows that the Covid-19 crisis increased both short– and long–term risk, the curves shifting in parallel much of the time. Interestingly, while the pandemic affected short-term risk more than the 2008 crisis, its effect on long-term risk was considerably smaller. The market never expected the Covid-19 crisis to have large effects on uncertainty beyond one year. These stark differences between the great financial crisis and Covid-19 are clearest in Figure 3.

Figure 2: S&P 500 risk neutral probabilities for a price drop larger than 20%, 2008-2020



This figure shows the time-series of the term structure for risk neutral probability of a price drop of more than 20%, i.e. $F_{t,\tau}(-20\%)$. For a specific date and maturity the risk neutral density is derived by taking the second derivative wrt the call price function, as per Breeden and Litzenberger (1978). We show monthly data from 1 January 2008 to 31 May 2018 and daily data from 1 June 2018 to 31 July 2020 provided by IHS Markit's totems service. The x-axis displays the date of the term structure, the y-axis give the maturity in months and the z-axis give the risk neutral probability of a 20% drop in the S&P 500.

3 Policy announcements

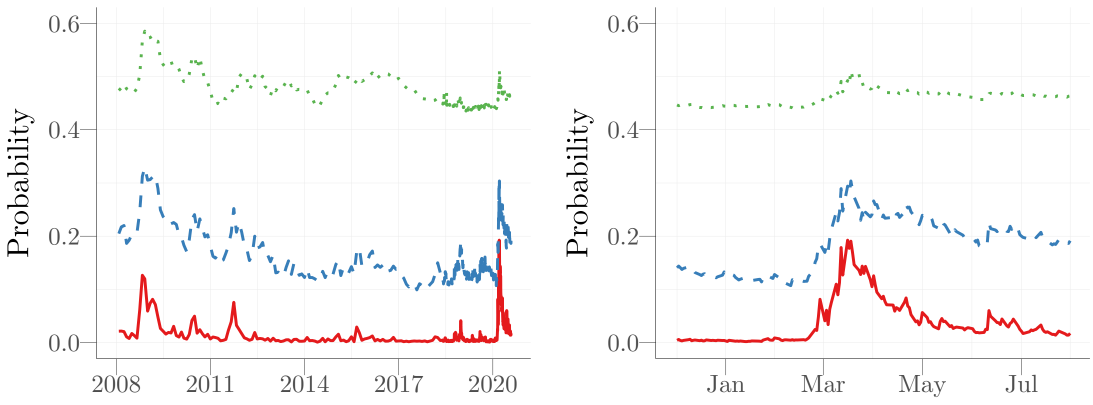
3.1 The Fed response to Covid-19

Starting in March 2020, the Fed introduced a series of actions and policies aiming to contain the economic contraction and market distress due to the Covid-19 pandemic. Here we identify the main policy announcements, facilities, and programs announced by the Fed. We collect data on economic and financial policies from the press releases section of the Fed's website.[4] In particular, we collect dates and timestamps of press releases regarding announcements and meetings spanning the 3 February 2020 to 29 July 2020.[5] We categorize the announcements and policies

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

[5]Our selection is similar to Cox et al. (2020), but we include macroprudential policies. We also add the following policies which are not included in Cox et al. (2020): four policies announced

Figure 3: S&P 500 risk neutral probabilities for a price drop larger than 20%



(a) Period since the 2008 crisis

(b) Covid-19 period

This figure shows the RN probability of a drop in the S&P 500 for various terms. The solid red line shows the variation of this probability for the one month horizon. The blue dashed line shows this for the six month horizon, and the green dotted line shows the variation in the probability for a ten year horizon. Panels (a) displays these probabilities over the period, including both the great financial crisis and the Covid-19 crisis. Panel (b) zooms into the Covid-19 sub-period. The risk neutral densities are extracted from SPX options provided by IHSMarkit's totem service.

into five main categories, "Credit to households, businesses, and public sector" (CHBP), "Foreign Exchange" (FX), "Interest rates" (IR), "Liquidity for financial intermediation" (LFI), and "Macroprudential regulations" (MPR). For the full list of the announcements used in this paper and for more details on each of them, see Table 2 in Appendix B. Altogether, there are 44 unique press releases and 51 (N) policy events subdivided into $N_{\text{CHBP}} = 16$, $N_{\text{FX}} = 5$, $N_{\text{IR}} = 5$, $N_{LFI} = 12$, $N_{\text{MPR}} = 13$. Some announcements are counted in multiple categories as they mention more than one policy.[6]

The rationale behind this five-category grouping stems from the fact that we are particularly interested in the heterogeneous impact of the crisis policies (instruments) and actions on stock market fear. Among these Covid-19 led actions, for instance, there are large scale asset purchases, new credit facilities to households and businesses, changes in leverage ratios as well as liquidity and capital buffers restrictions, and liquidity arrangements (swap lines) with other international central banks. The separation into five main categories allows us to better discern

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 don't include the policy announced at 17:45 on 23 April 2020 since it is considered information/proposal rather than an implementation.

[6]For more details about policy action and categorization, see Tables 2 in Appendix B.

the impact of each one of these unprecedented set of actions on the US financial market.

3.2 The importance of intraday shocks identification

Our empirical analysis is occasionally frustrated by the Fed announcing multiple interventions on the same day, necessitating us to identify how each intervention affects fear separately. For example, in the morning of 17 March, the Fed announced the establishment of a commercial paper funding facility (CPFF). On the same day, in the afternoon, the Fed announced establishing a primary dealer credit facility (PDCF). The next day a money market mutual fund liquidity facility (MMLF) was announced. On 19 March, facilities to support dollar swap lines with other international central banks were announced. This is just an example of the rapid succession of policy announcements during the peak of the Covid-19 crisis, calling for the need for a high-frequency approach to identify the effect of specific Fed actions separately.

Ideally, when creating the policy surprise measure, we would like to have minute-by-minute data to construct the risk neutral distribution for short intervals around the press releases. If we managed to do so, we could argue that there is no problem of omitted variable bias, e.g., a release of other information that affects both the policy decision and the risk-neutral distribution of returns or policies reacting to contemporaneous changes in the risk neutral distribution. Unfortunately, price data for medium and long-term options and a wide strike range are not available at these frequencies. The highest frequency these data are available at is daily. But daily data makes it challenging to disentangle policy from lockdown announcements, health care, pandemic, number of cases or deaths, and other economic or financial events also in the news, unobservables that occurred on any given day. These might have generated noise and volatility in financial markets, especially when the market reactions via the derivatives marks are measured at lower frequencies. Therefore, some of the Fed policy announcements are likely to have coincided with other news about the pandemic that could have also affected the financial market, especially if the announcement occurred outside of US trading hours.

Our strategy is to choose an intraday surprise variable that measures the surprise (news) of markets to the policies, and that will be the Ersatz surprise variable in an intraday event-study identification exercise. The aim is to isolate the innovation shocks to the perceived uncertainty in the US financial market due to Fed policy announcements only. We choose the innovation in the SPX (E-Mini futures if out-of-hours) in a window beginning 10 minutes prior to and ending 20 minutes after the announcement of a policy i (see Gürkaynak et al., 2005; Jarociński and Karadi, 2020).[7] In order to conduct this exercise, we adopt one minute aggregates of intraday prices of the S&P 500 and E-mini Futures collected from Bloomberg. We argue that on days with important announcements, this surprise in Fed policy (which is reduced to the innovation shock around the press release) explains a large part of the quantiles' daily variation.

Even if we had minute-by-minute return distribution functions, it still would be difficult to know the full extent of any one policy's effectiveness, even if one studied only the effectiveness on market fear, because some of the effects on fear could have been anticipated. In that sense, our findings, being 1) indirect (via SPX innovations), 2) end of day only, and 3) only corresponding to the surprise element of the policies, can be seen as lower bounds on the effectiveness of policies on fear. Indeed, a policy could be effective, and yet fear increases at the press release. For instance, the market may think. "Gosh, the Fed brings out the big guns, this must mean that affairs are much direr than I thought", or "Gosh, they are too hesitant, this will not end well."[8]

Following the policy's high-frequency identification, we aggregate the policies by category into daily variables to match the frequency of the Totem data. Price changes due to policies which are announced after 4pm are aggregated into the value of the policy variable for the following trading day because the press release time was after the pricing time of the option data.[9] So, the value of news contained in all Fed announcements belonging to category $i \in \{\text{CHBP}, \text{FX}, \text{IR}, \text{LFI}, \text{MPR}\} =: I$ which are released in the interval $(t-1, t]$, where t corresponds to the end of the

[7] If the timing of an announcement is such that the beginning or end of this 30 minute window would be outside of the trading hours of the S&P 500 (09:30 to 16:00), we instead use E-mini Futures data, if available, and use the quantiles and VIX of the *next day*. We perform robustness exercises in terms of window width and relegate them to the paper Appendix.

[8] Given the generally powerful calming effect of the Fed press release that we document, it does not seem likely to us that Fed policies were adversely affecting fears overall, with anticipative fear effects net net outdoing the positive surprises upon press release. In other words, we do not believe that markets systematically forecast detrimental and fear-inducing policies happening in the future and that this anticipated fear already created present fear. Then upon the press release, the market would have consistently found out that the Fed policies were not as fear-inducing as expected, and fear settles down. This scenario is both unlikely because surprises typically go one way and because it is not theoretically grounded in any explanatory mechanism for why adding liquidity in a liquidity crunch would lead to more fear, as opposed to less.

[9] Consequently, any price changes of the S&P 500 and E-mini changes around policies announced on weekends and holidays are aggregated into the policy variable on the next trading day.

trading day at 4 pm, is:

$$\Psi_t^i = \frac{1}{\bar{\Psi}} \sum_{\pi \in \Pi_t^i} \beta_{t,\pi}^i \left(\text{SPX}_{t,\pi+20} - \text{SPX}_{t,\pi-10} \right), \tag{3}$$
$$\text{where } \bar{\Psi} := \frac{1}{N} \sum_{t' \in T} \sum_{i \in I} \sum_{\pi \in \Pi_{t'}^i} \beta_{t,\pi}^i |\text{SPX}_{t',\pi+20}^i - \text{SPX}_{t',\pi-10}^i|$$

where $\text{SPX}_{t,\pi}$ is the price of the S&P 500 index on trading day t and minute π. Π_t^i is the set of time stamps for all policies in category i on day t and T is the set of days with Fed policy announcements. We sum over all the events of category i during $(t-1, t]$.[10] The coefficient $\beta_{t,\pi}^i$ measures the fraction of the market move at time π due to policy i being announced. We describe the construction of $\beta_{t,\pi}^i$ below. In the denominator we have $\bar{\Psi}$, the mean price impact of all the events in all categories, a normalising constant to simplify gauging the magnitudes of the effects. The set of all events in our dataset is represented by $\Pi := \cup_{i \in I, t \in T} \Pi_t^i$ with cardinality $|\Pi| = N = 51$. We find that the mean market move, the denominator in (3), is equal to \$15.31. In terms of interpretation, a term $\Psi_t^{\text{FX}} = -2$ means that on day t, in the intervals of 30 minutes immediately around any policy events of type i on that day, markets moved by $-$\$30.62 altogether.

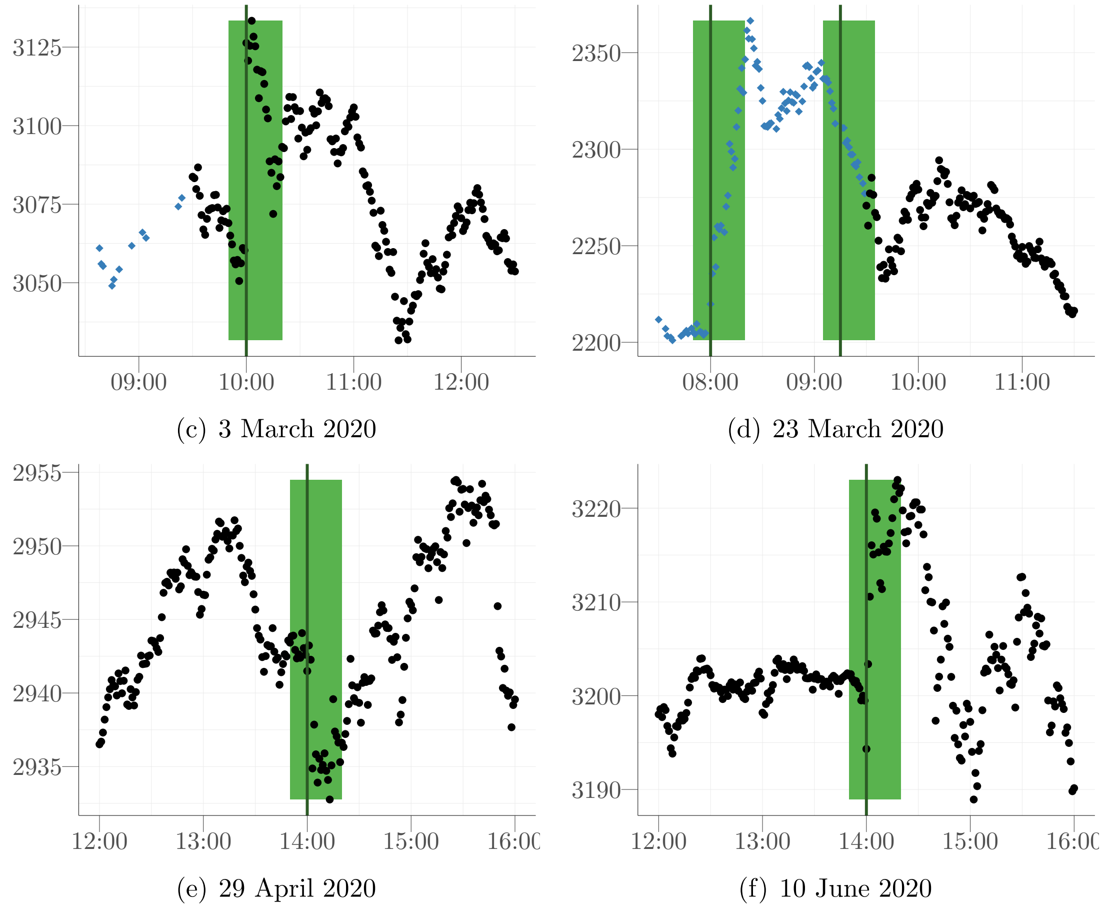
If the Fed only announced policies that fall into a single policy category, we set $\beta_{t,\pi}^i = 1$. Very occasionally, the Fed announces policies in multiple categories at the same time, and therefore the change in the S&P 500 or E-mini Futures shows the market response to this whole set of policies. We disaggregate the SPX market movement into the components corresponding to the policies announced at that press release as follows. We start by using the information from all the press releases, which only announce a single category policy. For the set of all such single category press releases Λ, we define $\beta_i > 0$ to be the mean surprise (in absolute value) in windows around pure policy i announcements. For instance, for a press release involving policies LFI and CHBP at time π on day t. We then use as weight $\beta_{t,\pi}^{\text{LFI}} := \beta_{\text{LFI}} / (\beta_{\text{LFI}} + \beta_{\text{CHBP}})$.[11]

As an illustration, consider Figure 4, which highlights the market reaction during two days with unscheduled and two days with scheduled FOMC meetings. In each

[10] Though only one day, 30/04/2020, had two press releases on same policy, CHBP, at 10:00 and 17:15.

[11] For robustness, we have also equally allocated the market move to each policy announced. For example, the Fed released two press statements at 8 am 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 more pronounced in the relative beta approach.

panel, the black dots show the 1 minute aggregates of S&P 500 prices and the blue dots of 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.



(c) 3 March 2020

(d) 23 March 2020

(e) 29 April 2020

(f) 10 June 2020

Figure 4: Change in the S&P 500 around announcements of the Federal Reserve. These figures illustrate the intraday changes in the S&P 500 index or E-mini Futures around Fed announcements. For the intraday level of the S&P 500, we show the 1 minute aggregates of the S&P 500 prices (black dots) obtained from Bloomberg. Outside trading hours, 1 minute aggregates of the E-mini Futures prices (blue dots) are used. To highlight the reaction of the S&P 500 to the Fed announcements, the event window starts 10 minutes prior to and ending 20 minutes after the announcement is displayed in green. The four events are: (a) unscheduled FOMC meeting at 10 am on 3 March (IR), (b) unscheduled FOMC meeting at 8 am (LFI, unlimited purchases, "all it takes" moment), and two press releases regarding CHBP at 8 am as well as regarding MPR at 9:15 am on 23 March, (c) scheduled FOMC meeting at 2 pm on 29 April (IR and LFI), and (d) scheduled FOMC meeting at 2 pm on 10 June (IR and LFI). The timestamps of the announcements are retrieved from the website of the Federal Reserve: https://www.federalreserve.gov/newsevents/pressreleases.htm.

Clearly, the stimuli announced after the unscheduled meetings on 3 March at 10 am (panel (a)) and on 23 March at 8 am (panel (b)), as well as after the scheduled meeting on 10 June at 2 pm (panel (d)) were well received by the market. In contrast, the statement following the scheduled meeting on 29 April at 2 pm (panel (c)) could not meet the expectations. The value of the news contained in the announcements on 3 March, which is classified as IR, for example, is calculated as $\Psi^{IR}_{3\text{ March}} = \$24.27/\$15.31 = 1.59$, because the S&P 500 changed by \$24.27 from \$3068.97 at 09:50 am to \$3093.24 at 10:20 am, and the absolute value of the mean market move of all events in the sample is \$15.31, and there has been no other announcement during the interval $(t-1, t]$.

4 The impact of Fed policy interventions on market fear

In order to investigate the effect of Fed policy interventions on market fear of loss in financial markets, we estimate regressions of the following form:

$$\Delta F^{a\leftarrow}_{t,\tau}(x) = \alpha^a_\tau(x) + \sum_{i\in I} \gamma^{i,a}_\tau(x)\Psi^i_t + \sum_{o=1}^{O} \upsilon^a_{o,\tau}(x)C_{t,o} + \epsilon^a_{t,\tau}(x) \qquad ; t \in T, \tag{4}$$

where $\Delta F^{a\leftarrow}_{t,\tau}(x)$ is the change from $t-1$ to t in the $x\%$ quantile of log excess returns on asset a for maturity τ, where t corresponds to the end of the trading day at 4 pm. $\alpha^a_\tau(x)$ is the constant in the regression with asset a, maturity τ, and RNP x. Ψ^i_t is the policy variable as defined in (3) on day t and in category i. Finally, $C_{t,o}$ is the set of control variables, including the change in the log of the 7-day rolling mean of new Covid-19 cases and the Bloomberg economic surprise index (ECSU). Daily data on the cumulative number of Covid-19 confirmed cases in the United States is collected from the Johns Hopkins Coronavirus Resource Center.[12] We calculate the daily number of new confirmed cases and the rolling mean over the past seven days (see Figure 10 in Appendix B), and include it as control in order to take into account any changes in the RND due to changes in Covid-19 cases. ECSU measures the difference between the actual announcement value and median survey expectations for different macro announcement types.[13] The sample period for the regressions is 3 February 2020 to 31 July 2020.

[12]The data can be downloaded from `https://github.com/CSSEGISandData/COVID-19` and visualized at `https://coronavirus.jhu.edu/map.html`.

[13]It is collected from Bloomberg, specifically from the Bloomberg economic surprise monitor, and it includes data for the following set of macro variables: nonfarm payroll, housing starts, new home sales, existing home sales, retail sales, initial jobless claims, unemployment rate, business inventories, factory orders, and construction spending data releases.

We also look at the effect of the policies on the VIX, by estimating regressions of the form:

$$\Delta\text{VIX}^a_{t,\tau} = \check{\alpha}^a_\tau + \sum_{i \in I} \check{\gamma}^{i,a}_\tau \Psi^i_t + \sum_{o=1}^{O} \check{\upsilon}^a_{o,\tau} C_{t,o} + \check{\epsilon}^a_{t,\tau} \qquad ; t \in T \tag{5}$$

Here, $\Delta\text{VIX}^a_{t,\tau}$ is the change in the VIX from $t-1$ to t of asset a for maturity τ and the remaining variables are defined as above.

The effect of the different policy categories is given by the coefficients $\gamma^{i,a}_\tau(x)$ and $\check{\gamma}^{i,a}_\tau$ respectively. They show the change of the excess log return for probability x, $F^{a\leftarrow}_{t,\tau}(x)$, or of $\text{VIX}^a_{t,\tau}$, associated with a policy in category i which increases the S&P 500 by an amount equal to the average change in the 30 minutes around the press release, \$15.31.

4.1 Effect of Fed policies on the S&P 500

To understand the impact of the different policy categories implemented by the Fed as a reaction to the Covid-19 pandemic on market risk, we first look at their effect on excess log returns for different tail probabilities and VIXs of the S&P 500.

Table 1 shows an example of the coefficients $\gamma^{i,a}_\tau(x)$ and $\check{\gamma}^{i,a}_\tau$ of estimated equation (4) for $x \in \{10\%, 90\%\}$ and (5) for $\tau \in \{1, 12\}$ (in months). For instance, a policy of the Fed in the category FX which increases the S&P 500 by an amount equal to the average change of all policies in the 30 minutes window, equal to \$15.31, is associated with an 11.2% increase (2.9% reduction) of the excess log return that the S&P 500 will take over the next 12 months with probability 10% (90%). In other words, a policy in this category which positively surprises the market shifting the risk neutral quantile for probability 10% to the right, reducing the losses at the 10% level by 11.2% over the next year, and for probability 90% to the left by 2.9% over the next year, making both tails thinner.

Table 1: Example Regression

	Dependent variable:						
	$\Delta F^{a\leftarrow}_{t,\tau}(x)$					$\Delta VIX^{a}_{t,\tau}$	
	$x = 10\%$		$x = 90\%$				
	$\tau = 1$	$\tau = 12$	$\tau = 1$	$\tau = 12$		$\tau = 1$	$\tau = 12$
	(1)	(2)	(3)	(4)		(5)	(6)
$\gamma_\tau^{CHBP,a}(x)$	0.004*	0.001	0	-0.001	$\tilde{\gamma}_\tau^{CHBP,a}$	-0.006	-0.002
	(0.002)	(0.004)	(0.001)	(0.001)		(0.004)	(0.002)
$\gamma_\tau^{FX,a}(x)$	0.049***	0.112***	-0.026***	-0.029***	$\tilde{\gamma}_\tau^{FX,a}$	-0.088***	-0.042***
	(0.011)	(0.009)	(0.005)	(0.005)		(0.022)	(0.005)
$\gamma_\tau^{IR,a}(x)$	-0.003	-0.004	0	0.002	$\tilde{\gamma}_\tau^{IR,a}$	0	-0.001
	(0.013)	(0.009)	(0.006)	(0.005)		(0.026)	(0.005)
$\gamma_\tau^{LFI,a}(x)$	0.024***	0.069***	-0.016***	-0.022***	$\tilde{\gamma}_\tau^{LFI,a}$	-0.045***	-0.026***
	(0.007)	(0.012)	(0.004)	(0.005)		(0.016)	(0.006)
$\gamma_\tau^{MPR,a}(x)$	0.02***	0.045***	-0.013***	-0.017***	$\tilde{\gamma}_\tau^{MPR,a}$	-0.036**	-0.018***
	(0.007)	(0.01)	(0.004)	(0.004)		(0.014)	(0.006)
Controls	Yes	Yes	Yes	Yes		Yes	Yes
Observations	124	124	124	124		124	124
R^2	0.212	0.376	0.191	0.243		0.168	0.304
Adjusted R^2	0.164	0.338	0.142	0.197		0.118	0.262

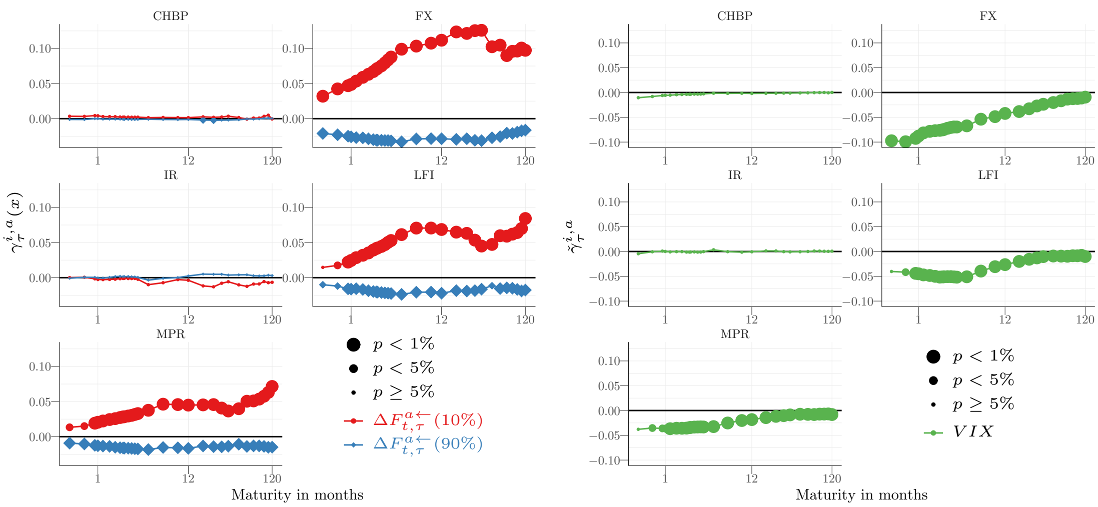
Notes: *p<0.1; **p<0.05; ***p<0.01. Heteroskedasticity and autocorrelation robust standard errors based on Newey and West (1987) are reported in parentheses. Sample period: daily data from 3 February 2020 to 31 July 2020. $\gamma_\tau^{i,a}(x)$ and $\tilde{\gamma}_\tau^{i,a}$ are the coefficients from running equations (4) and (5). The dependent variable $\Delta F^{a\leftarrow}_{t,\tau}(x)$ for regressions in columns (1) to (4) is the change in the excess log return for risk neutral probabilities $x = 10\%$ and $x = 90\%$, and for maturities $\tau = 1$ and $\tau = 12$ months (indicated by the column names), while the dependent variable $\Delta \text{VIX}^{a}_{t,\tau}$ for regressions in columns (5) and (6) is the change in the VIX for maturities $\tau = 1$ and $\tau = 12$ months (indicated by the column names). Each regression contains a constant and the two controls as specified above.

While these coefficients can shed light on the effect of Fed policies, there are a few caveats. *First*, they may underestimate the effect of the policies since they only capture the surprise component of the policy as captured by the SPX. If a policy has been expected, it could well have had a large effect on stock market risk, but, at the time of the press release, this effect has already been incorporated into the return distribution. *Second,* while the SPX innovations around the press release capture the surprise component for the SPX, this surprise component does capture all unexpected parts of the policy, but only those that relate to the SPX index level. *Third*, the press releases could have led the market to update its belief on the *current* state of the economy, which is not observable, typically referred to as an information effect. Also, a policy can be associated with a fatter tail not because the policy is ineffective or even contributes to uncertainty, but because the market has expected an even more drastic policy. All of these imply the coefficients should not be interpreted as measuring the overall total efficiency of the Fed policies. However, they do establish a causal link from Fed policy announcements to market fear.

While Fed policies in the categories CHBP, LFI, MPR, and FX similarly reduce market risk by making both tails thinner (although weakly statistically significant in terms of CHBP), the directionality of interest rate policies is in the opposite direction. Policies in the category IR which are more expansionary than expected make the tails of the risk neutral distribution sligtly fatter, although this effect is not statistically significant. Policies within the FX category are the ones found to strongly impact US market fear at all horizons. This is not surprising since the Fed's swap lines programs (both expansions of the existing ones and also the creation of new programs) have been among one of the main internationally coordinated economic policy responses during the Covid-19 crisis (see Bahaj and Reis, 2020a).

Figure 5 further highlights these results for additional maturities ranging from $\tau = 0.5$ months to $\tau = 120$ months. The results are similar across the term structure. In particular, the quantile regression term structures, whether at 10% or 90%, do not show any sign reversals. This result is reminiscent of results one finds in lower dimensional Markov models where an increase in one variate entails an increase in the endogenous variate at all horizons. The market does not expect, for instance, that an unexpected liquidity provision to market makers at first removes some market downside risk, say through more liquid and efficient market making as well as through a lower probability of dealers becoming illiquid or insolvent, but that this liquidity support also entices dealers to take larger or riskier gambles that may lead over time to increased longer term uncertainty to the markets. On the contrary, markets expect the lower tail to thin even more at the longer term horizon than at the short term horizon. Surprisingly, the two IR cuts during unannounced FOMC meetings on 3 March and 15 March did not affect the quantiles by much, even though they seemed to have surprised the equity market. And yet, we find that the effect on the quantiles was negligible.

Next, Figure 6 shows the impact of the different policy categories $\gamma_{\tau}^{i,a}(x)$ for $\tau = 12$ months across the RND for $x \in [5\%, 95\%]$. The blue lines show the magnitude of coefficient $\gamma_{\tau}^{i,a}(x)$, surrounded by the 95% confidence interval. The lines show that the results are not specific to the chosen tail quantiles, but also the more extreme and less extreme quantiles.



(a) Impact on $\Delta F_{t,\tau}^{a\leftarrow}(x)$

(b) Impact on ΔVIX

Figure 5: These figures show the impact of different policy categories on the risk neutral distribution for different terms τ (x-axis). The two panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% (panel (a)), and the VIX (panel (b)). In panel (a), the blue diamonds are the announcement effects $\gamma_{\tau}^{i,a}(x)$ for the upper tail and the red dots for the lower tail of the risk neutral distribution from running equation (4). The green dots in panel (b) are the announcements effects $\tilde{\gamma}_{\tau}^{i,a}$ from running equation (5). The sizes of the dots give the different levels of significance, $\cdot$ p≥0.05; • p<0.05; ● p<0.01, calculated using robust standard errors based on Newey and West (1987).

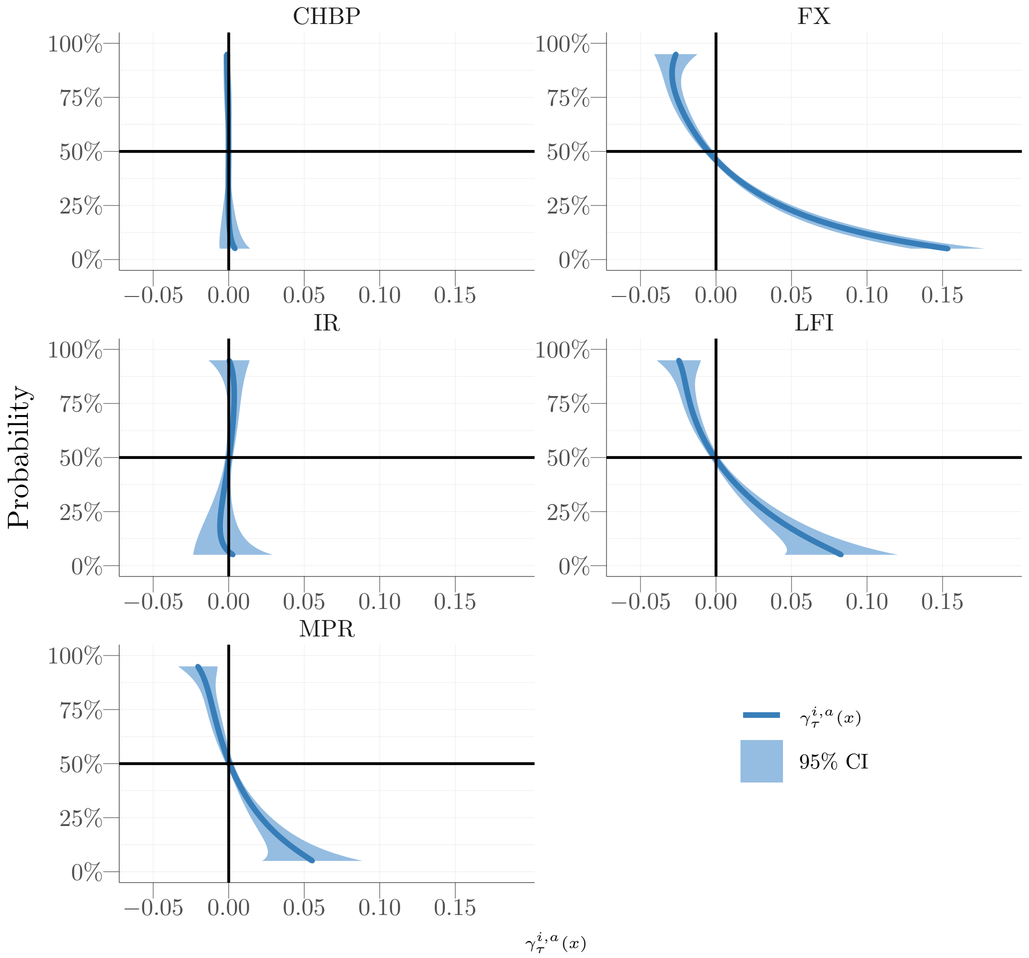


Figure 6: Impact of announcements of the Fed on all quantiles (τ=12 months). These figures show the impact of different policy categories on the risk neutral distribution for maturity $\tau = 12$ months. The x-axis corresponds to the magnitude of the coefficients $\gamma_\tau^{i,a}(x)$ estimated in (4). The y-axis indicates at which quantile level of the risk neutral distribution the reaction is measured. The 10% and 90% refer to the red and blue dots at the 12 month marks in corresponding panels in Figure 5. The confidence intervals are constructed using robust standard errors based on Newey and West (1987).

4.2 Robustness checks

We check the robustness of the results presented above by controlling for other variables in addition to the set of controls, $C_{t,o}$, which above includes the 7-day rolling mean of new Covid-19 cases, the Bloomberg Economic Surprise Index. 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. What this check shows is that our results are robust to the scheduled FOMC meetings; 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.[14]

Next, 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 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 3 in Appendix D, and the regressions results reported in Figure 12 in Appendix D. Once again, our results appear to be robust and are not affected by fiscal policy responses.

We also control for the increased buying of options in tech stocks, especially towards the end of our sample period. The option volume on the shares of the big technological companies, Alphabet (GOOGL), Amazon (AMZN), Facebook (FB), Apple (AAPL), and Microsoft (MSFT), is collected from Bloomberg. The corresponding results are shown in Figure 13 in Appendix D and are robust.

We also repeat the analysis checking the impact of Fed announcements with respect to different choices of the intraday window sizes around the announcements' timestamps, namely 15 minutes (-5, +10), 30 minutes (-10, +20) (the default window size we adopt in the main analyses of the paper), 60 minutes (-15, +45) and 90 minutes (-30, +60). We report the results in Figure 14 in the Appendix. We observe that the impact of the policies is, overall, robust to the choice of the window length around the policy announcements (Boguth et al. (2019)).

Finally, we redo our analysis by only leaving press releases in one of the five

[14] Nakamura and Steinsson (2018) identify news about monetary policy as the cause of unexpected changes in interest rates in a 30-minute window around scheduled Fed announcement.

categories if the release was about one single policy and was the only press release that day. All the joint releases are added to a sixth policy category. The results as to the effectiveness of FX, LFI, and MPR remain the same.

5 Individual US stocks and international market indices

We then investigate the impact of Fed policy interventions on market fear captured by some of the largest individual stocks in the S&P 500. We run the same equations as (4) and (5), where now a is indexed for one of the selected stocks in our sample collected from the Totem service of IHS Markit, with $a \in$ (AAL, ABBV, UNH, JNJ, AAPL, PG, JPM, AMZN, GM, XOM, NFLX, DIS, GOOG, TWTR, and ATT). The selection of stocks is motivated by a) option data availability and b) the ability to study the heterogeneity of policy impacts across US industries.

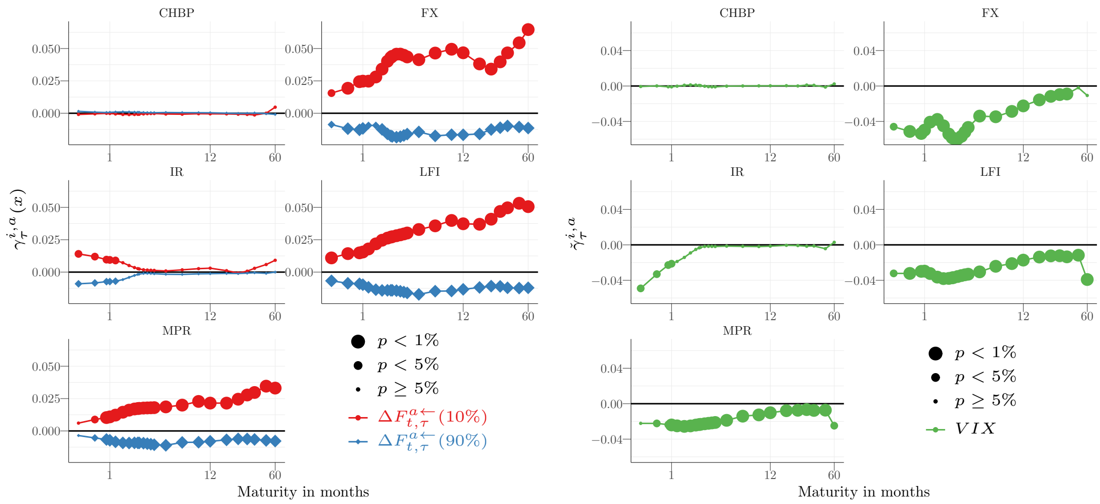
In Figure 7, we show an example of the impact of the Fed policies on US individual stocks risk with respect to Amazon (consumer discretionary). The results for Amazon mostly echo our findings for the S&P 500 index, FX, LFI, and MPR policies reducing the probability of extreme price movements at any maturity across our term structure, making both tails thinner, and also reducing future expected price volatility as measured by the VIX. Policies within the IR category only appear to have an impact on the very short horizon of the risk term structure. The CHBP policies category does not show a significant impact on Amazon fear. These findings are overall confirmed for other individual stocks, the exception being an even weaker impact of IR policies. We show the results for JPMorgan Chase (financials) and Apple (information technology) in the paper Appendix E, Figure 15 and Figure 16, respectively.[15]

We repeat the analysis, this time changing our proxy for the financial market to be the US RUSSELL 2000 Index. We report the results in Figure 17 in Appendix E. They confirm that our results are robust and similar to the ones obtained with either the S&P 500 as a market proxy or with individual stocks. Thus, the impact of Fed policies on the US market fear does not appear to be dependent on the market proxy we adopt.

We also repeat the analysis by looking at S&P 500 sectorial indices, the energy, and financial sectors. We do not find any significant impact with respect to the LFI and MPR policies. However, we confirm a strong impact of the FX policies in

[15] The whole set of results with respect to the other in list a is available from the authors upon request.

Figure 7: Impact of announcements of the Fed on Amazon



(a) Impact on $\Delta F^{a\leftarrow}_{t,\tau}(x)$ (b) Impact on ΔVIX

These figures show the impact of different policy categories on the risk neutral distribution of Amazon (AMZN) for different terms τ (x-axis). The two panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% (panel (a)), and the VIX (panel (b)). In panel (a), the blue diamonds are the announcement effects $\gamma^{i,a}_{\tau}(x)$ for the upper tail and the red dots for the lower tail of the risk neutral distribution from running equation (4), with a equal to AMZN. The green dots in panel (b) are the announcements effects $\tilde{\gamma}^{i,a}_{\tau}$ from running equation (5), with a equal to AMZN. 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).

reducing both the probability of extreme outcomes and reducing the VIX for these indices. We report the results in Figure 18 and 19 in Appendix E with respect to the financial and energy sectors, respectively.

6 International Spillovers of Fed Swap Lines

We further investigate the FX policy category, corresponding to swap line agreements between the Fed and a set of non-US central banks and the FIMA Repo Facility. The Fed's FX policies significantly impact US stock market fear at any horizons as well as on fear for US individual stocks. We now check whether such FX policies and swap line agreements also had a spillover effect on international stock markets during the Covid-19 pandemic. In fact, the main purpose of the US dollar swap lines is to help funding pressures for international investors borrowing in US dollars. For a detailed description of the swap lines mechanism, agreements and countries targeted, and a short timeline of events, see Bahaj and Reis (2020a).

We study this possible international financial market interconnectedness by repeating the main analysis of our paper with respect to several financial market indices for which we have good data coverage. In particular, these are the DAX 30 for Germany, the FTSE 100 for the UK, the NIKKEI 225 for Japan, and the KOSPI 200 for Korea. We check whether the swap lines announcements show an impact on the fear of extreme market outcomes (as measured by risk neutral quantiles for these indices) and market volatility (as measured by VIX measures) in these financial markets.

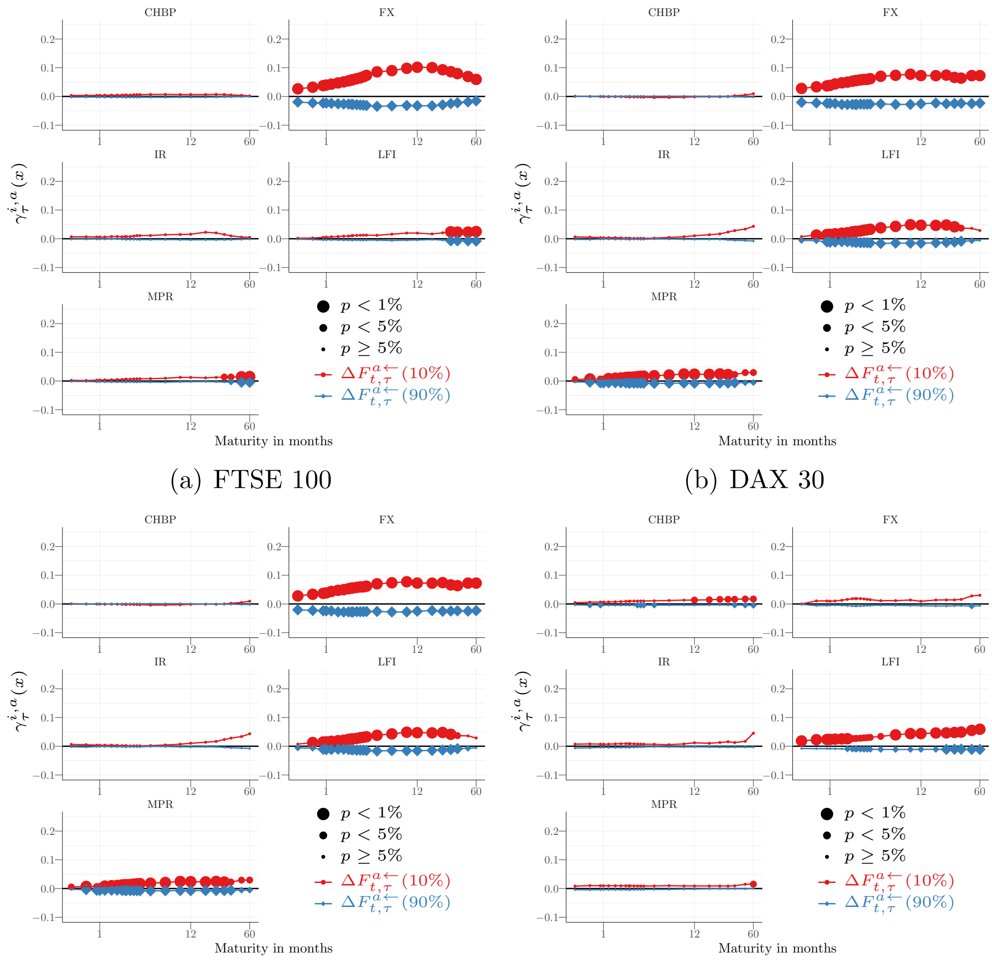
US swap line announcements occurred both when other countries' financial markets were open and when they were closed. We check such international spillover effect via the swap lines channel on the other economies' market fear on the same day if the markets elsewhere were open, otherwise on the following day. We run the same equations (4) and (5), where now a is indexed for one of the selected stock market indices, with $a \in$ (DAX30, FTSE100, NIKKEI225, KOSPI200). We adjust the policies to keep the cutoff at 4 pm in the country where the index is traded, taking into account the time zone of the other countries, namely FTSE100 (+5), DAX30 (+6), NIKKEI225 (+14), and KOSPI200 (+14).[16] We also include the other policies in the CHBP, IR, LFI, and MPR categories as to control for any other possible spillovers, not due to the swap line agreements and the daily new Covid-19 cases in each country (see Figure 10 in Appendix for the national Covid-19 cases).

In Figure 8, we observe a strong spillover effect from the US to other financial markets: UK, Germany, and Japan via swap line policies. For the UK, the FX policy category is the only Fed policy category that generates a significant spillover effect. In contrast, we do not find a spillover effect via swap lines for the Korean market. Some countries were already part of the swap line agreements with the US, these being expanded during the Covid-19 period, other countries joined the agreements for the first time. This may be a possible reason for the different impacts of the programs across countries (see Bahaj and Reis, 2020a). In our case, among the countries selected for this exercise, this can be a reason for the absence of spillover effects for the Korean market. Korea received access to US swap lines only in a second phase of the Covid-19 crisis from 19 March onwards.

We, therefore, split the swap line events into two groups. First, expansions of standing swap line agreements, as in the case of the ECB, Bank of England, and Bank of Japan on 15 and 20 March 2020. Second, new swap line agreements with countries such as Korea on 19 March and 29 July 2020, as well as the FIMA Repo

[16] As an example, the FOMC meeting on 29 April at 14:00 ET dated as 29 April for the S&P 500 quantiles will be dated as 30 April for the FTSE regression.

Figure 8: US swap lines and international spillovers



(a) FTSE 100 (b) DAX 30

(c) NIKKEI 225 (d) KOSPI 200

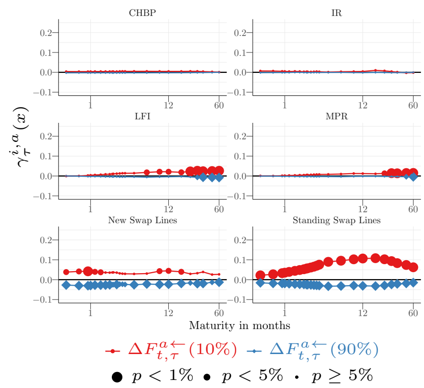
These figures show the impact of different policy categories on the risk neutral distribution for different terms τ (x-axis). The four panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% with respect to four international stock market indices, namely FTSE 100 for the UK, DAX 30 for Germany, NIKKEI 225 for Japan and KOSPI 200 for Korea. The dots are the $\gamma_{j,\tau}^{i,a}$ and $\check{\gamma}_{\tau}^{i,a}$ from running equation (4). 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).

Facility on 31 March 2020.[17] These two groups allow us to measure the effect on fear in the FTSE from an update of the standing swap line facilities and the

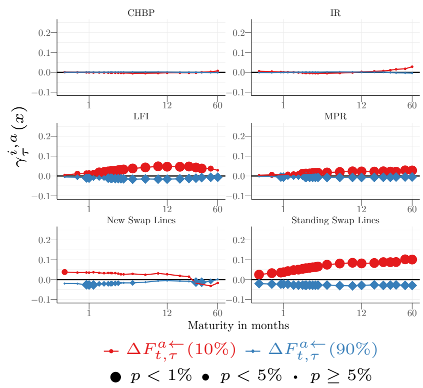
[17]On 19 March, the Fed created a new swap line arrangements with nine other countries: Australia, Brazil, Mexico, Denmark, Korea, Norway, New Zealand, Singapore, and Sweden.

spillover effect on the FTSE by adding new countries (e.g., Korea) to the swap line agreement. We present the regression results in Figure 9.

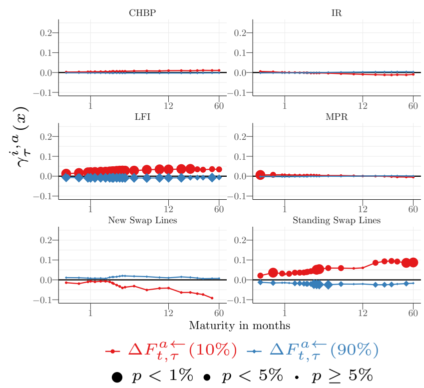
Figure 9: US swap lines and international spillovers: New vs Standing



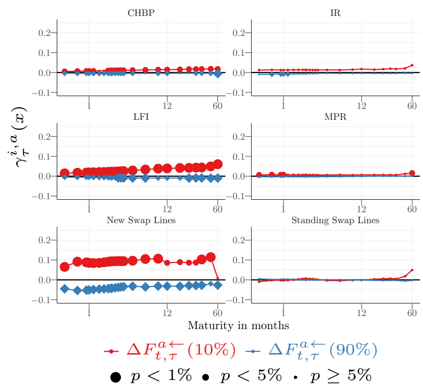
(a) FTSE 100



(b) DAX 30



(c) NIKKEI 225



(d) KOSPI 200

These figures show the impact of different policy categories on the risk neutral distribution for different terms τ (x-axis). The FX policy category has here been split into standing swap lines announcements (15 and 20 March 2020) and new swap lines announcements (19th and 31 March 2020, and 29 July 2020). The four panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% with respect to four international stock market indices, namely FTSE 100 for the UK, DAX 30 for Germany, NIKKEI 225 for Japan, and KOSPI 200 for Korea. The dots are the $\gamma^{i,a}_{j,\tau}$ and $\check{\gamma}^{i,a}_{\tau}$ from running equation (4). 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).

We indeed uncover a strong direct effect of the introduction of the Korean swap line on the fear in the Korean financial market, with all the significance now placed on the new swap line group. On the other hand, for other financial markets such as the UK and Germany, we confirm spillover effects driven by the expansions of standing swap line agreements with the US. Overall, we corroborate the importance of swap line agreements not only with respect to US market fear but also in a broader international context. The activation of swap lines was the first major coordinated economic policy response to the Covid-19 crisis. It affected the US economy, but also other countries internationally. The effect depended on whether swap lines were already in place or whether they were part of the newly created agreements. The strong effects we find are consistent with a risk premium channel. It speaks to the dominant role of the USD as an international funding currency and confirms it as an important global risk factor (e.g. Bruno and Shin, 2015).

7 Conclusion

This paper studies the impact of the Federal Reserve's policy interventions on market fear in the US stock market. The analysis is based on risk term structures 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 Federal Reserve System announcements to identify the importance of individual policy actions. We then classify these actions into five broad policy categories, namely credit, market liquidity, interest rate policies, foreign exchange policies and macroprudential policies, on study their effects on the risk term structure.

We find that those Federal Reserve's Covid-19 policies directed towards the money markets have impacted the market's fear at all horizons, typically reducing risk. The reduction in market fears of loss is strong at all horizons, while the reduction in market fear of variability is decreasing as the horizon recedes.

We find the Federal Reserve's swap line policies to have had the strongest effects, both in the US and internationally. This finding is consistent with the US dollar as a global risk factor (Bruno and Shin, 2015) due to its dominant role as funding currency in the international financial system. In fact, new swap lines had the strongest effects on the countries benefiting from them, while policies affirming existing swap lines had the strongest effects on the countries with pre-existing swap lines in place.

Liquidity support to financial institutions and macro-prudential policies also had strong effects. Those policies geared towards the broader economy, such as credit to households, businesses and public institutions, or reductions in the bands for Fed fund rates, had negligible effects on either of the market fears. These findings also hold for individual stocks, sectors or different market indices, and seem to be very robust.

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A From IVs to Risk Neutral Distributions (RNDs)

In this section we describe how we take implied volatilies from option, fit a curve through the implied volatities and subsequantly 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:

$$w_{\text{imp}}^{\text{SVI}}(x) = a + b(\rho(x - m) + \sqrt{(x - m)^2\sigma^2}) \tag{6}$$

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 $w_{\text{imp}}^{\text{SVI}}(x) \geq 0$ for all $x \in R$. This ensures that the minimum of the function $w_{\text{imp}}^{\text{SVI}}(x)$ 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 BS1973 model for a fine grid of strike prices $\underline{K} < K_2 < ... < \overline{K}$. The payoff at maturity of an 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 [formula here] 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:[18]

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

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

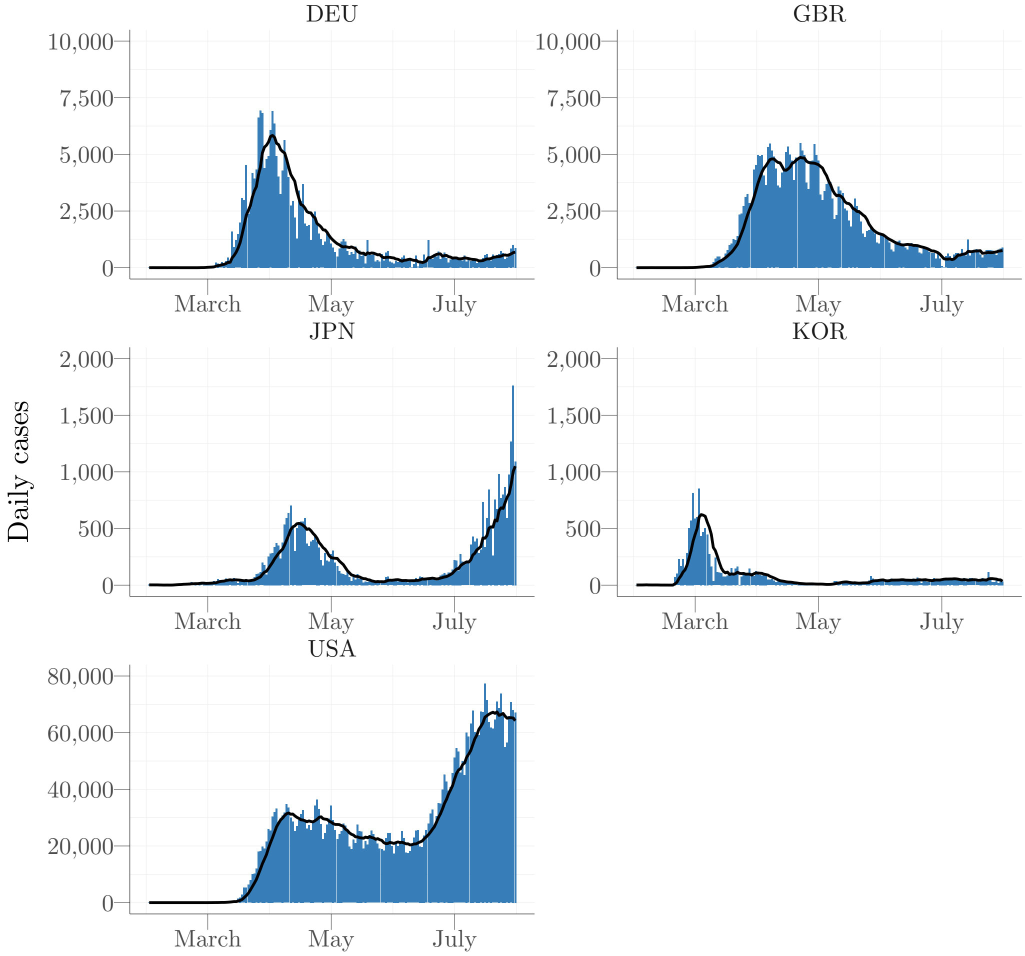
$$\begin{aligned}\pi_t(K) &\approx \frac{1}{\triangle}[\Pi_t(K+\frac{\triangle}{2}) - \Pi_t(K-\frac{\triangle}{2})] \\ &\approx \exp^{-r_{t,\tau}\tau}\frac{1}{\triangle^2}[\mathbb{C}(t,K+\triangle,\tau) + \mathbb{C}(t,K-\triangle,\tau) - 2\mathbb{C}(t,K,\tau)].\end{aligned}$$

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

[18] 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.

B Covid-19 data

Figure 10: Daily new Covid-19 cases



This figure shows the new Covid-19 cases per day and the 7-day rolling average for the Germany, the UK, Japan, South Korea, and the United States.

C Federal Reserve announcements

Table 2: Federal Reserve announcements March-July 2020

Date and Time Stamp	Category	Policy Description	△ SPX
03/03/2020 10:00	IR	FOMC lowered the target range for the federal funds rate by 1/2 percentage point, to 1 to 1-1/4 percent.	24.27
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.	-19.09
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.	-13.96
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.	-12.84
15/03/2020 17:00	FX	The Fed announced measures related to the U.S. dollar liquidity swap line arrangements.	-10.11
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.	31.41
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.	-10.79 -8.96
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.	23.31
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.	-13.22 -10.98
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.	77.28
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.	64.22

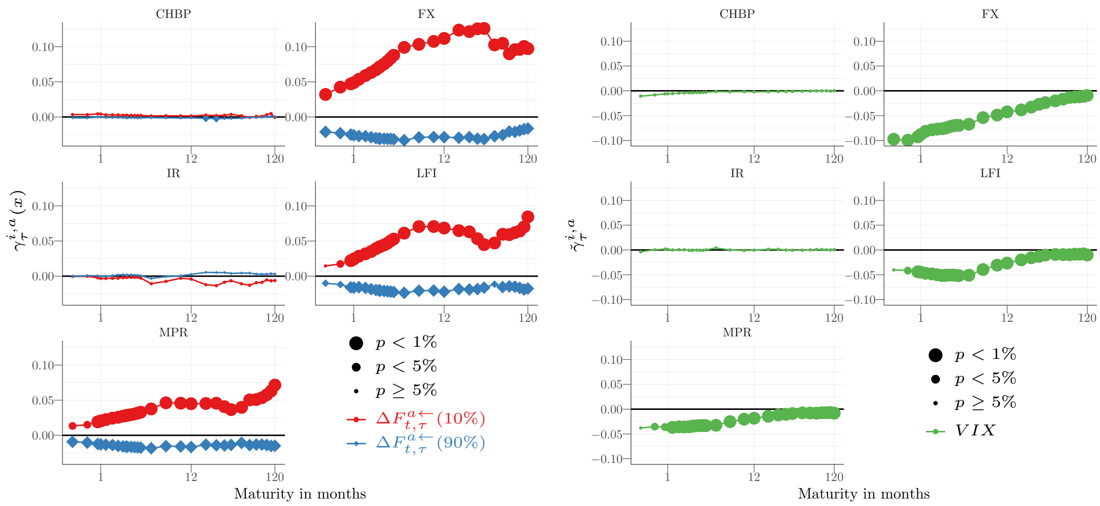
Date and Time Stamp	Category	Policy Description	△ SPX
23/03/2020 09:15	MPR	The Fed announced a change to automatic restrictions associated with a firm's "total loss absorbing capacity," or TLAC, buffer requirements, to support the U.S. economy and allow banks to continue lending to households and businesses.	-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.	0.21
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 requires 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).	-10.88
07/04/2020 15:00	MPR	Issued a revised interagency statement encouraging financial institutions to work constructively with borrowers affected by COVID-19.	-4.14
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.	4.54
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.	-3.93
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	-2.87

Date and Time Stamp	Category	Policy Description	△ SPX
30/04/2020 10:00	CHBP	The Fed announced an expansion with respect to loan options available to businesses.	8.08
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	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.	-11.51
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).	1.48
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.	10.12
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.	11.53
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.	8.43
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.	38.45
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.	-5.93
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.	7.9
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.	-2.46 -2.04
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.	0.51
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.	0.38
29/07/2020 14:00	FX	The Open Market Desk will continue to offer large-scale overnight and term repurchase agreement operations.	0.27

Notes: This table reports the Federal Reserve (Fed) announcements that we collect between March and July 2020. 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. The second column reports the category of the policy, namely "Credit to households, businesses, and public sector" (CHBP), "Forex" (FX), "Interest rate" (IR), "Liquidity for financial intermediation" (LFI), and "Macroprudential regulations" (MPR). The third column briefly describes the policy. For a more extensive description of the policy and more details see the Federal Reserve website above. In the last column the intradaily S&P 500 changes around the 30 minutes policy announcement window is reported.

D Additional results and robustness checks

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



(a) Impact on $\Delta F_{t,\tau}^{a\leftarrow}(x)$ (b) Impact on ΔVIX

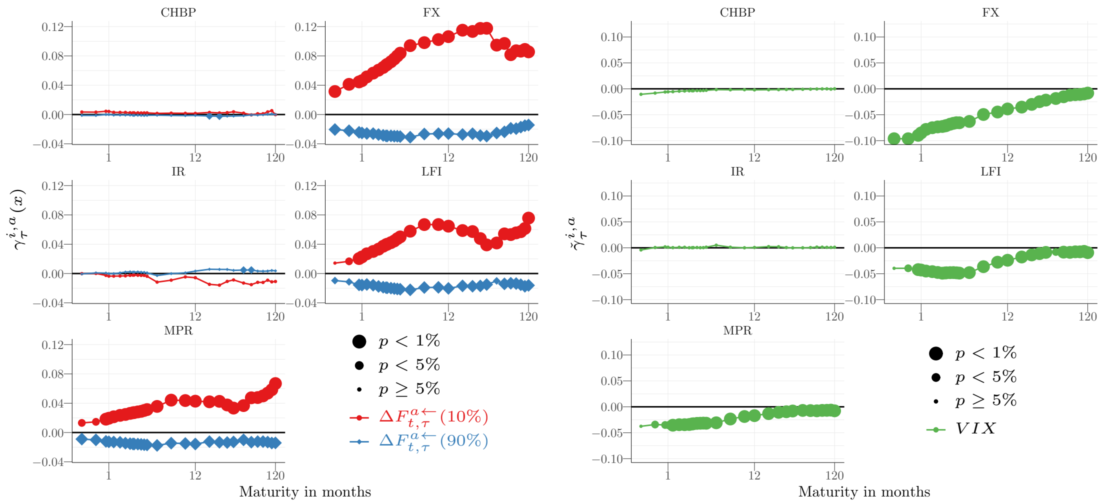
These figures show the impact of different policy categories on the risk neutral distribution for different terms τ (x-axis). The two panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% (panel (a)), and the VIX (panel (b)). The dots are the $\gamma_{j,\tau}^{i,a}$ and $\breve{\gamma}_{\tau}^{i,a}$ from running equations (4) and (5), where $C_{t,o}$ additionally includes a dummy for days with (scheduled and unscheduled) FOMC meetings. 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).

Table 3: Fiscal policy responses to Covid-19

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

Notes: This table reports the the key fiscal policy responses in the US to the Covid-19 pandemic. 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.

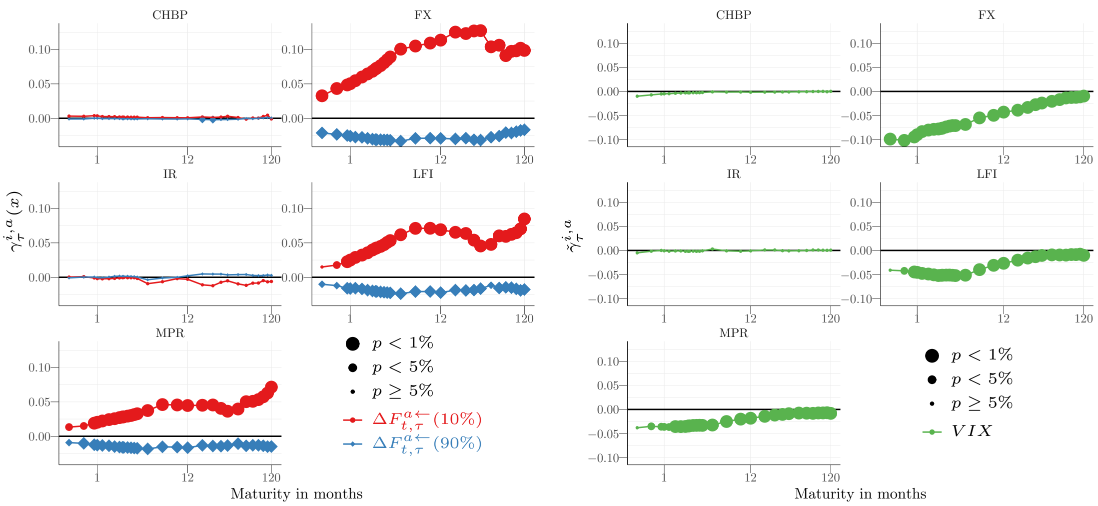
Figure 12: Impact of announcements of the Fed, controlling for fiscal policies



(a) Impact on $\Delta F_{t,\tau}^{a\leftarrow}(x)$ (b) Impact on ΔVIX

These figures show the impact of different policy categories on the risk neutral distribution for different terms τ (x-axis). The two panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% (panel (a)), and the VIX (panel (b)). The dots are the $\gamma_{j,\tau}^{i,a}$ and $\check{\gamma}_{\tau}^{i,a}$ from running equations (4) and (5), where $C_{t,o}$ additionally includes a dummy for days on which important fiscal policies passed the Senate or the House of Representatives, or were signed into law. 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

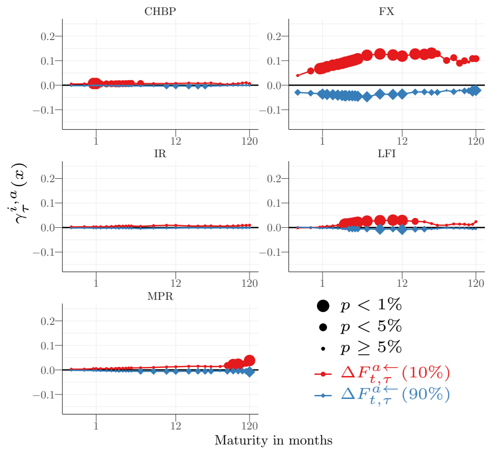


(a) Impact on $\Delta F_{t,\tau}^{a\leftarrow}(x)$

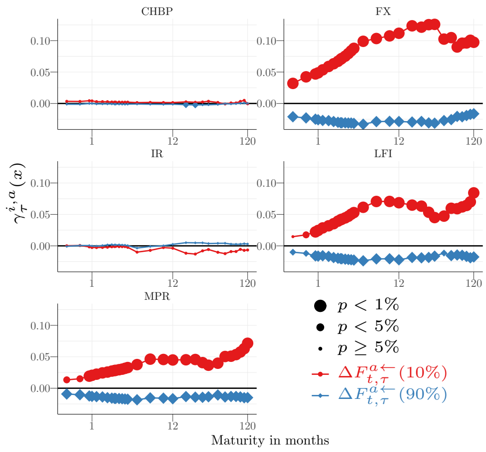
(b) Impact on ΔVIX

These figures show the impact of different policy categories on the risk neutral distribution for different terms τ (x-axis). The two panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% (panel (a)), and the VIX (panel (b)). The dots are the $\gamma_{j,\tau}^{i,a}$ and $\check{\gamma}_{\tau}^{i,a}$ from running equations (4) and (5), where $C_{t,o}$ additionally includes a dummy for the change in logs of the total volume of options on the shares of the big technological companies. 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).

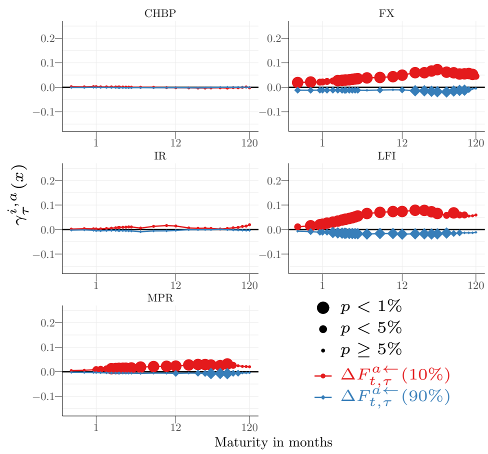
Figure 14: Impact of announcements of the Fed for different intraday window sizes around announcements' time stamps



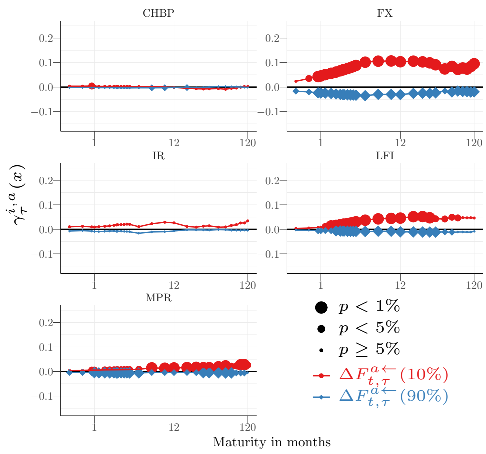
(a) 15min window



(b) 30min window



(c) 60min window

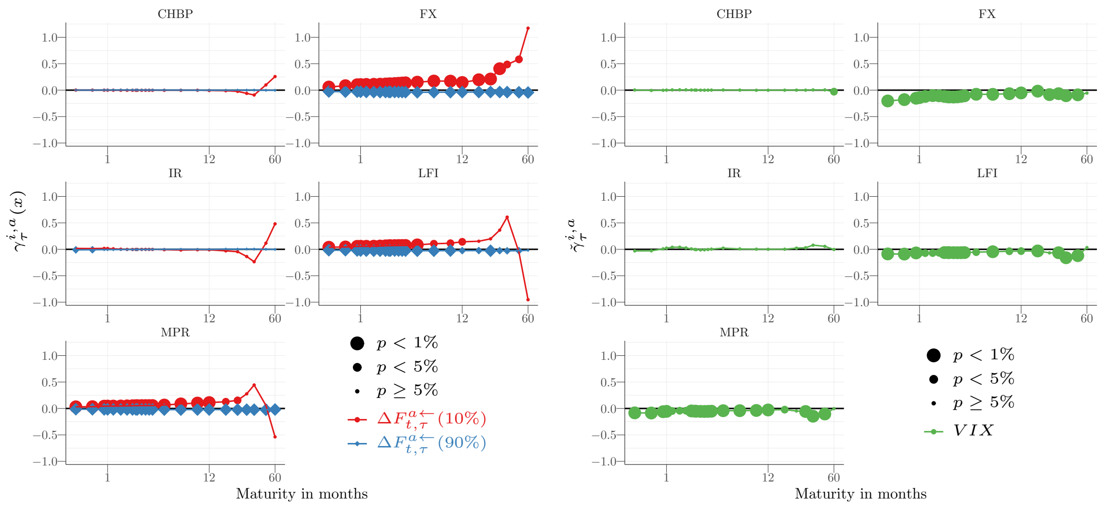


(d) 90min window

These figures show the impact of different policy categories on the risk neutral distribution for different terms τ (x-axis). The four panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% with different choice 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). The dots are the $\gamma_{j,\tau}^{i,a}$ and $\tilde{\gamma}_{\tau}^{i,a}$ from running equation (4). 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).

E Fed policies impact on US individual stocks and other market indices fears: additional results

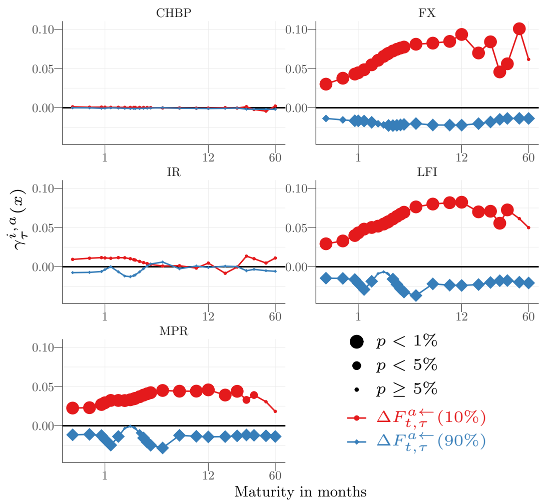
Figure 15: Impact of announcements of the Fed on JPMorgan Chase



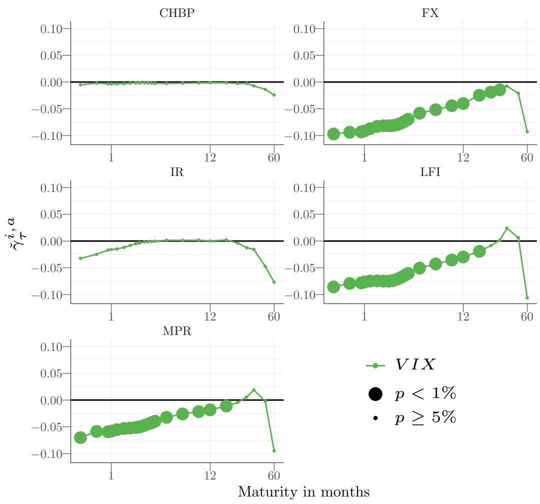
(a) Impact on $\Delta F_{t,\tau}^{a\leftarrow}(x)$ (b) Impact on ΔVIX

These figures show the impact of different policy categories on the risk neutral distribution of JPMorgan Chase (JPM) for different terms τ (x-axis). The two panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% (panel (a)), and the VIX (panel (b)). In panel (a), the blue dots are the announcement effects $\gamma_\tau^{i,a}(x)$ for the upper tail and the red dots for the lower tail of the risk neutral distribution from running equation (4), with a equal to JPM. The green dots in panel (b) are the announcements effects $\tilde{\gamma}_\tau^{i,a}$ from running equation (5), with a equal to JPM. 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 16: Impact of announcements of the Fed on Apple



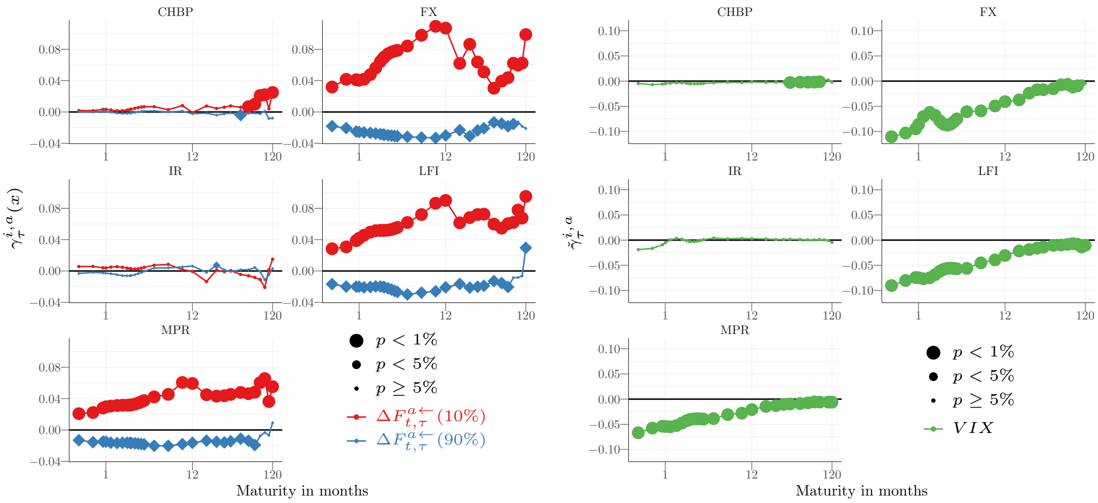
(a) Impact on $\Delta F_{t,\tau}^{a\leftarrow}(x)$



(b) Impact on ΔVIX

These figures show the impact of different policy categories on the risk neutral distribution of Apple (AAPL) for different terms τ (x-axis). The two panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% (panel (a)), and the VIX (panel (b)). In panel (a), the blue dots are the announcement effects $\gamma_{\tau}^{i,a}(x)$ for the upper tail and the red dots for the lower tail of the risk neutral distribution from running the equation (4), with a equal to AAPL. The green dots in panel (b) are the announcements effects $\check{\gamma}_{\tau}^{i,a}$ from running equation (5), with a equal to AAPL. 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).

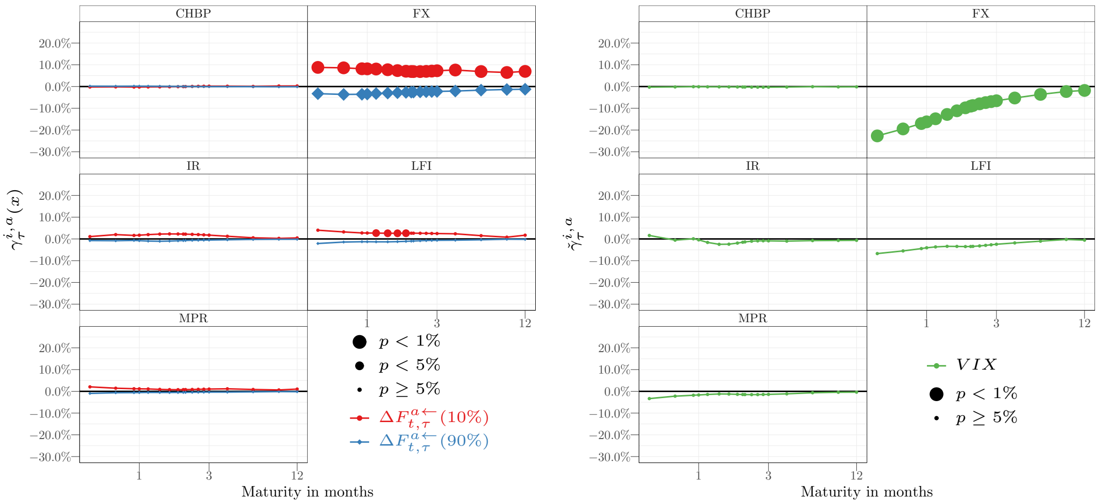
Figure 17: Impact of announcements of the Fed on RUSSELL 2000 Index



(a) Impact on $\Delta F_{t,\tau}^{a\leftarrow}(x)$ (b) Impact on ΔVIX

These figures show the impact of different policy categories on the risk neutral distribution of the RUSSELL 2000 Index for different terms τ (x-axis). The two panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% (panel (a)), and the VIX (panel (b)). The dots are the $\gamma_{j,\tau}^{i,a}$ and $\check{\gamma}_{\tau}^{i,a}$ from running equations (4) and (5). 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).

Figure 18: Impact of announcements of the Fed on the S&P 500 financial sub-sector index

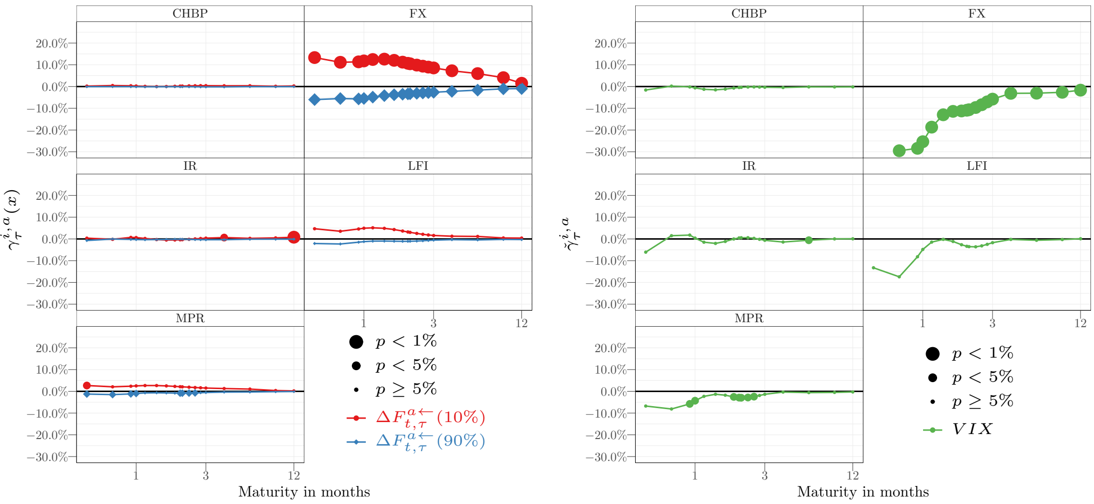


(a) Impact on $\Delta F_{t,\tau}^{a\leftarrow}(x)$

(b) Impact on ΔVIX

These figures show the impact of different policy categories on the risk neutral distribution of the S&P 500 financial sub-sector index for different terms τ (x-axis). The two panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% (panel (a)), and the VIX (panel (b)). The dots are the $\gamma_{j,\tau}^{i,a}$ and $\check{\gamma}_{\tau}^{i,a}$ from running equations (4) and (5). The sizes of the dots give the different levels of significance, $\cdot$ p≥0.05; • p<0.05; ● p<0.01, calculated using robust standard errors based on Newey and West (1987).

Figure 19: Impact of announcements of the Fed on the S&P 500 energy sub-sector index



(a) Impact on $\Delta F^{a\leftarrow}_{t,\tau}(x)$

(b) Impact on ΔVIX

These figures show the impact of different policy categories on the risk neutral distribution of the S&P 500 energy sub-sector index for different terms τ (x-axis). The two panels show the effect of a policy on the excess log return for the tail probabilities 10% and 90% (panel (a)), and the VIX (panel (b)). The dots are the $\gamma^{i,a}_{j,\tau}$ and $\check{\gamma}^{i,a}_{\tau}$ from running equations (4) and (5). 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).