An Unconventional FX Tail Risk Story

Carlos Cañon^{*a}, Eddie Gerba^b, Alberto Pambira^c, Evarist Stoja^d

^aBank of England & King's College London ^bBank of England & LSE & CES Ifo ^cBank of England ^dUniversity of Bristol

Abstract

We examine how the tail risk of currency returns over the past 20 years were impacted by central bank (monetary and liquidity) measures across the globe with an original and unique dataset that we make publicly available. Using a standard factor model, we derive theoretical measures of tail risks of currency returns which we then relate to the various policy instruments employed by central banks. We find empirical evidence for the existence of a cross-border transmission channel of central bank policy through the FX market. The tail impact is particularly sizeable for asset purchases and swap lines. The effects last for up to 1 month, and are proportionally higher for joint QE actions. This cross-border source of tail risk is largely undiversifiable, even after controlling for the U.S. dollar dominance and the effects of its own monetary policy stance.

Keywords: Unconventional and Conventional Monetary Policy, Liquidity measures,

Currency Tail Risk, Systematic and Idiosyncratic Components of Tail Risk

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Email addresses: carlos.canonsalazar@bankofengland.co.uk (Carlos Cañon*), eddie.gerba@bankofengland.co.uk (Eddie Gerba), alberto.pambira@bankofengland.co.uk (Alberto Pambira), E.Stoja@bristol.ac.uk (Evarist Stoja)

1. Introduction

Policy rates at the effective lower bound - and in some cases even negative - over sustained periods, substantially reduced the available headroom for central banks to respond using conventional interest rate instruments. As a result, many central banks resorted to other, non-traditional or unconventional policies to restore price stability when the standard bank rate proved ineffective due to the zero lower-bound (e.g. Swanson, 2021; Inoue and Rossi, 2019). These unconventional policies include *Large Scale Asset Purchases* – the purchase of large quantities of financial assets, typically Government or other highly-rated bonds, *Forward Guidance* – announcements about the future path of short-term interest rates or liquidity measures, and *Swap Lines* – readiness to increase the supply of domestic currency to other central banks.

However, little is known with regards to the impact of such policies on the tail risks of exchange rates. Anecdotal evidence highlights their importance and considerable impact on investors and financial markets.¹

In this paper, we set out to address the following question: What is the impact of central bank measures on the *realized* tail risk of exchange rate returns?² Our findings confirm the existence of a cross-border channel of central bank policy through the (tail risk of the) FX market which may have implications for portfolio allocations and

¹For example, one of the largest one-day depreciations of the JPY in recent years ensued the Bank of Japan's announcement of an expansion of its asset purchase program which led to substantial turbulence in the market (see "Currency-trading volumes jump" Wall Street Journal, January 27, 2015). Similarly, the de-pegging of the CHF from EUR by the Swiss National Bank in January 2015 gave rise to a tail event in the CHF/EUR exchange rate which in turn led to the bankruptcy of several financial firms with serious repercussions for financial stability. Yet another example is the sharp depreciation of the 'Fragile Five' (Brazil, India, Indonesia, Turkey, and South Africa) currencies in response to the U.S. Fed's announcement on 22 May 2013 that it intended to start tapering asset purchases at some future date. The capital outflows that ensued increased the large current account deficits of these countries with serious repercussions for their economies (see "'Fragile five' countries face taper crunch" Financial Times, December 17, 2013).

²With "realized tail risk" or "realized VaR", we mean the (α -) quantile of realized returns. Here, the aim not to extrapolate the tail risk (VaR) to the next period using its persistence properties, rather to encapsulate its *current* level (see, for example, the discussion of equation (16) in Bali, Demirtas, and Levy, 2009).

capital flows, risk management and financial stability. Though arguably short-lived (up to 1 month), the tail impact is particularly pronounced for some instruments. This cross-border source of tail risk is largely undiversifiable and present for all central banks, irrespective of whether they have an explicit exchange rate target, and even after controlling for the U.S. dollar dominance and the effects of their own monetary policy stance. Moreover, there is significant time and instrument variation. In addition, the impact is even larger if variation is proxied by the short end of the yield curve. Lastly, our empirical evidence confirms the central role played by the Fed's monetary policy.

Our focus on (tail) risk is part of a large body of international finance literature that stresses how time-varying risk is paramount for understanding exchange rates. For example, the large biases in the foreign exchange forward premium (see Bilson, 1981; Fama, 1984) provide compelling evidence of variations in risk premia as an explanation of the link between interest rates and exchange rates.³

The paper contributes to the literature, discussed in the next section, in several important ways. First, we construct a comprehensive dataset of all central bank (monetary and liquidity) measures implemented since January 2000 using information from the relevant central banks. This dataset has been manually and diligently

³Why is this important? An increase in monetary policy uncertainty does not necessarily lead to a depreciation of a currency although it may make the currency safer or more vulnerable relative to other currencies, therefore affecting its risk (see, for example, G. Benigno, P. Benigno, and Nisticò, 2012). Since investors are subject to risk constraints, the currency risk is simply transferred from borrowers' to lenders' balance sheets. Currency and rollover risk on the borrower's side transmute to duration and currency risk on the lender's side (see, for example, Carstens, 2019). Another reason why large swings in exchange rates matter is because they influence long-term interest rates. A strongly appreciating domestic currency is associated with compressed term premia and vice versa. Any swings in long-term rates would affect demand conditions. When financial stability considerations are taken into account, the impact of exchange rates is even larger. External and domestic borrowing interact. Evidence suggests that external borrowing increases relative to the domestic during credit booms, Avdjiev, Binder, and Sousa, 2021; Borio, McCaulev, and McGuire, 2011. Moreover, the strong credit expansion coupled with strong exchange rate appreciations typically precedes financial crises. In this way, global financial conditions and domestic financial cycles reinforce each other (see also El Hamiani Khatat, Buessings-Loercks, and Fleuriet, 2020; Carstens, 2019). Therefore, financial policies may need to be put in place to contain and mitigate this risk.

collected as part of this paper and is novel, both in scope and the horizon covered, and has a *daily* frequency.⁴ We focus on the actions that these central banks have taken in their monetary sphere for the G7 economies plus Switzerland, Denmark, Sweden, New Zealand and Australia. Using this original dataset, we examine the impact of both non-traditional measures *and* conventional monetary policy measures on the foreign exchange market. In the context of this paper, non-traditional measures (NTM) refer to all central bank measure other than changes in the policy rate. It's an umbrella term encompassing unconventional monetary policy measures and liquidity measures (e.g. swap lines and change in collateral requirements). This is important to understand whether such policies and measures have similar or different impact on the tail risk of currencies.

We examine the impact of policy announcements and actions undertaken by various central banks on *realizations*, rather than perceptions, of exchange rate tail risk that materialised over the period. This is an important conceptual difference. Our approach focuses on the actual (or realized) effect of policy, including any persistence. Alternatively, one could focus on the market expectations or prediction by extracting forward-looking measures from option prices with a maturity date at a specific point in the future. While interesting in its own right, our focus here is not on predictions, or their degree of accuracy in anticipation of monetary policy news. In this context, this paper differs from Hattori, Schrimpf, and Sushko (2016) which focuses on the impact of UMP on the tail perceptions but similar to Ahrens et al. (2023) who examine the impact of central bank actions on realized tail risk of asset returns but depart from the latter with regard to central bank actions. Ahrens et al. (2023) focus on central bank speeches on the realized (tail) risk of stocks and bonds at the intra-day frequency whereas we focus on monetary policy on the realized tail risk of

⁴Relative to Ferrari, Kearns, and Schrimpf, 2021, our dataset includes more countries, distinguishes between unconventional monetary policy instruments and includes liquidity measures.

currencies at the daily and lower frequency.⁵ Instead, we take a more comprehensive or "secular" view as we study the transmission effects of all monetary and liquidity actions over a period of more than 20 years across the bulk of advanced economies, on their respective currencies against USD.⁶ As far as we are aware, this is wider, deeper and covers a longer horizon than any existing study. It is also global in scope, as we cover around 85% of all FX trades in our study.⁷ We argue that changes in the medium and long-term implied yields shape currency tail risk but only through its impact on the front end of the curve. An additional argument we highlight is that after controlling for economic fundamentals, it's unlikely that changes in currency tail risk shape medium or long-term implied yields of sovereign bonds.

In addition, the paper contributes to the literature on the relationship between monetary policy and exchange rates. Classical finance argues that the disentangling of systematic from idiosyncratic risk is paramount for many applications as the latter can be diversified away and hence, should not matter but the former cannot, so it should be treated with care.⁸ To the extent that this argument holds for tail risk, if it is found that central bank measures impact currency *idiosyncratic* tail risk, this impact may be overlooked as idiosyncratic tail risk *can* be diversified away. However, if it is found that monetary policy instruments impact currency *systematic* tail risk,

 $^{^{5}}$ We expect to find lower effects relative to any forward-looking measure extracted from intraday data as information incorporation into prices at this frequency may well lead to tail events being netted out in our *end-of-day* tail measures.

⁶Our identification is therefore more robust as we use a more comprehensive (in both crosssection and time series dimensions) database of speeches and measures than previous studies.

⁷One may argue that there is risk of reverse causality (e.g. Ferrari, Kearns, and Schrimpf, 2021) such that the monetary policy reaction function systematically responds to financial imbalances (e.g. Filardo, Hubert, and Rungcharoenkitkul, 2022). To control for this possibility, we follow an instrumental variable approach in our empirical analysis. Our identifying assumption relies on the short-term dynamics of the FX market implying that potential reverse causality should operate through the short end of the implied yield curve. Following Rogers, Scotti, and Wright (2014), Chari, Dilts Stedmann, and Lundblad (2022), and Smith, Valcarcel, et al. (2020), we use daily changes of futures-implied yields on scheduled and unscheduled monetary policy decisions to isolate monetary policy surprises. In Section 4, we discuss this issue in detail.

⁸Classical finance, in our context, refers to the vast literature on portfolio theory and risk management.

this may be cause for concern as systematic tail risk *cannot* be diversified away. To this end, we carefully decompose the behavior of currency returns in the tails into systematic and *idiosyncratic* components in a novel and mutually-consistent way. We then investigate extensively the impact of policy on the components of tail risk of major currency returns. As a measure of tail risk we use the Value-at-Risk (VaR) which shows how much the investor is likely to lose with a given probability over a given horizon. VaR has been extensively embraced by regulators and practitioners in financial markets under the Basel II and III frameworks as the basis of risk measurement for the purpose of ensuring regulatory capital adequacy as well as risk management and strategic planning at industry level.⁹ Our extensive empirical analysis confirms the existence of a financial cross-border transmission channel of central bank (monetary and liquidity) measures, via the FX market. Specifically, we find that both conventional and unconventional policy tools have an impact on the tail risk of currencies and particularly on the systematic component. This transmission is larger for monetary measures such as Asset Purchase Programme and liquidity measures, such as Swap Lines, particularly since the Euro Area Debt Crisis. The effects are persistent for up to 1 month. Moreover, the effects are stronger for countries that have forcefully engaged in unconventional monetary policy. Perhaps most importantly, we find that joint QE actions increase substantially the systematic component of FX tail risk, and proportionally more relative to when only one central bank implements QE measures. This evidence suggests a reinforcement of monetary policy effects and enhancement of its international transmission channel. This discrimination across instruments, time **and** persistence is novel in the literature.

The paper proceeds as follows. In Section 2, we discuss the literature. Section 3 presents the central bank policy and currency data and then introduces the theoret-

⁹Because our study employs 20 years of data, an additional reason for using VaR is that it is consistent across the Basel II and Basel III regulatory regimes prevalent during this time.

ical framework and the properties of the benchmark measure of currency tail risk. Section 4 presents the variables of interest and our baseline regressions. We present extensive empirical results in Section 5. Section 6 offers some concluding remarks. Appendix contains further discussion of the literature and presents further results and technical details.

2. Relevant Literature

There is already an established body of literature examining the overall impact of monetary policy on exchange rates. These studies generally conclude that monetary policy has a significant impact on exchange rate returns. Indeed, extensive evidence suggests that a monetary policy easing (tightening) would result in depreciation (appreciation) of the domestic currency relative to other currencies (see for example, Clarida and Gali, 1994; Eichenbaum and Evans, 1995; Faust et al., 2003; Rosa, 2011; and for more recent evidence, Rogers, Scotti, and Wright, 2014; Kearns and Manners, 2018; Rogers, Scotti, and Wright, 2018; and Inoue and Rossi, 2019).

Similar to conventional policy, unconventional tools have a profound impact on exchange rates. Rogers, Scotti, and Wright (2018) argue that exchange rates are more sensitive to monetary policy during periods when the zero-lower bound binds relative to periods when it does not. Indeed, Stavrakeva and Tang (2015) find that the impact of unconventional monetary policy on exchange rates is larger since the zero lower bound became binding in the U.S. - see also Neely (2015); Wright (2012) and Swanson (2021) for evidence on the impact of the Federal Reserve's Large Scale Asset Purchase program on the USD. Moreover, Glick and Leduc (2013) find that both unconventional and conventional monetary policy have a similar impact on USD. Ferrari, Kearns, and Schrimpf (2021) extend this finding to other major currencies and conclude that both unconventional and conventional monetary policy have the same impact on exchange rates. The literature has also examined the impact of monetary policy instruments on the risk of financial assets and the consensus seems to suggest that such instruments have contributed to the reduction of risk. Some studies examine the relationship between conventional monetary policy and VIX - a forward-looking measure of market volatility extracted from stock options. Bekaert, Hoerova, and Lo Duca (2010) decompose VIX into a measure of uncertainty and risk aversion and find evidence that expansionary conventional monetary policy measured by the real Federal Funds Rate tends to reduce investor risk aversion. In a similar vein, Gambacorta, Hofmann, and Peersman (2012) find a significant decrease in VIX following implementation of unconventional monetary policy by the Fed. Moreover, Bruno and Shin (2015) empirically find that accommodative monetary policy drives down risk and leads to a pick-up of cross-border bank credit.

In contrast, the literature studying the impact of monetary policy instruments on the tails of exchange rates is very limited (see, for example, Farhi and Gabaix, 2016). Sannikov and Brunnermeier (2012) examine the impact of unconventional policies on tail risk in a *theoretical* framework. They argue that such policies can be an insurance against tail risk if adopted with a clear commitment device conditional on future states of the economy. Hattori, Schrimpf, and Sushko (2016) present evidence that unconventional monetary policy announcements and asset purchases by the Fed substantially reduce *perceptions* of tail risks in the market. However, they focus on the *stock* market and it is not clear whether this finding extends to other markets. In addition, rather than realizations of tail risk, they focus on perceptions (or signals) extracted from stock options. These are important considerations. Indeed, recent findings by Ahrens et al. (2023) suggest that UMP does *not* decrease the tail risk in stock and bond markets outside the cycles of FOMC press releases, directly contradicting the findings of Hattori, Schrimpf, and Sushko (2016). Ahrens et al. (2023) examine the impact of speeches by FOMC members¹⁰ on the realized tail risk. They find that speeches increase realized tail risk and therefore, conclude that these communications by central banks do not appear to reduce uncertainty and calm financial markets.

To the best of our knowledge, there are no studies that empirically examine the relationship between monetary policy and currency tail risk. This paper is a first attempt to examine this issue in detail and contribute to the expanding body of literature that studies the relationship between central bank instruments and (tail) risk in a global context (see, for example, Ahrens et al., 2023 and the references therein). In a different context, Eguren-Martin and Sokol (2022) examine the relationship between the tails of a large number of currencies and an index of Global Financial Conditions (GFC) and show that tight GFC have an important impact on the tails of currencies.

Our contribution in this paper is empirical, but the analysis has a clear theoretical motivation derived from models centered on *constrained intermediaries*. Mueller, Tahbaz-Salehi, and Vedolin (2017) building on the model of Gabaix and Maggiori (2015), propose a model of exchange rate determination based on capital flows in which constrained intermediaries with short investment horizons intermediate the demand for, and supply of currencies. These intermediaries engage in currency trading but have a downward-sloping demand curve for risk taking due to their limited risk bearing capacity ensuing from e.g. VaR constraints. Crucially, in addition to the fundamental risk of currencies, the intermediaries are also exposed to potential monetary policy shocks. They show that, in the presence of frictions, shocks to intermediary's risk-bearing capacity affect the level as well as the volatility of exchange rates. The intuition is that higher fundamental volatility tightens finan-

¹⁰The FOMC members' speeches may happen at any time throughout the year rather than only at the set dates of the FOMC announcements.

cial constraints, tighter constraints lead to higher volatility, thus generating a selfreinforcing feedback loop. This framework motivates our focus on whether shocks to monetary policy, in addition to volatility, affect the tails of exchange rate returns.

3. Data and Tail Metrics

3.1. Monetary Policy Data

In this section, we introduce and describe our dataset on conventional and nontraditional measures (NTM) of major central banks over the past two decades¹¹.

By non-traditional measures (NTM) we mean those central banks' policy interventions (monetary policy, liquidity measures or collateral related) which are used to promote or restore adequate financial intermediation and/or to facilitate the monetary policy transmission under financial sector impairment and/or in a near/at zero lower bound policy rates. The aforementioned interventions can be of different nature, but they broadly fall into one of the following categories: asset purchases, inter-bank swap lines, extension/modification of collateral eligibility, fund provisioning and forward guidance. Our (conventional and non-traditional) central bank measure dataset is a unique and novel collection of such events of the most important Central Banks, captured with a daily frequency¹². This set was built by collecting individual daily central bank communications for each of the categories above, e.g. asset purchase or swap line or collateral eligibility change or fund provisioning announcement date, as well as major speeches (at Director or Governor level) either announcing one of the above policy interventions, or signalling its intentions in relation to monetary policy or liquidity provision stance.

The 'strength' of each NTM's signal is determined as the daily change on the 1 month, 2 month, 2 year, 5 year or 10 year futures-implied yield of sovereign bonds

¹¹More details on the data and their statistics can be found in the Appendix, Table 4.

¹²We focus on the actions that these central banks have taken in their monetary sphere for the G7 economies plus Switzerland, Denmark, Sweden, New Zealand and Australia.

around the day of the announcement, and the three upcoming working days. Formally, $Strength_{NTM_{it}}^{\tau} = \Delta ImpYield_{it}^{\tau}$, where $NTM = \{APP, Coll, FG, Fund, Swap\}$, and ImpYield is the futures-implied yield of country i, at day t, of sovereign bond with maturity $\tau \in \{1m, 2m, 2y, 5y, 10y\}$. Finally, $Strength_NTM_{it}^{\tau} \neq 0$ at the day of the decision, and the next three working days.

In our NTM dataset, we differentiate between conventional and unconventional measures. In the first category, we include the changes to, or control of, the base rate applied to reserves (BASE RATE). In the second category, we split the actions into one of the following five types: Asset purchases (APP), Swap lines (SWAP), extension or modification of collateral eligibility (COLLATERAL), fund provisioning (FUND), and forward guidance (FG). In turn, following Ehrmann et al. (2019), we split this last type into further three sub-components, reflecting the emerging consensus on styles in forward guidance. Those styles are: conditions on the *state* of the economy, conditions on the *calendar* and *qualitative statements*.¹³

These tools and measures have their differences across jurisdictions, both in terms of their aim and operational implementation. Our categorization, however, is an attempt to reduce the relevant dimensions of each by clustering them while simultaneously recognizing their differences. Note that these categories are not mutually and dynamically exclusive. A central bank can take measures that fall within several categories at the same time, including those across conventional and unconventional territory.

To get a better sense for the historical record across the toolkit, the following figures depict their individual implementation over time. Figure 1 shows the move-

¹³Ferrari, Kearns, and Schrimpf (2021) also construct a monetary policy decisions dataset from the websites of several central banks. Our approach brings two improvements. First, we target a larger set of countries, in particular we also include Switzerland, Denmark, Sweden and New Zealand. Second, we decompose the unconventional monetary policy category into five and add two liquidity measures: asset purchases, swap lines, collateral, fund provisioning and three types of forward guidance.

ment in the base rate across time and currencies. The difference in rates across jurisdictions has got smaller since the Global Financial Crisis.

[Figure 1]

Figure 2 illustrates the number of times a particular policy measure has been implemented across time and currencies. The figure is a structured scatter plot so the intensity in colour represents the frequency a measure has been implemented at a particular point in time.

[Figure 2]

The dynamic correlations, shown in the Appendix, are generally higher between conventional instruments. For all economies, the number of interventions increased considerably since 2008, with the majority of interventions clustered around 2008-2010 and 2020-2021 period.

3.2. Currency Data

The data, obtained from Reuters Eikon, covers the period from 2 January 2000 to 28 February 2021, yielding 5520 daily observations for each currency. From these exchange rates, we calculate the returns of currency i at time t as:

$$s_{i,t} = \ln\left(\frac{X_{i,t}}{X_{i,t-1}}\right) \tag{1}$$

where $X_{i,t}$ is the spot of exchange rate of currency *i* per unit of USD at time *t*. For each currency *i*, in addition to the exchange rate against the USD, we obtain the base rate, fixed rate on Overnight-Index Swaps (OIS) with 1-month maturity as well as the 1-month forward rate. We calculate the OIS (IR) return of currency *i* at time *t* as:

$$f_{i,t} = \ln\left(\frac{1 + OIS_{i,t}}{1 + OIS_{i,t-1}}\right) \tag{2}$$

We then calculate excess returns of currency i at time t as:

$$R_{i,t} = s_{i,t} - f_{i,t-1} \tag{3}$$

To decompose tail risk, we account for systematic risk with a factor asset pricing model. The consensus on factor models in foreign exchange literature points to a relatively simple model. The benchmark we employ is a three-factor model where the factors are the first three principal components estimated from a large basket of 20 USD-denominated currencies. As an alternative to this model, we use the two-factor model of Lustig, Roussanov, and Verdelhan (2011).¹⁴

To estimate the principal components that proxy the systematic factors, we use the exchange rates of the 20 largest and most liquid currencies against USD. These currencies are: GBP, EUR, CAD, NZD, DKK, SEK, JPY, CHF, AUD, MXN, ARS, IDR, RUB, ZAR, INR, TRY, BRL, CNY, KRW, SAR. On the other hand, to examine the impact of monetary policy measures on the tails of currency returns, we use the following nine major currencies: EUR, GBP, JPY, CAD, AUD, NZD, CHF, SEK and DKK against USD.¹⁵

3.3. Currency Tail Risk - Theoretical framework

Any uncertainty of monetary policy can have an impact on exchange rates due to their close connection. Moreover, the size and the intensity of activity in these markets along with the concentration of the market participants and their ability to

 $^{^{14}\}mathrm{Results}$ from Lustig, Roussanov, and Verdelhan (2011) are available from the authors upon request.

¹⁵The 20 currencies we use to estimate the principal components that proxy the systematic factors represent around 97% of the global foreign exchange turnover for the last 20 years. On the other hand, the nine currencies on which we base our analysis of the central bank policy impact on FX tail risk represent around 85% of global foreign exchange turnover over the same period (see BIS, 2016; BIS, 2019). The analysis based on three principal components estimated from the smaller dataset of the largest nine currencies would lead to even stronger results although the turnover statistics suggest these PCs would leave out considerable common variation in the currency market.

operate with high levels of leverage imply that small changes in monetary policy can lead to large adjustments in exchange rates. If these potentially large adjustments in exchange rates materialised, they would affect their tail risk. In this paper, we examine whether this conjecture holds.

In particular, we examine a large number of currencies, policy actions and time effects. This allows us to examine long-run patterns in a systematic manner. Moreover, because we study a basket of currencies, we can study the multilateral (direct and indirect) linkages between currencies. Thus we are able to examine the direct impact of e.g. U.K. monetary policy on JPY, as well as indirectly through USD (or any of the other currencies). We also focus on the effects on the tail of the currency returns as opposed to their mean. Thus, our aim is to investigate whether there is any evidence of a cross-border channel that works via FX market volatility and higher moments.

Our tail risk measures are based on a factor model for asset returns. We pin them down next before empirically examining the transmission of shocks from NTM.

The Evolution of Currency Returns

Suppose that currency excess returns are priced according to a n-factor model and excess returns of currency i are equal to

$$R_i = \sum_{j=1}^n \beta_{ij} F_j + \epsilon_i \tag{4}$$

where β_{ij} is the sensitivity of currency *i* to the excess return of factor F_j and ϵ_i is an idiosyncratic shock.

The aggregate systematic factor of currency i is $R_{s(i)} = \sum_{j=1}^{n} \beta_{ij} F_j$ and is denoted $r_{s(i)}$ ($R_{s(i)}$) when it is smaller (larger) than a given threshold which happens with probability f (1 - f). Further, with probability p_i (1 - p_i) the independent idiosyncratic shock to currency i's excess returns is "small" ("large") and is denoted

 ϵ_i (E_i). When the idiosyncratic term is ϵ_i , currency *i*'s excess returns do not diverge significantly from the prediction of the model. However, when the idiosyncratic term is E_i , this divergence can be significant and, in some cases, can overturn the impact of the aggregate systematic factor. With probability q_i $(1 - q_i)$, E_i can be large negative (moderate as well as large positive) and is denoted E_i^- (E_i^+). Therefore, currency *i* exceeds its own VaR when the idiosyncratic shock is small and the aggregate systematic factor has exceeded its VaR or *independently* of the aggregate systematic factor due to a large negative idiosyncratic shock. Figure 3 brings all this together and shows the paths to possible outcomes.

[Figure 3]

The final nodes in the tree in Figure 3 correspond to the four possible outcomes: no VaR exceedance has occurred, depicted in $T_{\{\emptyset\}}$; the aggregate systematic factor has exceeded its VaR but not currency *i*, depicted in $T_{\{s(i)\}}$; currency *i* has exceeded its VaR but not the aggregate systematic factor, depicted in $T_{\{i\}}$; and finally, both have exceeded their respective VaRs, depicted in $T_{\{i,s(i)\}}$. These outcomes are depicted in Figure 4.

[Figure 4]

Definition of the Components of Currency Tail Risk

Classical finance argues that the disentangling of systematic from idiosyncratic risk is paramount as the latter can be diversified away but the former cannot (see, for example, Statman, 1987 or the textbook by Bodie, Kane, and Marcus, 2014).¹⁶ This reasoning can be directly applied to tail risk. Intuition suggests that a monetary policy action taken by a central bank in isolation, may contribute only to the risk of

¹⁶This has important applications for, amongst others, portfolio theory and risk management.

its domestic currency which would count as idiosyncratic risk since it would not affect the fundamentals of other currencies. If so, this would matter little to investors, institutions and economies with exposure to this currency because idiosyncratic risk can be diversified away. However, because these actions are often taken simultaneously – whether coordinated or otherwise – by several central banks, it may be that this would lead to common variation across currencies and hence, may impact the systematic risk of currencies.¹⁷ If so, this would be a serious matter because systematic risk cannot be diversified away so it would increase the overall risk exposure of investors, institutions and economies relying on the FX market for investments and trade. Therefore, to test these hypotheses, the decomposition of the currency tail risk into its idiosyncratic and systematic components is essential.

We now formally derive formulae for the systematic and the idiosyncratic components of currency tail risk. Assigning the following respective probabilities x_0 , $x_{s(i)}$, x_i and $x_{i,s(i)}$ to outcomes $T_{\{\emptyset\}}$, $T_{\{s(i)\}}$, $T_{\{i\}}$ and $T_{\{i,s(i)\}}$ then the outcome tree in Figure 3 leads to the following system of linear equations:

$$\begin{cases} Pr(T_{\{i,s(i)\}}) = x_{i,s(i)} = f \cdot p_i + f \cdot (1 - p_i) \cdot q_i \\ Pr(T_{\{s(i)\}}) = x_{s(i)} = f \cdot (1 - p_i) \cdot (1 - q_i) \\ Pr(T_{\{i\}}) = x_i = (1 - f) \cdot (1 - p_i) \cdot q_i \\ Pr(T_{\{\emptyset\}}) = x_0 = (1 - f) \cdot p_i + (1 - f) \cdot (1 - p_i) \cdot (1 - q_i) \end{cases}$$

In the following, we set the thresholds for the aggregate systematic factor and currency *i* equal to $VaR_{s(i)}^{\alpha_{s(i)}}$ and $VaR_i^{\alpha_i}$ at the respective significance levels $\alpha_{s(i)}$ and α_i . This implies $x_{s(i)} = \alpha_{s(i)} - x_{i,s(i)}$ and $x_i = \alpha_i - x_{i,s(i)}$. Then, the following unique solution for p_i obtains since the probabilities of the four outcomes add up to one:

¹⁷See, for example, Avdjiev, Gambacorta, et al. (2020) who find that the main driver of *variation* in exposure to U.S. monetary policy was the degree of convergence among advanced economy monetary policies which had a crucial impact on global liquidity.

$$p_i = \frac{x_{i,s(i)} - \alpha_{s(i)}\alpha_i}{\alpha_{s(i)} - \alpha_{s(i)}^2}.$$
(5)

Note that p_i is bounded between 0 and 1¹⁸. When $p_i = 1$, currency *i* exceeds its VaR whenever the aggregate systematic factor does, while $p_i = 0$ implies that VaR exceedances by currency *i* and the systematic factor are independent. Probability p_i captures, therefore, the systematic part of the tail risk of currency *i*. The remainder, $1 - p_i$, can be interpreted as the idiosyncratic part of tail risk of currency *i*. These observations can be summarised formally:

Systematic Component:

$$STC_i(\alpha_i, \alpha_{s(i)}) \equiv p_i = \frac{x_{i,s(i)} - \alpha_{s(i)}\alpha_i}{\alpha_{s(i)} - \alpha_{s(i)}^2}$$
(6)

Idiosyncratic Component:

$$ITC_{i}(\alpha_{i}, \alpha_{s(i)}) \equiv 1 - p_{i} = \frac{(\alpha_{s(i)} + \alpha_{s(i)}\alpha_{i}) - (x_{i,s(i)} + \alpha_{s(i)}^{2})}{\alpha_{s(i)} - \alpha_{s(i)}^{2}}$$
(7)

Clearly, these components sum up to one. This, in turn, allows for their interpretation as shares of the total tail risk of currency i measured by its VaR.

Under the factor model of Arzac and Bawa (1977), omitting the risk free rate, $\beta_i^{AB} = VaR_i^{\alpha}/VaR_{s(i)}^{\alpha}$, which implies $\alpha_{s(i)} = \alpha_i = \alpha$. Then, the systematic component becomes:

$$p_i = \frac{x_{i,s(i)} - \alpha^2}{\alpha - \alpha^2} \tag{8}$$

¹⁸ p_i is well-defined only if $\alpha_{s(i)}^2 \leq x_{i,s(i)} \leq \alpha_{s(i)}$.

The Remark below shows that this special case of the systematic tail component p_i converges to the classic lower tail-dependence coefficient of Sibuya (1960) as $\alpha \to 0$. This coefficient is usually denoted λ_L and is paramount in the EVT literature (see, for example, Joe, 1997).

Remark:

If $\alpha_i = \alpha_{s(i)} = \alpha$, then

$$\lim_{\alpha \to 0} p_i = \lim_{\alpha \to 0} \frac{x_{i,s(i)}/\alpha - \alpha}{1 - \alpha} = \lim_{\alpha \to 0} \frac{x_{i,s(i)}}{\alpha} = \lambda_L,$$
(9)

where,

$$\lambda_L = \lim_{\alpha \to 0} \Pr\left\{ X_i \le F_i^{-1}(\alpha) | X_{s(i)} \le F_{s(i)}^{-1}(\alpha) \right\}.$$
 (10)

In the next section, we use (6) and (7) to construct *measures* of systematic tail risk and idiosyncratic tail risk and then, in the empirical section we study their relation to conventional and non-traditional measures.

Measures of Systematic and Idiosyncratic Tail Risks

Arzac and Bawa (1977) derive an asset pricing theory in a safety-first framework and show that the beta of asset i is the slope given by the ratio of the VaR of asset i over the VaR of the systematic factor. Adapting slightly the notation, we obtain a measure of tail risk for currency i:

$$\beta_i^{AB} = \frac{VaR_i^{\alpha}}{VaR_{s(i)}^{\alpha}} \tag{11}$$

We interpret the RHS of (11) as a (normalized) risk measure and decompose it using the systematic and idiosyncratic components in (6) and (7):

$$\frac{VaR_i^{\alpha}}{VaR_{s(i)}^{\alpha}} = STR_i + ITR_i \tag{12}$$

where

$$\begin{split} STR_i &= STC_i \frac{VaR_i^{\alpha}}{VaR_{s(i)}^{\alpha}} = p_i \frac{VaR_i^{\alpha}}{VaR_{s(i)}^{\alpha}},\\ ITR_i &= ITC_i \frac{VaR_i^{\alpha}}{VaR_{s(i)}^{\alpha}} = (1-p_i) \frac{VaR_i^{\alpha}}{VaR_{s(i)}^{\alpha}}. \end{split}$$

Note the similarity between STR_i and the classic CAPM β . The first term, the tail dependence coefficient is similar to the correlation coefficient in CAPM and the second term, the ratio of tail risks, is the analogue of the ratio of standard deviations in CAPM. When $p_i = 1$, currency *i* is totally tail dependent on the aggregate systematic factor and $STR_i = \frac{VaR_i^{\alpha}}{VaR_{s(i)}^{\alpha}}$. This is intuitive because when the systematic factor return decreases by $VaR_{s(i)}^{\alpha}$ then currency *i* return, in direct response, decreases by VaR_i^{α} . However, if $p_i = 0$ then currency *i* is tail-independent of the systematic factor and $STR_i = 0$. This is also intuitive as under independence, currency *i* returns are not sensitive to moves in the aggregate systematic factor. These measures therefore, capture the systematic and idiosyncratic tail risks and can be employed as independent variables in empirical exercises that seek to uncover their relationship with central bank policy.

Estimation

To estimate our currency tail risk measures, we proceed as follows. First, for each currency i, we obtain the currency excess return R_i as the difference between the currency spot return and the risk free rate. As an alternative, in the robustness analysis, we use the difference between today's currency forward rate and currency spot rate at the forward expiry date. Then, we create a set of reference currency factors representing the overall systematic risk of the currency market. In our analysis, these factors are obtained with two methods. In the first, we apply Principal Component Analysis (PCA) to the currency excess returns of a wide set of representative currencies detailed below. Then, we regress our currency excess returns on the first three PCA factors¹⁹:

$$R_{i,t} = \beta_{i,1} P C_{1,t} + \beta_{i,2} P C_{2,t} + \beta_{i,3} P C_{3,t} + \epsilon_{i,t}$$
(13)

The aggregate systematic factor of currency *i* is then defined as $R_{s(i),t} = \sum_{j=1}^{3} \beta_{i,j} PC_{j,t}$. In the second method, we construct the two currency risk factors, *RX* and *HML*, of Lustig, Roussanov, and Verdelhan (2011) and use these as pricing risk factors for our currencies as follows:

$$R_{i,t} = \beta_{i,RX} R X_t + \beta_{i,HML} H M L_t + \epsilon_{i,t} \tag{14}$$

In this case, the aggregate systematic factor of currency i is defined as $R_{s(i),t} = \beta_{i,RX}RX_t + \beta_{i,HML}HML_t$ ²⁰

Then, for each currency, we calculate the quantiles at a given confidence level for the currency excess returns as well as their corresponding aggregate systematic risk factor. This allows us to partition the currency outcome space into four quadrants, which we label "joint tails". These are respectively $T_{\{i\}}$, $T_{\{s(i)\}}$, $T_{\{i,s(i)\}}$ as well as the empty joint tail $T_{\{\emptyset\}}$ illustrated in Figure 4. From these, we estimate the systematic tail risk and idiosyncratic tail risk of currency *i* given in (12) as the product of the systematic and idiosyncratic shares of tail risk in (6) and (7) with the ratio of VaRs.

¹⁹These factors can be interpreted as follows: the first factor proxies a USD index factor capturing the analogue of the market return; the second factor can be seen as a carry factor proxying the excess total return for going long on high-yield currencies and short on low-yield currencies. The third factor can be interpreted as a momentum factor, proxying the risk emanating from a portfolio that goes long on recently well-performing currencies and short on those that perform poorly.

²⁰Both methods used to define the aggregate systematic factor seemingly lead to a contradiction: the aggregate systematic factor is dependent on the currency. This is only partially true. While the systematic risk factors are the same for all currencies, the aggregate systematic factor $R_{s(i)}$ includes currency-specific information through the betas. While this is unusual in the empirical asset pricing literature, adding up the systematic risk factors scaled by betas is to simplify the analysis and does not alter it - $R_{s(i)}$ captures the total impact of systematic tail risk to currency *i* originating in undiversifiable sources²¹. The alternative approach of treating each systematic risk factor separately is possible but would complicate the analysis considerably since the systematic and idiosyncratic tail risks would be factor-specific and for an *n*-factor model there would be 2nsystematic and idiosyncratic tail risk components (see Chabi-Yo, Huggenberger, and Weigert, 2022).

These measures can be estimated on a rolling window, yielding a set of time series of the above metrics for each currency. We choose a rolling window of 250 days although qualitatively similar results were obtained from experimenting with other window sizes. More specifically, the tail risk attributable to policy tool is estimated as the difference over one day, of the tail risks estimated over the windows t-249...t+1 and t-250...t. We experiment also with differences calculated over 3, 10 and 15 days, but they didn't lead to material estimation differences. Once we obtain the time series of currency tail risk measures, we can examine their relation with the NTM data.

Implementation

We estimate the currency systematic risk factors by means of Principal Component Analysis (PCA) on the excess returns of the 20 currencies. The PCA allows for identification of the main common factors of variation of the currencies which in turn allows for the partition of the return outcome space and hence, the estimation of the systematic and idiosyncratic tail risk measures.

After having estimated the currency systematic risk factors, we turn the focus to G9 currencies to model tail risk. Some of the G9 economies did not face the constraints of the zero lower bound for interest rates and as a result did not resort to unconventional monetary policy, continuing instead to rely on conventional monetary policy. We use this heterogeneity to enhance the identification. Furthermore, the relatively large panel dimensions of our data allow us to explore the effects in panel (IV-panel) domain. For the latter, we control for simultaneity in actions and transmission while accounting for the different currency weights based on their global economic importance.

Having obtained the systematic risk factors proxied by the first three principal components, we regress the currency excess returns on the systematic risk factors. The results of this regression are shown in Table 1. Note the significance of the systematic risk factors proxied by the PCs.

[Table 1]

Then with the components and their loadings we obtain the aggregate systematic factor $R_{s(i)}$ for currency *i*. This, in turn allows for the separate estimation of the systematic and the idiosyncratic tail risks for each currency. Panel A of Table 2 shows the 2.5, 5 and 10% quantiles of the empirical distribution for each currency. Panel B shows the 2.5, 5 and 10% quantiles of the empirical distribution for the aggregate systematic risk factor $R_{s(i)}$. Consistent with intuition, the quantiles of a currency excess return are, in absolute value, larger than those of the aggregate systematic risk factor due to idiosyncratic tail risk.

[Table 2]

Figure 5 shows that the quantiles for both currencies and the aggregate systematic risk factors fluctuate widely over time. Even though they appear strongly correlated, there appears to be instances of divergence in tail risk between a currency and the aggregate systematic risk factor. It is during these instances that the idiosyncratic, i.e. diversifiable tail risk becomes particularly important.

[Figure 5]

Having constructed the aggregate systematic risk factor and partitioned the outcome space for each currency, we then estimate the tail dependence coefficient p_i of currency *i* on the aggregate systematic risk factor with equation (4) at nominal level α where $\alpha = 2.5$, 5 or 10%. Under independence, the probabilities presented in Panel A of Table 3 should be close to α^2 . However, at $\alpha = 5\%$ these probabilities are more than 10 times larger in almost all cases. The strength of the tail dependence between a currency and the aggregate systematic risk factor is illustrated more clearly in Panel B where the tail dependence coefficient is above 50% in the majority of cases.

[Table 3]

With the tail dependence coefficient p_i estimated for each currency, it is straightforward to obtain that currency's systematic and idiosyncratic tail risk measures shown in Figure 6. It is clear that the systematic tail risk generally accounts for the largest proportion of tail risk.

[Figure 6]

Estimating these measures in a rolling window of 250 observations with an exponentiallyweighted moving average, we obtain time-varying measures of tail risk shown in Figure 7.

[Figure 7]

The tail risk measures are persistent and vary widely over time. The systematic tail risk is generally the largest component of tail risk although there are instances when its prominence is more subdued. Idiosyncratic tail risk on the other hand is smaller although there are instances where it dominates the systematic component, for example, in the case of JPY. This supports recent findings in the literature on the distinctive dynamics of JPY which appear to have a looser relation to the systematic asset pricing factors (Harris et al., 2022).

Next, Figure 8 depicts the dynamic correlations of measures in the conventional space across central banks. Due to the large number of NTM instruments, the figure depicting their dynamic correlations is also very large so it is not shown but it is available upon request.

[Figure 8]

The dynamic correlations between conventional measures generally seem to be higher than those between unconventional ones. Moreover, UMP and liquidity measures are generally distributed evenly across time, with no particular pattern across countries. Yet for all economies, the number of interventions increased considerably since 2008, with the majority of interventions clustered around 2008-2010 and 2020-2021.

For the main part, we proceed to empirically measure the correlation between the tail risk and central bank measures. Because of the structure of our data, we employ panel data techniques. Our sample includes multiple regimes, both in terms of structural factors and monetary policy stances. To test the variation across those regimes, we run rolling linear regressions across sub-samples. The results from this analysis are available upon request from authors. Next section outlines the estimation strategy for causal inference.

4. Estimation framework

4.1. Extraction of monetary policy surprises

High frequency identification is a common approach to isolate monetary policy surprises. Depending on the research question, and data availability, windows around the announcement oscillate from a few minutes up to a day. The latter option, e.g. using daily frequency, is better suited under the prior that surprises take some time to fully materialize. Rogers, Scotti, and Wright (2014), following Gürkaynak (2005), Gürkaynak, Sack, and Swanson (2005) Gürkaynak, Sack, and Swanson (2007), measure monetary policy surprises from the US with daily changes of futures-implied yields around scheduled and unscheduled FOMC announcements. More recently, Chari, Dilts Stedmann, and Lundblad (2022), Dilts Stedman (2019) Smith, Valcarcel, et al. (2020) uses the same approach to assess the impact of UMP or balance sheet unwinds. Our approach falls in line with this stream of work.²²

We use future-implied yields from representative points of the yield curve, specifically for maturities of: 1 month, 2 months, 2 years, 5 years and 10 years, to capture different horizons of the yield curve. We proxy the intensity of CMP or NTM decisions as the daily change of future-implied yields, given a particular maturity, at the decision day and the following three working days.²³

In the final dataset of NTM surprises we will have for each country individual daily time-series for each possible action, e.g. CMP, UMP components and other liquidity measures, with non-zeros at days where decisions occur and three additional days.²⁴ The reason behind this choice is that we should allow a few days for the market to react and fully incorporate all relevant information.

Moreover, in all specifications, the dependent variable is the country's tail risk, or any of its components. To preserve space, we present the results for the total and the systematic component of tail risk. The systematic component of tail risk attributable to a policy event at time t is estimated as the difference of systematic tail risk estimated over two windows: t-250,...,t and t-251,...,t-1 from the returns for each currency. The covariates of interest are CMP, APP, FG, SWAP, COLLATERAL and FUND. We also include the same covariates from the U.S.

 $^{^{22}}$ Another reason for not using short windows is that it would be impossible to decide on the optimal window size in a large cross-section of central banks and monetary policy measures. The "probability of arrival" of a policy surprise regarding measure j from central bank i at time t is non-negligible. Therefore, you would need to employ a moving event window across the entire sample, which would produce very erratic estimates, as well as biases, as some currencies and measures may require larger windows compared to others. The suitable approach here is, therefore, to use daily windows.

²³Formally, $Strength_{it}^{\tau} = \Delta ImpYield_{it}^{\tau}$, for CMP or $NTM = \{APP, Coll, FG, Fund, Swap\}$, and ImpYield is the futures-implied yield of country i, at day t, of sovereign bond with maturity $\tau \in \{1m, 2m, 2y, 5y, 10y\}$. Finally, $Strength_{it}^{\tau} \neq 0$ at the day of the decision, and the next three working days. Results are robust to incorporate from zero to five extra working days.

²⁴The results are robust to including up to five days or none at all.

4.2. Panel Data Methodology

The panel contains data from the central banks of Australia, Canada, Switzerland, Japan, U.K., Euro Area, New Zealand and Sweden. We use information from the Fed as a common control for the remaining countries. The sample covers the period from January 2000 until February 2021, at daily frequency.

We implement two model specifications. In the first one, in addition to other explanatory variables detailed below, we include CMP and non-traditional measures (NTM) of country i at time t, that gather unconventional monetary policies and other liquidity measures undertaken by central banks. In the second, we disentangle the NTM variable into asset purchases (APP), forward guidance (FG), swaps (SWAP), funding (FUND) and collateral (COLLATERAL). Table 4 in the appendix provide further description of the main variables.

$$y_{i,t} = \alpha + \beta_1 CMP_{i,t}^{\tau} + \beta_2 NTM_{i,t}^{\tau} + \beta_3 H_{i,t} + \beta_4 X_t + \gamma_i \delta_t + \eta_i + \epsilon_{i,t}$$

$$y_{i,t} = \alpha + \beta_1 CMP_{i,t}^{\tau} + \sum_{C \in NTM} \beta_{2C} C_{i,t}^{\tau} + \beta_3 H_{i,t} + \beta_4 X_t + \gamma_i \delta_t + \eta_i + \epsilon_{i,t}$$

where $NTM = \{APP, Coll, FG, Fund, Swap\}$. The dependent variable $y_{i,t}$ is the tail risk, or any of its components, of country *i* at time *t*. $CMP_{i,t}^{\tau}$ is the impact of conventional monetary policy decisions, and is calculated as the daily change of the futures-implied yield of country i at day t, given a sovereign bond with maturity $\tau \in \{1m, 2m, 2y, 5y, 10y\}$. We follow a similar approach for every NTM. In both specifications, $H_{i,t}$ contains dummy variables for the zero lower bound, for any of the three types of forward guidance and for the implementation of quantitative easing. X_t is a vector of controls from the U.S. Fed including CMP and NTM.²⁵ $\gamma_i \delta_t$ is an interaction term of time and country fixed effect, and η_i are country fixed-effect. In

²⁵We include the U.S. Fed's CMP, APP, COLLATERAL, FG, FUND, SWAP, QE, ZLW and the three types of forward guidance. We do not present the full table to simplify the exposition but is available upon request.

particular, we use the triple interaction of *month*, *year* and *country* fixed effects to control for unobserved time-varying confounding effects for each country.²⁶ These fixed-effects should help to incorporate time-varying country-level determinants that are difficult to include given our analysis uses daily (or weekly) frequency. Finally, as the panel has a small N but a large T, we correct for cross-sectional and intertemporal dependence with Driscoll-Kraay standard errors.

The main econometric challenge is a potential endogeneity across FX market, in particular the joint occurrence of tail events and monetary policy decisions. Recently, Ferrari, Kearns, and Schrimpf (2021) show evidence of the monetary policy transmission channel through the exchange rate, and Filardo, Hubert, and Rungcharoenkitkul (2022) argue monetary policy reaction function could systematically respond to financial imbalances threatening financial stability.²⁷

We follow an instrumental variable approach to correct for this. We want to assess the causal impact of NTM surprises, measured by daily changes in the futureimplied yield curve, over FX tail risk. The short-term dynamics of the FX market suggests that the (above) reverse causality should mainly operate through the short end of the implied yield curve. The identifying assumption we use is that medium and long-term implied yield changes do shape currency tail risk but *only* through its impact on the front end of the curve.²⁸ An additional argument we highlight is that, after controlling for economic fundamentals, it's unlikely that changes in currency tail risk shape implied yields of sovereign bonds of 10 years or more.

 $^{^{26}}$ We replace the monthly with weekly fixed-effects and the results remain qualitatively similar.

²⁷Theoretically, Gourinchas, Ray, and Vayanos (2022) show that bond and FX markets are interlinked. We further posit that the intensity of this relationship is not homogeneous along the yield curve. The literature suggests that QE is particularly effective in lowering medium and longerterm interest rates. Under particular conditions, the effects could even last up to two years (see, for example, Busetto et al., 2022).

²⁸Changes in the short-term treasury yields and in the medium to long-term treasury yields should be correlated as we take different points of the same curve. Recently, Finlay, Titkov, and Xiang (2022) find supporting evidence with Australian data (see also Busetto et al., 2022 for a general discussion).

Our instrument is the daily change of the implied yield of future contracts for 10 year treasuries. For example, for each country we instrument the change in monetary policy, typically captured by the change in the 1 month implied yield, with the change in the 10 year implied yield of CMP, APP, COLLATERAL, FG, FUND and SWAP. Additionally, we use instruments in levels and squares to capture nonlinearities in the data.²⁹ We report a summary of the first stage results in Table 14. In the vast majority of cases instruments are strong and informative.

5. Panel Data Results

5.1. Full sample period

Tables 5 - 8 report the results, at daily frequency, addressing the potential endogeneity concerns.³⁰ Each column reports estimates at different points on the implied yield curve. For example, the first column uses information from the five year bonds. The last two columns are robustness checks for alternative ways to construct Euro Area (EA) yields.³¹

We include additional control variables for QE, including the zero lower bound (ZLB) and the type of implemented forward guidance. To conduct this analysis, we follow Ehrmann et al. (2019) and Beck, Duca, and Stracca (2019). We split forward guidance into one that conditions on the state of the economy (FG_{sg}) , another that

²⁹As an alternative, we also use lagged values of the instruments and the interaction of the instruments with monthly dummy variables. In all cases, the performance of the instruments is supported by the Angrist-Pischke weak IV test.

³⁰As described earlier, endogeneity may arise because policymakers respond systematically to imbalances in financial markets, e.g. Filardo, Hubert, and Rungcharoenkitkul (2022), and/or because they internalise the impact of MP decision on their currency against a benchmark, e.g. Ferrari, Kearns, and Schrimpf, 2021.

³¹Since there are no European bonds, usually one relies on German or French bonds as a proxy. However, for the front end of the curve, e.g. 1 month and 2 months, we employ the yields of Italian bonds instead. The rationale for this choice is the higher sensitivity of Italian bond yields to ECB monetary policy decisions relative to those of either the German or French bonds. We examine the robustness of our findings with yields extracted from Spanish bonds and find no qualitative differences.

conditions on the calendar day (FG_{tg}) and a third that conditions on qualitative statements (FG_{og}) .

Table 5 reports the results of the regressions estimated over the entire sample. The results suggest that while the CMP has no detectable impact on the tail risk of currencies, the NTM increases the systematic component of currency tail risk. Breaking down NTM into its various components, APP and SWAP have a considerable impact and although with opposite signs, APP appears to have a stronger significance.³² We further observe that the dummies for ZLB and FG_{og} are statistically significant and, again, have opposite signs. Finally, exchanging ZLB with CMP and FG_{og} with FG, we don't observe any qualitative differences in the results.³³

[Table 5]

5.2. Sub-sample estimates

Tables 6 and 7 present the results for the same analysis as above, but with the sample split into two: one pre- and one post-Global Financial Crisis. As intuition suggests, before the crisis neither NTM nor any of its components are significant. Indeed, only the dummmy variables for ZLB and FG_{og} are statistically significant. Instead, after the crisis, APP and SWAP become statistically significant. Finally, in the latter sub-sample only the FG_{og} element of forward guidance is significant.

Tables 6 - 7

In Table 8, we narrow the post-GFC sample even further to fine-tune the dynamic effects. In particular, we examine whether there are any substantial differences be-

³²Preliminary correlation analysis also highlight the relationship between these variables and the tail risk, or any of its components. At most maturities, the systematic component of tail risk correlates strongly with APP and SWAP. Two other instruments, COLLATERAL and CMP, correlate with the systematic component of tail risk, but only at the 2-month yield. Moreover, only APP has a statistically significant *positive* correlation with the systematic component. The remaining statistically significant coefficients are all negative See table 15 in the Appendix.

 $^{^{33}\}mathrm{To}$ preserve space, we do not present the results of this specification. They are available from the authors upon request.

tween the 2009-2012, 2012-2018 and 2019-2021 sample split.³⁴ Note however, that this analysis could not include the dummy variables for QE, ZLB and FG because of the small panel, which made an adjustment of standard errors unfeasible. Again, we find that APP and SWAP are statistically significant after 2012, which corresponds to the end of the Eurozone crisis.

[Table 8]

5.3. Lower frequency

Finally, Tables 9 - 11 report the results for the same set-up, but conducted at a weekly frequency. We do not find statistically significant results for CMP, NTM or any of its components.³⁵ Moreover, the results remain unchanged if we further break down the sample based on the Global Financial Crisis. However, the dummy variables for ZLB, QE and FG are statistically significant, in line with the evidence at the daily frequency presented previously.

[Tables 9 - 11]

5.4. Further discussion of the results

The panel results above provide evidence that central bank (monetary and liquidity) measures have an impact on the tail risk of currencies. This effect is particularly pronounced for APP which appears to lead to increases in the systematic part of tail risk. In other words, this increase of tail risk is undiversifiable for investors and institutions with exposure to currencies or at least those examined in this study.

³⁴These periods were specifically chosen as they represent: 1) the immediate GFC-monetary response including QE1 and QE2; 2) the Euro Area sovereign debt, negative rates and ECB QE period; and finally 3) the U.S. repo market and COVID stresses. While one could obviously chose other cut-off dates, our analysis suggests that the ones currently employed capture the various monetary stances and regimes while also allowing the sub-samples to be large enough to permit identification.

³⁵Preliminary correlation at the weekly frequency is different vis-a-vis daily frequency. The correlation between FG and the systematic tail risk becomes significant, while that of APP turns insignificant. See Table 16 in the Appendix.

However, while this effect is detected at all maturities, it is only statistically significant at daily frequency, suggesting that the impact dissipates relatively quickly. Moreover, the effect is most significant during the post-Great Financial Crisis subsample. SWAP, on the other hand, reduces systematic tail risk, especially in the post-Eurozone crisis sample. In the case of APP, investors receive cheap funding and invest them where the yield is higher. Because the yields on sovereign and highgrade corporate bonds is around zero, there is no alternative but to invest in riskier securities to satisfy the yield demands. In an international context, this would give investors an incentive to engage in large-scale carry trade and invest in currencies promising higher returns, depreciating their own currency. This, in turn, increases the systematic component of tail risk. For SWAP, on the other hand, the measure is designed to satisfy a surge in external demand, usually from a central bank, for its domestic currency. Because the supply is provided as an exchange (or swap) for the selling of domestic currency, the measure is designed to reduce potential (liquidity) stress in the domestic currency so is explicitly designed to reduce the tail probability mass, which the empirical evidence seems to support.

In addition, there is some evidence to suggest that COLLATERAL reduces the systematic tail risk, even if the effect is only detected at the short end (2m) of the yield curve. Although we find some evidence that FG is able to reduce systematic tail risk at the lower (weekly) frequency, it is only the qualitative statements of FG, FG_{og} , that are statistically significant at higher frequency for both the pre- and post-GFC sub-samples. This suggests that only the qualitative forward guidance is effective for the FX market. Finally, we find that QE and ZLB are significant across all regimes and throughout the entire sample period.

To corroborate these findings, we ran a number of robustness exercises based on simpler frameworks. Those include country-level rolling-window linear regressions of NTM measures on tail risk, the same as above but segmented using pre-defined regimes (*GFC, Second QE and EU sovereign debt crisis, 2013-19, Covid*), as well as measuring the impact of central bank announcements on rates, with a 3-week decay factor. The effects found in those models are quantitatively smaller and have wider confidence bands, but point in the same direction as the benchmark exercise.³⁶

5.5. GVAR methodology

5.5.1. Motivation

In this section, we turn to the time series analysis using Bayesian Global Vector AutoRegressive (BGVAR) model. For a detailed technical discussion of the model see Section 6 in the Appendix.³⁷ To the best of our knowledge, this is the first study to apply a general equilibrium-type of estimation to a large basket of high-frequency currency returns data, and including an array of central bank policy measures.³⁸

This method complements the panel data analysis in three ways. First, the panel data does not include cross-section general equilibrium effects. Aside from the impact of the U.S. on every country, the panel data analysis does not account for the loops between the other central banks, for instance between the UK and Japan, or Japan and Euro Area. Second, using this framework we are able to depict the dynamic evolution of the transmission of MP, in particular how long it lasts, when peaks occur and whether there is any cross-country heterogeneity. Third, we are able to isolate the global from the domestic effects.

5.5.2. Set-up

For this analysis, we use information on monetary policy measures from the central banks of Canada, Switzerland, Japan, U.K., Euro Area, New Zealand and

³⁶The results of these analyses are available upon request.

³⁷The GVAR model is estimated with the BGVAR package in R. See *this link* for details.

³⁸Moreover, the literature examining the impact of UMP announcements has so far analysed a small group of advanced economies so the computational issues are considerably more limited.

the U.S.³⁹ The sample covers the period from January 2000 to February 2021 and the frequency is daily. We use the weighting matrix of Feldkircher and Huber (2016) whose estimates are based on the annual *bilateral trade flows including services*, averaged over the period 2000-2012 which largely overlaps with our sample.

The matrix of endogenous variables includes three variables for each currency: the tail risk or its systematic component, conventional (CMP) and unconventional policy (UMP, or asset purchase programmes, (APP) alternatively). As in the panel method, we proxy the monetary policy impact through the daily change of the implied yield extracted from futures contracts of treasury bonds with maturity 1 month, 2 months, 2 years, 5 years and 10 years

In order to keep the BGVAR analysis consistent with the panel analysis, we treat the U.S. Fed's (CMP and UMP) policy actions as well as their components as exogenous variables in relation to other currencies. We model the U.S. data independently as in Mohaddes and Raissi (2019). In particular, we assume the Fed determines its CMP and UMP (or one of their components) using two inputs, a weighted average of the tail risk of currencies and a weighted average of UMP (or one of its components). Under this particular modelling specification, it is assumed the U.S. Fed, knowing its impact on monetary policies and currencies of other countries', determines its policy first. This assumption largely reflects the dominant role played by the U.S. in the global economy.

A few technical remarks are necessary. First, in order to improve the convergence we smooth the daily systematic tail risk measure with a moving average filter estimated over a 10-day window. The results are robust to using windows of 5 or 15 days. Second, the BGVAR is estimated in first differences, particularly important for the systematic component. Third, the model estimation uses stochastic search

³⁹We have omitted Sweden and Denmark for model dimensionality issues. Moreover, their currencies follow closely the dynamics of EURO, so we don't expect it to be structurally different from the Euro Area.

variable selection with 5 lags, 20,000 posterior draws and the same number of burnins (see George, Sun, and Ni, 2008). Finally, the full estimation takes between 30 to 40 minutes depending on the processing capacity of the computer.

5.5.3. Identification

To identify the shocks, we impose three sign restrictions. First, using inference from our panel analysis, for each country we impose a five-days increase in the systematic component following a policy event. Increasing this window to ten days does not result in a material change in our inference. Second, for each country we impose a one-day zero impact on CMP. This assumption reflects the fact that before the Global Financial Crisis, there was effectively no response of policy rates to UMP while afterwards, they were bound by the ZLB. Third, using insights from the literature, we assume that UMP or APP from EUR, UK and Japan decreases the systematic component of tail risk of the other two countries. For example, an UMP announcement by the ECB will reduce the systematic component for the U.K. and Japan (see, for example, Sosvilla-Rivero and Fernandez, 2016; Inoue and Rossi, 2019; Tran and Pham, 2020). However, we make no assumption about the impact of UK, Eurozone or Japan over Switzerland, Canada and New Zealand. The agnostic approach we take with respect to the latter does not condition our results since the impulse response functions (IRFs) tend to be qualitatively very similar to the model where we impose the sign restriction on the remaining countries. Yet, doing the latter often delays or prevents the estimation convergence of the IRFs. It can also lead to overidentification. For the global shock, we only assume a one-day positive effect for all countries.

In addition, unless otherwise stated, the shock pertains to the domestic monetary policy. The response function depicted is also in the same currency. So for instance, in Figure 9, we report the transmission of one standard deviation increase in the Bank of England's unconventional policy on the GBP tail risk. We also model the 95% distribution of IRFs. Exceptions are Figures 46-48, where the shock is in one single APP measure, but the transmission is restricted to be positive in the other jurisdictions/currencies. Next, to identify the particular channels, we orthogonalise the transmission of domestic shocks by estimating different pairs of shocks, and then incrementally add one shock at the time. This approach provides insights into the marginal contribution of specific domestic shocks on the global system. Lastly, we estimate the model using global (UMP, APP and CMP) shocks. A global shock is identified as one originating from the U.S., since U.S. is exogenous to the system, but impacts all countries simultaneously.

First, we discuss the results for UMP shocks, both domestic and global, and then proceed to discuss the APP shock results. Unless otherwise stated, the reported charts from Figure 14 onwards, and from top left to right and down represent those of: Canada (CA), Switzerland (CH), Euro Area (EU), UK (GB), Japan (JP) and New Zealand (NZ).

5.6. Results

5.6.1. Unconventional Policy

Figures 9-13 report the IRFs for the country-specific systematic tail risk following a local, but simultaneously-introduced UMP shock. The horizontal axis depicts the number of business days, and the vertical axis depicts the change in the systematic component of tail risk. Since the magnitudes on the vertical axis are based on a compounded tail risk, the easiest way to interpret the changes in the y-axis is as movements in an index.

We find that the systematic tail component increases consistently across all currencies. The response peaks at around one week and fades out between three to four weeks after the shock. This further confirms our panel analysis results that UMP has a short-term effect. It seems the effect is strongest for CAD and JPY while weakest for CHF. Yet, for CAD, the confidence intervals are also the widest, which points to considerable uncertainty regarding the true value. Considering the (central) Bank of Canada has employed a limited number of unconventional policy measures, the wide interval is not surprising.

[Figures 9-13]

To better understand the cross-border spill-overs of domestic shocks, a good proxy for the currency ties, we run a number of counterfactual exercises whereby we sequentially introduce shocks. We begin with different combinations of two shocks and gradually add one more and observe the impact on the IRFs. The difference in IRFs should capture the international transmission of that particular unconventional policy instrument.

Figure 14 depicts the transmission of a domestic UMP shock in Euro Area and Japan. Figure 15 presents the same for UK and Japan, and then sequentially so until Figure 20 where all shocks are simultaneously introduced. We end with a global shock reported in Figure 21.

In the two-shock scenario in Figures 14 to 16, the only jurisdictions that seem to significantly respond to movements in the domestic UMP are Euro Area, UK, Japan and New Zealand. That includes both the case when we impose a shock on their domestic currency, as well as when not. Obviously when the shock is in the domestic currency, the magnitude of that IRF is between 10 and 20 times higher. Nevertheless, in all cases, the entire 95% empirical distribution of the IRF is above or below 0. Moreover, the impact is persistent, both in the positive and negative territory. Following the positive domestic UMP shock, the response remains positive for about 4-5 weeks, and the peak is at around 1 and 3 weeks. The infimum of this interval represents the jurisdictions where a domestic shock has been applied, meanwhile the supremum is for jurisdictions that have imported the effects. Also, the reversal is weaker and occurs later for the jurisdictions that import the shock. This indicates a delay or friction in the cross-border transmission of UMP shocks. Adding more shocks does not change the dynamics. The responses of these four jurisdictions remain significant and persistent. Only when we introduce shocks in the other economies, do we also find significant transmission in those. In terms of magnitude, the largest responses for Euro Area, UK, Japan and Switzerland are for the case with simultaneous domestic UMP shocks in all those economies. The IRFs in this case are larger or equal to those of a scenario when all (seven) jurisdictions are shocked. In terms of marginal spill-overs of domestic UMP to total transmission, Switzerland appears to have the largest *contribution*. In contrast, a New Zealand UMP shock appears to *reduce* the overall transmission by greatest amount.

[Figures 14 to 20]

Turning now to the global UMP shock in Figure 21, the overall response functions are much much smaller. The difference is 1000-fold, if not more. Yet the IRFs are significant and persistent for 1 week or longer. The largest and most persistent response is on the Swiss franc, that remains above 0 for almost 4 weeks. This implies that the Swiss franc is the most exposed to US monetary policy, followed by Japan and Canada.

[Figure 21]

5.6.2. Asset Purchase Programs

Next, we contrast the impact of QE shocks. Figures 22 to 28 report the IRFs for domestic APP shocks. The results are qualitatively similar to those of UMP, although the responses seem somewhat more persistent. The only difference is that in the two-shock scenario, the largest responses arise when the shocks are UK- and Euro Area-specific. This means that the largest cross-border QE transmission comes from these two economies. This is in line with the intuition since these two central banks are amongst those that have most actively used this tool. Yet, when we sequentially add shocks, we find a slightly different behaviour compared to the UMP case. In particular, the largest increase in responses occurs when we add Canadian APP shock, suggesting that Canadian QE has had significant spill-overs. A New Zealand APP shock leads to a mixed picture. While the IRFs of New Zealand, UK and Japan increase, those of Euro Area and Canada decrease.

[Figures 22 to 28]

Turning to the global APP shock in Figure 29, the responses are again smaller compared to the domestic shocks, yet larger than those for the global UMP shock. Also this time, UK and Japan respond heaviest to a U.S. QE shock, followed by the Euro Area and Switzerland. Therefore, Fed's QE policy has had a wider and larger cross-border impact, disproportionally contributing to the international transmission of the latter.

[Figure 29]

Ceteris paribus, the responses to a QE shock are larger than those following an UMP shock. This implies a stronger cross-border transmission of a QE shock compared to the average UMP shock. We take this as evidence that QE increases considerably the (systematic) tail risk in the FX market, which may give rise to financial stability concerns, either through a global portfolio effect, or through common FX exposure.

5.6.3. Forecast Error Variance Decomposition

Figures 30 to 34 report the Forecast Error Variance Decomposition (FEVD) of the (systematic) tail measure for the domestic UMP shocks. For UK, variation in the tail measure is almost fully explained by domestic UMP. The share is between 60 and 100%, with the upper end at lower horizons. Even after two weeks, the share of domestic shocks explaining the total variation is above 50%. Similar pattern is observed for Switzerland, although the share is initially somewhat higher and then lower after two weeks. Japan also presents a similar case for about two weeks, but then drops much quicker. For the other two economies, the decay is much faster, although for the case of Canada it swings a bit in the first two weeks. While the variation in tail risk of Canada, Japan and, to some extent the Euro Area, are largely caused by non-domestic shocks, for the UK and to some extent Switzerland, the opposite is true.

[Figures 30 to 34]

Next, Figures 35 to 39 report the same exercise but with a domestic QE shock. Overall, a QE shock explains less of the variation in (systematic) tail risk compared to the UMP shock. That is true for all except Euro Area and Canada, where it somewhat outperforms the UMP shock at lower horizons. Yet, the largest difference is for UK, where QE explains around 70% less of the total variation in the measure after horizon 1. At horizon 1, the reduction is around 40%. This implies that comparatively, QE has mattered less for the variation in GBP tail compared to e.g. Switzerland or Canada, after controlling for the Fed QE.

[Figures 35 to 39]

5.6.4. Additional Robustness Checks

To better disentangle the transmission of each domestic QE shock for the three economies where the effects were the largest, UK, Euro Area and Japan, we ran independent simulation chains introducing only one shock and comparing the transmission to joint-shock scenarios. Figures 46 to 49 report the IRFs. Overall, the responses to an orthogonal shock are smaller than to joint shocks, with the Euro Area as the exception. The cross-border transmission to other economies seems, however, to be somewhat delayed in the one shock scenario. Taken together, this means that joint QE actions increase substantially the systematic component of FX tail risk, and proportionally more relative to when only one central bank implements QE measures. This evidence suggests a reinforcement of monetary policy effects and enhancement of its international transmission channel.

[Figures 46 to 49]

6. Conclusion

In this paper, we examine the relationship between central bank (monetary and liquidity) policy toolbox and the tail risk of exchange rates. We find that *both* conventional and unconventional policy tools have an impact on the tail risk - particularly the systematic component - of currencies. Ahrens et al. (2023) find that speeches by members of FOMC of the U.S. Fed seem to increase the tail risk of stocks and bonds. Our findings complement and expand on their findings by documenting that a similar finding holds for other central bank actions and currency markets. This transmission is larger for measures such as APP and SWAP, and in particular since the Euro Area Debt Crisis. Moreover, the effects are stronger for countries that have more forcefully engaged in unconventional monetary policy, shedding new light on the (unintended) consequences of non-traditional measures on financial markets. The effects last for up to 1 month, and are proportionally higher for joint QE actions. This suggests a reinforcement of monetary policy effects. Our empirical analysis confirms the existence of a financial cross-border transmission channel of central bank policy, via the FX market. Future research should aim to formalize such link to better understand the structural aspects of the transmission and any implications for investors, financial markets and potentially, financial stability.

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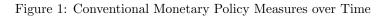
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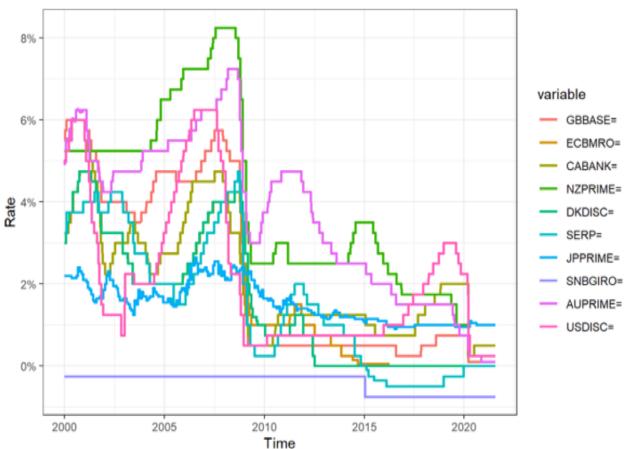
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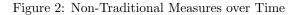
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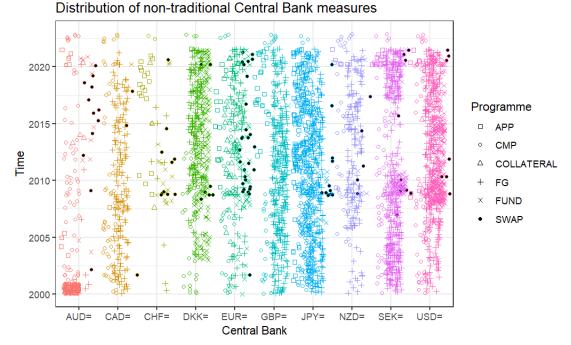




Base rates of main currencies

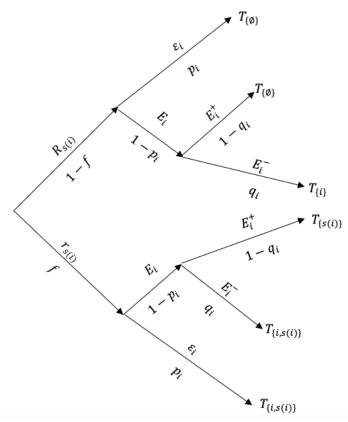
This figure shows the movement in the base interest rate controlled by the respective main central banks over the sample period from January 2000 to February 2021. These base rates pertain to the following currencies: GBP, EUR, CAD, NZD, DKK, SEK, JPY, AUD and USD.





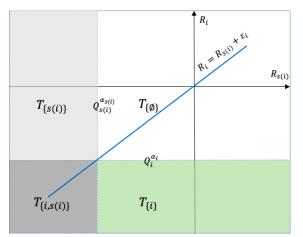
This figure shows the number of times a particular measure has been implemented over the sample period from January 2000 to February 2021. The currencies are: GBP, EUR, CAD, NZD, DKK, SEK, JPY, AUD and USD. The figure is a structured scatter plot where the intensity of colour represents the frequency the respective central bank has intervened with monetary policy measures implemented during that particular period.

Figure 3: The Evolution of Currency Returns



This figure shows the evolution of the currency returns determined by aggregate systematic factor and an idiosyncratic term. Aggregate systematic factor can be smaller $r_s(i)$ or larger $R_s(i)$ than a given threshold with probability f or (1-f) respectively. The idiosyncratic term can be "small" (ϵ_i) or "large" (E_i) with probability p_i and $(1-p_i)$ respectively. When the idiosyncratic term is large, it can be negative E_i^- with probability $\Pr(E_i^-) = q_i$ or positive E_i^+ with probability $\Pr(E_i^+) = 1 - q_i$. The term below each branch is the probabilities of the term above that branch and the terms in the final nodes are the tails of the joint distribution (see also Figure 2)





Partition of the outcome space into tails where the dash lines depict the thresholds, in this case quantiles $Q_s(i)^{\alpha} = F_s(i)^{-1}(\alpha_s(i))$ and $Q_i = F_i^{-1}(\alpha_i)$. The four tails are the final nodes in the event tree in Figure 1: in T_{\emptyset} no quantile exceedance has occurred (the white area), in $T_{s(i)}$ the aggregate systematic factor has exceeded its quantile but not the currency (the light grey area), in T_i the currency has exceeded its quantile but not the the aggregate systematic factor (the green area) and finally in $T_{i,s(i)}$ both have exceeded their quantiles (the dark grey area).

Table 1: Linear Regression of the Currency Excess Returns on the first three the PCs

This table shows the estimated parameters of linear regressions of the excess returns of the various currencies on the first three the PCs. Statistical significance notation follows the conventional standard where * indicates that the p-value < 0.1; **indicates that the p-value < 0.05; *** indicates that the p-value < 0.01.

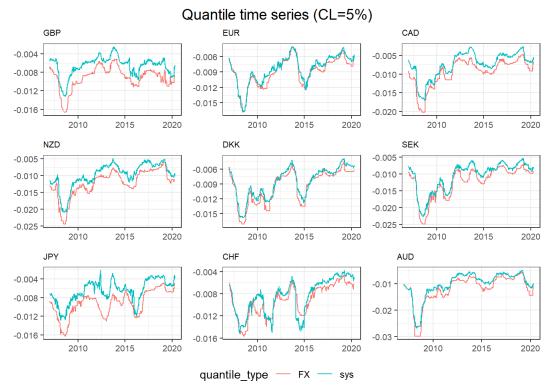
				Dependent v	Dependent variable: FX excess returns	ss returns			
	GBP	EUR.	CAD	NZD	DKK	SEK	YqI.	CHF	AUD
PCA1	-0.092***	-0.117***	0.077***	-0.132***	0.116^{***}	0.137^{***}	0.042^{***}	0.108^{***}	-0.136***
	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
PCA2	0.089***	0.201^{***}	0.047^{***}	-0.006	-0.198^{***}	-0.154^{***}	-0.199^{***}	-0.267***	-0.036^{***}
	-0.004	-0.002	-0.003	-0.004	-0.002	-0.003	-0.004	-0.003	-0.004
PCA3	-0.030***	0.039^{***}	-0.023^{***}	-0.002	-0.041^{***}	-0.053^{***}	0.156^{***}	0.014^{**}	-0.001
	-0.008	-0.004	-0.007	-0.009	-0.004	-0.007	-0.009	-0.07	-0.008
Constant	0.00003	0.0003	0.0001^{*}	-0.0001^{*}	-0.0003	-0.00002	-0.0001	0	-0.0001^{*}
	-0.0001	-0.00003	-0.0001	-0.0001	-0.00003	-0.00005	-0.0001	-0.00005	-0.0001
Obs.	5,621	5,621	5,621	5,621	5,621	5,621	5,621	5,621	5,621
\mathbb{R}^2	0.519	0.89	0.52	0.613	0.883	0.75	0.345	0.725	0.679
Adj. R2	0.519	0.89	0.52	0.612	0.883	0.75	0.345	0.724	0.679
Res. Std. Error	0.004	0.002	0.004	0.005	0.002	0.004	0.005	0.004	0.004
(df 5617)									
F Statistic	$2,020.299^{***}$	$15,125.640^{***}$	$2,028.147^{***}$	$2,961.786^{***}$	$14,190.500^{***}$	$5,609.974^{***}$	986.765^{***}	$4,926.957^{***}$	$3,957.689^{***}$
(df 3; 5617)									

Table 2: Quantiles of the Empirical Distribution

Panel A of this table shows the 2.5, 5 and 10% quantiles of the empirical distribution of the currency excess returns. Panel B shows the 2.5, 5 and 10% quantiles of the empirical distribution of the aggregate systematic risk factor of each currency. The 5% quantile in bold is used as a benchmark.

		Р	anel A: Ç	Juantiles	of the cur	rency exc	cess retur	ns	
	GBP	EUR	CAD	NZD	DKK	SEK	JPY	CHF	AUD
0.025	-0.011	-0.012	-0.011	-0.015	-0.013	-0.015	-0.012	-0.012	-0.015
0.05	-0.009	-0.01	-0.009	-0.012	-0.01	-0.012	-0.009	-0.01	-0.011
0.1	-0.007	-0.007	-0.006	-0.009	-0.007	-0.009	-0.007	-0.007	-0.008
	Par	nel B: Qu	antiles of	the aggr	egate sys	tematic fa	actor for a	each coun	try
	GBP	EUR	CAD	NZD	DKK	SEK	\mathbf{JPY}	CHF	AUD
0.025	-0.008	-0.012	-0.008	-0.012	-0.012	-0.013	-0.007	-0.011	-0.012
0.05	-0.007	-0.009	-0.006	-0.009	-0.009	-0.01	-0.005	-0.009	-0.01
0.1	-0.005	-0.007	-0.004	-0.007	-0.007	-0.008	-0.004	-0.007	-0.007

Figure 5: The Evolution of the Tail Risk of Currencies and Their Systematic Risk Factors over Time



This figure shows the evolution of the quantiles at nominal probability level $\alpha = 5\%$ of currencies and their aggregate systematic risk factors.

Table 3: Joint Probability of a Tail Event and the Tail Dependence Coefficient

Panel A of this table shows the joint probability of a currency and its aggregate systematic risk factor exceeding their respective 2.5, 5 and 10% quantiles of the empirical distribution. Panel B shows the tail dependence coefficient of a currency on its aggregate systematic risk factor estimated at the 2.5, 5 and 10% quantiles of the empirical distribution. The 5% quantile in bold is used as a benchmark.

				-	v	f a curre or exceed	v		
	GBP	EUR	CAD	NZD	DKK	SEK	JPY	CHF	AUD
0.025	0.012	0.019	0.012	0.015	0.019	0.015	0.007	0.016	0.014
0.05	0.024	0.037	0.025	0.027	0.037	0.031	0.015	0.035	0.027
0.1	0.055	0.079	0.055	0.056	0.077	0.068	0.039	0.071	0.059
		Panel		-		coefficien atic risk		rrency	
	GBP	\mathbf{EUR}	\mathbf{CAD}	\mathbf{NZD}	DKK	\mathbf{SEK}	\mathbf{JPY}	CHF	AUD
0.025	0.449	0.755	0.485	0.602	0.741	0.58	0.274	0.617	0.558
0.05	0.449	0.734	0.475	0.524	0.73	0.599	0.262	0.674	0.524
0.1	0.496	0.771	0.496	0.506	0.743	0.642	0.32	0.674	0.547

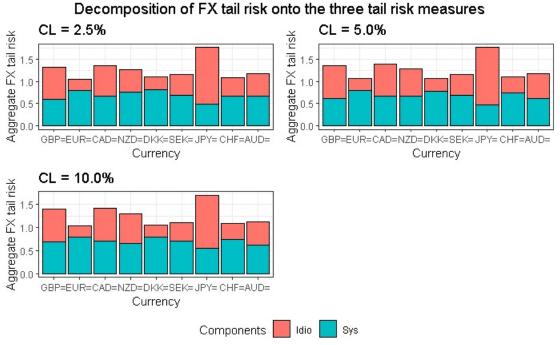


Figure 6: Decomposition of Currency Tail Risk into the Tail Risk Measures

This figure shows the decomposition of currency tail risk into the systematic tail risk, idiosyncratic tail risk and tail risk cushioning measures.

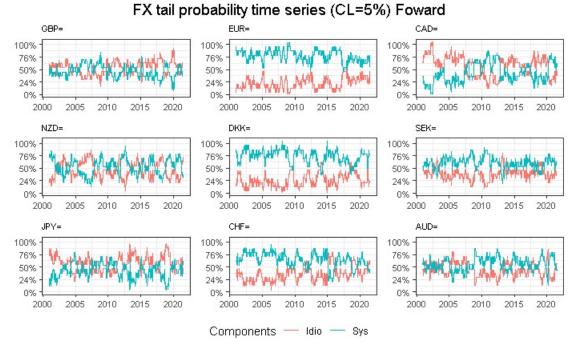


Figure 7: Currency Tail Risk Measures over Time

This figure shows the decomposition of currency tail risk into the systematic tail risk and idiosyncratic tail risk measures.

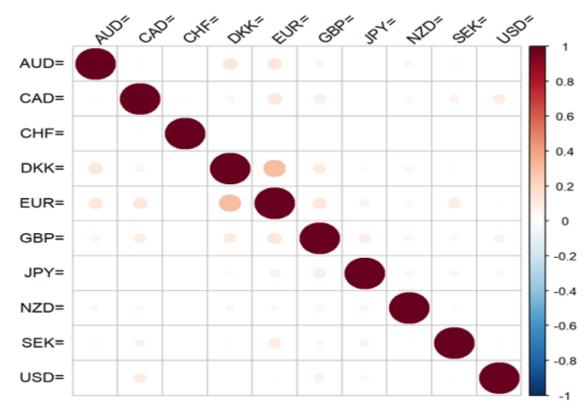


Figure 8: Dynamic Correlations of Conventional Monetary Policy Measures Across Countries

This figure shows the the dynamic correlations of measures in the conventional monetary policy space over the sample period from January 2000 to February 2021. The currencies are: GBP, EUR, CAD, NZD, DKK, SEK, JPY, AUD and USD.

Table 4: Description of Main Variables

These are the variables we use in the econometric analysis. The impact of CMP, APP, Coll, FG, Fund and Swap is measured as $\Delta ImpYield_{it}^{\tau}$, where ImpYield is the futures-implied yield of country i, at day t, of sovereign bond with maturity $\tau \in \{1m, 2m, 2y, 5y, 10y\}$. Finally, the impact will be different from zero at the day of the decision, and the next three working days.

Variable	Description
Tail Risk	Full tail risk, systematic tail risk or idyosincratic tail risk component following the procedure described in the paper
CMP	Impact of Central Bank announcement about the reference rate*
APP	Impact of Central Bank announcement about asset purchase programs*
Coll	Impact of Central Bank announcement about assets eligible as collateral*
\mathbf{FG}	Impact of Central Bank forward guidance announcement*
Fund	Impact of Central Bank announcement about funding facilities*
Swap	Impact of Central Bank announcement about swap lines with other central banks*
ZLB	Dummy variable for periods when the reference rate reached the zero lower bound
FGsg, og, tg	Dummy variables following Ehrmann et al., 2019; Beck, Duca, and Stracca, 2019
QE	Dummy variable for periods of QE/QT

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standard errors in square brackets. The dependent variable is the systematic component of the tail risk calculated with the The table reports the estimated parameters of the short panel correcting for endogenous regressor, and their corresponding last year of observations. Variables of interest are the daily changes of implied yields from future contracts at monetary policy guidance and effective lower bound are included. Additional controls are daily changes of implied yields from future contracts at conventional and unconventional monetary policy announcements dates from the United States. Country, month and year announcements dates. We also include three days posterior to the announcements. We use as IV the daily change of implied yields of future contracts of 10 year treasury bonds. Dummy variables for QE implementations, different type of forward fixed effects are included, as well as their triple interaction. We are using weekly data from January 1, 2000 to July 30, 2020. Standard errors are Driscoll-Kraay adjusted with 2 lags. The symbols *, **, *** denote significance at the 10%, 5% and 1% level, respectively.

-	<i>°</i>												
I		5y	v	2y	y	2m	п	lm	n	2m(r)	(r)	1m(r)	(r)
	MTN	0.010 [0.007]		0.012* 0.07]		0.015** [0.006]		0.015** [0.006]		0.015** [0.006]		0.016^{**}	
	CMP	-0.010	-0.008	-0.00	-0.007	-0.012	-0.010	-0.012	-0.008	-0.011	-0.009	-0.011	-0.007
	APP	[0.009]	[0.009] 0.028^{***}	[0.010]	[0.010] 0.028***	[0.012]	[0.012] 0.029***	[0.010]	[0.010] 0.028***	[0.012]	[0.012] 0.029***	[0.010]	[0.010] 0.028***
			[0.00]		[0.008]		0.008]		[0.008]		0.008]		0.08]
	Collateral		[0.074]		[620.0-		-0.003 [0.062]		[990.0]		-0.000 [0.062]		-0.020 [0.064]
	Forward G.		0.006 [0.007]		0.007		0.007		0.007 [0.009]		0.007		0.007
	Fund		-0.000		0.000		0.000		0.004		0.002		-0.003
	τ		[0.013]		[0.016]		[0.017]		[0.016]		[0.017]		[0.018]
	Swap		-0.068* [0.041]		-0.116°		-0.094 [0.067]		8c0.0- [1.30.0]		-0.186* [0.111]		-0.146 [0.123]
	ZLB	-0.011^{**}	-0.011^{**}	-0.011^{**}	-0.011^{**}	-0.012^{**}	-0.012^{**}	-0.012^{**}	-0.012^{**}	-0.012^{**}	-0.012^{**}	-0.012^{**}	-0.012^{**}
		[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
	FG_{sg}	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
		[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
	FG_{og}	0.025^{***}	0.025^{***}	0.025***	0.025^{***}	0.025^{***}	0.025^{***}	0.025^{***}	0.025^{***}	0.025^{***}	0.025***	0.025^{***}	0.025***
	$FG_{t,a}$	[0.003 -0.003	-0.003	-0.003	-0.003	[0.003 -0.003	-0.003	[0.003 -0.003	-0.003	-0.003	-0.003	[0.003 -0.003	-0.003
	'n	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
	QE	-0.019	-0.019	-0.019	-0.019	-0.019	-0.019	-0.019	-0.019	-0.019	-0.019	-0.019	-0.019
		[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]
	Obs	30,720	30,720	30,720	30,720	30,720	30,720	30,720	30,720	30,720	30,720	30,720	30,720
	U.S. Controls	\mathbf{YES}	\mathbf{YES}	YES	YES	YES	YES	YES	YES	\mathbf{YES}	YES	YES	YES
	C_M_Y FE	\mathbf{YES}	\mathbf{YES}	YES	YES	YES	\mathbf{YES}	\mathbf{YES}	\mathbf{YES}	\mathbf{YES}	YES	\mathbf{YES}	YES

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monetary policy announcements dates. We also include three days posterior to the announcements. We use as IV the sum of The table reports the estimated parameters of the short panel correcting for endogenous regressor, and their corresponding standard errors in square brackets. The dependent variable is the weekly average systematic component of the tail risk calculated with the last year of observations. Variables of interest are the sum of daily changes of implied yields from future contracts at daily change of implied yields of future contracts of 10 year treasury bonds. Dummy variables for QE implementations, different Country, month and year fixed effects are included, as well as their triple interaction. We are using weekly data from January 1, 2000 to July 30, 2020. Standard errors are Driscoll-Kraay adjusted with 2 lags. The symbols *,**, *** denote significance at type of forward guidance and effective lower bound are included. Additional controls are the sum of daily changes of implied yields from future contracts at conventional and unconventional monetary policy announcements dates from the United States. the 10%, 5% and 1% level, respectively.

Before GFC 5y NTM 5y NTM 0.008 CMP [0.009] CMP 0.009 CMP [0.013] APP [0.013] Collateral 0.046 Forward G. [0.041]		2y		2m		1m		2m(r)	(r)	1 m(r)	· ,
0.008 [0.009] 0.009 0.013] eral ard G.			_		-		-		-	\ 	1)
0.009 0.009 feral ard G.		0.008 0.0101		-0.006 0.016		0.018 0.013		-0.005		0.018	
[0.013] teral ard G.	0.009	0.011	0.010	0.018	0.017	0.008	0.006	0.017	0.018	[ct0.0]	0.007
teral ard G.	[0.013]	[0.014]	[0.014]	[0.021]	[0.021]	[0.016]	[0.016]	[0.019]	[0.019]	[0.015]	[0.015]
	-0.019		-0.012	1	0.038		0.039	1	0.032	1	0.038
	[0.046]		[0.051]		[0.084]		[0.075]		[0.079]		[0.075]
	0.042		0.043		0.021		-0.017		0.025		-0.031
	[0.044]		[0.045]		[0.067]		[0.044]		[0.072]		[0.045]
	0.010		0.009		0.014		0.007		0.015		0.008
	[0.011]		[0.013]		[0.021]		[0.015]		[0.022]		[0.015]
Fund (0.002		0.000		0.028		0.076		0.020		0.095
	[0.024]		[0.024]		[0.056]		[0.064]		[0.058]		[0.078]
Swap	-0.013		-0.014		-0.379		0.039		-0.313		0.008
	[0.075]		[0.084]		[0.275]		[0.133]		[0.218]		[0.121]
	.037***	-0.036^{***}	-0.036^{***}	-0.036^{***}	-0.036***	-0.037***	-0.037***	-0.036^{***}	-0.036^{***}	-0.037***	-0.037***
[0:002]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
	.044***	0.044^{***}	0.044^{***}	0.044^{***}	0.044^{***}	0.044^{***}	0.044^{***}	0.044^{***}	0.044^{***}	0.044^{***}	0.044^{***}
[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.007	-0.008	-0.008	-0.008	-0.007
[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.012]	[0.013]	[0.013]	[0.013]	[0.012]
	13,758	13,758	13,758	13,758	13,758	13,758	13,758	13,758	13,758	13,758	13,758
uared 0.006	0.006	0.006	0.005	0.005	-0.015	0.004	-0.009	0.005	-0.009	0.004	-0.015
YES	YES	\mathbf{YES}	YES	YES	YES	\mathbf{YES}	YES	YES	YES	YES	YES
YES	YES	YES	YES	YES	YES	YES	YES	\mathbf{YES}	YES	\mathbf{YES}	YES

The table reports the estimated parameters of the short panel correcting for endogenous regressor, and their corresponding	standard errors in square brackets. The dependent variable is the weekly average systematic component of the tail risk calculated	with the last year of observations. Variables of interest are the sum of daily changes of implied yields from future contracts at	monetary policy announcements dates. We also include three days posterior to the announcements. We use as IV the sum of	daily change of implied yields of future contracts of 10 year treasury bonds. Dummy variables for QE implementations, different	type of forward guidance and effective lower bound are included. Additional controls are the sum of daily changes of implied	yields from future contracts at conventional and unconventional monetary policy announcements dates from the United States.	Country, month and year fixed effects are included, as well as their triple interaction. We are using weekly data from January	1, 2000 to July 30, 2020. Standard errors are Driscoll-Kraay adjusted with 2 lags. The symbols *, **, *** denote significance at	the 10% , 5% and 1% level, respectively.	After GFC 5v 2v 2m 1m 2m(r) 1m(r)
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Table 7: Causation through IV: After GFC

— _I																					
1m(r)		-0.020 [0.014]	0.029^{***}	[0.008]	-0.061 $[0.101]$	0.003	0.000-	[0.017]	-0.144^{*}	[0.076]	0.000	[0.005]	-0.004	[0.005]	0.015^{**}	[0.006]	-0.003	[0.002]	-0.027	[0.039]	16,956 YES
1n	0.014^{*} [0.008]	-0.025* [0.014]	[#10.0]								0.000	[0.005]	-0.004	[0.005]	0.015^{**}	[0.006]	-0.002	[0.002]	-0.027	[0.039]	16,956 YES
(r)		-0.024 [0.015]	0.031***	[0.009]	0.041 [0.084]	0.001	0.005	[0.020]	-0.142^{*}	[0.076]	0.000	[0.005]	-0.003	[0.005]	0.015^{**}	[0.006]	-0.002	[0.002]	-0.027	[0.039]	16,956 YES
2m(r)	0.014^{**} $[0.007]$	-0.025*	[ernn]								0.000	[0.005]	-0.003	[0.005]	0.015^{**}	[0.006]	-0.002	[0.002]	-0.028	[0.039]	16,956 YES
n n		-0.020	0.029^{***}	[0.008]	-0.066 $[0.105]$	0.003	0.000	[0.017]	-0.097*	[0.059]	0.000	[0.005]	-0.004	[0.005]	0.015^{**}	[0.006]	-0.002	[0.002]	-0.027	[0.039]	16,956 YES
1m	0.013^{*} [0.008]	-0.025*	[#10.0]								0.000	[0.005]	-0.004	[0.005]	0.015^{**}	[0.006]	-0.002	[0.002]	-0.027	[0.039]	16,956 YES
		-0.024 [0.016]	0.031***	0.009]	0.029 [0.084]	0.001	0.007	[0.021]	-0.094	[0.060]	0.000	[0.005]	-0.003	[0.005]	0.015^{**}	[0.006]	-0.002	[0.002]	-0.027	[0.039]	16,956 YES
2m	0.013* [0.007]	-0.025*	[et0.0]								0.000	[0.005]	-0.003	[0.005]	0.015^{**}	[0.006]	-0.002	[0.002]	-0.028	[0.039]	16,956 YES
۲ 		-0.018	0.029***	[0.008]	-0.086 [0.123]	0.003	0.003	[0.022]	-0.145^{*}	[0.079]	0.000	[0.005]	-0.004	[0.005]	0.015^{**}	[0.006]	-0.002	[0.002]	-0.027	[0.039]	16,956 YES
2y	0.013^{*} [0.008]	-0.022*	[etn:n]								0.000	[0.005]	-0.003	[0.005]	0.015^{**}	[0.006]	-0.002	[0.002]	-0.028	[0.039]	16,956 YES
_		-0.020	0.029^{***}	[0.009]	-0.081 [0.109]	0.002	0.003	[0.017]	-0.085*	[0.051]	0.000	[0.005]	-0.004	[0.005]	0.014^{**}	[0.007]	-0.002	[0.002]	-0.027	[0.039]	16,956 YES
5y	0.011 [0.008]	-0.024^{*}	[410.0]								0.000	[0.005]	-0.003	[0.005]	0.015^{**}	[0.006]	-0.002	[0.002]	-0.028	[0.040]	16,956 YES
After GFC	NTM	CMP	APP		Collateral	Forward G.	Fund		Swap		ZLB		FG_{sg}		FG_{og}		FG_{tg}		QE		Obs. U.S. Controls

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with the last year of observations. Variables of interest are the sum of daily changes of implied yields from future contracts at monetary policy announcements dates. We also include three days posterior to the announcements. We use as IV the sum of The table reports the estimated parameters of the short panel correcting for endogenous regressor, and their corresponding standard errors in square brackets. The dependent variable is the weekly average systematic component of the tail risk calculated daily change of implied yields of future contracts of 10 year treasury bonds. Dummy variables for QE implementations, different Country, month and year fixed effects are included, as well as their triple interaction. We are using weekly data from January 1, 2000 to July 30, 2020. Standard errors are Driscoll-Kraay adjusted with 2 lags. The symbols *,**, *** denote significance at type of forward guidance and effective lower bound are included. Additional controls are the sum of daily changes of implied yields from future contracts at conventional and unconventional monetary policy announcements dates from the United States. the 10%. 5% and 1% level. respectively.

1 m(r)	-0.041	[0.036] -0.027	[0.038]	[0.184]	0.022	[0.025]	0.011	[0.039]	0.023	[0.056]	2,484 -0.000 YES YES
2m(r)	-0.040	[0.035] -0.025	[0.036]	[0.168]	0.021	[0.025]	0.010	[0.039]	0.023	[0.056]	2,484 -0.000 YES YES
$\int an 2019 \\ 1m$	-0.029	[0.033] -0.029	[0.036]	0.255]	0.020	[0.025]	0.021	[0.038]	0.007	[0.022]	2,484 0.001 YES YES
After J 2m	-0.028	[0.032] -0.027	[0.035]	[0.226]	0.019	[0.024]	0.019	[0.038]	0.007	[0.022]	2,484 0.001 YES YES
$_{2y}$	-0.048	[0.041] -0.009	[0.033]	0.160	0.022	[0.023]	-0.019	[0.060]	1.532	[1.419]	2,484 -0.003 YES YES
5y	-0.035	[0.030] -0.010	[0.026]	[0.121]	0.018	[0.021]	0.012	[0.037]	0.010	[0.024]	2,484 0.004 YES YES
1 m(r)	-0.022	$[0.019]$ 0.032^{***}	[0.010]	-0.072	0.012	[0.016]	0.096	[0.105]	-0.417^{**}	[0.182]	10,176 0.001 YES YES
2m(r)	-0.030	[0.023] 0.035^{***}	[0.013]	0.169]	-0.000	[0.010]	0.120	[0.123]	-0.399**	[0.178]	10,176 -0.045 YES YES
- Dec 2018 1m	-0.022	[0.020] 0.032***	[0.010]	[0.173]	0.012	[0.016]	0.094	[0.096]	-0.387**	[0.162]	10,176 0.002 YES YES
July 2012 - 2m	-0.030	[0.023] 0.035^{***}	[0.012]	[0.169]	-0.000	[0.010]	0.114	[0.109]	-0.373**	[0.159]	10,176 -0.032 YES YES
$_{2y}$	-0.019	$[0.018] 0.032^{***}$	[0.010]	-0.122	0.009	[0.015]	0.084	[0.078]	-0.330**	[0.144]	10,176 0.003 YES YES
5y	-0.020	$[0.020]$ 0.034^{***}	[0.010]	[0.160]	0.007	[0.012]	0.071	[0.061]	-0.287**	[0.125]	10,176 0.002 YES YES
1m(r)	-0.005	[0.023] 0.033	[0.041]	-0.077]	-0.036^{*}	[0.022]	0.005	[0.020]	-0.065	[0.086]	4,302 0.004 YES YES
2m(r)	-0.007	[0.025] 0.034	[0.043]	-0.083]	-0.040	[0.027]	0.000	[0.028]	-0.064	[0.086]	4,302 0.004 YES YES
June 2012 1m	-0.006	[0.024] 0.032	[0.042]	-0.073]	-0.036^{*}	[0.022]	0.005	[0.021]	-0.063	[0.081]	4,302 0.004 YES YES
Oct 2009 - June 201 2m 1m	-0.009	[0.027] 0.034	[0.044]	-0.079]	-0.040	[0.027]	-0.000	[0.029]	-0.062	[0.081]	4,302 0.004 YES YES
2y	-0.005	[0.022] 0.029	[0.042]	[690.0]	-0.036^{*}	[0.021]	0.008	[0.022]	-0.059	[0.076]	4,302 0.004 YES YES
5y	-0.004	[0.021] 0.028	[0.040]	[0.068]	-0.035	[0.021]	0.006	[0.021]	-0.052	[0.068]	4,302 0.004 YES YES
	CMP	APP	TIOD	COLL	FG		Fund		Swap		Obs R-squared U.S. Controls C_M_Y FE

he est re bræ bservæ bservæ ncem race races ræ racts ræ racts reer fiy evel, i	The table reports the estimated parameters of the short panel correcting for endogenous regressor, and their corresponding standard errors in square brackets. The dependent variable is the weekly average systematic component of the tail risk calculated with the last year of observations. Variables of interest are the sum of daily changes of implied yields from future contracts at monetary policy announcements dates. We also include three days posterior to the announcements. We use as IV the sum of daily change of implied yields of future contracts of 10 year treasury bonds. Dummy variables for QE implementations, different	type of forward guidance and effective lower bound are included. Additional controls are the sum of daily changes of implied yields from future contracts at conventional and unconventional monetary policy announcements dates from the United States. Country, month and year fixed effects are included, as well as their triple interaction. We are using weekly data from January 1, 2000 to July 30, 2020. Standard errors are Driscoll-Kraay adjusted with 2 lags. The symbols $*, **, ***$ denote significance at the 10% , 5% and 1% level, respectively.	2v 2m 1m 2m(r) 1m(r)
	timated parameters ackets. The depende ations. Variables of nents dates. We als ls of future contract	nd effective lower be at conventional and xed effects are inclu andard errors are D respectively.	2v

Table 9: Causation through IV: weekly frequency

$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$																						
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$			-0.005	[0.020] 0.016	[0.013]	[0.062]	0.004 [0.014]	0.015	[0.028]	-0.109	[0.097]	-0.009	[0.007]	-0.010	[0.011]	0.071***	[0.016]	0.007	-0.024^{**}	[0.012]	7,126	VES YES YES
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	1 m(r)	0.009	-0.006	[0.019]							000	-0.009	[0.007]	-0.010	[0.011]	0.071***	[0.016]	[0.07]	-0.023^{**}	[0.012]	7,126	VES YES YES
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$			-0.008	[0.022] 0.017	[0.013]	[0.098]	0.004	0.027	[0.038]	-0.111	[0.091]	-0.009	[0.007]	-0.009	[0.011]	0.071***	[0.016]	[0.007]	-0.024^{**}	[0.012]	7,126	VES YES YES
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	2m(r)	0.010 [0.008]	-0.006	[0.022]								-0.009	[0.007]	-0.009	[0.011]	1.0.0 1.0.0	[0.016]	[0.007]	-0.024^{**}	[0.012]	7,126	VES YES YES
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$			-0.006	[0.020] 0.016	[0.013]	[0.055]	0.003	0.015	[0.027]	-0.080	[0.072]	-0.009	[0.007]	-0.010	[0.011]	0.071***	[0.016]	[0.007]	-0.024^{**}	[0.012]	7,126	V.U14 YES YES
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$1 \mathrm{m}$	0.009	-0.006	[0.020]							000	-0.009	[0.007]	-0.010	[0.011]	0.071***	[0.016]	[0.007]	-0.023^{**}	[0.012]	7,126	VES VES YES
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$			-0.008	[0.023] 0.017	[0.013]	[0.089]	0.004 [0.012]	0.025	[0.038]	-0.076	[0.065]	-0.009	[0.007]	-0.009	[0.011]	1/0.0	[0.016]	[0.007]	-0.024^{**}	[0.012]	7,126	VES YES YES
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$2\mathrm{m}$	0.009 0.008]	-0.006	[0.022]							00000	-0.009	[0.007]	-0.009	[0.011]	0.071***	[0.016]	[0.007]	-0.024^{**}	[0.012]	7,126	VES YES YES
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			-0.007	[0.018] 0.017	[0.013]	[0.055]	0.004	0.018	[0.032]	-0.089	[0.069]	-0.010	[0.007]	-0.009	[0.011]	1.0.0 ***17'0.0	[0.016]	[0.007]	-0.024^{**}	[0.012]	7,126	V.U10 YES YES
$\begin{array}{c} 5_{y} \\ 0.007 \\ [0.015] \\ -0.007 \\ [0.015] \\ 0.011 \\ -0.010 \\ [0.011] \\ -0.011 \\ [0.016] \\ -0.011 \\ [0.016] \\ -0.011 \\ [0.016] \\ -0.011 \\ [0.016] \\ -0.011 \\ [0.016] \\ -0.011 \\ [0.016] \\ -0.011 \\ VES \end{array}$	2y	0.008 0.008	-0.007	[0.018]							0	-0.010	[0.007]	-0.009	[0.011]	1.0.0 T	[0.016]	[0.007]	-0.024^{**}	[0.012]	7,126	V.UID YES YES
	I		-0.07	[0.015] 0.016	[0.012]	[0.053]	0.003	0.013	[0.028]	-0.058	[0.044]	-0.010	[0.008]	-0.009	[0.011]	0.071***	[0.016]	[0.07]	-0.023^{**}	[0.012]	7,126	VES YES YES
NTM CMP CMP APP Collateral Forward G. Fund Swap Fund FG _{sg} FG _{sg} FG _{sg} FG _{tg} QE Colss C.M.Y FE C.M.Y FE	5y	0.007 0.007	-0.007	[0.015]								-0.010	[0.007]	-0.010	[0.011]	0.071***	[0.016]	[0.007]	-0.024^{**}	[0.012]	7,126	VES YES YES
		MTN	CMP	APP	Collateral		Forward G.	Fund		Swap		ZLB	i	FG_{sg}	Č F	FG_{og}	$FG_{4,2}$	5	QE		Obs	K-squared U.S. Controls C_M_Y FE

ı — I																	
(r)		0.005	[0.030] -0.285	[0.487] 0.220	[0.177] 0.019	[0.029]	-0.039	[0.041]	[0.172]	-0.025^{**}	[0.011]	0.024^{***}	[0.000] -0.061***	[0.016]	3,192	$_{ m YES}^{ m 0.010}$	YES
1m(r)	0.017 $[0.021]$	0.016	[0.029]							-0.025**	[0.011]	0.024^{***}	0.060***	[0.016]	3,192	0.021 YES	\mathbf{YES}
(r)		0.020	[0.037] 0.579	$\begin{bmatrix} 1.014 \\ 0.137 \end{bmatrix}$	[0.174] 0.013	[0.038]	-0.091	0.088]	[0.314]	-0.023^{**}	[0.011]	0.024^{***}	-0.057***	[0.017]	3,192	0.012 YES	YES
2m(r)	-0.000 [0.029]	0.019	[0.036]							-0.025^{**}	[0.011]	0.024^{***}	-0.061***	[0.016]	3,192	0.021 YES	\mathbf{YES}
в		0.010	[0.033] -0.197	[0.463] 0.155	[0.115] 0.020	[0.029]	-0.041	0.043	[0.166]	-0.024^{**}	[0.011]	0.024^{***}	-0.061***	[0.016]	3,192	0.014 YES	YES
1m	0.018 [0.022]	0.019	[0.031]							-0.025**	[0.011]	0.024^{***}	-0.060***	[0.016]	3,192	0.021 YES	YES
2m		0.019	[0.041] 0.449	[0.918] 0.116	[0.141] 0.017	[0.038]	-0.116	0.087] -0.066	[0.212]	-0.023^{**}	[0.011]	0.024^{***}	[0.058***	[0.017]	3,192	0.017 YES	\mathbf{YES}
2	0.001 $[0.029]$	0.023	[0.040]							-0.025**	[0.011]	0.024^{***}	[0.00] -0.061***	[0.016]	3,192	0.022 YES	YES
2y		0.008	[0.028] - 0.106	[0.217] 0.105	[0.103] 0.024	[0.024]	-0.034	[0.043] -0.063	[0.082]	-0.026^{**}	[0.010]	0.024^{***}	[0.061***	[0.016]	3,192	0.019 YES	\mathbf{YES}
	0.011	0.009	[0.028]							-0.025**	[0.010]	0.024^{***}	000.0- -0.060***	[0.016]	3,192	0.019 YES	YES
5y		0.005	[0.024]-0.059	[0.224] 0.093	[0.102] 0.020	[0.021]	-0.036	0.047]	[0.081]	-0.026^{**}	[0.010]	0.025^{***}	-0.061***	[0.016]	3,192	0.020 YES	\mathbf{YES}
Ω	0.009 [0.018]	0.006	[0.024]							-0.026^{**}	[0.010]	0.024^{***}	[000.0- -0.060***	[0.016]		0.019 YES	
5y -	MTN	CMP	APP	Collateral	Forward G.		Fund	Suran		ZLB	Ì	FG_{og}	QE		Obs	R-squared U.S. Controls	C_M_Y FE

Table 10: Causation through IV: weekly frequency before GFC

rs of the short panel correcting for endogenous regressor, and th dent variable is the weekly average systematic component of the t of interest are the sum of daily changes of implied yields from fu laso include three days posterior to the announcements. We use cts of 10 year treasury bonds. Dummy variables for QE implemen bound are included. Additional controls are the sum of daily cl and unconventional monetary policy announcements dates from t fluded, as well as their triple interaction. We are using weekly d Driscoll-Kraay adjusted with 2 lags. The symbols *,**,*** denc	5v $2v$ $2m$ $1m$ $2m$ $2m$ $1m$ $2m(r)$ $1m(r)$
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Table 11: Causation through IV: weekly frequency after GFC

I — I	l																			
1 m(r)		-0.016	[0.018]	[0.013] -0.055	[0.070] -0.007	[0.015]	0.041	[0.071	[0.081]		-0.010	[0.010]	0.088*** [0.01a]	-0.011	[0.010]	0.001 0.016	[010.0]	3,934	VES VES	YES
1m	0.006 [0.009]	-0.018 [0.035]	[670.0]						**0000		-0.010	[0.010]	0.088*** [0.01a]	-0.011	[0.009]	0.002	[ern'n]	3,934	U.U30 YES	YES
(r)		-0.017	0.019	[0.013] -0.032	[0.124]	[0.012]	0.057	-0.071	[0.083]	[0 000]	600.0-	[0.010]	0.088*** [0.010]	-0.011	0.009]	0.000	[010.0]	3,934	VES YES	YES
2m(r)	0.007 [0.008]	-0.017	[120.0]						**0000		-0.00 -0.00	[0.010]	0.088*** [0.010]	-0.011	[0.009]	0.002 [0.015]	[ernn]	3,934	VES YES	\mathbf{YES}
u u		-0.017	[0.020] 0.017	[0.013] -0.049	-0.007	[0.015]	0.041	-0.050	[0.061]		-0.010	[0.010]	0.088*** [0.01a]	-0.011	[0.010]	0.001	[0TO:0]	3,934	VES YES	YES
1m	0.006 [00.00]	-0.017 [0.035]	[070.0]						**0000		-0.010	[0.010]	0.088*** [0.01a]	-0.011	[0.009]	0.002 [0.015]	[ern·n]	3,934	U.U30 YES	YES
		-0.018	0.019	[0.013] -0.025	[0.115]	[0.012]	0.056	-0.051	[0.062]		-0.009	[0.010]	0.088*** [0.010]	-0.011	[0.009]	0.000	[oro.o]	3,934	U.U30 YES	YES
2m	0.007 [0.008]	-0.015 [0.036]	[070.0]						*******		-0.009	[0.010]	0.088*** [0.010]	-0.011	[0.009]	0.002	[ernn]	3,934	VES	\mathbf{YES}
v		-0.015	0.018	[0.013]-0.046	[0.068] -0.004	[0.013]	0.053	-0.109	[0.122]		600.0-	[0.010]	0.088*** [0.01a]	-0.011	[0.010]	[0 015]	[etn.u]	3,934	VES VES	YES
2y	0.007 [0.008]	-0.015 [0.033]	[770.0]						**0000		-0.010	[0.010]	0.088*** [0.01a]	-0.011	[0.009]	0.002 [0.015]	[etn'n]	3,934	VES VES	YES
/		-0.014	0.018	[0.013] -0.041	[0.063]	[0.012]	0.040	-0.043	[0.053]		-0.010	[0.010]	0.088*** [0.010]	-0.011	[0.010]	0.003	[ern·n]	3,934	U.U34 YES	YES
5y	0.006 [0.008]	-0.014	[otu.u]						**0000		-0.010	[0.010]	0.088*** [0.01a]	-0.011	[0.010]	0.002 [0.015]	[ern/n]	3,934	VES YES	\mathbf{YES}
	MTN	CMP	APP	Collateral	Forward G		Fund	Swap	C 12	7110	FG_{sq}	, [FG_{og}	FG_{ta}) [ЧE.		Obs D	K-squared U.S. Controls	C_M_Y FE

ling ons. We	s of und	nal l as	aay	
neters of the short panel correcting for endogenous regressor, and their corresponding e dependent variable is the tail risk calculated with the last year of observations. of implied yields from future contracts at monetary policy announcements dates. We	s of future contraction of effective lower bound	al and unconventic tre included, as wel	rors are Driscoll-Kr ly.	1m(r)
genous regressor, a ated with the last onetary policy ann	ge of implied yield rward guidance an	cacts at convention year fixed effects a	2020. Standard er $\%$ level, respective	2m(r)
orrecting for endog he tail risk calcula ure contracts at me	IV the daily chang different type of for	s from future conti- untry, month and ;	2000 to July 30, 2 he 10%, 5% and 19	1m
f the short panel c ident variable is t lied yields from fut	ements. We use as implementations,	ges of implied yield United States. Co	ekly data from January 1, 2000 to July 30, 2020. Standard erron ** denote significance at the 10%, 5% and 1% level, respectively.	2m
nated parameters c ackets. The deper aily changes of imp	ior to the announc ny variables for QE	rols are daily chang nts dates from the	re using weekly dat nbols *,**,*** denc	2Y
The table reports the estimated parameters of the short panel correcting for endogenous regressor, and their corresponding standard errors in square brackets. The dependent variable is the tail risk calculated with the last year of observations. Variables of interest are the daily changes of implied yields from future contracts at monetary policy announcements dates. We	also include three days posterior to the announcements. We use as IV the daily change of implied yields of future contracts of 10 year treasury bonds. Dummy variables for QE implementations, different type of forward guidance and effective lower bound	are included. Additional controls are daily changes of implied yields from future contracts at conventional and unconventional monetary policy announcements dates from the United States. Country, month and year fixed effects are included, as well as	their triple interaction. We are using weekly data from January 1, 2000 to July 30, 2020. Standard errors are Driscoll-Kraay adjusted with 2 lags. The symbols $*, **, **$ denote significance at the 10%, 5% and 1% level, respectively.	5Y
The standar Variable	also inc 10 year	are incl moneta	their tr adjuste	

														-												
	1m(r)		0.008	[0.025]	-0.055***	[0.020]	-0.005	[0.084]	0.012	0.029	[0.035]	-0.019	[0.116]	0.010^{***}	[0.003]	0.014^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.065	[0.097]		30,720 YES	YES
	lm	-0.026^{**}	0.012	[0.024]										0.010^{***}	[0.003]	0.014^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.065	[0.097]		30,720 YES	YES
here very	2m(r)		0.002	[0.029]	-0.055***	[0.021]	0.022	[0.109]	0.006	-0.036	[0.037]	0.091	[0.074]	0.010^{***}	[0.003]	0.014^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.065	[0.097]		$_{\rm YES}^{30,720}$	YES
ICACI, ICK	2m	-0.024^{**}	0.003	[0.028]										0.010^{***}	[0.003]	0.014^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.066	[0.097]		30,720 YES	YES
denote argumente at the IO/0, J/0 and I/0 level, respectively	lm		0.007	[0.025]	-0.056***	[0.020]	-0.006	[0.083]	0.012 [0.014]	-0.027	[0.031]	0.026	[0.035]	0.010^{***}	[0.003]	0.014^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.065	[0.097]		30,720 YES	YES
TU/0, 0/	1	 -0.026** [0.011]	0.012	[0.025]										0.010^{***}	[0.003]	0.014^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.065	[0.097]		30,720 YES	YES
THE OF PTIC	2m		0.002	[0.029]	-0.055***	[0.021]	0.020	[0.107]	0.006 [0.010]	-0.037	[0.035]	0.060	[0.045]	0.010^{***}	[0.003]	0.014^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.065	[0.097]		$_{\rm YES}^{30,720}$	YES
10011111QT	3	-0.023** [0.011]	0.002	[0.029]										0.010^{***}	[0.003]	0.013^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.066	[260.0]		30,720 YES	YES
annian	2Y		0.005	[0.023]	-0.058***	[0.021]	-0.019	[0.085]	0.008 [0.019]	-0.010	[0.025]	0.047	[0.044]	0.010^{***}	[0.003]	0.014^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.065	[0.097]		$_{\rm YES}^{30,720}$	YES
, , ,	2	-0.023** [0.011]	0.008	[0.023]										0.010^{***}	[0.003]	0.014^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.066	[0.097]		30,720 YES	YES
TOOTTI Ge O	5Y		0.002	[0.022]	-0.059***	[0.022]	-0.018	[0.079]	0.008	-0.014	[0.025]	0.043	[0.027]	0.010^{***}	[0.003]	0.014^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.065	[0.097]		$_{\rm YES}^{30,720}$	YES
111 .cgp1	വ	-0.021^{**}	0.006	[0.022]										0.010^{***}	[0.003]	0.014^{**}	[0.006]	-0.002	[0.005]	0.007	[0.006]	0.066	[0.097]		$_{\rm YES}^{30,720}$	YES
ernanne ont east z min noven		MTM	CMP		APP		Collateral	t -	Forward G.	Fund	5	Swap		ZLB		FG_{-sc}		FG_oe		FG_{-tc}		QE		;	U.S. Controls	C_M_Y FE

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The table reports the estimated parameters of the short panel correcting for endogenous regressor, and their corresponding standard errors in square brackets. The dependent variable is the idiosyncratic tail risk component calculated with the last year of observations. Variables of interest are the daily changes of implied yields from future contracts at monetary policy guidance and effective lower bound are included. Additional controls are daily changes of implied yields from future contracts at conventional and unconventional monetary policy announcements dates from the United States. Country, month and year yields of future contracts of 10 year treasury bonds. Dummy variables for QE implementations, different type of forward announcements dates. We also include three days posterior to the announcements. We use as IV the daily change of implied fixed effects are included, as well as their triple interaction. We are using weekly data from January 1, 2000 to July 30, 2020. Standard errors are Driscoll-Kraay adjusted with 2 lags. The symbols *, **, denote significance at the 10%, 5% and 1% level, respectively.

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	ъ,	5Y	2Y	Y	2m	n	lm	n	2m(r)	(r)	1 m(r)	r)
MTN	-0.031^{**}		-0.036^{**}		-0.038** [0.016]		-0.041^{***} $[0.016]$		-0.039^{**}		-0.042^{***} [0.016]	
CMP	$[0.016]{0.07]}$	0.010 [0.027]	0.018	0.011 0.027]	[0.014 [0.035]	0.012 [0.035]	0.024	0.016 0.030]	0.014 0.034]	0.011 [0.034]	0.023 0.023	0.015
APP	[170:0]	-0.087***		-0.086***	6000	-0.085^{***}	0.040]	-0.084***	[±00.0]	-0.085^{***}	[070.0]	-0.084^{***}
Collataral		[0.027]		[0.027]		[0.027]		0.026		[0.027]		[0.026]
COLLANCE AL		[0.074]		[0.081]		[0.122]		0.085]		[0.124]		[0.087]
Forward G.		0.001		0.001 $[0.016]$		-0.000 [0.015]		0.005 [0.018]		-0.001 [0.015]		0.004 [0.018]
Fund		-0.014		-0.010		-0.037		-0.030		-0.038		-0.026
č		[0.032]		[0.032]		[0.046]		[0.040]		[0.048]		[0.045]
Swap		0.111^{**}		0.163^{**}		0.154 $[0.094]$		0.084 [0.064]		0.278° [0.145]		0.126 [0.143]
ZLB	0.021^{***}	0.021^{***}	0.021^{***}	0.021^{***}	0.022^{***}	0.022^{***}	0.022^{***}	0.022***	0.022^{***}	0.022^{***}	0.022^{***}	0.022^{***}
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
FG_{-sc}	0.016^{**}	0.016^{**}	0.016^{**}	0.016^{**}	0.016^{**}	0.016^{**}	0.016^{**}	0.016^{**}	0.016^{**}	0.016^{**}	0.016^{**}	0.016^{**}
i	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
$FG_{-}oe$	-0.027^{***} [0.010]	-0.027^{***}	$[-0.027^{***}]$	-0.027^{***} [0.010]	-0.027^{***} [0.010]	-0.027^{***} [0.010]	-0.027^{***} [0.010]	-0.027^{***}	-0.027^{***} [0.010]	-0.027^{***}	-0.027^{***} [0.010]	-0.027^{***}
FG_{-tc}	0.009	0.009	0.009	0.010	0.009	0.010	0.009	0.010	0.009	0.010	0.009	0.010
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
QE	0.084	0.084	0.085	0.084	0.085	0.084	0.084	0.084	0.085	0.084	0.084	0.084
	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]
Obs.	30,720	30,720	30,720	30,720	30,720	30,720	30,720	30,720	30,720	30,720	30,720	30,720
U.S. Controls	\mathbf{YES}	YES	YES	\mathbf{YES}	\mathbf{YES}	YES	\mathbf{YES}	YES	\mathbf{YES}	\mathbf{YES}	\mathbf{YES}	\mathbf{YES}
C_M_Y FE	YES	YES	YES	YES	\mathbf{YES}	\mathbf{YES}	YES	YES	YES	YES	\mathbf{YES}	YES

Table 14: Instrumental Variable Tests

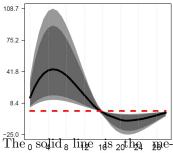
Panel A presents Angrist - Pischke weak IV test for estimates using daily frequency data. Panel B presents Angrist -Pischke weak IV test for estimates using weakly frequency data. Also, panels A and B present present Kleibergen - Paap underidentification test. Panel C presents Kleibergen - Paap weak identification test for estimates using daily and weekly frequency data. The symbols *, **, ** denote significance at the 10%, 5% and 1% level, respectively.

				Fanel /	A: Angrist -	Pischke We	Panel A: Angrist - Pischke Weak IV with Daily Frequency	aily Freque	ncy			
NTN	5 ye 85299	5 years	2 ye 5272.6	2 years	2 mo 4161.82	2 months 82	1 month 4338.73	nth	2 mon 4443.05	2 months (r) 3.05	1 month (r) 4568.48	th (r)
CMP	18906.93	3039.57	10065.88	1130.11	197.66	105.9	900.59	187.27	340.12	110.01	1966.28	153.55
APP		2.90E + 05		1.20E + 05		9568.04		51120.75		880.09		39894.11
Collateral		790.19		234.16		8.82		81.69		8.04		75.4
Forward G.	_	2886.72		587.49		83.27		126.52		74.49		111.53
Fund	_	4577.99		252.68		362.98		757.37		489.84		1325.33
Swap		1360.62		134.67		15.13		227.29		10.13		164.27
Stock-Yogo (5% Max IV bias)	21.01	21.01	21.01	21.01	21.01	21.01	21.01	21.01	21.01	21.01	21.01	21.01
Stock-Yogo (10% Max IV bias)	11.52	11.52	11.52	11.52	11.52	11.52	11.52	11.52	11.52	11.52	11.52	11.52
Underident. (K-P)	115.68^{***}	94.99^{***}	354.35^{***}	37.99^{***}	74.01^{***}	17.86^{***}	297.37^{***}	8.67	64.76^{***}	17.66^{***}	290.88^{***}	8.19
				Panel B	3: Angrist -]	Pischke Wea	Panel B: Angrist - Pischke Weak IV with Weekly Frequency	eekly Freque	ency			
	5 ye	5 years	2 years	ears	2 mo	2 months	1 month	nth	2 mont	2 months (ita)	1 month (ita)	h (ita)
NTM	1631.26		178.3		32.64		75.71		30.25		77.09	
CMP	368.88	541.7	148.87	217.91	46.59	76.01	66.59	100.63	41.4	65.41	56.33	87.26
APP	-	114.41		35.74		19.16		13.71		19.2		13.39
Collateral		253.89		92.02		10.93		21.8		11.02		13.07
Forward G.		1470.78		245.31		16.59		75.16		16.42		76.91
Fund		991.05		40.23		30.96		26.89		19.58		23.32
Swap		437.36		10.69		12.86		9.27		14.04		7.27
Stock-Yogo (5% Max IV bias)	21.01	21.01	21.01	21.01	21.01	21.01	21.01	21.01	21.01	21.01	21.01	21.01
Stock-Yogo (10% Max IV bias) Underident. (K-P)	11.52 108.99***	11.52 100.69^{***}	11.52 104.16^{***}	11.52 24.95^{***}	11.52 47.55^{***}	11.52 16.15^{***}	11.52 $106.73***$	11.52 14.43^{***}	11.52 46.86^{***}	11.52 15.14^{***}	$11.52 \\ 104^{***}$	11.52 $13.28**$
				Panel	el C: Weak I	dentification	C: Weak Identification Test (Kleibergen - Paap)	ergen - Paap	()			
	Daily	5 years Weekly	2 ye Daily	2 years Weekly	2 mo Daily	2 months ly Weekly	1 month Daily W	nth Weekly	2 mon Daily	2 months (r) aily Weekly	1 month (r) Daily We	th (r) Weekly
CMP, NTM	220.19 10.4	306.57	202.01	110.22	3803.29	29.52°	3941.84	44.85	4078.71	27.5	4182.39	41.42
Stock-Yogo (10% Max IV bias)	19.4	19.4 10.78	19.4 10.78	19.4 10.78	19.4 10.78	19.4 10.78	19.4 10.78	19.4 10.78	19.4 10.78	19.4 10.78	19.4 10.78	10.78

Impulse Response Functions in the GVAR model

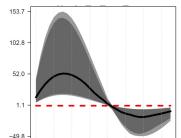
Unconventional Monetary Policy (UMP) shocks

Figure 9: UMP: U.K. domestic shock



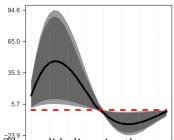
dian response, the dark (light) grey shaded area are the 68% (95%) confidence intervals.

Figure 11: UMP: Japan domestic shock



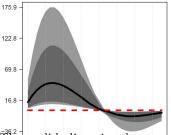
 $T_{\rm he}^{4\%}$ solid s line is 2the period of the line is 2the period of the line is 2the period of the line (light) grey shaded area are the 68% (95%) confidence intervals.

Figure 10: UMP: Euro Area domestic shock



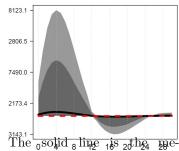
The $_{0}^{239}$ d solid $_{8}$ lipe $_{16}$ s $_{20}$ the $_{16}$ gree dian response, the dark (light) grey shaded area are the 68% (95%) confidence intervals.

Figure 12: UMP: Switzerland domestic shock



 ${}^{362}_{0} = \frac{1}{0} \frac{1}{$

Figure 13: UMP: Canada domestic shock



ine $_{0}$ sould $_{8}$ inte $_{16}$ $_{20}$ inte $_{16}$ $_{20}$ intervals dian response, the dark (light) grey shaded area are the 68% (95%) confidence intervals.

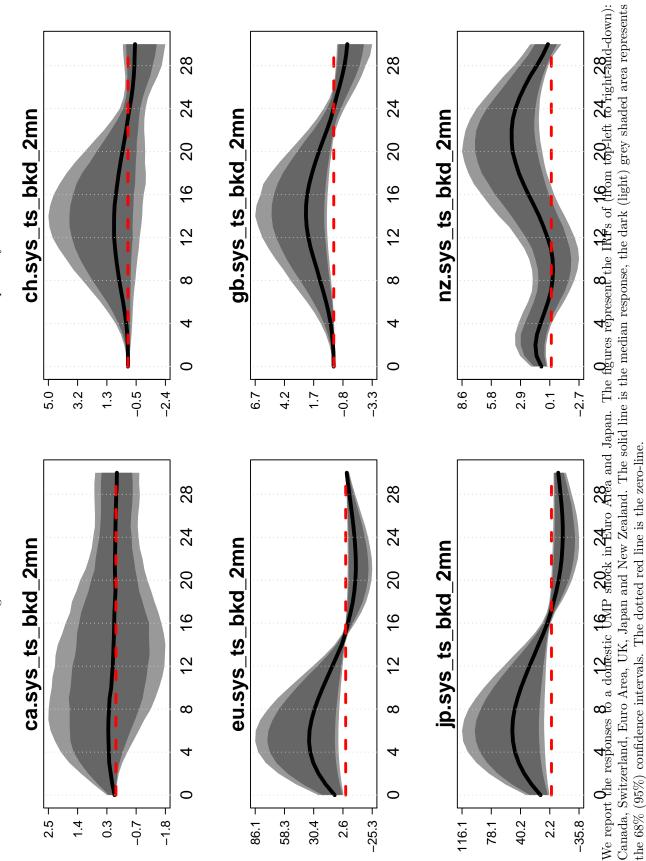


Figure 14: UMP: domestic shocks to Euro Area and Japan only

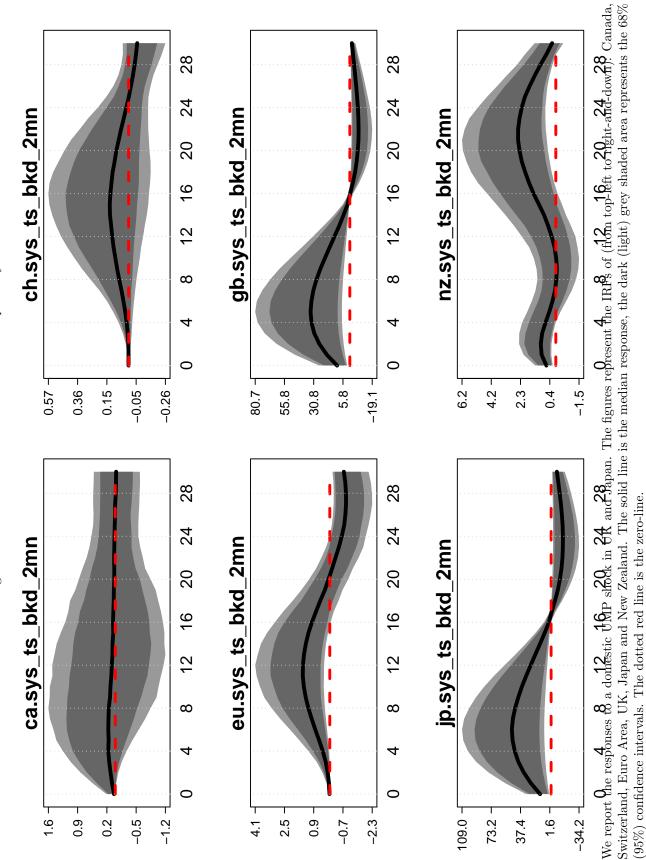


Figure 15: UMP: domestic shocks to UK and Japan only

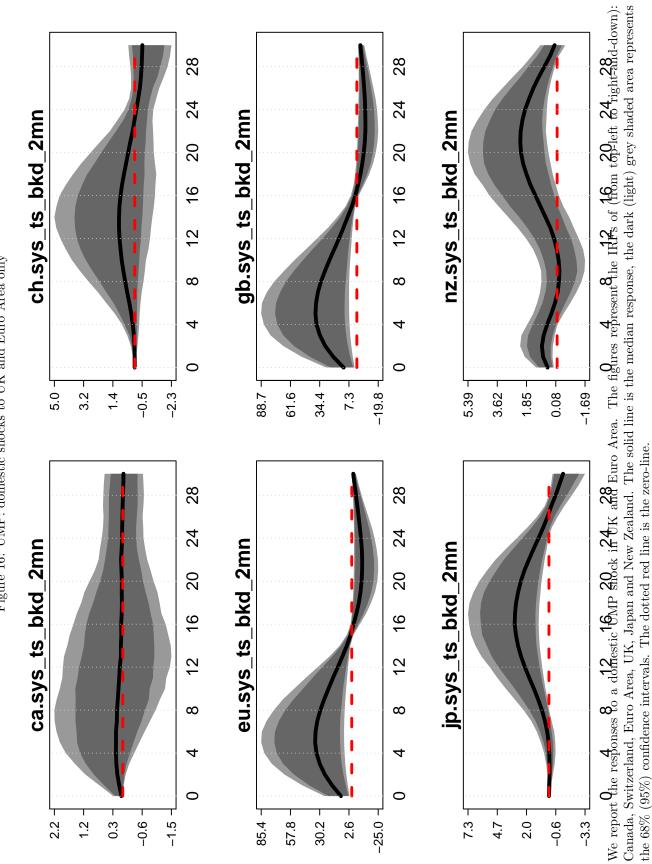


Figure 16: UMP: domestic shocks to UK and Euro Area only

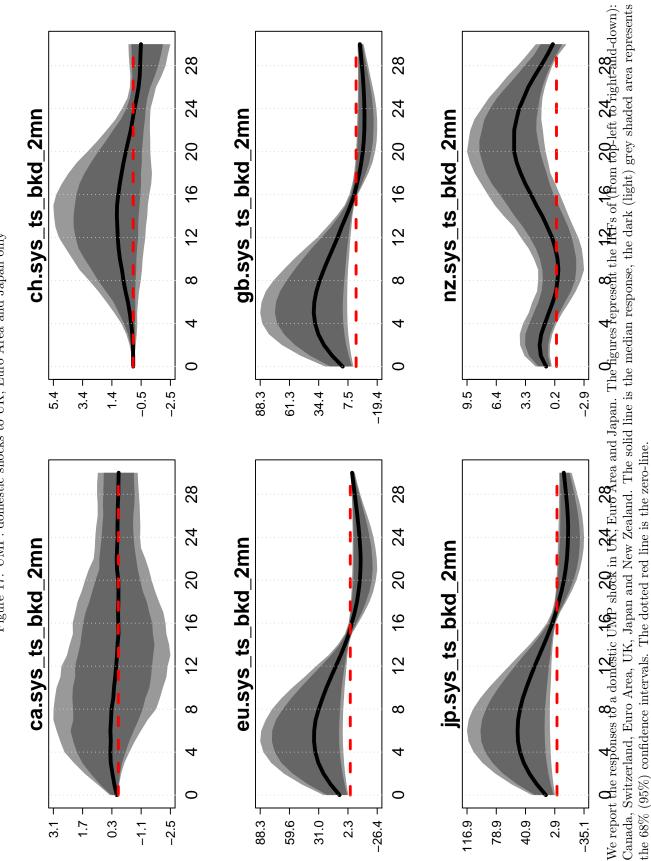


Figure 17: UMP: domestic shocks to UK, Euro Area and Japan only

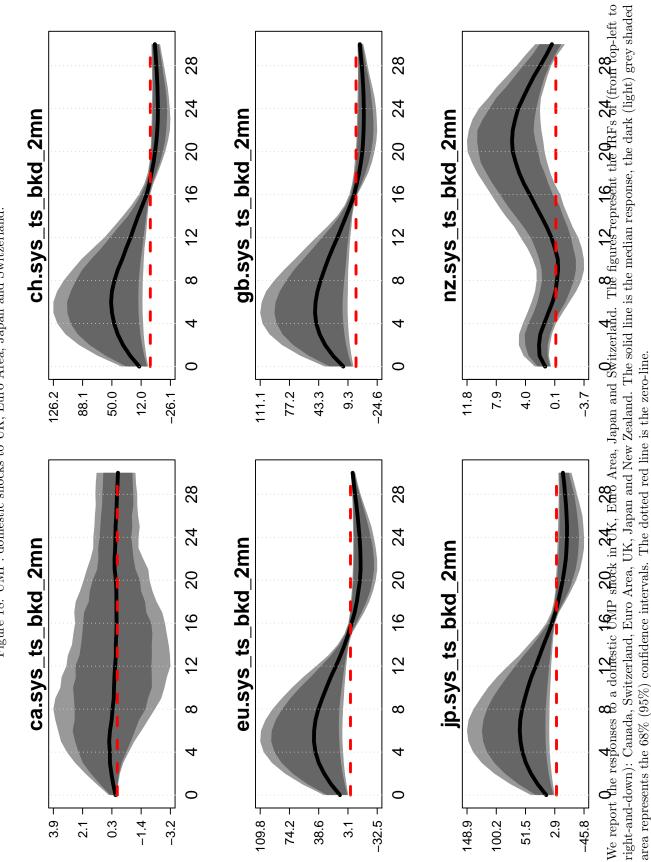


Figure 18: UMP: domestic shocks to UK, Euro Area, Japan and Switzerland.

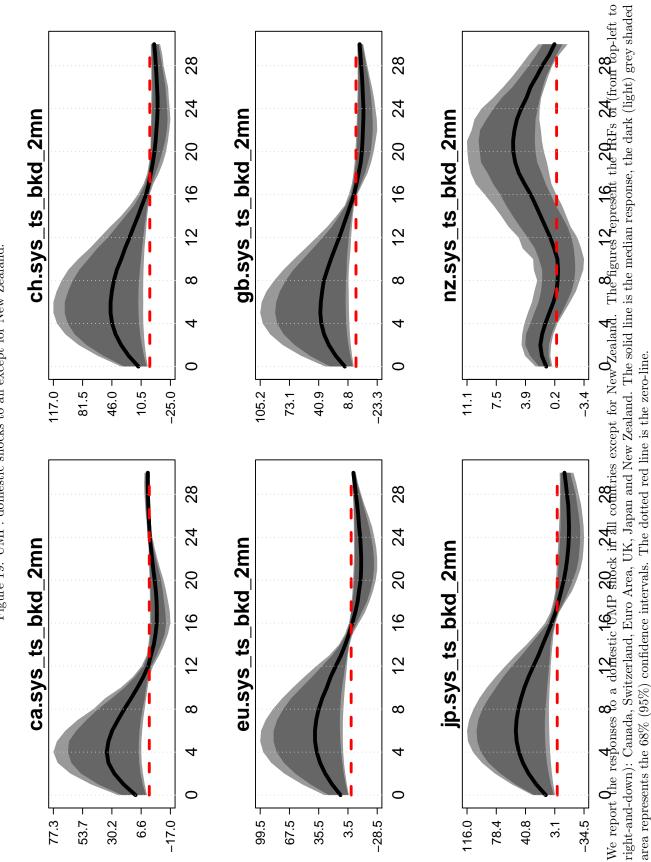


Figure 19: UMP: domestic shocks to all except for New Zealand.

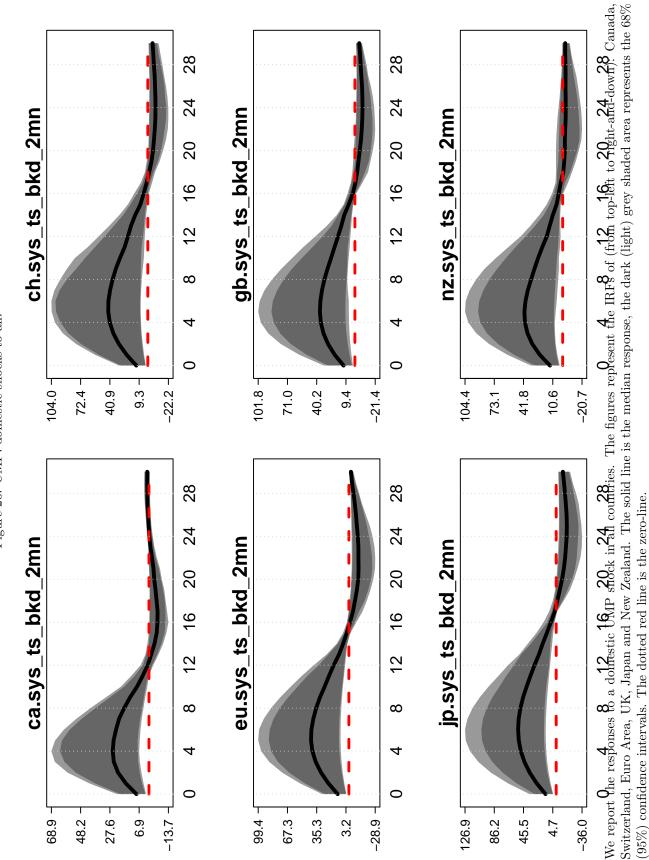
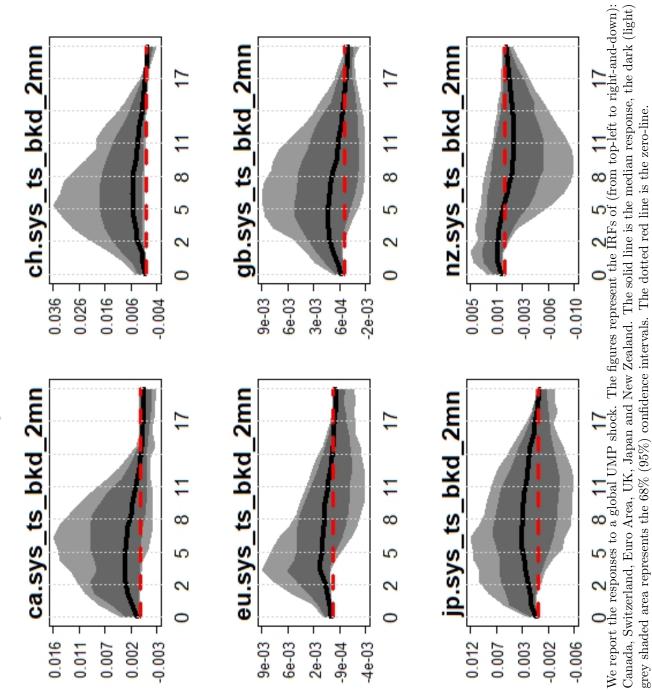


Figure 20: UMP: domestic shocks to all.

75





Impulse Response Functions in the GVAR model

 $QE \ shocks$

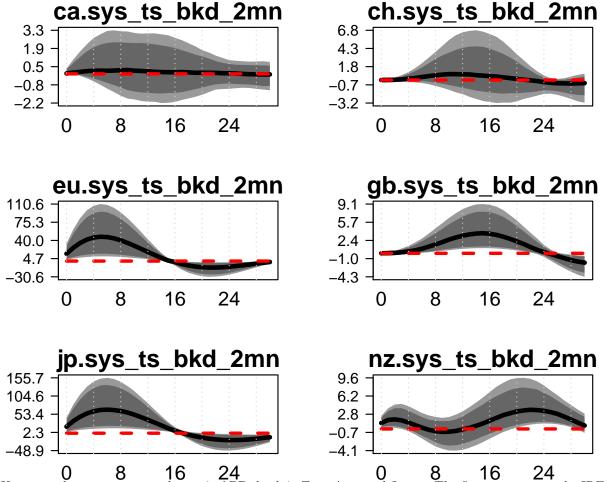


Figure 22: QE: domestic shocks to Euro Area and Japan only

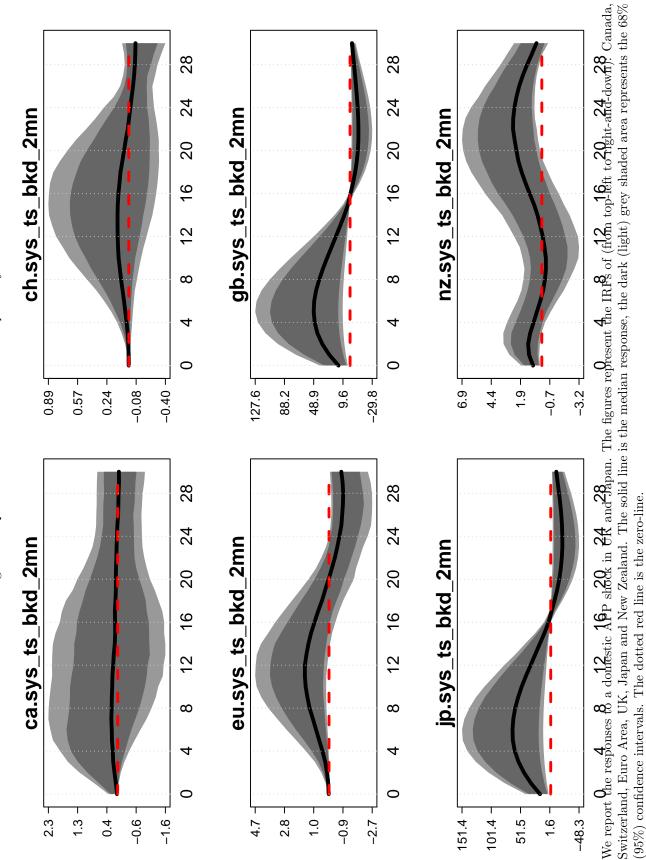
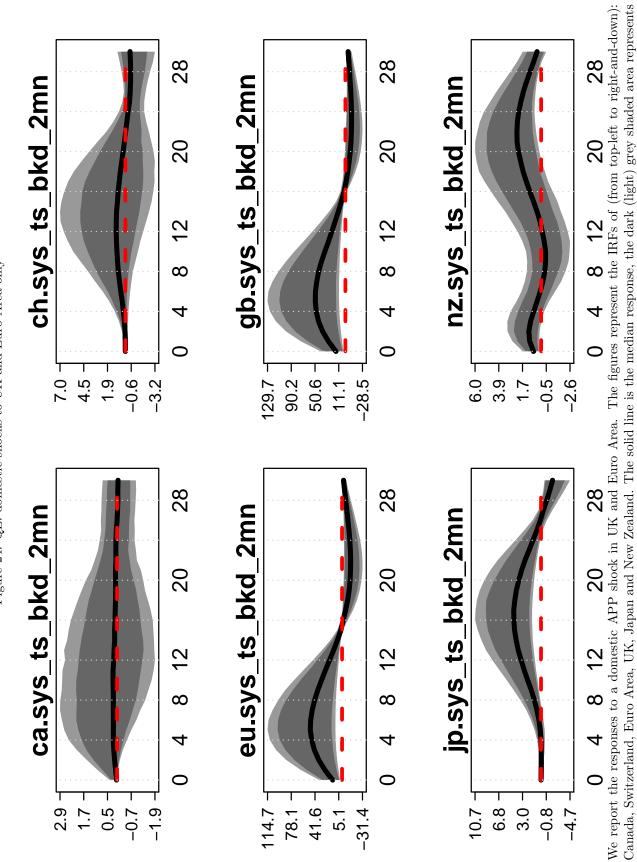


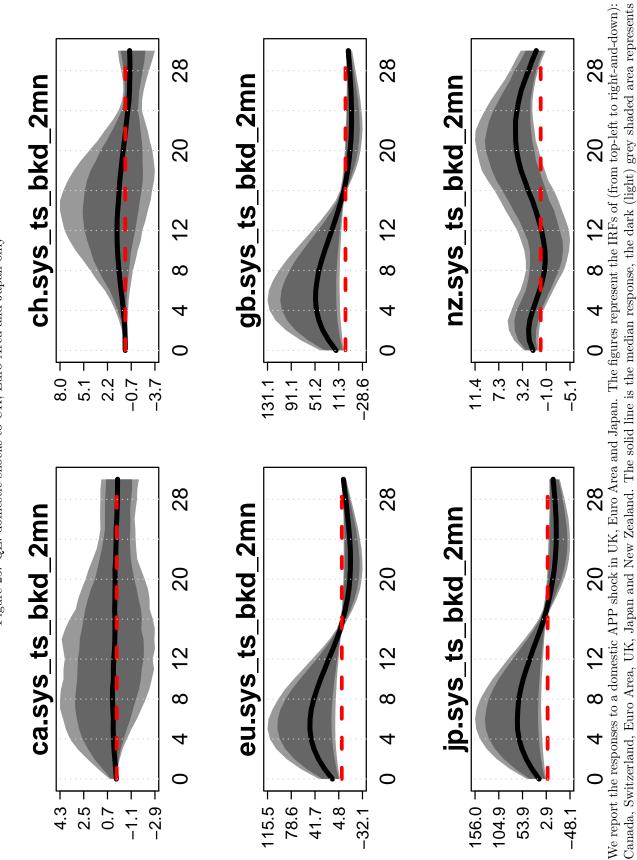
Figure 23: QE: domestic shocks to UK and Japan only



the 68% (95%) confidence intervals. The dotted red line is the zero-line.

Figure 24: QE: domestic shocks to UK and Euro Area only

79



the 68% (95%) confidence intervals. The dotted red line is the zero-line.



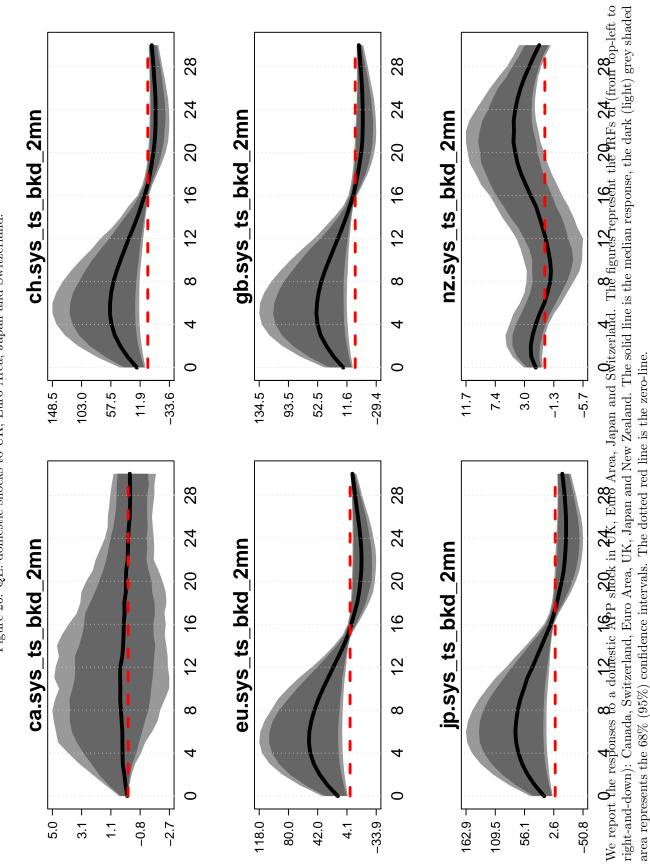


Figure 26: QE: domestic shocks to UK, Euro Area, Japan and Switzerland.

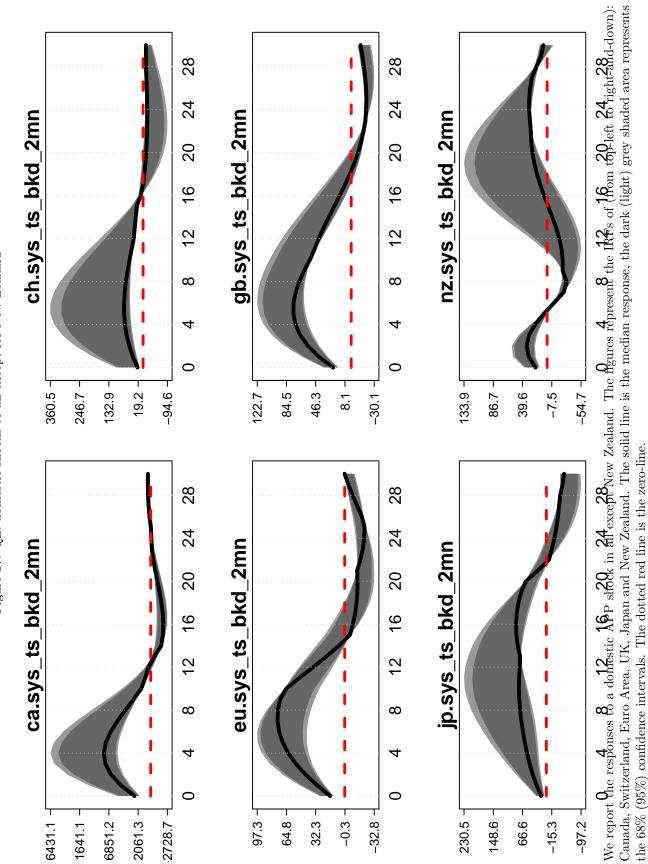
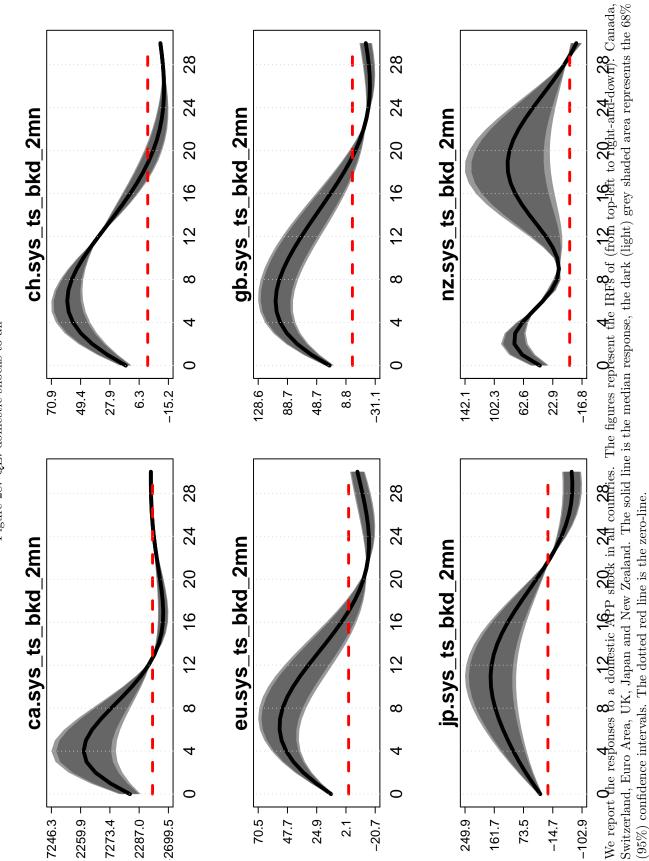


Figure 27: QE: domestic shocks to all except for New Zealand

82





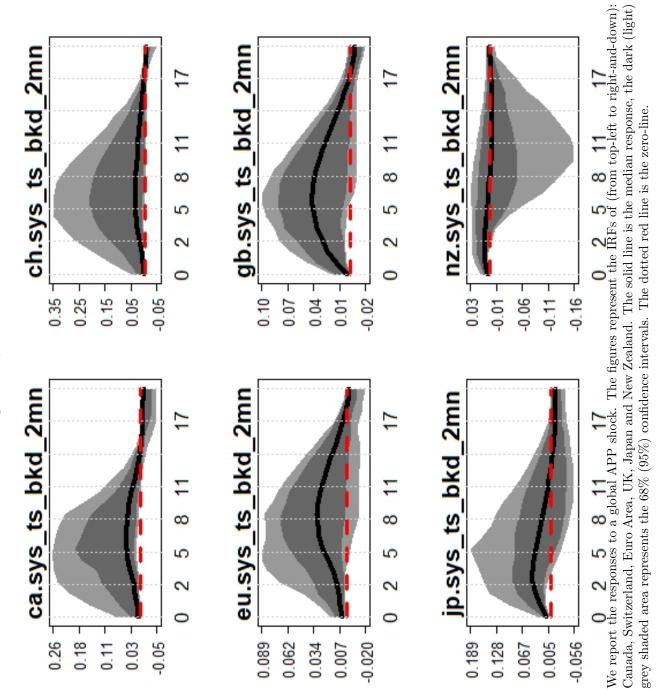
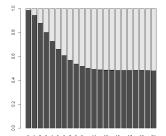


Figure 29: QE Global shock

Forecast Error Variance Decomposition (FEVD)

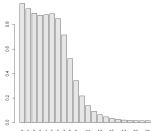
Domestic Unconventional Monetary Policy (UMP) shocks

Figure 30: FEVD: UK domestic UMP shock



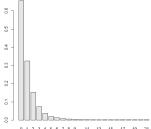
Share of UK tail risk variation explained by the domestic UMP shock.

Figure 32: FEVD: Japan domestic UMP shock



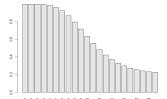
Share of Japan tail risk variation explained by the domestic UMP shock.

Figure 31: FEVD: Euro Area domestic UMP shock



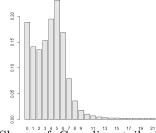
Share of Euro Ärea tail risk variation explained by the domestic UMP shock.

Figure 33: FEVD: Switzerland domestic UMP shock



Share' of Swiiss "tail "risk "variation explained by the domestic UMP shock.

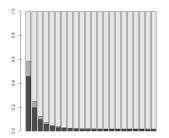
Figure 34: FEVD: Canada domestic UMP shock



Share of Canadian tail risk variation explained by the domestic UMP shock.

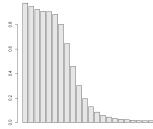
Domestic QE shocks

Figure 35: FEVD: UK domestic APP shock



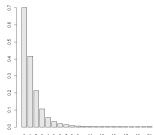
Share of UK tail risk variation explained by the domestic APP shock.

Figure 37: FEVD: Japan domestic APP shock



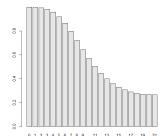
Share of Japan tail risk variation explained by the domestic APP shock.

Figure 36: FEVD: Euro Area domestic APP shock



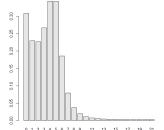
Share of Euro Ärea tail risk variation explained by the domestic APP shock.

Figure 38: FEVD: Switzerland domestic APP shock



Share of Świss tail risk variation explained by the domestic APP shock.

Figure 39: FEVD: Canada domestic APP shock



Share of Canadian tail risk variation explained by the domestic APP shock.

Appendix

Additional Discussion of the Literature

Theoretical support for our empirical investigation can also be found in Gourinchas, Ray, and Vayanos (2022) and Greenwood et al. (2020). Both these studies model simultaneous trade in international bond and currency markets through global arbitrageurs, and provide a rationale for non-negligible cross-border effects on foreign bond yields and currency values by relaxing the UIP and allowing for partially segmented financial markets. In Gourinchas, Ray, and Vayanos (2022), both conventional and unconventional monetary policy are comparable in terms of their exchange rate effects. Yet only UMP has sizeable international spill-over effects on the term structure because of the increased demand for foreign long-term bonds.

Another related strand of literature regards the high-frequency identification of monetary policy shocks. Considering that the monetary policy impact on exchange rates is (almost) instantaneous, many papers use a short event window around a monetary policy announcement and central bank speeches to identify any potential FX effects. Some studies use intraday data to capture the effect of an announcement or speech on exchange rates or interest rates (see Altavilla et al., 2019; Bauer and Swanson, 2022; Kohlscheen, 2014; Rosa, 2011. Generally, these studies find an improved identification of monetary policy shocks and find evidence of a signaling (or expectations) channel. However, these studies cannot identify longitudinal effects or examine their dynamics over an extended period which is one of the objectives of this paper. First, in these studies the time window is rather narrow which makes it difficult to say anything about the persistency of effects. Second, the sample period is relatively short - a constraint mainly imposed by data availability especially at high frequency - which makes it hard to say anything about long term patterns or structural effects. Third, the identified effects cannot shed light on the total effect from a policy change. In other words, the effect may be transitory, neutralised or even

fully reversed after a monetary policy action is taken and the markets fully absorb the new information. Fourth, the impact across the yield curve is not considered. Fifth, the number of currency pairs that these studies consider is small, generally around four. This study attempts to address these shortcomings.

FX tail risk data and summary statistics

Daily mean returns are close to zero and the standard variation is much larger suggesting the daily variation is considerable.⁴⁰ Moreover, the daily minimum and maximum returns fluctuate widely, suggestive of tail risk. This is further confirmed by the kurtosis parameters well in excess of 3. Visual depiction of the time series of excess returns for the 20 currencies split into two groups is shown in Figure 41. Note the larger number of tail events, particularly on the downside for non-G9 currencies.

[Figure 41]

Figure 40 shows the excess return correlations for the 20 currencies. The size of the circle corresponds to the magnitude of the correlation coefficient while the color of the circle corresponds to the proximity of the correlation coefficient to perfect positive (in red) or negative (in blue) correlation. Note the strength of the correlations, albeit with different signs, of those (G7 currencies plus DKK, SEK, CHF, AUD, NZD) currencies in the top left-hand corner. Interestingly, these currencies display relatively strong correlations with non-G9 currencies, depicted in the top right-hand corner. The correlations of non-G9 currencies with each-other on the other hand, although positive seem to be considerably weaker.

[Figure 40]

Figure 42 shows the plot of the explained variance by the first three principal components. Note that the first three components account for 52.76% of the variance.

⁴⁰These results are available from the authors upon request.

Figure 42 also shows a plot of the contribution of each variable to the first two components (or dimensions) - note that arrows in the same direction imply stronger positive correlation.

[Figure 42]

Figure 43 shows the currency excess return coordinates for the first nine principal components. It is clear that largest proportion of variance for all currencies is accounted for by the first two components with the third having a considerably smaller but still noticeable impact. Beyond this, the incremental ability of the components to explain the variation of the currency returns becomes negligible.

[Figure 43]

Figure 45 shows the joint distribution of the excess returns and aggregate systematic risk factor for each currency where the dashed lines demarcate the benchmark case of 5% quantile. Note that, for comparison, the scale is the same across the nine distributions.

The figure also shows the estimated asset pricing model. Clearly currencies differ as regards to how closely their returns cluster around the prediction of the asset pricing model. Some currency returns (e.g. DKK) cluster much more tightly around the asset pricing line than other currency returns (e.g. JPY). Moreover, some tail events are a lot more extreme for some currencies such as AUD or NZD relative to other currencies (such as DKK).

[Figure 45]

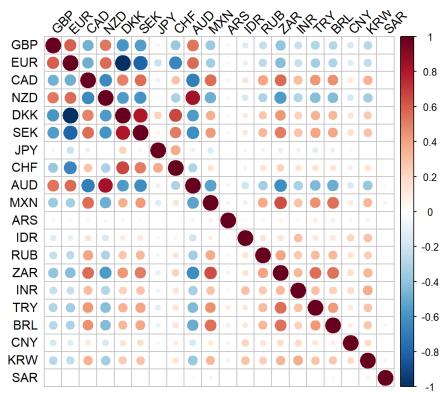


Figure 40: Currency Excess Return Correlations

This figure shows the excess return correlations for the 20 currencies. The size of the circle corresponds to the magnitude of the correlation coefficient - the bigger the circle, the stronger the correlation between the two currencies. The color of the circle corresponds to the proximity of the correlation coefficient to perfect positive and negative correlation - the deeper the red color, the closer the correlation between two currencies is to +1 and the deeper the blue color, the closer that correlation is to -1. Note the strength of the correlations, albeit with different signs, of the G9 currencies in the top left-hand corner.

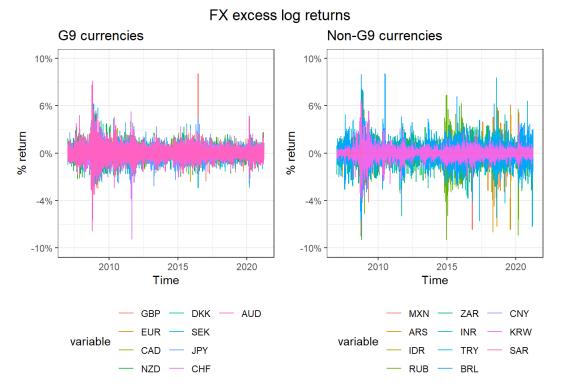
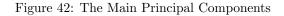
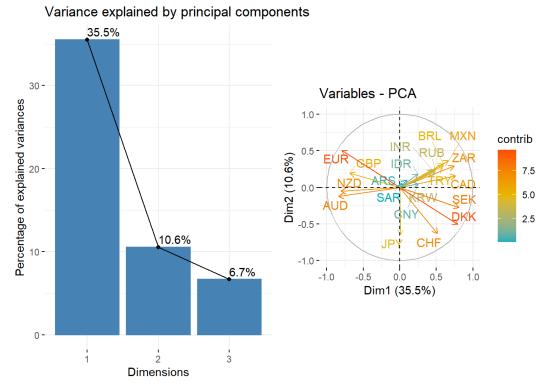


Figure 41: Currency Excess Returns

This figure shows excess returns for the 20 currencies split into two groups. The first group, labelled G9 currencies depicted in the left-hand side panel, contains the currencies of developed economies against USD. The second group, labelled non-G9 currencies depicted in the right-hand side panel, contains the currencies of the remaining 11 developing economies against USD. This group displays considerably higher volatility and more tail events, particularly on the downside.





The left-hand side panel of this figure shows the proportion of variance of currency excess returns explained by the first three principal components. The right-hand side panel of the figure shows the contribution of each currency to the first two principal components (or dimensions). Note that arrows in the same direction show stronger positive correlation.



Figure 43: Principal Components Coordinates

The figure shows the coordinates of principal components for G9 currencies. The PCs have been computed using the full set of 20 currencies.

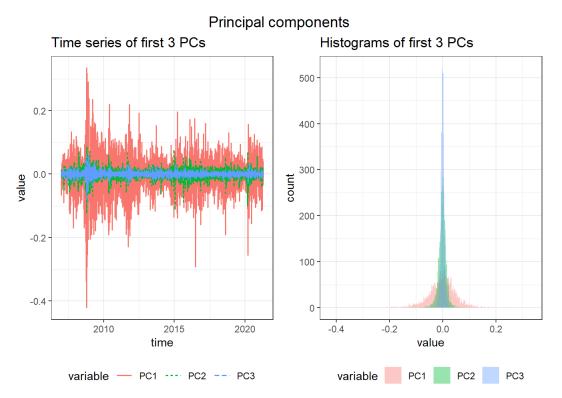
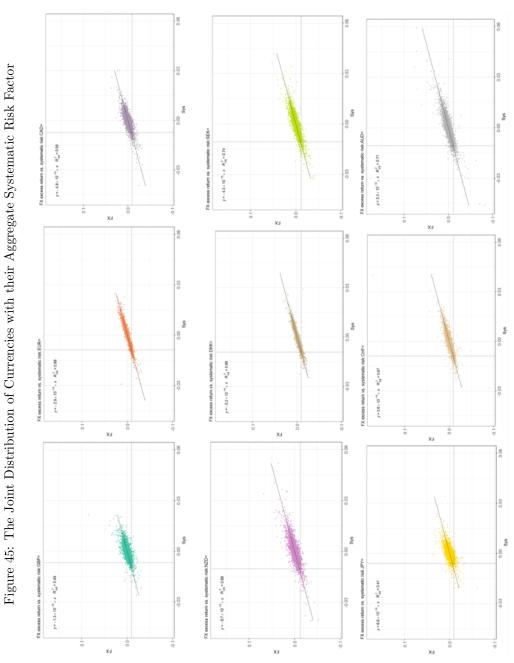


Figure 44: The Time-Series and the Empirical Distribution of the First Three PCs

The left-hand side panel of this figure shows the time-series of the first three principal components computed using the full set of 20 currencies while the right-hand side panel of the figure shows their empirical distribution.



This figure shows the joint distribution of each currency with its aggregate systematic risk factor. The dash lines depict the 5% quantiles.

Other estimation results

Table 15: Correlation: daily frequency

The table reports the estimated parameters of the short panel without correcting for endogenous regressor, and their corresponding standard errors in square brackets. The dependent variable is the systematic component of the tail risk calculated with the last year of observations. Variables of interest are the daily change of implied yields from future contracts at monetary policy announcements dates. We also include three days posterior to the announcements. Additional controls are daily changes of implied yield from future contracts at conventional and unconventional monetary policy announcements dates from the United States. Country, month and year fixed effects are included, as well as their triple interaction. We are using daily data from January 1, 2000 to July 30, 2020. Standard errors are Driscoll-Kraay adjusted with 2 lags. The symbols *,**,*** denote significance at the 10%, 5% and 1% level, respectively.

	10y	5y	2y	$2\mathrm{m}$	$1\mathrm{m}$	2m(r)	1 m(r)
APP	0.031^{***}	0.025^{***}	0.024^{***}	0.026^{***}	0.025^{***}	0.026^{***}	0.025^{***}
	[0.010]	[0.009]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]
Collateral	-0.042	-0.044	-0.027	-0.024**	-0.032	-0.024***	-0.039
	[0.068]	[0.041]	[0.039]	[0.009]	[0.031]	[0.009]	[0.030]
Forward G.	0.006	0.003	0.009	0.002	0.001	0.002	0.002
	[0.007]	[0.004]	[0.009]	[0.002]	[0.002]	[0.002]	[0.002]
Fund	-0.001	-0.001	0.006	0.002	0.002	0.000	0.001
	[0.012]	[0.012]	[0.015]	[0.009]	[0.007]	[0.008]	[0.007]
Swap	-0.066*	-0.063*	-0.081*	-0.049**	-0.003	-0.050**	-0.001
	[0.038]	[0.034]	[0.046]	[0.021]	[0.019]	[0.023]	[0.019]
CMP	-0.006	-0.001	-0.009	-0.012*	-0.010	-0.010*	-0.009
	[0.008]	[0.002]	[0.007]	[0.007]	[0.007]	[0.006]	[0.005]
Obs	30,720	30,720	30,720	30,720	30,720	30,720	30,720
C_M_Y FE	YES						

Table 16: Correlation: weekly frequency

The table reports the estimated parameters of the short panel without correcting for endogenous regressor, and their corresponding standard errors in square brackets. The dependent variable is the weekly average systematic component of the tail risk calculated with the last year of observations. Variables of interest are the sum of daily change of implied yields from future contracts at monetary policy announcements dates. We also include three days posterior to the announcements. Additional controls are the sum of daily changes of implied yield from future contracts at conventional and unconventional monetary policy announcements dates from the United States. Country, month and year fixed effects are included, as well as their triple interaction. We are using weekly data from January 1, 2000 to July 30, 2020. Standard errors are Driscoll-Kraay adjusted with 2 lags. The symbols *,**,*** denote significance at the 10%, 5% and 1% level, respectively.

	10y	5y	2y	$2\mathrm{m}$	$1\mathrm{m}$	2m(r)	1 m(r)
APP	-0.035	-0.032	-0.017	0.004	-0.001	0.002	-0.001
	[0.035]	[0.033]	[0.024]	[0.013]	[0.015]	[0.014]	[0.015]
Collateral	-0.050	-0.061	-0.060	0.014	-0.020	0.017	-0.033
	[0.082]	[0.079]	[0.070]	[0.018]	[0.053]	[0.019]	[0.055]
Forward G.	0.021	0.014	0.026	0.021^{***}	0.006	0.021^{***}	0.007
	[0.023]	[0.022]	[0.023]	[0.007]	[0.023]	[0.007]	[0.022]
Fund	0.050	0.044	0.036	-0.024	0.009	-0.039	-0.008
	[0.042]	[0.042]	[0.045]	[0.045]	[0.028]	[0.038]	[0.027]
Swap	-0.133	-0.125^{*}	-0.147^{*}	-0.132***	-0.032	-0.119**	-0.016
	[0.083]	[0.071]	[0.083]	[0.050]	[0.047]	[0.049]	[0.042]
CMP	-0.043	0.008	-0.060**	-0.017	-0.026	-0.016	-0.021
	[0.030]	[0.012]	[0.028]	[0.029]	[0.027]	[0.023]	[0.022]
Obs	$7,\!147$	$7,\!147$	$7,\!147$	$7,\!147$	$7,\!147$	$7,\!147$	$7,\!147$
$C_M_Y FE$	YES	YES	YES	YES	YES	YES	YES

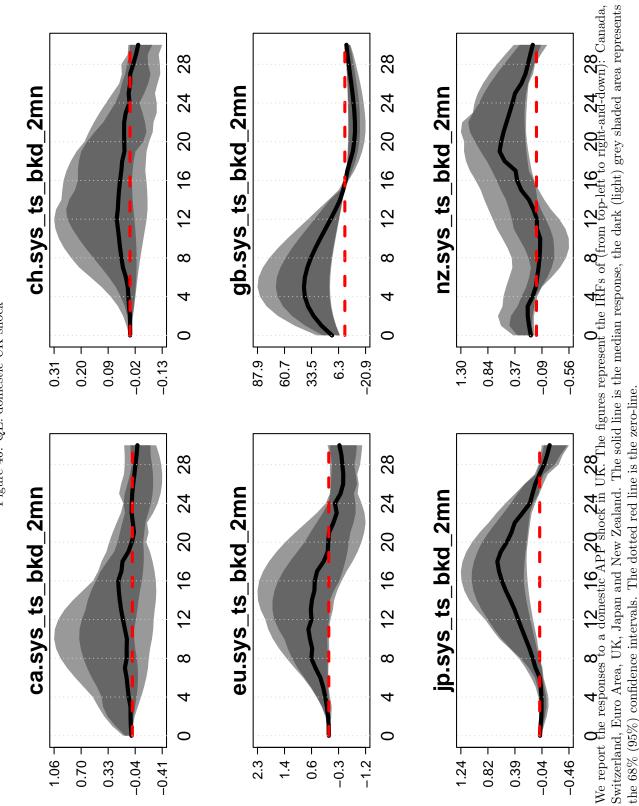


Figure 46: QE: domestic UK shock

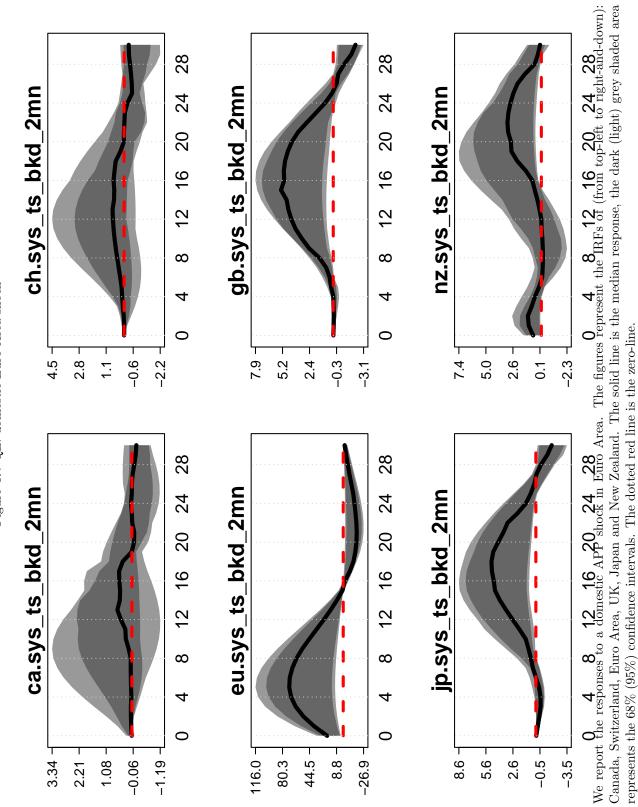


Figure 47: QE: domestic Euro Area shock

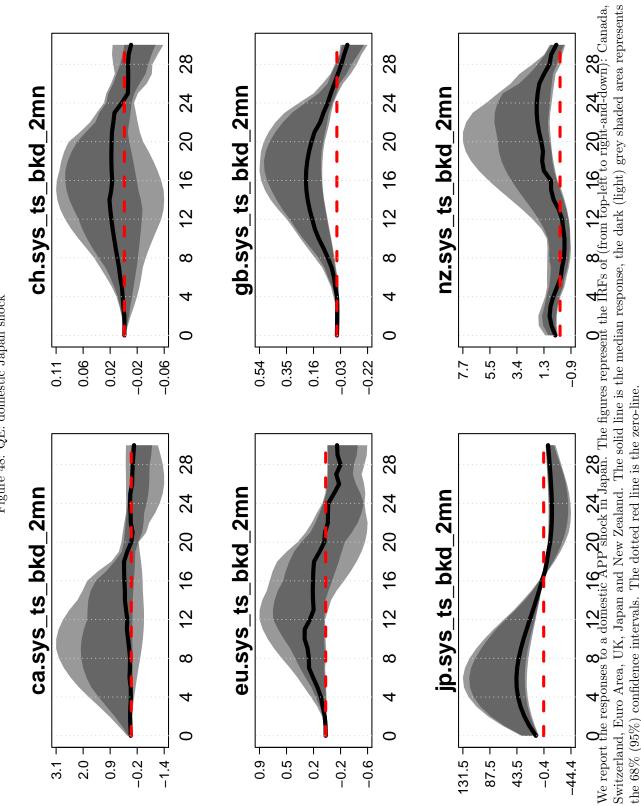
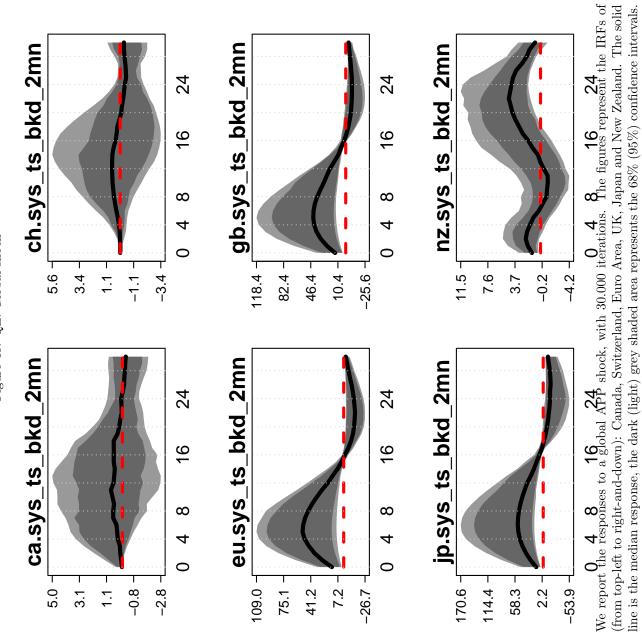


Figure 48: QE: domestic Japan shock





The dotted red line is the zero-line.

Technical description of the GVAR model

We consider N countries, indexed by i = 1, ..., N. All countries relative to the United States are small open economies, and we use country-specific vector autoregressive model with foreign variables (VARX^{*}) to build the GVAR. All country specifications, except for the United States, incorporate the systematic component of the tail risk, the conventional monetary policy announcements, and the unconventional monetary policy announcements (or any of its components).⁴¹

The model for country i is

$$\Phi_i(L, p_i)\mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{\Gamma}_i(L, q_i)\mathbf{x}_{it}^* + \mathbf{u}_{it}$$

where \mathbf{x}_{it} is a $k_i \times 1$ vector of domestic variables, \mathbf{x}_{it}^* is a $k_i \times 1$ vector of foreign variables, time is t = 1, 2, ..., T, \mathbf{a}_{i0} is a $k_i \times 1$ vector of fixed intercept, and \mathbf{u}_{it} is a $k_i \times 1$ vector of country-specific shocks such that $\mathbf{u}_{it} \sim i.i.d(0, \Sigma_{i,i})$.⁴² Additionally, $\Phi_i(L, p_i) = I - \sum_{i=1}^{p_i} \Phi_i L^i$ and $\Gamma_i(L, q_i) = \sum_{i=0}^{q_i} \Gamma_i L^i$ are the matrix lag polynomial of coefficients associated with domestic and foreign variables. Finally, p_i and q_i are the corresponding lag orders for domestic and foreign variables. For this particular case we assume it's equivalent for five working days, results are robust to including lags up to ten working days.

Country-specific foreign variables are cross-country averages of domestic variables using bilateral trade data as weights, i.e. $\mathbf{x}_{ij}^* = \sum_j^N \omega_{ij} \mathbf{x}_{jt}$. For this project we use bilateral trade date from 2000-2012 borrowed from Dovern, Feldkircher, and Huber, 2016.

Once country-specific individual estimation is complete, all endogenous variables are collected in vector $\mathbf{x}_t = (\mathbf{x}'_{1t}, \mathbf{x}'_{2t}, ..., \mathbf{x}'_{Nt})'$ and simultaneously solved exploit-

⁴¹The models follow closely the work of Dovern, Feldkircher, and Huber, 2016 and Mohaddes and Raissi, 2019.

⁴²The exogenous variables could be included here, although in our case we restrain from that.

ing the relationship through the country-specific weights. Following Mohaddes and Raissi, 2019, it is possible to construct a compact expression of the full model as $G(L,p)\mathbf{x}_t = \psi_t$ where $\mathbf{G}(L,p) = (\mathbf{A}_1(L,p)\mathbf{W}_1, \mathbf{A}_2(L,p)\mathbf{W}_2, ..., \mathbf{A}_N(L,p)\mathbf{W}_N)',$ $\mathbf{A}_i(L,p) = \mathbf{\Phi}_i(L,p_i) - \mathbf{\Gamma}_i(L,q_i),^{43} \psi_t = (\psi_{1t}, \psi_{2t}, ..., \psi_{Nt})'$ and $\psi_{it} = \mathbf{a}_{i0} + \mathbf{u}_{it}.$

For all countries, except for the United States, the domestic endogenous variables are

$$\mathbf{x}_{it} = [Syst_Tail_{it}, CMP_{it}, UMP_{it}]'$$

or we replace UMP_{it} with APP_{it} . Foreign variables are

$$\mathbf{x}_{it}^* = [Syst_Tail_{it}^*, CMP_{it}^*, UMP_{it}^*]'$$

or we replace UMP_{it}^* with APP_{it}^* . Finally, exogenous variables are $[UScmp_{it}, USump_{it}]'$.

For the United States, the domestic variables are $[UScmp_{it}, USump_{it}]'$, or we replace $USump_{it}$ with $USapp_{it}$. The foreign variables are the weighted average of the systematic tail-risk $(Syst_Tail_{it}^*)$, and the weighted average of UMP (UMP_{it}^*) or any of it's components. For this project we are using equal weights for all countries.⁴⁴

This approach to capturing the United States requires a few remarks. We do not model U.S. (or any other) monetary policy akin to a Taylor rule. For example, there is no proxy for the GDP or inflation gap in our framework. Instead, this way of modelling assumes that the U.S. strategically responds to the systematic tail-risk component of the rest of the block, as well as to their UMP decisions. Because our interest lies in the FX/financial cross-border effects only, this is a reasonable approximation without complicating the (already large) GVAR model too much. However, we recognise that this is a reduced-form approach and assumes away any

⁴³Note $\mathbf{A}(\mathbf{L}, \mathbf{p})$ depends on \mathbf{p} . The latter is $p = \max\{p_1, p_2, ..., p_N, q_1, q_2, ..., q_N\}$ and augmenting the $p - p_i$ or $p - q_i$ additional terms in the power lag of the operator by zeros.

⁴⁴We could amend that to reflect their individual trade volumes or market power in the FX market, but the conclusions would hold.

indirect cross-border channels going through the real economy (trade or UIP).

Identification of country-specific shocks is through sign restrictions. They are of cross-sectional and dynamic nature, as in Feldkircher, Gruber, and Huber, 2020. In particular we employ three such restrictions: (*i*) From our panel data analysis we observe that UMP or APP increase the systematic component, so we impose a five-days increase⁴⁵ within each country. (*ii*) Since the beginning of the UMP episode, the (bank) policy rate has remained very stable and close to zero. So, within each country, we assume that UMP or APP does not affect CMP announcement for five days. (*iii*) Finally, previous literature (see reference at the beginning of the document) suggest that UMP appreciates the currency of other countries. This evidence is mostly between small groups of advanced economies, e.g. U.S. vs EUR. Thus, we assume UMP or APP decreases the systematic component for one day. This will only be applied to the following cohort of countries: Japan, Euro Area and the UK.

Identification of U.S. shocks is also through sign restrictions. The panel analysis shows that UMP or APP has a positive effect on the systematic tail risk. We therefore assume a five-days positive shock for all countries.

The country models in the GVAR are estimated using Bayesian shrinkage priors. For the country-specific VARs, the priors consist of standard non-conjugate Minnesota (see Koop, Korobilis, et al., 2010 or Litterman, 1986 and Normal-Gamma priors (Feldkircher and Huber, 2016) combined with Stochastic Search Variable Selection prior as in George, Sun, and Ni, 2008. To find the impulse responses, the impulse function draws rotation matrices using the algorithm provided in Rubio-Ramirez, Waggoner, and Zha, 2010. Finally, the FEVD are based on the posterior median of the corresponding rotation matrix that fulfills all sign restrictions at the point estimate of the posterior median of the reduced form coefficients.

⁴⁵Also tested up to ten days and results hold.