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Abstract

We examine how the tail risk of currency returns of nine countries, from 2000 to 2020, 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 one month, and are proportionally higher in a hypothetical joint QE action scenario. This cross-border source of tail risk is largely undiversifiable, even after controlling for the US dollar dominance and the effects of its own monetary policy stance.

Key words: Unconventional and conventional monetary policy, liquidity measures, currency tail risk, systematic and idiosyncratic components of tail risk.

JEL classification: E44, G12, G15, E52.

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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 and financial stability (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.

Little is known regarding the impact of such policies on the tail risks of exchange rates. However, 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 tail risk of exchange rate returns?

Our theoretical framework allows for a decomposition of FX tail risk into its components which are then relatively straightforward to estimate; these tail risk components are based on a factor model for asset returns and disentangle systematic from idiosyncratic tail risks using VaR-type thresholds in an intuitive and mutually-

[1]For example, one of the largest one-day depreciation 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 potential impact to 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).

consistent way. We then regress these metrics of the tail risk components against a number of policy measure indicators.

Our extensive empirical analysis suggests there is a cross-border transmission channel of central bank (monetary and liquidity) measures, via the tail risk of the FX market. This can have sizeable implications for portfolio allocations and capital flows, risk management and financial stability.

Indeed, we find that unconventional (or non-traditional) policy measures have an impact on the systematic component of tail risk of currencies. This transmission is larger for measures such as Asset Purchase Programme and 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 and rather intuitively, we find that joint QE actions increase substantially the systematic component of FX tail risk, and proportionally more 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 distinction across instruments, time *and* persistence is novel in the literature.

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, 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.

We examine the impact of policy announcements and actions undertaken by various central banks on *realizations*[2], rather than perceptions, of exchange rate tail risk that materialised over the period. This is an important conceptual difference, as our approach focuses on the actual (or realized) effect of policy, including any persistence.[3]

We take a longer or more "secular" view as we study the transmission effects of monetary and liquidity actions over a period from January 2000 to July 2020 across the bulk of advanced economies (nine in total), on their respective currencies against USD. 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. 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 is unlikely that changes in currency tail risk shape medium or long-term implied yields of sovereign bonds.[4]

The paper proceeds as follows. In Section 2, we review briefly the extensive literature that straddles several areas of finance and economics. Section 3 presents the central bank policy and currency data and then introduces the theoretical framework employed to disentangle systemic from idiosyncratic tail risk as well as the properties of the benchmark measure of currency tail risk. Section 4 presents the panel data analysis, and Section 5 presents the GVAR analysis. Section 6 offers some concluding

[2]With "realized tail risk" or "realized VaR", we mean the (α-) quantile of realized returns (see, for example, the discussion of equation (16) in Bali, Demirtas, and Levy, 2009).

[3]Alternative approaches in the past literature are explored in the following section.

[4]One 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.

remarks. The Online Appendix contains technical details and presents the results of robustness analysis.

2. Relevant Literature

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.[5]

The paper contributes to the literature in several important ways. First, we construct a comprehensive dataset of the central bank monetary and liquidity measures implemented in nine major economies from January 2000 to July 2020 using information from the relevant central banks. This dataset has been manually collected as part of this paper and is novel, both in scope and the horizon covered, and has a *daily* frequency. We focus on the actions that the central banks of the G7 economies plus Switzerland, Denmark, Sweden, New Zealand and Australia have taken in their monetary sphere. 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 measures other than changes in the policy rate. It is an umbrella term encompassing unconventional monetary policy measures and liquidity measures (e.g. swap lines and changes in collateral requirements). This

[5]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. 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).

is important when examining whether such policies and measures have similar or different impact on the tail risk of currencies.

In addition, the paper contributes to the literature on the relationship between monetary policy and exchange rate risk. The classical literature on portfolio theory and risk management 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. 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. However, if it is found that monetary policy instruments impact currency *systematic* tail risk, this may be cause for concern. 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.

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.

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 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 members 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.

We note that we build our metrics using the markets realisations of the exchange rate tail risk, as these provide more stability and robustness in the estimation of the metrics.

Alternatively, one could focus on the market expectations 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) who focus on the impact of UMP on the tail perceptions but is similar to Ahrens et al. (2023) who examine the impact of central bank actions on realized tail risk of asset returns although it departs 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 currencies at the daily and lower frequency.

This paper contributes to the growing literature that studies the relationship between central bank instruments and the tail risk of assets in a global context (see also Ahrens et al., 2023). 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). To the best of our knowledge, this paper is a first attempt to examine this relationship in detail. 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 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 financial constraints. Tighter constraints, in turn, lead to higher volatility, thus generating a self-reinforcing feedback loop. This framework motivates our focus on whether changes in monetary policy, in addition to the first two, affect the higher moments of the distribution and therefore, the tails of exchange rate returns.

3. Data and Tail Metrics

3.1. Monetary Policy Data

In this section, we discuss our dataset on conventional and non-traditional measures (NTM) of major central banks over the past two decades. Table 1 provides more details on the data.

[Table 1]

By *non-traditional measures (NTM)*, we refer to those central bank interventions which are used to promote or restore adequate financial intermediation and/or facilitate the monetary policy transmission under financial sector impairment and/or near/at zero lower bound policy rates. These include monetary policy, liquidity or collateral-related measures.

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 dataset is a unique and novel collection of conventional and non-traditional measures at daily frequency from some of the largest and most important central banks[6]. This dataset was built by collecting individual daily central bank communications for each of the categories above, as well as major speeches at Governor or Director level either announcing one of the above policy interventions or signalling intentions in relation to monetary policy or liquidity provision.

The 'intensity' of each NTM 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 around the day of the announcement, and the three subsequent working days. Formally, $Strength_{NTM}{}^{\tau}_{it} = \Delta ImpYield^{\tau}_{it}$, where $NTM = \{APP, Coll, FG, Fund, Swap\}$, and $ImpYield$ is the futures-implied yield of sovereign bond of country i, at day t, with maturity $\tau \in \{1m, 2m, 2y, 5y, 10y\}$. Finally, $Strength_{NTM}{}^{\tau}_{it} \neq 0$ at the day of the decision, and the subsequent three working days.

In our monetary policy dataset, we differentiate between conventional and NTM measures. In the first category, we include the changes to, or control of, the base rate

[6]We have collected data from the following central banks: Bank of England, ECB, Bank of Canada, New Zeland's Central Bank, Danmarks NationalBank, Sveriges Riskbank, Bank of Japan, Swiss National Bank and Reserve Bank of Australia, from 2000 to 2020.

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*.[7]

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 somewhat the 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 NTM 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 movement 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.

[7]Ferrari, Kearns, and Schrimpf (2021) also construct a monetary policy decisions dataset from the websites of several central banks. Our approach brings three 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. Third, our time series is 10 years longer, starting 4 years earlier (2000 instead of 2004), and finishing 6 years later (2021 instead of 2015) compared to Ferrari, Kearns, and Schrimpf (2021). On the other hand, their dataset in intra-day, while ours is daily.

[Figure 2]

NTMs 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.

Interestingly, the dynamic correlations shown in Figure 3 are generally higher between conventional instruments. Due to the large number of NTM instruments, the figure depicting their dynamic correlations is very large and hence, not shown but it is available upon request.

[Figure 3]

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).

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. We note that the above currencies are used to create the necessary metrics for our analysis, but are not all part of our database describing the actions of central banks.

On the other hand, to examine the impact of central bank 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.[8]

3.3. Theoretical Framework of Currency Tail Risk

Any monetary policy uncertainty 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

[8]The 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). We use the larger dataset to extract principal components to ensure maximum information on common drivers of FX market are captured. 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 principal components 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 materialise, 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 relationships and patterns in a systematic manner. Moreover, because we study a basket of currencies, we can study the multilateral (direct and indirect) linkages across 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, in addition to FX return volatility, works also through the FX return tail risk.

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 central bank actions.

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 4 brings all this together and shows the paths to possible outcomes.

[Figure 4]

The final nodes in the tree in Figure 4 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 5.

[Figure 5]

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 which has important implications for, amongst others, portfolio allocation and risk management (see, for example, Statman, 1987). 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 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.[9] 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. 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 following system of linear equations obtains from Figure 4:

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

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:

[9]See, for example, Avdjiev 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.

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

Note that p_i is well-defined only if $\alpha^2_{s(i)} \leq x_{i,s(i)} \leq \alpha_{s(i)}$ and is bounded between 0 and 1. 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:

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

Idiosyncratic Component:

$$ITC_i(\alpha_i, \alpha_{s(i)}) \equiv 1 - p_i = \frac{(\alpha_{s(i)} + \alpha_{s(i)}\alpha_i) - (x_{i,s(i)} + \alpha^2_{s(i)})}{\alpha_{s(i)} - \alpha^2_{s(i)}} \tag{7}$$

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, $\beta_i^{AB} = VaR_i^\alpha / VaR^\alpha_{s(i)}$, which implies $\alpha_{s(i)} = \alpha_i = \alpha$. Then, the systematic component becomes:

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

The Remark below shows that this special case of 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

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

where,

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

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, assuming the risk free rate is zero, 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

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

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. Therefore, these measures 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 factors[10]:

$$R_{i,t} = \beta_{i,1} PC_{1,t} + \beta_{i,2} PC_{2,t} + \beta_{i,3} PC_{3,t} + \epsilon_{i,t} \tag{13}$$

The aggregate systematic factor of currency i is then defined as $R_{s(i),t} = \sum_{j=1}^{3} \beta_{i,j} PC_{j,t}$.

[10]These 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.

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:

$$R_{i,t} = \beta_{i,RX} RX_t + \beta_{i,HML} HML_t + \epsilon_{i,t} \tag{14}$$

In this case, the aggregate systematic factor of currency i is defined as $R_{s(i),t} = \beta_{i,RX} RX_t + \beta_{i,HML} HML_t$.[11]

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 5 (see also Figure 6 in the Online Appendix).

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.

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 a policy tool is estimated as the difference over one day, of the tail risks estimated over the windows

[11] Both 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 sources. 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 $2n$ systematic and idiosyncratic tail risk components (see Chabi-Yo, Huggenberger, and Weigert, 2022).

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 differences. Once we obtain the time series of currency tail risk measures, we can examine their relation with our data on central bank toolbox.

Implementation

We estimate the currency systematic risk factors by means of PCA on the excess returns of the 20 currencies. To preserve space, the results with the Lustig, Roussanov, and Verdelhan (2011) systematic risk factors are not presented but are available upon request. 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.

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. We use this heterogeneity to enhance the identification. Furthermore, the relatively large panel dimensions of our data allow us to explore the effects in the 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.

Then, with 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 2. Note the significance of the systematic risk factors proxied by the principal components.

[Table 2]

Next, 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 3 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 3]

Figure 6 shows that the quantiles for both currencies and the aggregate systematic risk factors fluctuate widely over time. Even though they appear strongly correlated, there are 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 6]

Having constructed the aggregate systematic risk factor and partitioned the outcome space for each currency, we then estimate the systematic component p_i of currency i with equation (6) at nominal level α where α = 2.5, 5 or 10%. Under independence, the probabilities presented in Panel A of Table 4 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 4]

With the systematic component estimated for each currency, it is straightforward to obtain that currency's systematic and idiosyncratic tail risk measures shown in

Figure 7. It is clear that the systematic tail risk generally accounts for the largest proportion of tail risk.

[Figure 7]

Estimating these measures in a rolling window of 250 observations with an exponentially-weighted moving average, we obtain time-varying measures of tail risk shown in Figure 8.

[Figure 8]

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 (see Harris, Shen, and Yilmaz, 2022). Next section outlines the estimation strategy for causal inference.

4. Panel Data Analysis

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 announcements vary 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 impact prices. Rogers, Scotti, and Wright (2014), following Gürkaynak (2005), Gürkaynak, Sack, and Swanson (2005) Gürkaynak, Sack, and Swanson (2007), measure monetary policy surprises from the U.S. 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) use the same approach to assess the impact of UMP or balance sheet unwinds. Our approach falls in line with this stream of work.[12]

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 and proxy the intensity of Conventional Monetary Policies (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.

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

In all specifications, the dependent variable is the change in country i's currency 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: $t\text{-}249,\ldots,t\text{+}1$ and $t\text{-}250,\ldots,t$ from the returns for each currency. The window size of *250* observations is simply to allow for a sufficient number of observations to fall into the tails and is in line with previous studies of tail risk in asset returns (see, e.g., Bali, Demirtas, and Levy, 2009 and the references therein). An implication assumption is that other than monetary

[12] Another reason for not using shorter windows is that it would be difficult 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, one would need to employ a moving event window across the entire sample, which would produce erratic estimates, as well as biases, as some currencies and measures may require larger windows relative to others. Therefore, using a daily window is a convenient choice that sidesteps these issues.

policy news on event window (day t), other news has a negligible impact on currency returns and their systematic tail risk component. The covariates of interest are CMP, APP, FG, SWAP, COLLATERAL and FUND. We also include the same covariates from the U.S.

4.2. Benchmark and Identification

The panel contains data from the central banks of G7 + Switzerland, Denmark, Sweden, New Zealand and Australia. We use information from the Fed and USD 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 NTM undertaken by the central banks of country i at time t. In the second, we decompose the NTM variable into asset purchases (APP), forward guidance (FG), swaps (SWAP), funding (FUND) and collateral (COLLATERAL).

$$\begin{aligned}
y_{i,t} &= \alpha + \beta_1 CMP^{\tau}_{i,t} + \beta_2 NTM^{\tau}_{i,t} + \beta_3 H_{i,t} + \beta_4 X_t + \gamma_i \delta_t + \eta_i + \epsilon_{i,t} \\
y_{i,t} &= \alpha + \beta_1 CMP^{\tau}_{i,t} + \sum_{C \in NTM} \beta_{2C} C^{\tau}_{i,t} + \beta_3 H_{i,t} + \beta_4 X_t + \gamma_i \delta_t + \eta_i + \epsilon_{i,t}
\end{aligned}$$

where $NTM = \{APP, Coll, FG, Fund, Swap\}$. The dependent variable $y_{i,t}$ is the change in the tail risk, or any of its two components, of country i's currency at time t. $CMP^{\tau}_{i,t}$ is the impact of conventional monetary policy decisions, and is calculated as the daily change of the futures-implied yield of a sovereign bond with maturity $\tau \in \{1m, 2m, 2y, 5y, 10y\}$ of country i at day t. 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. $\gamma_i \delta_t$ is an interaction term of time and country fixed effect and η_i is a country fixed effect. In particular, we use the triple interaction of *month*, *year* and *country* fixed effects to control for unobserved time-varying confounding effects for each country.[13] These fixed effects incorporate time-varying country-level determinants that are difficult to include otherwise 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 inter-temporal dependence with Driscoll-Kraay standard errors.

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

We follow an instrumental variable approach to correct for this confounding effect. We want to assess the causal impact of NTM surprises, measured by daily changes in the future-implied yield curve on changes of FX returns tail risk. The short-term dynamics of the FX market suggest that the reverse causality, referred to above, 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.After controlling for economic fundamentals, it is unlikely that changes in currency tail risk shape implied yields of sovereign bonds of 10 years or more.

Therefore, our instrument is the daily change of the implied yield of future contracts for 10 year treasuries. For example, for each currency we instrument the change in monetary policy, typically captured by the change in the 1 month implied yield,

[13]In unreported analysis, we replace the monthly with weekly fixed effects and the results remain qualitatively similar.

with the change in the 10 year implied yield due to CMP, APP, COLLATERAL, FG, FUND and SWAP. Additionally, we use instruments in levels and squares to capture nonlinearities in the data.[14] To simplify the exposition, we do not present the full table which is available upon request. We report a summary of the first stage results in Table 5 highlighting the fact that in the vast majority of cases, instruments are strong and informative.

[Table 5]

4.3. Results

4.3.1. Full sample period

Tables 6 - 8 report the results of the analysis addressing the potential endogeneity concerns at the daily frequency. Each column reports estimates at different points on the implied yield curve. For example, the first two columns use information from the five year bonds, and the last two from two months bonds. [15] In the Online Appendix, in Tables 1 - 10 we present the results for maturities 5-year, 2-year, 2-month, and 1-month.

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

[14]As 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.

[15]Since 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.

Table 6 reports the results of the regressions estimated over the entire sample. The first four columns show the results for the systematic component of the tail risk, and the other four columns show the results for the total tail risk. On the former, we observe that while the CMP has no detectable impact on the systematic tail risk component 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.[16] We further observe that the dummies for ZLB and FG_{og} are statistically significant and, again, have opposite signs. Finally, replacing ZLB with CMP and FG_{og} with FG, we do not observe any qualitative differences in the results.

The last four columns of Table 6 show the impacts on the total tail risk. In line with the previous results, the impact of APP and swaps are statistically significant, but now their impact has the opposite sign vis-a-vis the systematic component case. This implies that the impact on the idiosyncratic tail risk component has the opposite sign, and outweigh the impact on the systematic tail risk component. The only qualitative difference is that FG_{og} is no longer the relevant type of forward guidance but is replaced by FG_{sg} - the type of forward guidance that explicitly conditions an intervention on the state of the economy.

[Tables 5 - 6]

4.3.2. Sub-sample estimates

Table 7 presents the same analysis on tail risk, but with the sample split into pre- and post-Global Financial Crisis. As intuition suggests, before the crisis neither

[16]Unreported correlation analysis also highlight the relationship between these variables and currency tail risk or 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*.

NTM nor any of its components are significant. Indeed, only the dummy 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.

Subsequently, we decompose the post-GFC sample further to narrow the dynamic effects. In particular, we examine whether there are any substantial differences between the 2009-2012, 2012-2018 and 2019-2021 samples and present the results in Table 8.[17] Note however, that this analysis does 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 (and up until 2019) which corresponds to the end of the Eurozone crisis.

[Tables 7 - 8]

We conduct the same analysis at a weekly frequency and present the results in Tables 5 to 7 in the Online Appendix. We do not find statistically significant results for CMP, NTM or any of its components.[18] Moreover, the results remain unchanged if we further break down the sample based on the Global Financial Crisis.[19] However, the dummy variables for ZLB, QE and FG are statistically significant, in line with the evidence at the daily frequency presented previously.

[17]These periods were specifically chosen as they represent: 1) the immediate GFC-monetary response including QE1 and QE2; 2) the Euro Area sovereign debt crisis, negative rates and ECB QE period; and finally 3) the U.S. repo market and COVID stresses. While one could obviously choose 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.

[18]Correlations at the weekly frequency are different vis-a-vis their counterparts at daily frequency. In particular, the correlation between FG and the systematic tail risk becomes significant, while that of APP turns insignificant. See Tables 11 and 12 in the Online Appendix.

[19]If we instead cast the weekly data in a structural time-series model, we will capture the cross-correlated autoregressive components better, hence why our results are significant in our GVAR. See more details in Section 5.

4.3.3. Detailed discussion of the results

The panel results above provide evidence that central bank measures have an impact on the tail risk of currencies. This effect is particularly pronounced for APP which increases in the systematic part of tail risk. 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 sub-sample. 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 high-grade 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 sell-off 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. These include country-level rolling-window linear regressions of tail risk on NTM measures, similar to the analysis 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. The results from these robustness are available upon request.

5. GVAR Analysis

In this section, we discuss the analysis conducted using a Bayesian Global Vector Auto-Regressive (BGVAR) model. For a detailed technical discussion of the model see Section 2 of the Online Appendix. 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 an array of central bank policy measures.[20]

This method complements the panel data analysis in three ways. First, the panel data does not include cross-sectional general equilibrium effects. Aside from the impact of the U.S. on every country, the panel data analysis does not account for the feedback loops between the other currencies, 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 monetary policy, 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.

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

5.1. Set-up

For this analysis, we use information on NTMs from the central banks of Canada, Switzerland, Japan, U.K., Euro Area, New Zealand and the U.S.[21] 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.

For each currency, the matrix of endogenous variables includes three variables: the tail risk or its systematic component, CMP and NTM (or alternatively APP). As in panel analysis, we proxy for 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 NTM) 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 NTM (or one of their components) using two inputs, a weighted average of the tail risk of currencies and a weighted average of NTM (or their 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

[21] We have omitted Sweden, Denmark and Australia for model dimensionality reasons. Moreover, Danish and Swedish Krona follow closely the dynamics of Euro, so we do not expect it to be structurally different from the Euro Area.

15 days. Second, particularly important for the systematic component, the BGVAR is estimated in first differences. Third, the model estimation uses stochastic search variable selection with 5 lags, 20,000 posterior draws and the same number of burn-ins (see George, Sun, and Ni, 2008). The estimation takes between 30 to 40 minutes depending on computer processing capacity.

5.2. 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 NTM while afterwards, they were bound by the ZLB. Third, using insights from the literature, we assume that NTM or APP from EUR, UK and Japan decreases the systematic component of tail risk of the other two countries. For example, an NTM 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 and 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. 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% confidence bands of IRFs.[22] 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 a time. This approach provides insights into the marginal contribution of specific domestic shocks on the global system. Lastly, we additionally estimate the model with global (NTM, APP and CMP) shocks. A global shock is identified as one originating from the U.S. (since the U.S. is exogenous to the system) but impacts all countries simultaneously. We first discuss the results for NTM shocks, both domestic and global, and then proceed to discuss the APP shock results.

5.3. Non-Traditional Measure Results

Figures 9-13 show the IRFs for the country-specific systematic tail risk following a local, but simultaneously-introduced NTM 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 (or indexed) measure, 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 NTM has a relatively 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

[22]The exception is the analysis on APP that we present in Figures 7-23 in the Online Appendix where the shock is in one single APP measure but the transmission is restricted to be positive in the other jurisdictions/currencies.

(central) Bank of Canada has employed a limited number of unconventional policy measures, the wide interval is perhaps not that surprising.

[Figures 9-13]

To better understand the cross-border spill-overs of domestic shocks, a good proxy for 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 captures the international transmission of that particular policy instrument.

The graphs in Figures 14 to 21, moving from (top) left to right (and then down) represent those of Canada (CA), Switzerland (CH), Euro Area (EU), UK (GB), Japan (JP) and New Zealand (NZ). Figure 14 depicts the transmission of a domestic NTM shock in the 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. This analysis concludes 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 NTM are the 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 we do 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 parts. Following the positive domestic NTM shock, the response remains positive for about 4-5 weeks, and the peak is at around 1 - 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 NTM 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 the Euro Area, UK, Japan and Switzerland are for the case with simultaneous domestic NTM 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 NTM to total transmission, Switzerland appears to have the largest contribution. In contrast, a New Zealand NTM shock appears to *reduce* the overall transmission by greatest amount.

[Figures 14 to 20]

Turning now to the global NTM shock in Figure 21, the overall response functions are substantially smaller. 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 U.S. monetary policy, followed by Japan and Canada.

[Figure 21]

5.4. Robustness Analysis

To better disentangle the transmission of each domestic QE shock for the three economies where the effects were the largest, UK, the Euro Area and Japan, we ran independent simulations introducing only one shock and comparing the transmission to joint-shock scenarios. In Figures 7-23 of the Online Appendix, we report the corresponding 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.

6. Conclusion

We examine the relationship between central bank policy toolbox and the tail risk of exchange rates. We find that *NTM* (or 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 non-traditional policy measures, 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. Our empirical analysis confirms the existence of a financial cross-border transmission channel of central bank policy, via the tails of the FX market returns. Future research should aim to formalize such link to better understand the structural aspects of the transmission and any implications for financial stability.

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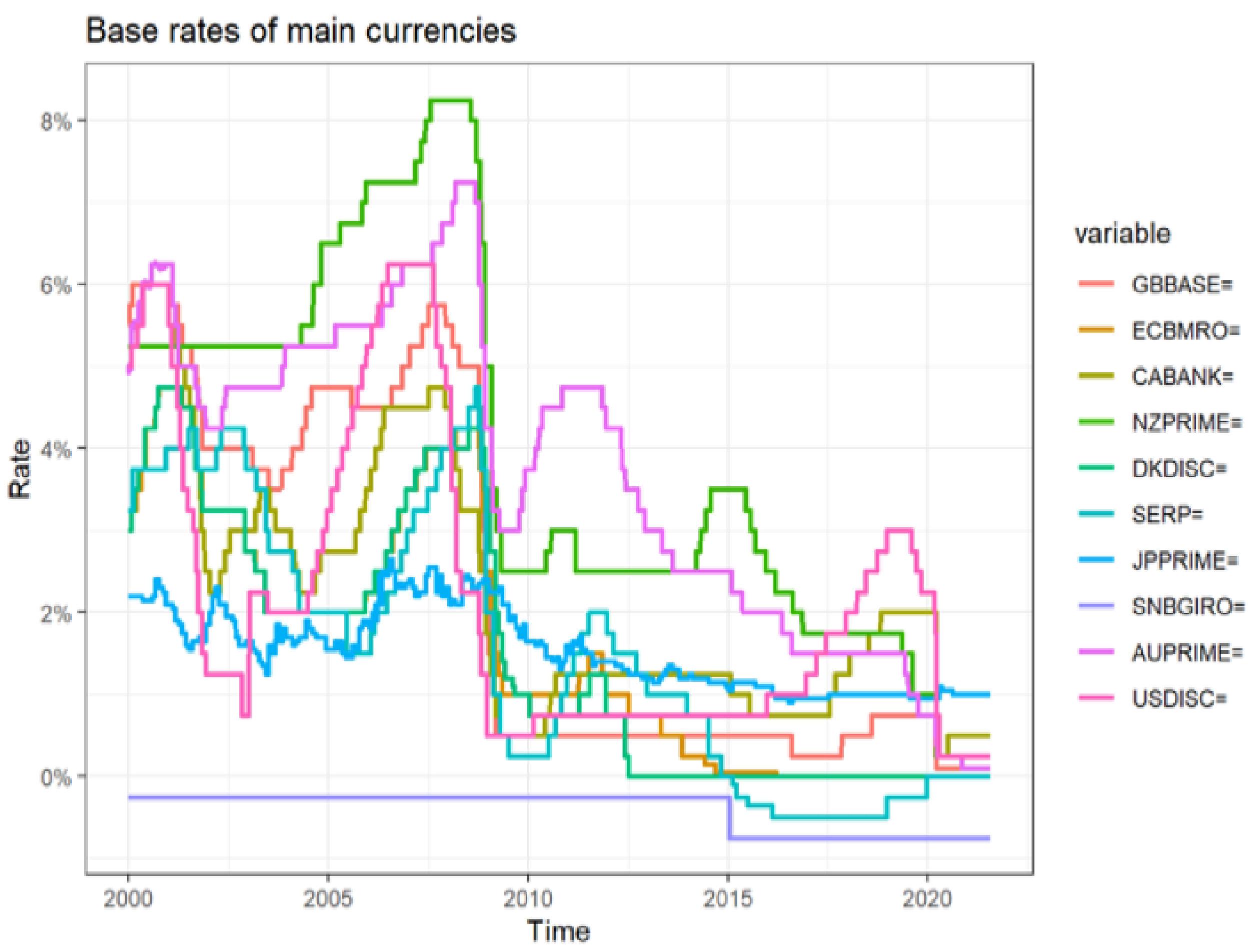
Table 1: Description of Main Variables

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.

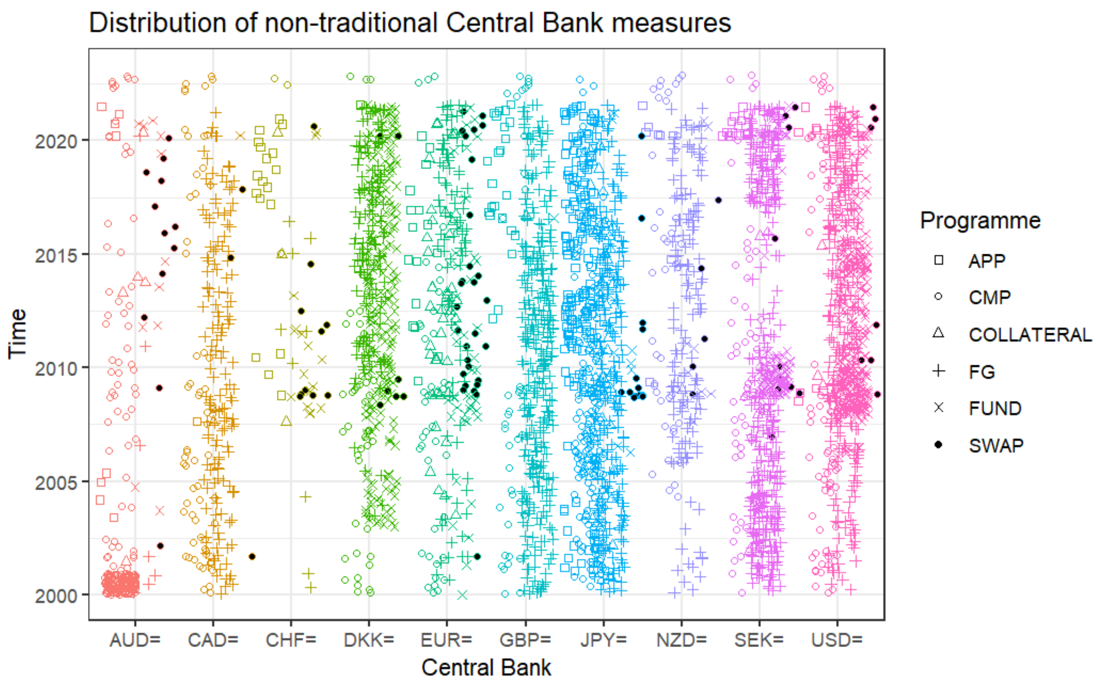
Variable	Description
Tail Risk	Full tail risk, systematic tail risk or idyosincratic tail risk component following the procedure described in the paper
CMP	Impact of Central Bank announcement about the reference rate*
APP	Impact of Central Bank announcement about asset purchase programs*
Coll	Impact of Central Bank announcement about assets eligible as collateral*
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

Figure 1: Conventional Monetary Policy Measures over Time



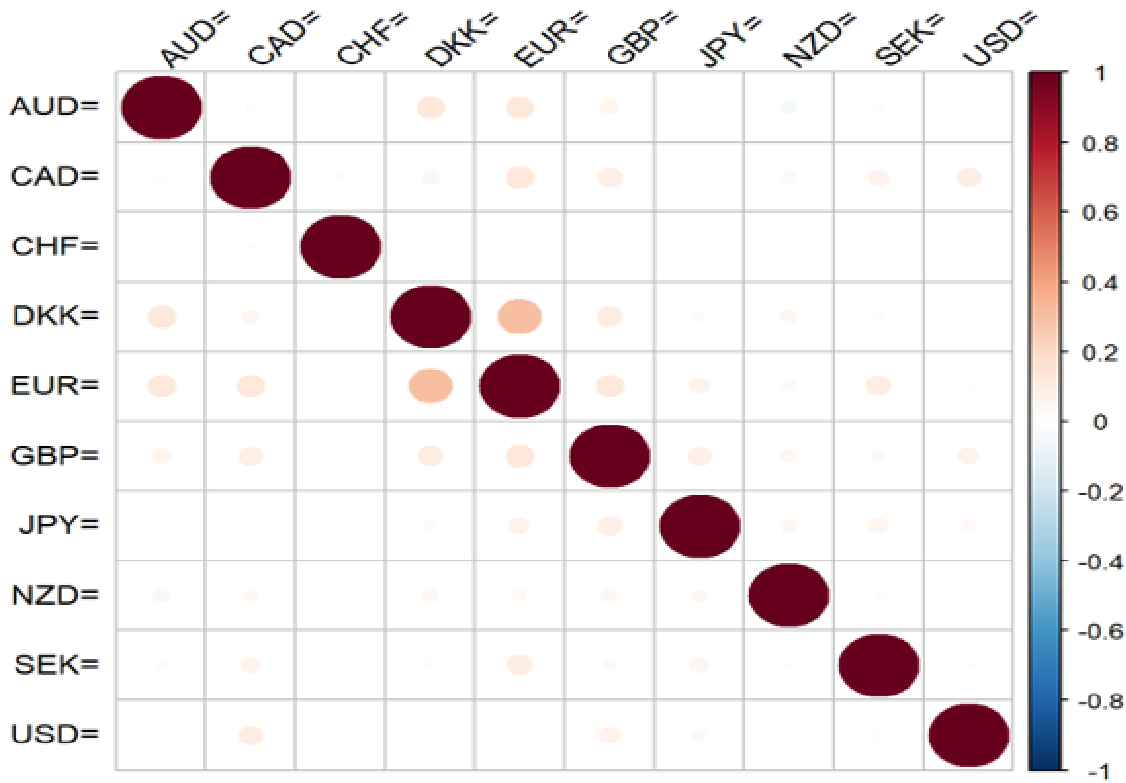
This figure shows the movement in the base interest rate controlled by the respective main central banks over the sample period from January 2000 to February 2021. These base rates pertain to the following currencies: GBP, EUR, CAD, NZD, DKK, SEK, JPY, AUD and USD.

Figure 2: Non-Traditional Measures over Time



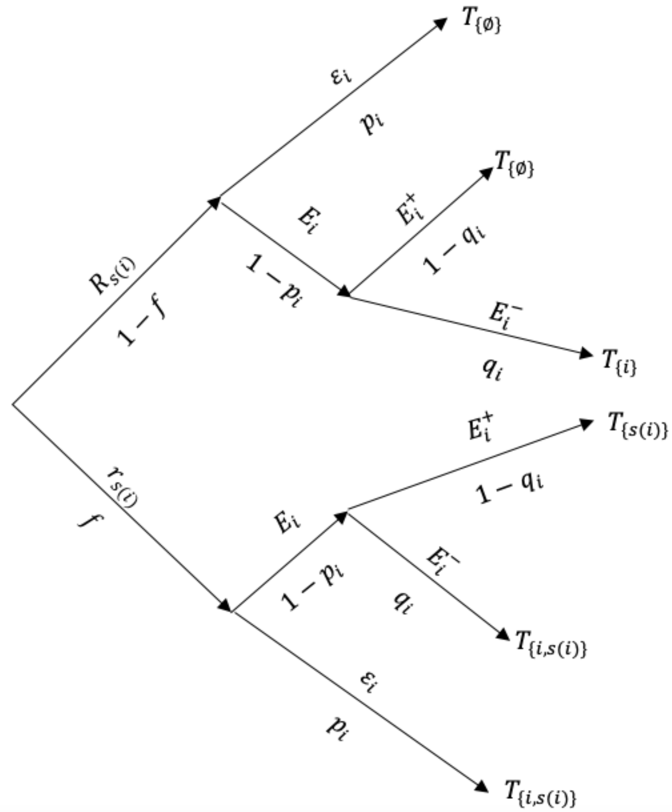
This figure shows the number of times a particular measure has been implemented over the sample period from January 2000 to February 2021. The currencies are: GBP, EUR, CAD, NZD, DKK, SEK, JPY, AUD and USD. The figure is a structured scatter plot where the intensity of colour represents the frequency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

Figure 3: 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.

Figure 4: 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 5)

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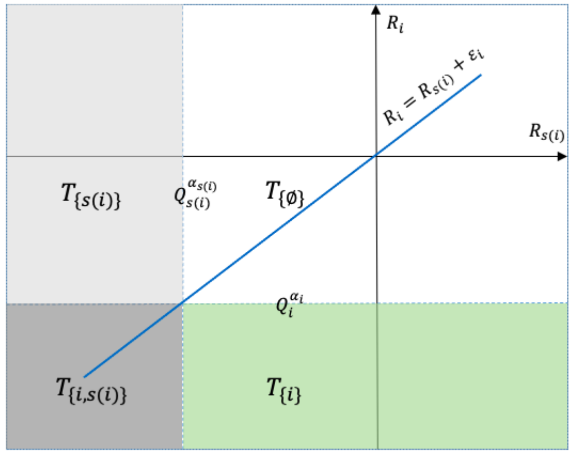
Figure 5: The Partition of Outcome Space of Aggregate Systematic Factor and Currency Returns



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 4: 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 2: Linear Regression of the Currency Excess Returns on the first three the principal components

This table shows the estimated parameters of linear regressions of the excess returns of the various currencies on the first three the principal components. 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.

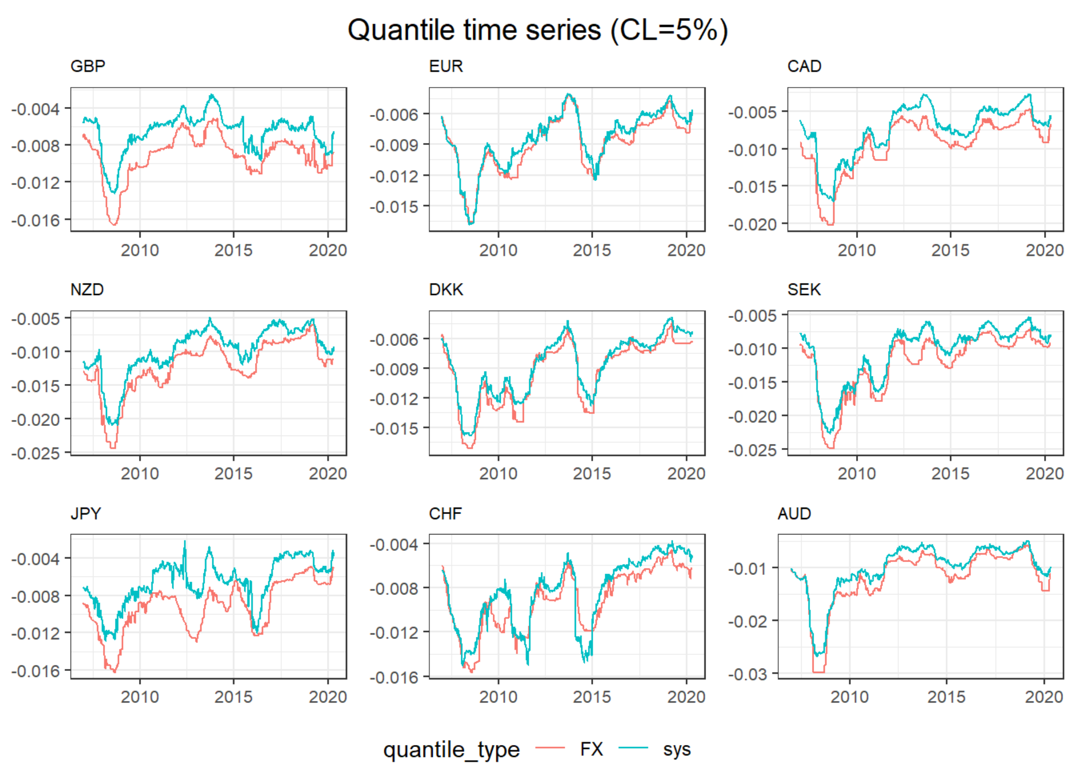
	Dependent variable: FX excess returns								
	GBP	EUR	CAD	NZD	DKK	SEK	JPY	CHF	AUD
PCA1	-0.092***	-0.117***	0.077***	-0.132***	0.116***	0.137***	0.042***	0.108***	-0.136***
	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
PCA2	0.089***	0.201***	0.047***	-0.006	-0.198***	-0.154***	-0.199***	-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	-0.007	-0.008
Constant	0.00003	0.00003	0.0001*	-0.0001*	-0.00003	-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
R2	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 (df 5617)	0.004	0.002	0.004	0.005	0.002	0.004	0.005	0.004	0.004
F Statistic (df 3; 5617)	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***

Table 3: 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.

	Panel A: Quantiles of the currency excess returns								
	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
	Panel B: Quantiles of the aggregate systematic factor for each country								
	GBP	**EUR**	**CAD**	**NZD**	**DKK**	**SEK**	**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 6: The Evolution of the Tail Risk of Currencies and Their Systematic Risk Factors over Time



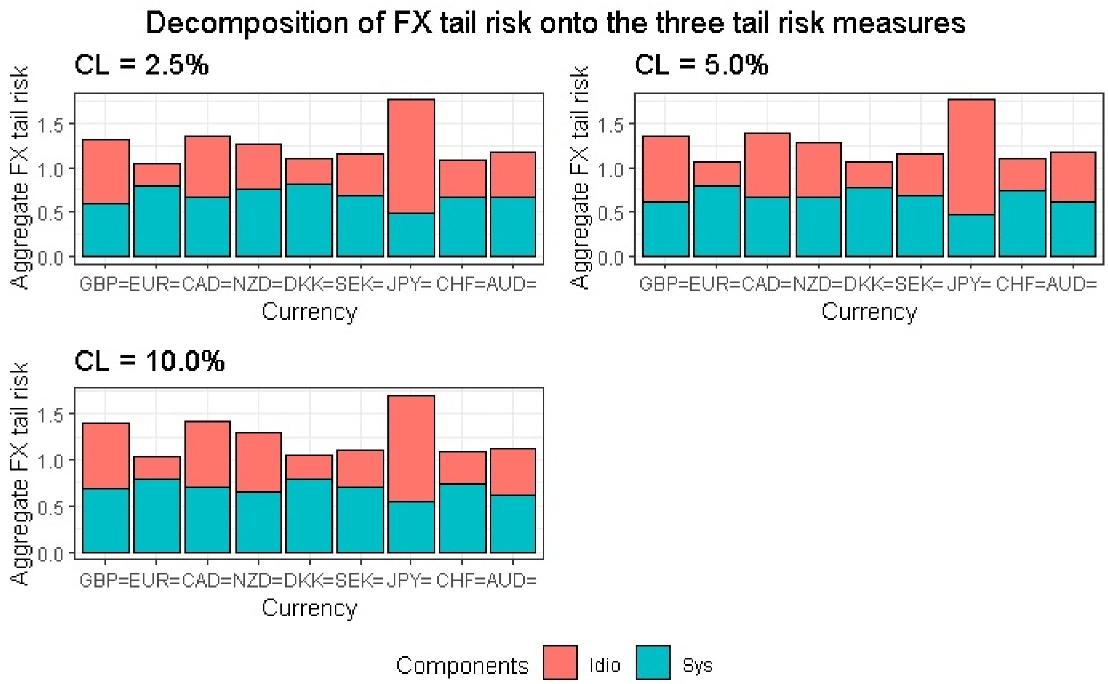
This figure shows the evolution of the quantiles at nominal probability level $\alpha = 5\%$ of currencies and their aggregate systematic risk factors.

Table 4: 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.

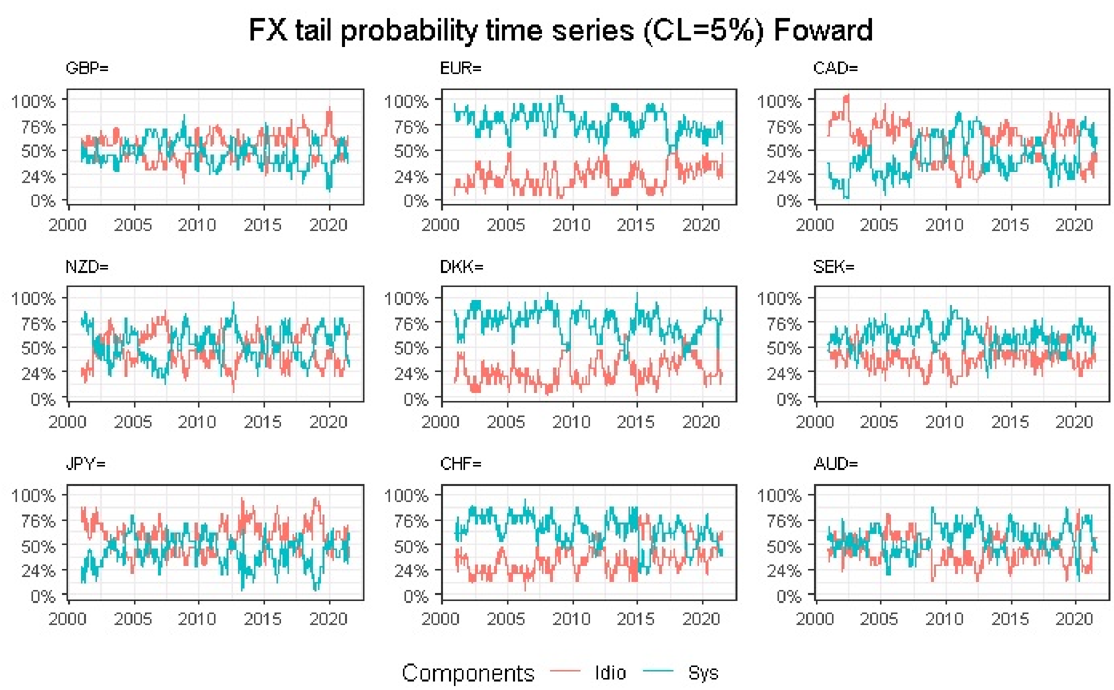
	Panel A: Joint probability of a currency and its aggregate systematic risk factor exceeding a quantile								
	GBP	**EUR**	**CAD**	**NZD**	**DKK**	**SEK**	**JPY**	**CHF**	**AUD**
0.025	0.012	0.019	0.012	0.015	0.019	0.015	0.007	0.016	0.014
0.05	**0.024**	**0.037**	**0.025**	**0.027**	**0.037**	**0.031**	**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 B: The tail dependence coefficient of a currency on its aggregate systematic risk factor								
	GBP	**EUR**	**CAD**	**NZD**	**DKK**	**SEK**	**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 7: 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 8: 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.

Table 5: 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.

	Panel A: Angrist - Pischke Weak IV with Daily Frequency											
	5 years		2 years		2 months		1 month		2 months (r)		1 month (r)	
NTM	85299		5272.6		4161.82		4338.73		4443.05		4568.48	
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		8880.09		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: Angrist - Pischke Weak IV with Weekly Frequency											
	5 years		2 years		2 months		1 month		2 months (ita)		1 month (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)	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)	108.99***	100.69***	104.16***	24.95***	47.55***	16.15***	106.73***	14.43***	46.86***	15.14***	104***	13.28**
	Panel C: Weak Identification Test (Kleibergen - Paap)											
	5 years		2 years		2 months		1 month		2 months (r)		1 month (r)	
	Daily	Weekly	Daily	Weekly	Daily	Weekly	Daily	Weekly	Daily	Weekly	Daily	Weekly
CMP, NTM	220.19	306.57	202.01	110.22	3803.29	29.52	3941.84	44.85	4078.71	27.5	4182.39	41.42
Stock-Yogo (5% Max IV bias)	19.4	19.4	19.4	19.4	19.4	19.4	19.4	19.4	19.4	19.4	19.4	19.4
Stock-Yogo (10% Max IV bias)	10.78	10.78	10.78	10.78	10.78	10.78	10.78	10.78	10.78	10.78	10.78	10.78

Table 6: Full sample

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, in the first four columns, is the systematic component of the tail risk calculated with the last year of observations, and the entire tail risk in the last four columns. 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.

	Systematic Component				Tail Risk			
	5Y		2m(r)		5Y		2m(r)	
NTM	0.010		0.015**		-0.021**		-0.024**	
	[0.007]		[0.006]		[0.010]		[0.011]	
CMP	-0.010	-0.008	-0.011	-0.009	0.006	0.002	0.003	0.002
	[0.009]	[0.009]	[0.012]	[0.012]	[0.022]	[0.022]	[0.028]	[0.029]
APP		0.028***		0.029***		-0.059***		-0.055***
		[0.009]		[0.008]		[0.022]		[0.021]
Collateral		-0.041		-0.000		-0.018		0.022
		[0.074]		[0.062]		[0.079]		[0.109]
Forward G.		0.006		0.007		0.008		0.006
		[0.007]		[0.008]		[0.011]		[0.010]
Fund		-0.000		0.002		-0.014		-0.036
		[0.013]		[0.017]		[0.025]		[0.037]
Swap		-0.068*		-0.186*		0.043		0.091
		[0.041]		[0.111]		[0.027]		[0.074]
ZLB	-0.011**	-0.011**	-0.012**	-0.012**	0.010***	0.010***	0.010***	0.010***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.003]	[0.003]	[0.003]	[0.003]
FG_{sg}	-0.003	-0.003	-0.003	-0.003	0.014**	0.014**	0.014**	0.014**
	[0.005]	[0.005]	[0.005]	[0.005]	[0.006]	[0.006]	[0.006]	[0.006]
FG_{og}	0.025***	0.025***	0.025***	0.025***	-0.002	-0.002	-0.002	-0.002
	[0.007]	[0.007]	[0.007]	[0.007]	[0.005]	[0.005]	[0.005]	[0.005]
FG_{tg}	-0.003	-0.003	-0.003	-0.003	0.007	0.007	0.007	0.007
	[0.002]	[0.002]	[0.002]	[0.002]	[0.006]	[0.006]	[0.006]	[0.006]
QE	-0.019	-0.019	-0.019	-0.019	0.066	0.065	0.066	0.065
	[0.023]	[0.023]	[0.023]	[0.023]	[0.097]	[0.097]	[0.097]	[0.097]
Observations	30,720	30,720	30,720	30,720	30,720	30,720	30,720	30,720
R-squared	0.002	0.003	0.001	0.001	0.001	0.002	0.000	0.001
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
C_M_Y FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 7: Before and After GFC

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.

	Before GFC				After GFC			
	5y		2m(r)		5y		2m(r)	
NTM	0.008		-0.005		0.011		0.014**	
	[0.009]		[0.017]		[0.008]		[0.007]	
CMP	0.009	0.009	0.017	0.018	-0.024*	-0.02	-0.025*	-0.024
	[0.013]	[0.013]	[0.019]	[0.019]	[0.014]	[0.014]	[0.015]	[0.015]
APP		-0.019		0.032		0.029***		0.031***
		[0.046]		[0.079]		[0.009]		[0.009]
Collateral		0.042		0.025		-0.081		0.041
		[0.044]		[0.072]		[0.109]		[0.084]
Forward G.		0.01		0.015		0.002		0.001
		[0.011]		[0.022]		[0.009]		[0.009]
Fund		0.002		0.02		0.003		0.005
		[0.024]		[0.058]		[0.017]		[0.020]
Swap		-0.013		-0.313		-0.085*		-0.142*
		[0.075]		[0.218]		[0.051]		[0.076]
ZLB	-0.037***	-0.037***	-0.036***	-0.036***	0	0	0	0
	[0.007]	[0.007]	[0.007]	[0.007]	[0.005]	[0.005]	[0.005]	[0.005]
FG_{sg}					-0.003	-0.004	-0.003	-0.003
					[0.005]	[0.005]	[0.005]	[0.005]
FG_{og}	0.044***	0.044***	0.044***	0.044***	0.015**	0.014**	0.015**	0.015**
	[0.010]	[0.010]	[0.010]	[0.010]	[0.006]	[0.007]	[0.006]	[0.006]
FG_{tg}					-0.002	-0.002	-0.002	-0.002
					[0.002]	[0.002]	[0.002]	[0.002]
QE	-0.008	-0.008	-0.008	-0.008	-0.028	-0.027	-0.028	-0.027
	[0.013]	[0.013]	[0.013]	[0.013]	[0.040]	[0.039]	[0.039]	[0.039]
Obs	13,758	13,758	13,758	13,758	16,956	16,956	16,956	16,956
R-squared	0.006	0.006	0.005	-0.009	0	0.002	0	-0.001
U.S. Controls	YES	YES	YES	YES	YES	YES	YES	YES
C_M_Y FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 8: Subperiods GFC

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.

	Oct 09 - Jun 12		Jul 12 - Dec 18		After Jan 19	
	5y	2m(r)	5y	2m(r)	5y	2m(r)
CMP	-0.004	-0.007	-0.02	-0.03	-0.035	-0.04
	[0.021]	[0.025]	[0.020]	[0.023]	[0.030]	[0.035]
APP	0.028	0.034	0.034***	0.035***	-0.01	-0.025
	[0.040]	[0.043]	[0.010]	[0.013]	[0.026]	[0.036]
COLL	-0.057	-0.078	-0.111	0.159	0.062	0.273
	[0.068]	[0.083]	[0.160]	[0.169]	[0.121]	[0.168]
FG	-0.035	-0.04	0.007	0	0.018	0.021
	[0.021]	[0.027]	[0.012]	[0.010]	[0.021]	[0.025]
Fund	0.006	0	0.071	0.12	0.012	0.01
	[0.021]	[0.028]	[0.061]	[0.123]	[0.037]	[0.039]
Swap	-0.052	-0.064	-0.287**	-0.399**	0.01	0.023
	[0.068]	[0.086]	[0.125]	[0.178]	[0.024]	[0.056]
Obs	4,302	4,302	10,176	10,176	2,484	2,484
U.S. Controls	YES	YES	YES	YES	YES	YES
C_M_Y FE	YES	YES	YES	YES	YES	YES

Impulse Response Functions in the GVAR model

Non-Traditional Measures (NTM) shocks

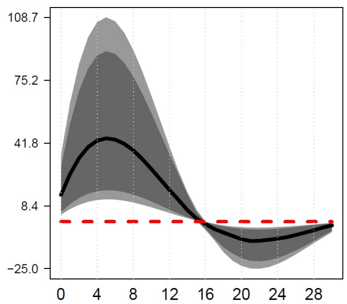


Figure 9: NTM: U.K. domestic shock

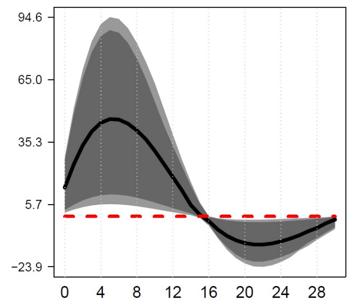


Figure 10: NTM: Euro Area domestic shock

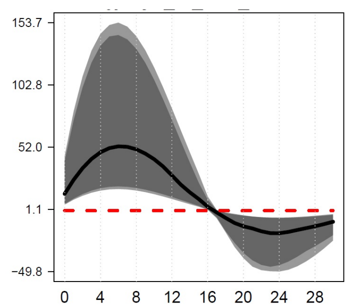


Figure 11: NTM: Japan domestic shock

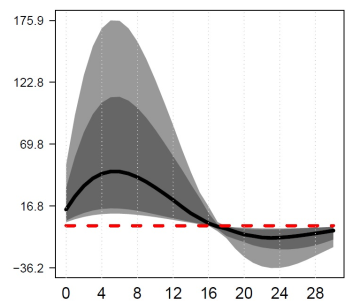


Figure 12: NTM: Switzerland domestic shock

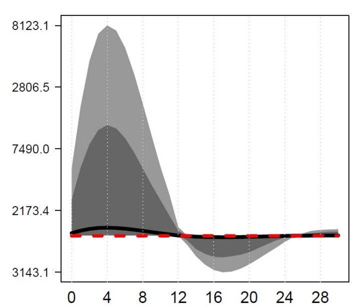
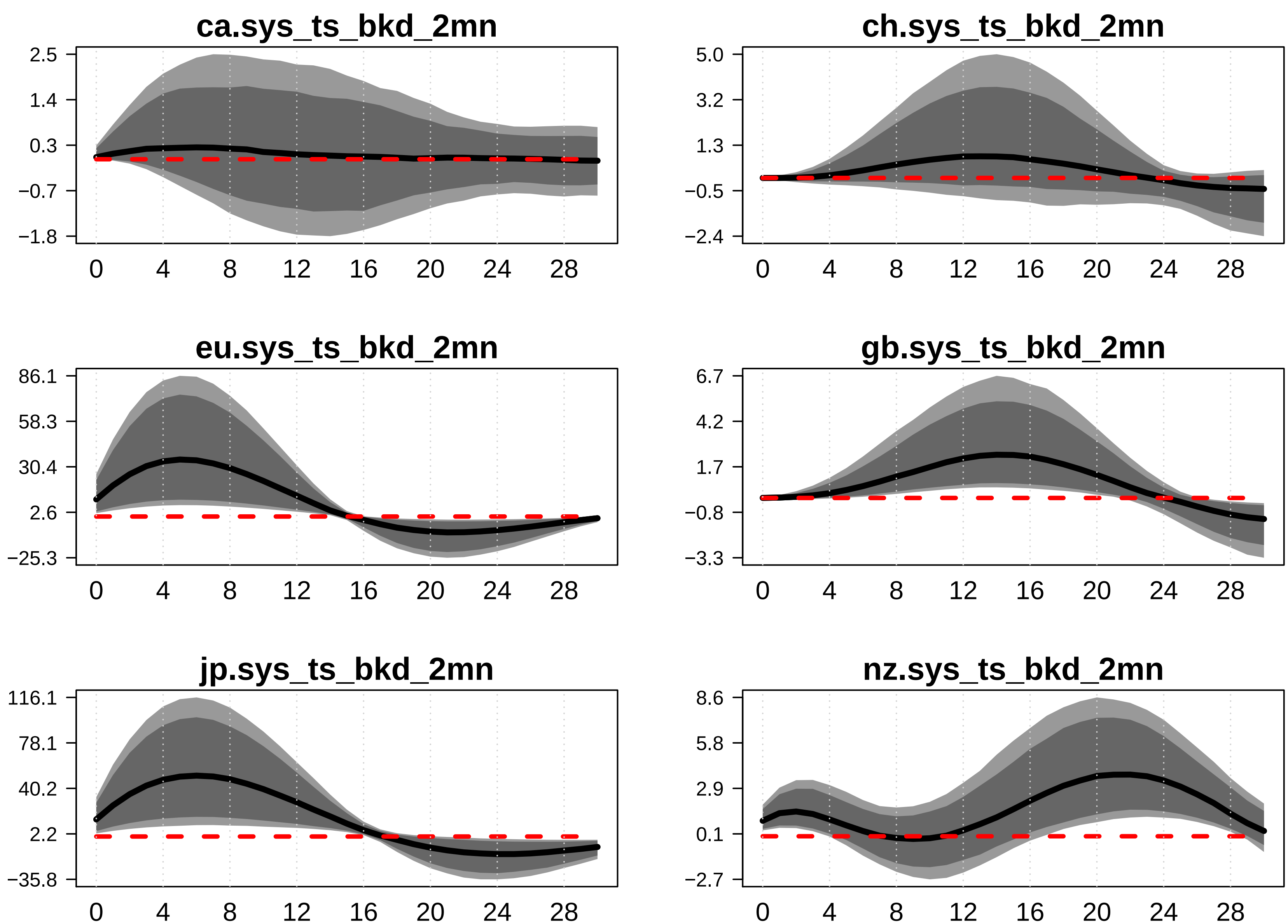


Figure 13: NTM: Canada domestic shock

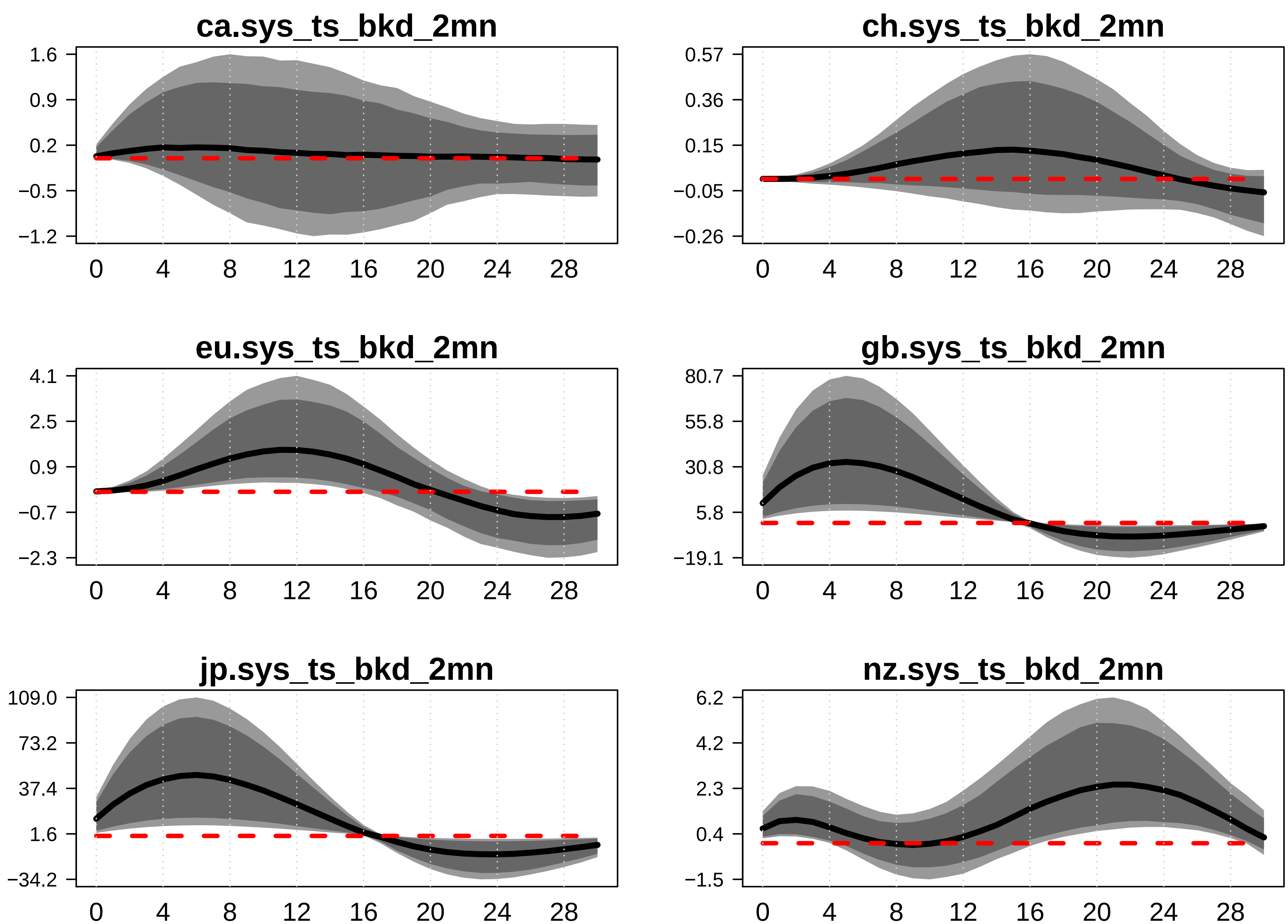
The solid line is the median response, the dark (light) grey shaded area are the 68% (95%) confidence intervals.

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



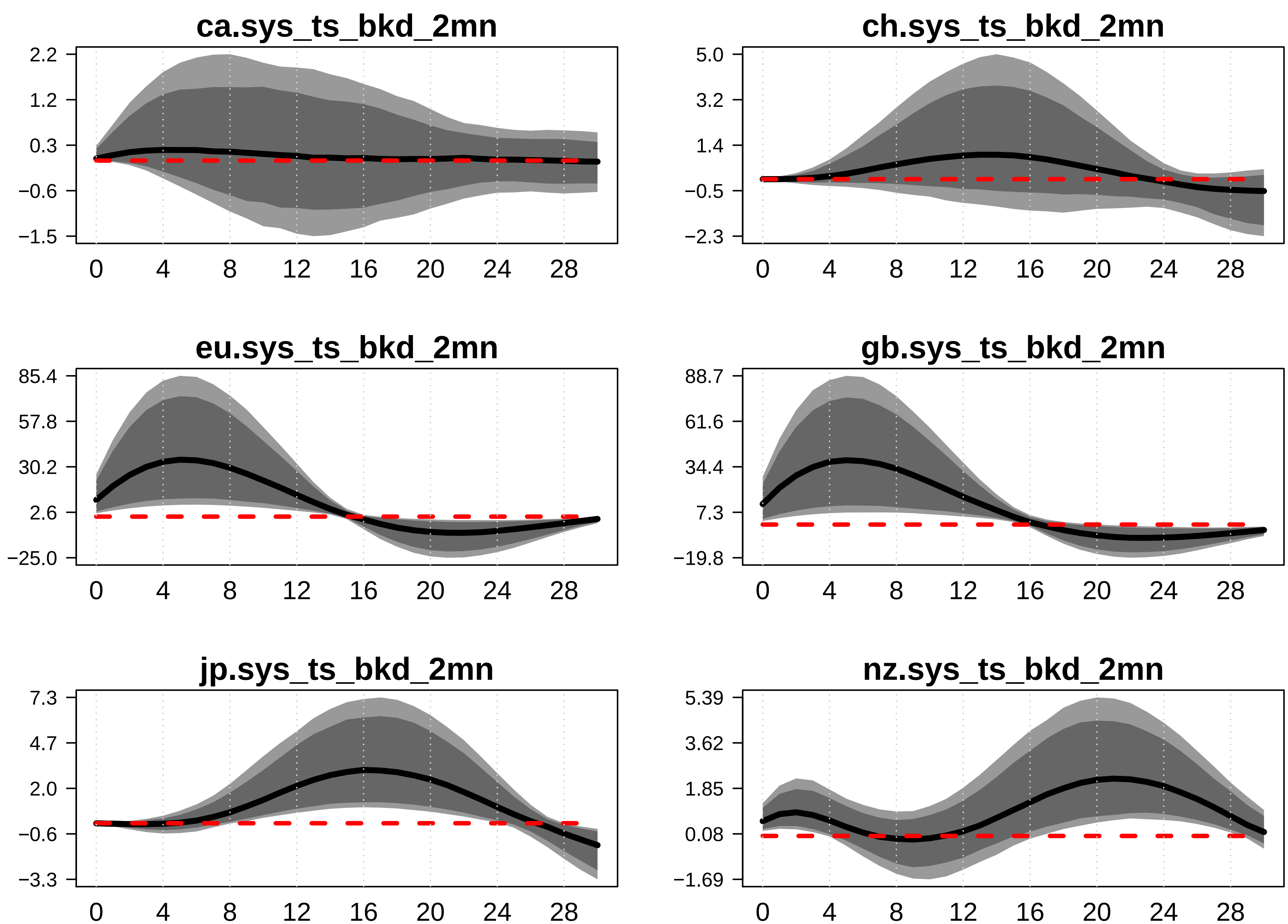
We report the responses to a domestic NTM shock in Euro Area and Japan. The figures represent the IRFs of (from top-left to right-and-down): Canada, Switzerland, Euro Area, UK, Japan and New Zealand. The solid line is the median response, the dark (light) grey shaded area represents the 68% (95%) confidence intervals. The dotted red line is the zero-line.

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



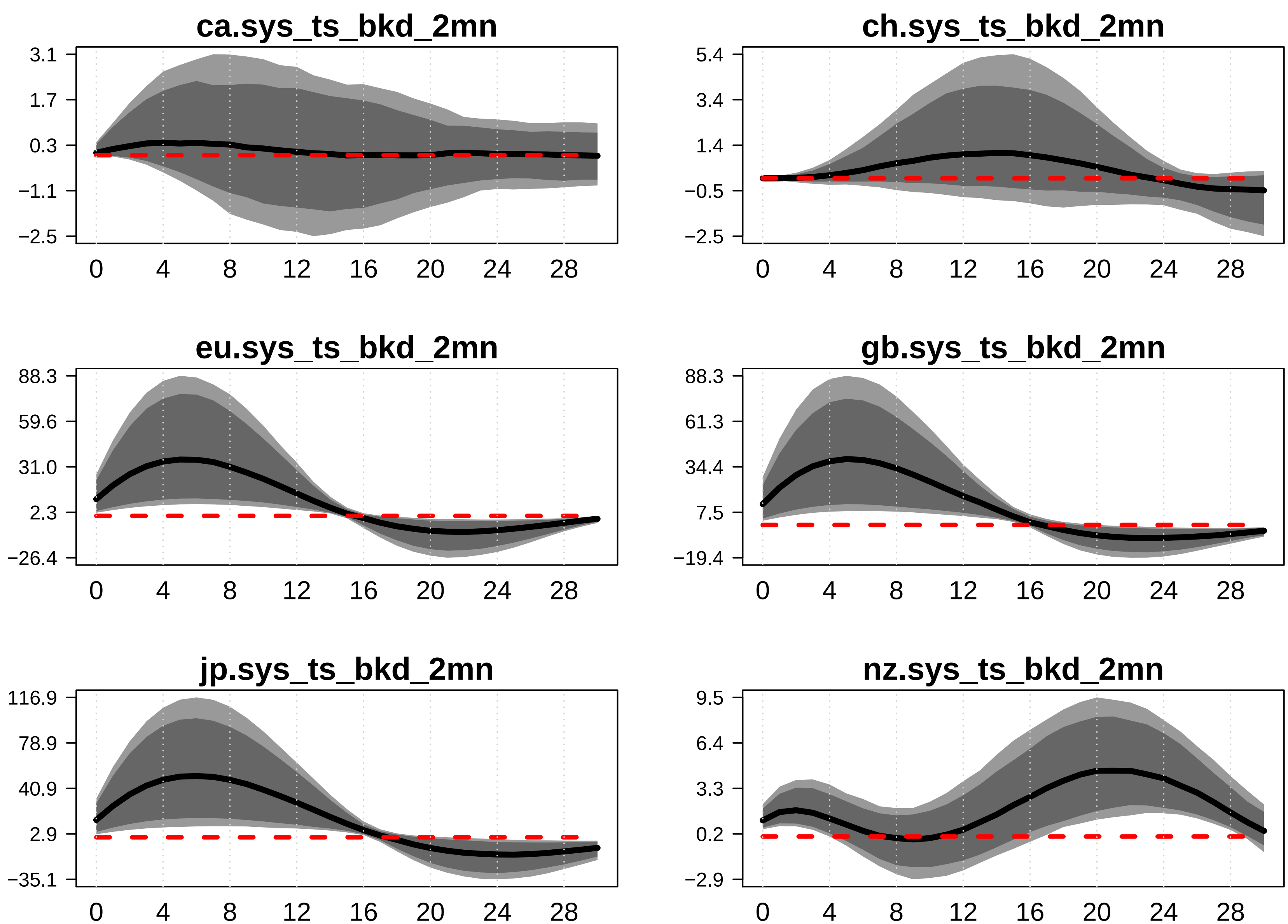
We report the responses to a domestic NTM shock in UK and Japan. The figures represent the IRFs of (from top-left to right-and-down): Canada, Switzerland, Euro Area, UK, Japan and New Zealand. The solid line is the median response, the dark (light) grey shaded area represents the 68% (95%) confidence intervals. The dotted red line is the zero-line.

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



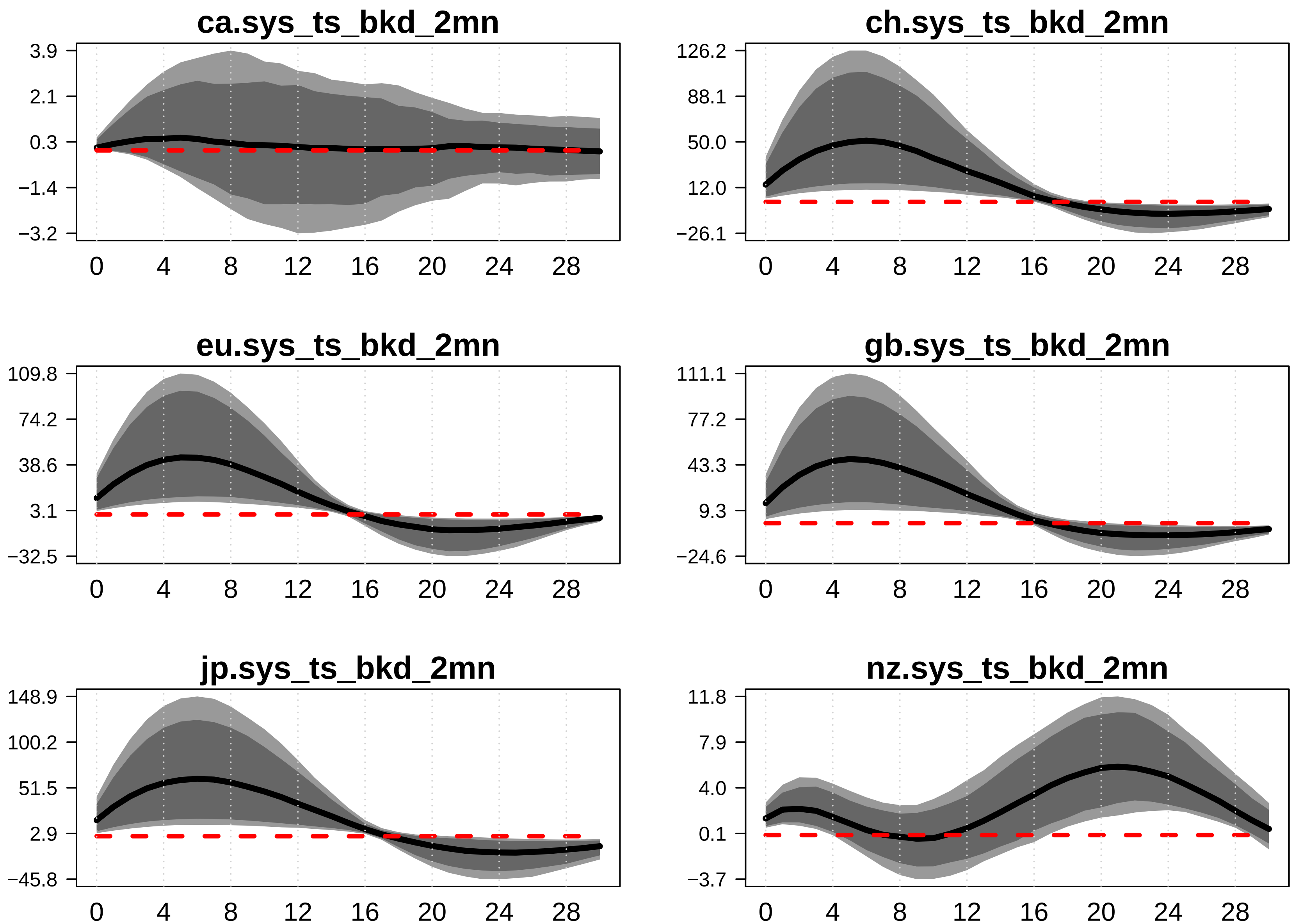
We report the responses to a domestic NTM shock in UK and Euro Area. The figures represent the IRFs of (from top-left to right-and-down): Canada, Switzerland, Euro Area, UK, Japan and New Zealand. The solid line is the median response, the dark (light) grey shaded area represents the 68% (95%) confidence intervals. The dotted red line is the zero-line.

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



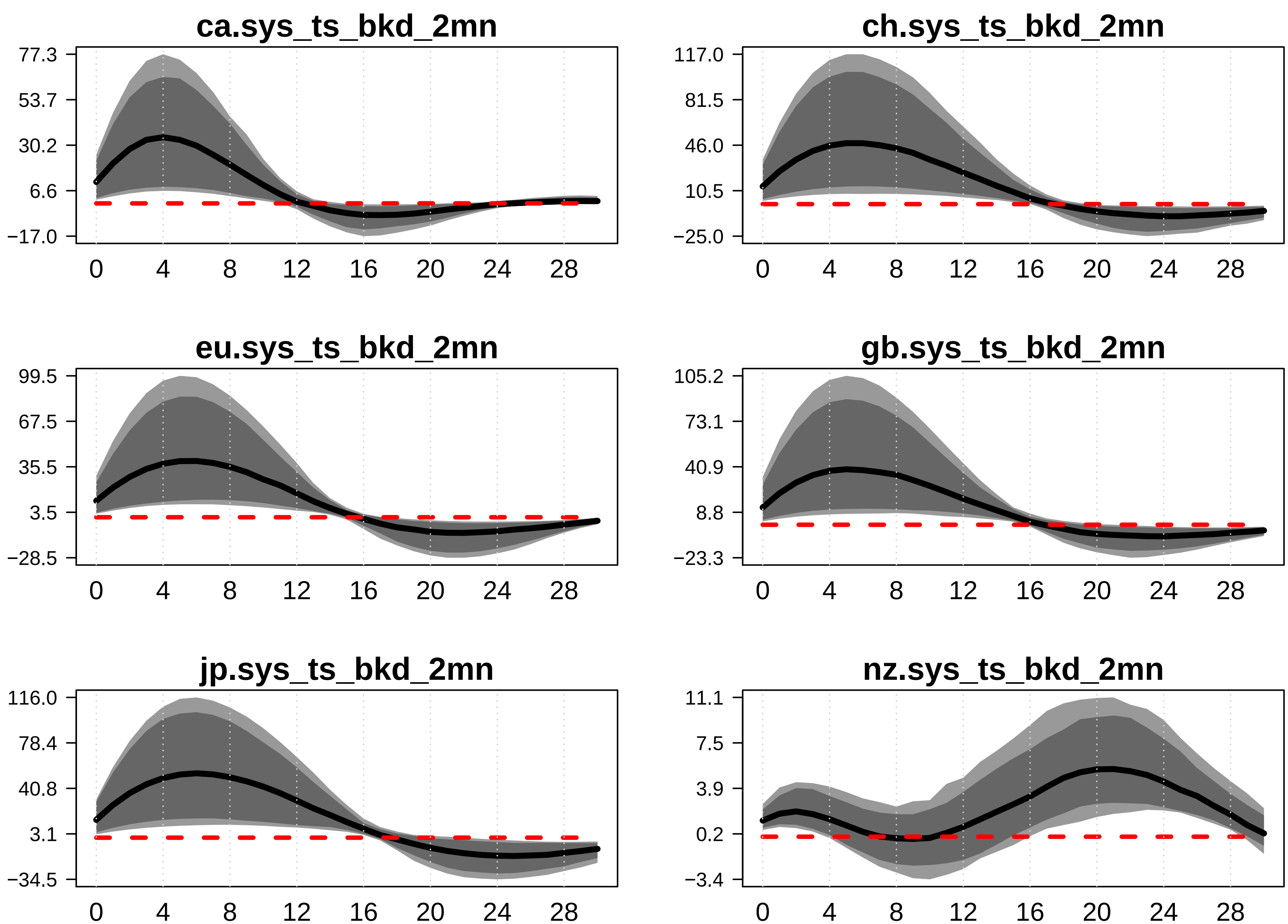
We report the responses to a domestic NTM shock in UK, Euro Area and Japan. The figures represent the IRFs of (from top-left to right-and-down): Canada, Switzerland, Euro Area, UK, Japan and New Zealand. The solid line is the median response, the dark (light) grey shaded area represents the 68% (95%) confidence intervals. The dotted red line is the zero-line.

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



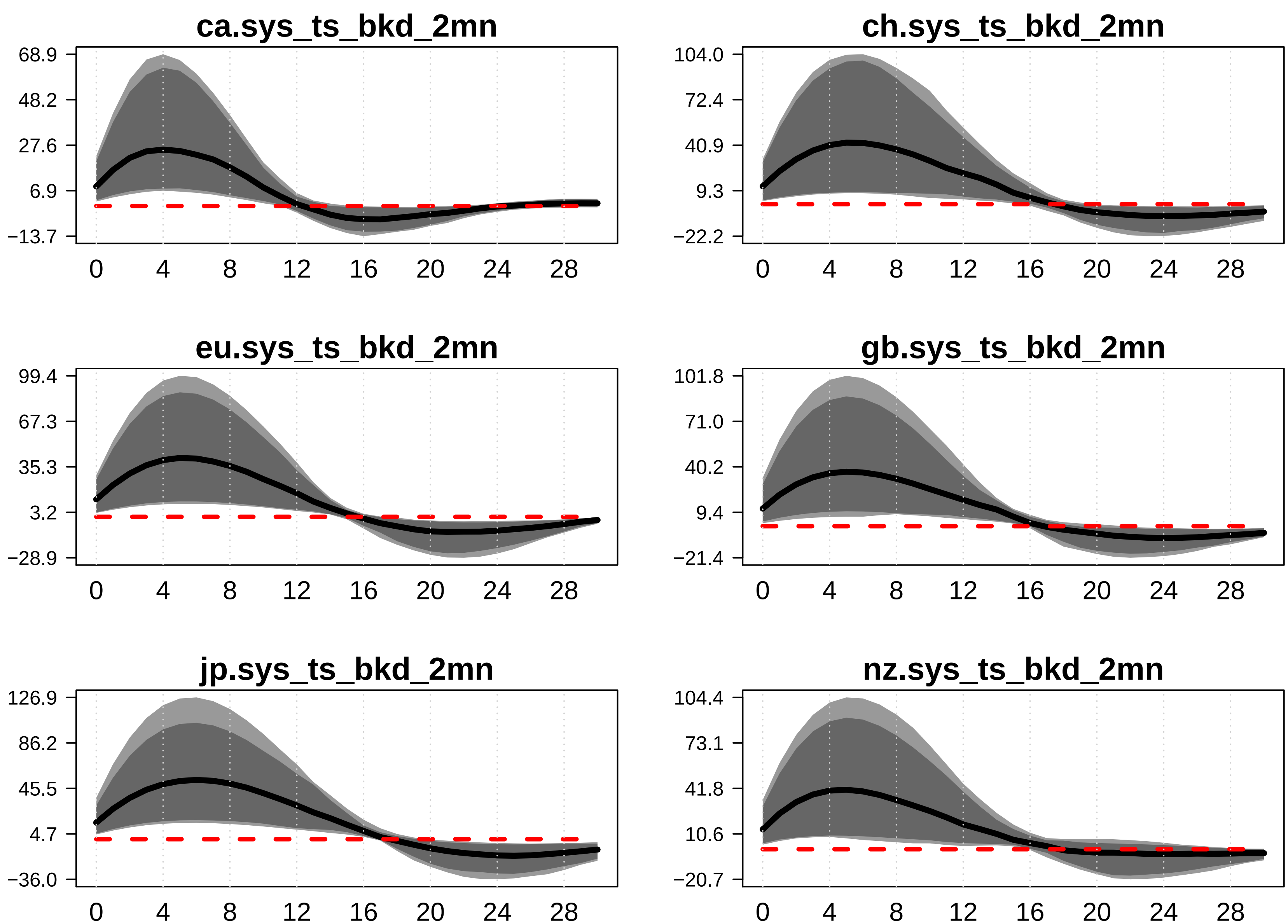
We report the responses to a domestic NTM shock in UK, Euro Area, Japan and Switzerland. The figures represent the IRFs of (from top-left to right-and-down): Canada, Switzerland, Euro Area, UK, Japan and New Zealand. The solid line is the median response, the dark (light) grey shaded area represents the 68% (95%) confidence intervals. The dotted red line is the zero-line.

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



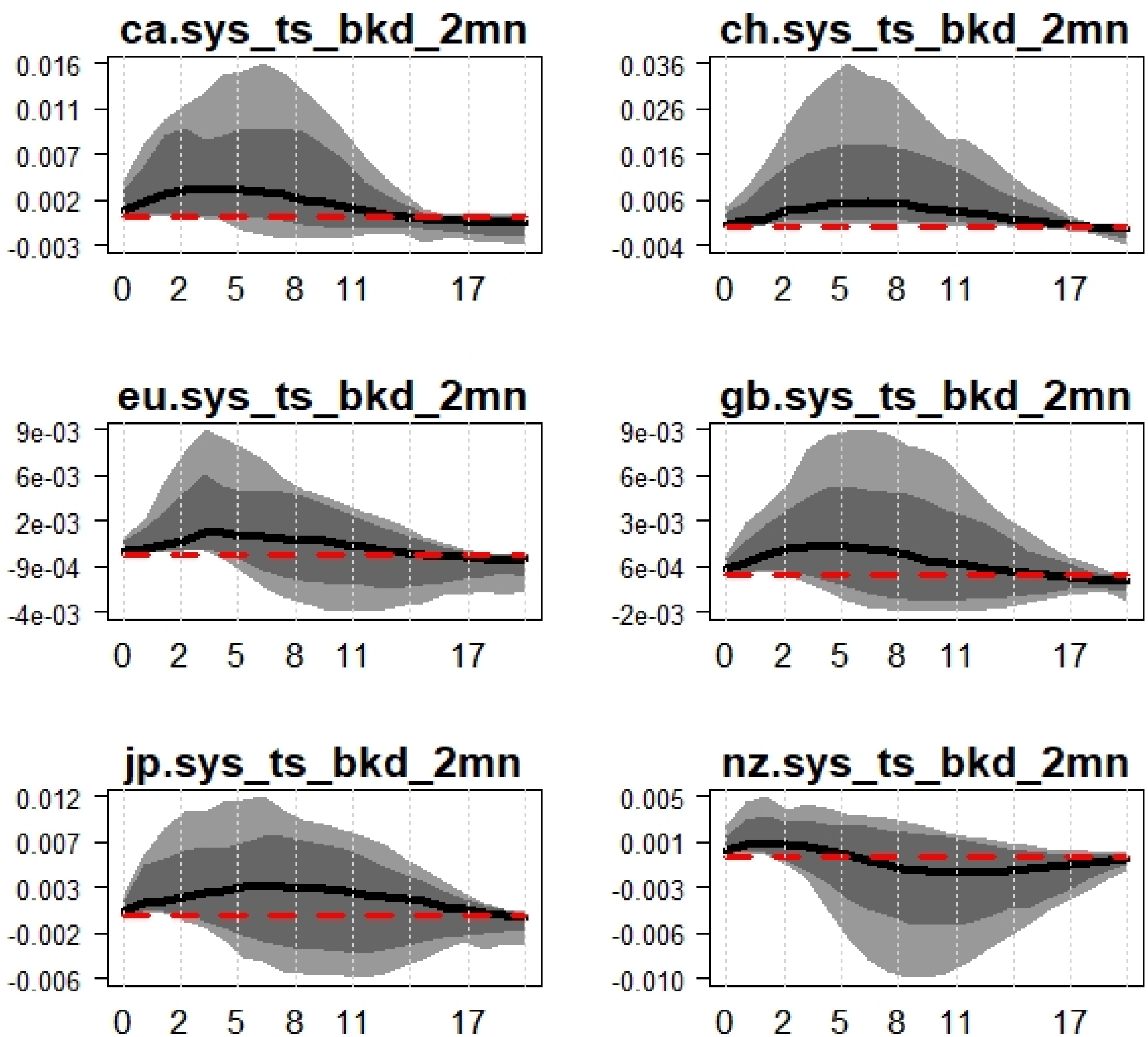
We report the responses to a domestic NTM shock in all countries except for New Zealand. The figures represent the IRFs of (from top-left to right-and-down): Canada, Switzerland, Euro Area, UK, Japan and New Zealand. The solid line is the median response, the dark (light) grey shaded area represents the 68% (95%) confidence intervals. The dotted red line is the zero-line.

Figure 20: NTM: domestic shocks to all.



We report the responses to a domestic NTM shock in all countries. The figures represent the IRFs of (from top-left to right-and-down): Canada, Switzerland, Euro Area, UK, Japan and New Zealand. The solid line is the median response, the dark (light) grey shaded area represents the 68% (95%) confidence intervals. The dotted red line is the zero-line.

Figure 21: NTM Global shock

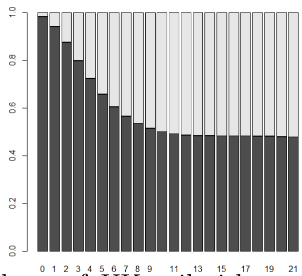


We report the responses to a global NTM shock. The figures represent the IRFs of (from top-left to right-and-down): Canada, Switzerland, Euro Area, UK, Japan and New Zealand. The solid line is the median response, the dark (light) grey shaded area represents the 68% (95%) confidence intervals. The dotted red line is the zero-line.

Forecast Error Variance Decomposition (FEVD)

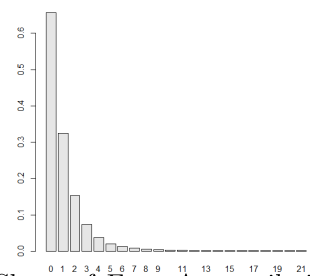
Domestic Non-Traditional Measures (NTM) shocks

Figure 22: FEVD: UK domestic NTM shock



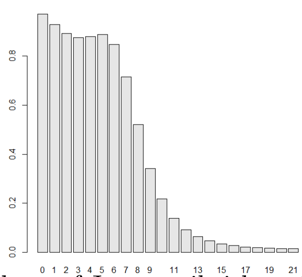
Share of UK tail risk variation explained by the domestic NTM shock.

Figure 23: FEVD: Euro Area domestic NTM shock



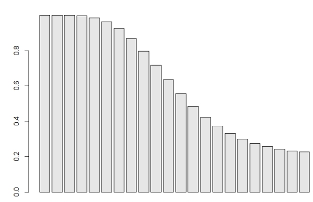
Share of Euro Area tail risk variation explained by the domestic NTM shock.

Figure 24: FEVD: Japan domestic NTM shock



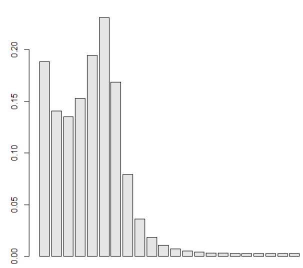
Share of Japan tail risk variation explained by the domestic NTM shock.

Figure 25: FEVD: Switzerland domestic NTM shock



Share of Swiss tail risk variation explained by the domestic NTM shock.

Figure 26: FEVD: Canada domestic NTM shock



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