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Financial stability considerations in the conduct of monetary policy

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Abstract

We empirically analyze the interaction of monetary policy with financial stability and the real economy in the euro area. For this, we apply a quantile vector autoregressive model and two alternative estimation approaches: simulation and local projections. Our specifications include monetary policy surprises, real GDP, inflation, financial vulnerabilities and systemic financial stress. We disentangle conventional and unconventional monetary policy by separating interest rate surprises into two factors that move the yield curve either at the short end or at the long end. Our results show that a build-up of financial vulnerabilities tends to be accompanied initially by subdued financial stress which resurges, however, over a medium-term horizon, harming economic growth. Tighter conventional monetary policy reduces inflationary pressures but increases the risk of financial stress. We find unconventional monetary policy to be similarly effective in reducing inflation, but with a lower adverse effect on growth and financial stress. Tighter unconventional monetary policy is also found to have a dampening effect on the build-up of financial vulnerabilities.

Non-technical summary

The interplay of monetary policy, financial conditions and the real economy has been part of a long-standing macro-financial debate. Monetary policy transmits to the real economy by affecting financial conditions which themselves are taken into consideration in the conduct of monetary policy to stabilize inflation and the real economy. In this transmission process, monetary policy may enhance financial stability during slowdowns by supporting the debt servicing capacity of economic and financial sectors, while tighter monetary policy during exuberant times can attempt to mitigate financial imbalances by implicitly leaning against the wind of frothy market conditions.

By expanding the empirical quantile regression framework of Chavleishvili and Kremer (2021) to include monetary policy shocks, inflation and financial vulnerabilities we analyze the interaction of monetary policy with financial stability conditions and the real economy. We estimate impulse response functions of a quantile vector autoregressive model via two estimation techniques. First, using a simulation approach, following Ruzicka (2021b), and, second, using local projections as in Ruzicka (2021a). These quantile methods capture potential asymmetries in the interactions between economic activity, financial stability variables and monetary policy over the full distribution of the variables. Our specifications contain a range of interest rate shocks along the euro area yield curve as measure for monetary policy, euro area real GDP, euro area HICP inflation, the Systemic Risk Indicator (SRI) of Lang et al. (2019) as a measure of financial vulnerabilities and the Composite Indicator of Systemic Stress (CISS) of Hollo et al. (2012) as a measure of financial stress. All models are estimated on monthly euro area data from 2002 to 2019.

Our results show that surging financial stress has a strong short-term impact on economic growth, especially on the lower tail of the GDP distribution, in line with Adrian et al. (2018). A build-up of financial vulnerabilities tends to initially be accompanied by subdued financial stress, but financial stress surges over the medium term. Finally, tightening conventional monetary policy reduces real GDP growth and inflationary pressures accompanied by increasing financial stress. Unconventional monetary policy, such as quantitative easing, identified as surprises in longer-term interest rates are found to be similarly effective in reducing inflation but have a smaller 'sacrifice ratio' for GDP growth and financial stress. We also find that financial vulnerabilities tend to mildly recede following tighter unconventional monetary policy.

The empirical results lend themselves to counterfactual analysis on the trade-offs that monetary policy faces when pursuing price stability. The implemented exercises using 1-year ahead forecasts reveal that monetary policy has faced a trade-off during the global financial crisis: either tighten to stabilize inflation forecasts at 2% or loosen to curb stress and prevent tail risks to economic growth to increase.

1 Introduction

The interplay of monetary policy, financial conditions and the real economy has been part of a long-standing macro-financial debate. Monetary policy transmits to the real economy to a large extent by affecting financial conditions. Equally, monetary policy takes financial conditions into account to stabilize inflation and the real economy (Mishkin, 2007; European Central Bank, 2021). During slowdowns monetary policy can enhance financial stability by supporting the debt servicing capacity of the non-financial sector and by containing losses for the financial sector. In the extreme event of a financial crisis, monetary policy – especially through liquidity support – is crucial to contain financial stress and to avoid the materialisation of adverse equilibria (Mishkin, 2009; Bekaert et al., 2013). At the same time, however, the theoretical literature suggests that accommodative monetary policy could create financial vulnerabilities by raising asset values, lowering risk premia, increasing leverage and increasing maturity and liquidity mismatches (Ajello et al., 2022).

During financial exuberant times tighter monetary policy can help mitigate financial imbalances by implicitly leaning against the wind of frothy market conditions. This would help reduce the likelihood and severity of future financial crises. However, the empirical evidence on the general effect of monetary policy on financial vulnerabilities and its effectiveness in leaning against the wind is mixed and entails trade-offs (Svensson, 2017; Kockerols and Kok, 2019; Schularick et al., 2021; Boyarchenko et al., 2022). One monetary policy trade-off involves interactions between macro variables such as inflation and GDP growth, and financial stability, as measured by financial stress and vulnerabilities. A second trade-off in the conduct of monetary policy relates to the management of tail risks for the real economy relative to tail risks for financial stability. Finally, an intertemporal trade-off relates the potential impact of monetary policy on short-term financial stress relative to adjustments to economic and financial vulnerabilities in the medium-term.

In this paper, we empirically analyze the interaction of monetary policy shocks, financial stability conditions and the real economy in the euro area. We do so by estimating impulse response functions of a quantile vector autoregressive model via two estimation techniques, namely through simulation, following Ruzicka (2021b), and local projections as in Ruzicka (2021a). The specifications include five variables: a range of interest rates from the euro area yield curve as measure for monetary policy, euro area real GDP, euro area HICP inflation, the Composite

Indicator of Systemic Stress (CISS) of Hollo et al. (2012) as a measure of financial stress, and the Systemic Risk Indicator (SRI) of Lang et al. (2019) as a measure of financial vulnerabilities. Importantly, quantile methods capture potential asymmetries in the interactions between economic activity (GDP and inflation), financial stability conditions (SRI and CISS) and monetary policy shocks over the full distribution of the variables, including for impulse response analysis.

While macroeconomic conditions are typically summarized by real GDP and inflation, financial stability conditions are less clearly defined. The SRI is our vulnerability metric and characterizes the general state of the financial environment and serves as a 'barometer' for the financial system (Duprey and Roberts, 2017). In exuberant times with elevated vulnerabilities, the propagation of small shocks may result in amplifications for the economy, absent in normal times (Lang et al., 2019). While vulnerability indicators contain forward-looking information, they provide only limited information for the materialisation of stress at a specific point in time in the future, given the uncertainty surrounding the future materialisation of shocks. For this, our stress metric, the CISS, captures the materialization of financial instability and serves as a 'thermometer' for the financial system (Chavleishvili and Kremer, 2021). The distinction of financial vulnerability and stress is especially important to capture the intertemporal relation between the initial build-up of vulnerabilities and subsequent downside tail risks to the financial system and real economy.

Similarly to financial conditions, the monetary policy stance is only imperfectly summarized by the short-term policy interest rate, given purchases of longer-term securities. Since the global financial crisis, central banks have made active use of their balance sheets and forward guidance. Monetary policy rates predominantly impact short-term market rates, forward guidance affects interest rates further into the future, and purchases of medium- to long-term securities affect interest rates over longer maturities. To capture monetary policies and their effects in an empirical macro-financial estimation framework, we use monetary policy surprises in risk-free interest rates between one month and ten years over a narrow time window (covering press release and subsequent press conference) around the communication of ECB monetary policy decisions contained in the "Euro Area Monetary Policy Event-Study Database" developed and regularly updated by Altavilla et al. (2019). From these surprises we estimate a short- and long-term factor of interest rate surprises and identify monetary policy shocks following Gürkaynak et al. (2005), Jarociński and Karadi (2020) and Giuzio et al. (2021). The approach separates surprises related to conventional monetary policy (short-term rates) from those related to unconventional

monetary policy (longer-term maturities).

Our results show that surging financial stress has a strong short-term impact on economic growth, especially on the lower tail of the GDP distribution, in line with earlier findings such as Adrian et al. (2018). We also find that while a build-up of financial vulnerabilities tends to initially be accompanied by subdued financial stress – i.e. below-average financial market volatility, risk-pricing and excess returns – stress surges over the medium term. This provides for evidence that financial market tranquility during the initial phase of a financial expansion hits back with a vengeance down the road. Finally, the estimation indicates that tightening conventional monetary policy reduces inflationary pressures at the cost of slower real GDP growth and surging financial stress. Tightening unconventional monetary policy, identified as surprises in longer-term interest rates, is found to be similarly effective in reducing inflation as shorter-term rates, but has a smaller impact on growth and financial stress, while financial vulnerabilities mildly recede. This indicates that conventional and unconventional monetary policies may at times be complementary for stabilizing the economy and financial system.

The empirical results allow for a quantitative assessment of monetary policy using counterfactuals to shed light on monetary policy trade-offs in its pursuit of price stability. A first counterfactual traces out the effects of monetary policy on Growth-at-Risk (GaR; the 10th percentile of the forecasted GDP growth distribution one year ahead) when setting price stability at the objective of 2% annual inflation. Especially during the global financial crisis, monetary policy faced a trade-off: either tightening to stabilizing inflation forecasts at 2% or loosening to prevent Growth-at-Risk to deteriorate. This analysis indicates the potential beneficial use of alternative policy measures to offer a complementary angle for stabilisation of the real economy.

Having established the relative efficiency of different policy tools, we illustrate how the estimation results could inform a monetary and macroprudential policy mix to enhance stabilisation over the sample period. We assume policy objectives of a 2% median inflation forecast one year ahead and stabilization of GaR at its sample average of -1.08%. Given the relative efficiencies the policymaker uses a mix of monetary policy (long-end interest rate factor) and macroprudential policy (SRI). The GaR objective is non-symmetric, implying that the policymaker avoids that GaR falls below the value of -1.08% while focussing solely on the objective of inflation otherwise. The policymakers thus provides a hedge against crisis outcomes. We compute the needed counterfactual policies based on the cumulated impulse response functions and find that relatively large monetary policy shocks would have been needed to bring inflation forecasts back

to their target over the period 2005 until the first half of 2009. In contrast, over the earlier as well as later parts of the sample period our results would have called for looser monetary policy. Our results also indicate that looser macroprudential policy would have been needed starting in September 2007 and throughout the global financial crises until September 2009 and again on a few occasions during the euro area debt crisis to maintain GaR above its historical value. Forecasts implied by these policy counterfactuals show that they would have been effective in meeting combined inflation and growth targets, while limiting financial stress.

The remainder of the paper is structured as follows. Section 2 reviews the core elements of financial stability conditions and monetary policy in the recent literature. In section 3 we describe our data set, including the indicators used to measure financial stability conditions and the identification of monetary policy shocks. Next, in section 4 we describe the econometric specifications. Section 5 presents impulse responses from our quantile vector autoregressions and uncovers the dynamic interactions of financial vulnerabilities and stress with the real economy, and the impact of monetary policy shocks. Section 6 covers counterfactual analysis and illustrates trade-offs between price stability and financial stability objectives for monetary policy. It further assesses interactions between monetary policy and macroprudential policy. Finally, section 7 concludes.

2 Monetary policy and financial stability interactions

Monetary policy frameworks around the globe focus on price stability as their main objective, often accompanied with additional objectives such as full employment or financial stability. Monetary policy's role for financial stability is often subsumed in the effectiveness of monetary policy transmission or delegated to other policy domains such as macroprudential policy. While it is generally accepted that monetary policy takes financial stability into account at least in some form, quantitative trade-offs are less prominent in the literature. Smets (2014) indicates that the degree to which monetary policy should take financial stability considerations into account depends crucially on its effectiveness in addressing risks to financial stability, but also to what degree the financial stability considerations undermine the credibility of the central bank's price stability mandate.

Monetary policy faces several challenges when including financial stability considerations. First, narrow indicators of financial conditions, stress and vulnerabilities (such as metrics of

risk-taking, liquidity and leverage) offer only partial measures of financial stability, especially when considered in isolation, but are not fully comprehensive of prevailing financial stability conditions. In turn, monetary policy instruments are multiple, and each one may interact differently with financial stability. Furthermore, at least theoretically, monetary policy may create an inter-temporal trade-off for financial stability whereby accommodative monetary policy improves current financial conditions in the short run at the cost of increasing future financial vulnerabilities Adrian and Liang (2018). Empirically, it appears unclear to date whether monetary policy itself can influence financial vulnerabilities, partly because financial cycles are typically much longer than the business cycles monetary policy reacts to (Boyarchenko et al., 2022). Ultimately, monetary policy's efficacy as a tool for financial stability will depend on the cost-benefit trade-off of tighter monetary policy for economic activity and inflation.

Our paper relates to different strands of the literature. First, we contribute to the literature that investigates the empirical relationship between monetary policy and financial stability. The primary focus of existing studies lies on financial vulnerabilities. However, a (surprise) monetary tightening could also lead to acute episodes of surging financial stress and an abrupt tightening of financial conditions. Recent literature (Adrian et al., 2019; Figueres and Jarociński, 2020) points to the importance of associated indicators for short-term (up to one year ahead) downside risks to economic growth. Boyarchenko et al. (2022) provide a recent and detailed review of the empirical literature studying the relationship between monetary policy and financial vulnerabilities. Overall, the authors conclude that empirical evidence on the link between monetary policy and financial vulnerabilities is limited.

However, the current literature does not rule out causal effects of monetary policy on financial vulnerabilities. Several research gaps emerge from this existing literature, some of which our paper attempts to fill: Existing studies focus primarily on the United States while analyses for the euro area are scarce. Furthermore, existing studies differ in their measurement of financial vulnerabilities and focus mostly on narrow concepts such as asset valuations in selected markets, risk-taking by banks or other intermediaries, leverage and liquidity-maturity mismatches or leverage of financial intermediaries, households and businesses. However, vulnerabilities that have material impacts on the real economy appear to emerge from the interplay of asset prices and credit (Jordà et al., 2015) and we therefore employ a broad indicator of financial vulnerabilities in this paper.

Second, we estimate the dynamic interactions of macroeconomic, financial and monetary pol-

icy variables using multivariate quantile regression techniques. Quantile regressions of Koenker and Bassett Jr (1978) have been extended to multivariate dynamic frameworks in various ways. One approach involves multiple equations and iteration or simulation (White et al., 2015; Chavleishvili and Manganelli, 2019; Montes-Rojas, 2022; Ruzicka, 2021b). The other approach focuses on a single-equation setup and direct estimation through local projections of Jordà (2005) in combination with quantile regression – a prominent example is the work of Adrian et al. (2019). Identification, smooth estimation, and inference for quantile regression local projections is studied by Ruzicka (2021a). A unique feature of our paper is that we employ both estimation approaches by using the methods from Ruzicka (2021b) as well as from Ruzicka (2021a). Doing so, we obtain two valid estimates, which trade off bias and variance of impulse response functions differently. In a least squares regression setting, Plagborg-Møller and Wolf (2021) show that at shorter forecast horizons local projections are comparable with structural vector autoregressions (Sims, 1980, SVAR), whereas at longer forecast horizons the local projections have lower bias but higher variance. We expect that the same phenomenon arises in a quantile regression setting, as well.

Third, our assessment of the impact of monetary policy on financial stability focuses on an assessment of the tails of the distribution of real economic and financial variables. The estimation provides impacts for the lower and upper quantiles of these distributions and offers thereby risk considerations beyond the impact on median or average effects. This relates to other work on the stance of monetary and macroprudential policy using quantile reqressions, such as in Cecchetti (2006), Kilian and Manganelli (2008), Duprey and Ueberfeldt (2018), Aikman et al. (2019) and Carney (2020). The common feature of these approaches resides in the use of the tail of forecasted variables to infer assessment of risks to the economy or a policy stance. And finally, we relate to the empirical literature that identifies effects of monetary policy on asset prices and the macroeconomy using high-frequency financial market surprises around central bank monetary policy announcements going back to Kuttner (2001), as well as literature about the identification of monetary policy from such event-study data (Gürkaynak et al., 2005; Altavilla et al., 2019; Jarociński and Karadi, 2020; Giuzio et al., 2021).

3 Financial stability indicators and identification of monetary policy shocks

Our data consists of a set of aggregate euro area macro-financial and monetary policy variables, starting in the beginning of 2002 and running through the end of June 2019 at monthly frequency. Our baseline model input consists of two macroeconomic variables, namely real GDP growth and HICP inflation, the Composite Indicator of Systemic Stress (CISS) as a measure of financial stress (Hollo et al., 2012; Chavleishvili and Kremer, 2021), and the Systemic Risk Indicator (Lang et al., 2019, SRI) as a measure of financial vulnerabilities, monetary policy shocks built from surprise rate changes over narrow time windows covering the communication of monetary policy decisions through press release and the subsequent press conference on ECB Governing Council monetary policy meeting dates using a data set developed and regularly updated by Altavilla et al. (2019). The computation of these shocks is explained in detail further below in Section 3.3.

Figure 1 plots the macro-financial variables used in our estimation which are further summarized in Table 1. We deliberately represent financial stability aspects in our models with two separate variables, distinguishing between short-term financial stress which can trigger instability and medium-term vulnerabilities which make the financial system more susceptible to destabilizing triggers. We approximate monthly GDP by interpolating a quarterly GDP series with a monthly index of industrial production for the euro area.

3.1 Financial stress

The CISS serves as our measure of financial stress and captures the severity of financial crises, serving as a 'thermometer' of financial instability. It is a timely, frequent and publicly available indicator based on 15 individual indicators grouped into five sub-indices: financial intermediaries, bond markets, equity markets, foreign exchange markets, and money markets. The contribution from financial intermediaries is around 30%, that of equity markets around 25%, and each of the three remaining sub-indexes around 15%.[1] Importantly, the CISS takes into account the

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[1]The equity market sub-index comprises stock price volatility of non-financial corporations (NFC), a measure of maximum cumulated stock price losses and a measure of stock-bond correlation. The FX market sub-index captures the volatility of EUR/USD, EUR/JPY and EUR/GBP exchange rates. The financial intermediaries sub-index reflects bank stock return volatility, financial-nonfinancial bonds spread, and the cumulated loss of the book-price ratio of banks. The bond market sub-index captures the volatility of German sovereign bonds (at 10-year maturity), the spread between A-rated NFC and sovereign bonds, and the 10Y interest rate swap spread.

Figure 1: Macro-financial variables, monthly
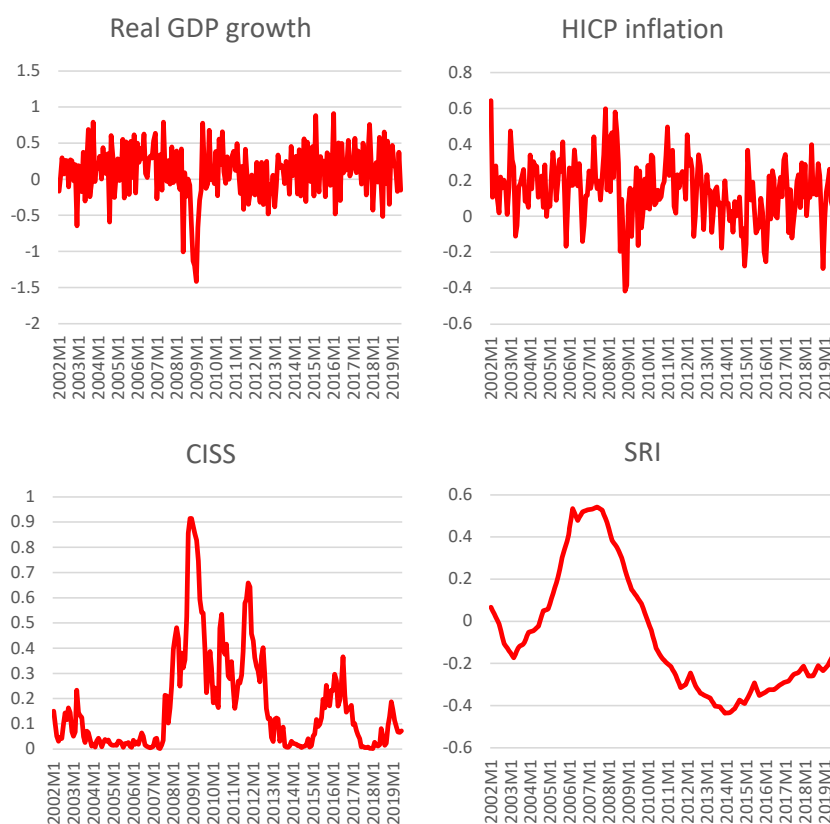
Notes: Monthly data 2002M1-2019M6. Variables are displayed as they enter our models: real GDP and HICP in first differences of logs (in %), CISS and SRI in levels.

correlation across sub-components, whereby higher correlation implies higher values of systemic stress. The CISS leads GDP by up to one quarter (Chavleishvili and Kremer, 2021) and has been shown to outperform narrower measures of financial conditions in the prediction of one-year ahead tail risks to euro area output growth (Figueres and Jarociński, 2020).

3.2 Financial vulnerabilities

We capture medium-term financial vulnerabilities with the Systemic Risk Indicator (SRI): a broad-based cyclical indicator that captures risks stemming from potential overvaluation of property prices, credit conditions, external imbalances, private sector debt burden and the potential mispricing of risk that serves as a 'barometer' of financial instability (Lang et al., 2019). With the exception of the credit category, the authors use one variable for each of the aforemen-

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The Money market sub-index comprises the 3M EURIBOR volatility, its spread to the 3M French T-bill spread, and a measure of emergency lending of the Eurosystem.

Table 1: Summary statistics

Statistic	T	Mean	St. Dev.	Min	Max
Real GDP	210	0.100	0.359	−1.416	0.910
HICP	210	0.138	0.171	−0.413	0.644
CISS	210	0.177	0.201	0.002	0.913
SRI	210	−0.068	0.296	−0.436	0.542

Notes: Real GDP and HICP is in first differences of monthly logs (in %). CISS and SRI are in monthly levels.

tioned categories, selecting from a larger pool of potential variables and transformations those with the best predictive ability for systemic financial crises. In total, Lang et al. (2019) derive six indicators which are normalized and aggregated as an optimally weighted average in terms of overall predictive power of the composite indicator.[2]

Measures of financial vulnerabilities are typically used to inform macroprudential policies. For example, the credit-to-GDP gap is instrumental in the calibration of countercyclical capital buffers. The SRI increases on average several years before the onset of systemic financial crises with superior early-warning properties in comparison to the credit-to-GDP gap. In this capacity, it also has significant predictive power for large declines in real GDP growth three to four years into the future and its level at the onset of systemic financial crises is highly correlated with measures of subsequent crisis severity. The SRI therefore provides useful information about both the probability and the likely cost of systemic financial crises which makes it our preferred measure of the financial cycle in comparison to other available indicators.

Financial vulnerabilities evolve more slowly and more gradually than the other variables in our models, reflecting that financial cycles tend to last longer than economic cycles. Indeed, the within-month interactions between the SRI and the other variables, measured by quantile impulse responses, are negligible and insignificant – except for financial stress (CISS) at the 90th percentile. On the other hand, financial vulnerabilities can be controlled by a range of financial stability instruments, microprudential and macroprudential. Due to the negligible contemporaneous interactions, we can interpret SRI changes as exogenous shocks, and treat the SRI as the third policy tool, in addition to conventional and unconventional monetary policy.

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[2]The six sub-indicators used are the two-year change in the bank credit-to-GDP ratio, the two-year growth rate of real total credit, the two-year change in the debt-service-ratio, the three-year change in the RRE price-to-income ratio, the three-year growth rate of real equity prices, and the current account-to-GDP ratio.
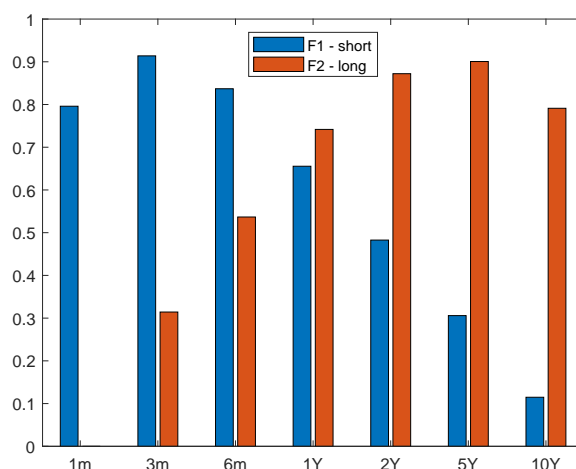
3.3 Monetary policy shocks

A large empirical literature, going back to Kuttner (2001), identifies effects of monetary policy on asset prices and the macroeconomy using high-frequency, intra-day, financial market price changes over short time windows covering central bank monetary policy announcements. Based on such high-frequency event-study data, Gürkaynak et al. (2005) find that two independent factors constructed from federal funds futures – the first related to short rates and an independent second factor related to rates of longer maturities – summarize the effects of U.S. monetary policy on bond prices and stock returns.

We use their approach to extract two factors from intra-day overnight index swap (OIS) rate changes over narrow time windows covering the press release as well as the subsequent press conference about monetary policy decisions on ECB Governing Council monetary policy meeting dates using the "Euro Area Monetary Policy Event-Study Database", developed and regularly updated by Altavilla et al. (2019). These two factors capture surprises along the yield curve as they are constructed by fitting the time series of surprises in OIS rates of seven maturities (one, three and six months as well as one, two, five and ten years). Surprises in OIS rates of maturities longer than two years are only available from August 2011 onward and we proxy these series by surprises in German government bond yields of the same maturity for the period from January 2002 to July 2011.

To provide a structural interpretation of the two factors, we rotate them as in Gürkaynak et al. (2005) such that the second factor is not impacted by surprises in the OIS rate of the shortest maturity, i.e. its factor loading on the 1-month OIS surprises is set to zero, while imposing orthogonality between the two rotated factors. Finally, the rotated factors are rescaled to match the standard deviations of 3-month OIS surprises for the first factor and 10-year OIS surprise for the second factor. In this way, the first factor corresponds to shorter maturities – reflecting surprises related to conventional monetary policy – and the second factor corresponds to longer maturities, capturing surprises related to unconventional monetary policy. For convenience we label these factors short- and long-end factors, in line with Gürkaynak et al. (2005). The corresponding factor loadings are shown in Figure 2.

The short- and long-end factors provide information about interest rate surprises along the yield curve. Jarociński and Karadi (2020) point out that such surprises reveal, additionally to information about the monetary policy stance, also private central bank information

Figure 2: Monetary policy surprise factors - loadings

Notes: The figure shows the estimated factor loadings after rotation.

about the state of the economy. To separate monetary policy from central bank information shocks, Jarociński and Karadi (2020) use an identification strategy with sign restrictions on high-frequency stock price changes around monetary policy announcements. A positive co-movement between intra-day interest rates and intra-day stock prices is interpreted as an information shock as the central bank reveals new information about the state of the economy. In turn, a negative co-movement reflects a monetary policy surprise whereby higher interest rates imply a decline in stock prices, while a fall in interest rates implies higher stock prices. While intuitive, this method yields implausible results for the euro area; in particular, the response of the monthly stock index remains insignificant while a monthly BBB bond spread index used in their model declines after a contractionary monetary policy shock. However, the analysis in our paper builds on a consistent identification between high-frequency monetary policy shocks and asset price responses to assess the financial stability implications of monetary policy.

As an alternative to stock prices, we therefore identify monetary policy and information shocks based on daily changes of non-financial corporate (NFC) bond spreads instead of intra-day stock price changes, as suggested by Giuzio et al. (2021). More specifically, we identify monetary policy shocks from positive co-movement of our interest rate factors with daily changes in BBB-rated euro-denominated NFC bond spreads (at 5-year maturity). Thus, a contractionary monetary policy shock occurs when interest rates rise and bond spreads widen simultaneously whereas an expansionary monetary policy shock is characterized by falling interest rates and narrowing bond spreads. Consequently, central bank information shocks are identified from

negative co-movement between interest rate surprises and bond spreads. This identification strategy improves not only the response of monthly bond spreads but also the response of monthly stock prices to monetary policy shocks. We use bond spreads from Bank of America obtained through Bloomberg until March 2007, while from April 2007 we use bond spreads from iBoxx, which we found to be more liquid compared to those from Bank of America but not continuously available before April 2007. Summary statistics of the interest rate series, bond spreads, and identified surprises can be found in Table 2.

Table 2: Summary statistics for monthly interest rate factors and monetary policy surprises (January 2002 - June 2019), $T = 210$, in bps.

|	Mean	St. Dev.	Min	Max
Short-end factor	-0.09	2.87	-13.20	16.70
Short-end factor, MP shock	0.03	1.54	-6.34	16.70
Short-end factor, CB info shock	-0.11	2.39	-13.20	10.27
Long-end factor	0.00	4.09	-25.77	13.22
Long-end factor, MP shock	0.06	1.97	10.09	-10.21
Long-end factor, CB info shock	-0.12	3.52	-25.77	13.22
BBB-rated NFC bond spread changes	0.13	3.40	-8.94	23.52

The cumulated factors of surprises in OIS rates are displayed in Figure 3 together with their information and monetary policy components, based on the identification using BBB-rated NFC bond spreads. Increasing values indicate tightening of interest rates relative to the prevailing market expectations before monetary policy statements.

The short-end factor indicates a tightening of surprises in short rates during the early part of our sample, followed by a period of loosening leading up to the Global Financial Crisis, then a short period of tightening at the peak of Global Financial Crisis and finally an overall loosening of rates over the remainder of our sample period. These dynamics were mainly driven by surprises identified as central bank information shocks, while monetary policy shocks often moved in opposite direction and indicate an overall tightening.

In turn, the cumulated long end factor falls strongly in July and August 2008, driven by central bank information shocks, while gradually tightening for most of the remainder of the sample period. This long tightening episode appears to be driven at least partially by monetary policy shocks.

Figure 3: Cumulated monetary policy factors 2002-2019
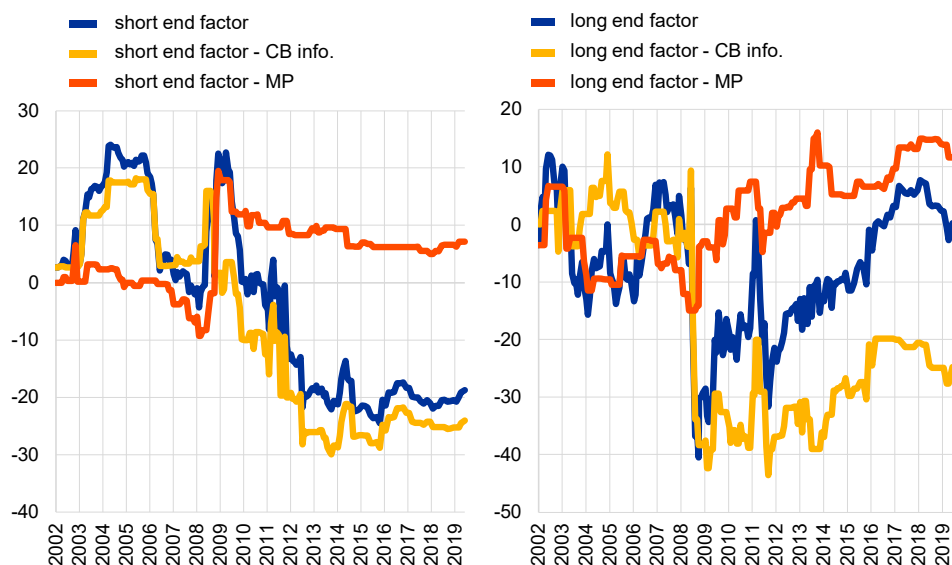
Notes: The figure shows cumulated factors before and after identification with BBB-rated NFC bond spreads in basis points.

The factors are extracted in a first step using maximum likelihood estimation to employ them in a second step for estimating quantile treatment effects of policy interventions by minimizing asymmetric l_1 loss functions. As a result, the two steps of the empirical strategy employ different loss functions. While it may be possible to use the l_1 loss functions in factor extraction, such an approach has not been used in the literature on monetary policy event study factors as far as we know and is not considered in this work either.

4 Quantile modelling

4.1 Estimating quantile treatment effects of structural shocks

The main goal of our estimations is to quantify the impact of exogenous shocks on vulnerabilities in the real economy and the financial sector. We do so by estimating the effect of structural shocks on different parts of the distribution of the response variables, namely real GDP growth, HICP inflation, financial vulnerabilities and financial stress. However, this task is complex because we need to model the distributions of our endogenous variables, along with their contemporaneous and dynamic interactions. Specifically, we estimate *quantile treatment effects* (see Koenker, 2005, pp. 26–32) of structural shocks. A quantile treatment effect measures how each quantile of a response variable is affected by a treatment. In our case, the treatment

is an exogenous impulse, also called a shock.

We estimate the quantile treatment effects by two different methods. The first is a simulation-based, two-step approach in form of a quantile vector autoregressive model, while the second one relies on direct estimation and regularization in form of a quantile local projection approach. Both methods identify the shocks by recursive short-run restrictions and provide valid estimates of the quantile treatment effect. However, the methods differ in their finite sample performance and in robustness to misspecification, especially at longer forecast horizons. In the following, we provide the general features of the two estimation methods together with basic technical notions of their setup and refer the reader for additional details to the referenced papers.

The first method – simulation-based – follows Ruzicka (2021b) and is based on the estimation of the quantile regression process for a system of equations, with subsequent simulation using the approach proposed by Koenker and Xiao (2006), described in detail in Koenker et al. (2018, pp. 328–329), and also used by Montes-Rojas (2022). It is similar to Chavleishvili and Manganelli (2019) and Montes-Rojas (2022). However, unlike Chavleishvili and Manganelli (2019), we do not set any sample paths to their median values and instead consider the full set of possible sample paths. This increases the computational complexity, but gives a more complete and agnostic picture of the effects we estimate. Unlike Montes-Rojas (2022) and Chavleishvili and Manganelli (2019), we do not discretize the model on an ex-ante chosen grid of quantile indices, but instead estimate the entire quantile regression process, that is, we estimate each quantile regression for all quantile indices in (0,1). The practical consequence is that our estimates don't suffer from unnecessary approximation errors due to discretization. In addition, unlike Chavleishvili and Manganelli (2019) and Montes-Rojas (2022), we construct confidence intervals for the quantile treatment effects as in Ruzicka (2021b).

The second method estimates the quantile treatment effects directly by employing the local projections of Jordà (2005) in a quantile regression setting. Local projections estimated by quantile regressions have become a popular way to capture heterogeneous effects of macroeconomic shocks. However, applied research based on plain quantile regression local projections is challenging: The estimated impulse response functions tend to wiggle a lot, it is unclear what the underlying identification conditions are, and it is unclear how to construct closed-form confidence intervals. Ruzicka (2021a) overcomes these challenges by introducing roughness penalties to smooth the impulse response functions, by establishing the identification conditions, and by providing closed-from as well as weighted bootstrap confidence intervals.

These features are essential for our results for the following reasons. First, if it were not for the smoothing, the estimated impulse response functions would change abruptly from one forecast horizon to the next, making them difficult to interpret and less accurate. Second, the theoretical result of Ruzicka (2021a) reveals which control variables must be included (and which must not) in order to identify the quantile treatment effect of interest. This is essential for causal interpretation and to prevent simultaneity bias. Third, the weighted bootstrap doesn't entail any tuning parameters, unlike the stationary bootstrap proposed Han et al. (2022) which depends on a parameter (average block length), whose appropriate choice is nontrivial in practice.

Next, we present the basic technical notions underlying both estimation methodologies: the data generating process and the impulse response function that measures the quantile treatment effect of interest. For random variables X and Y we denote $Q_\tau(Y|X)$ the τth conditional quantile of Y given X. For a stochastic process $\{Y_t\}$, let $\{\mathcal{F}_t\}$ be its filtration (the information known up to time t). We assume the data follow an I-dimensional stochastic process[3] $\{Y_t\} = \{[y_{1,t}, y_{2,t}, \ldots, y_{I,t}]\}$ given by

$$Q_{\tau_1}(y_{1,t}|\mathcal{F}_{t-1}) = \sum_{i=1}^{I}\sum_{p=1}^{P} a_{p1i}(\tau_1)y_{i,t-p} + \varepsilon_1(\tau_1)$$

$$Q_{\tau_2}(y_{2,t}|y_{1,t}, \mathcal{F}_{t-1}) = a_{021}(\tau_2)y_{1,t} + \sum_{i=1}^{I}\sum_{p=1}^{P} a_{p2i}(\tau_2)y_{i,t-p} + \varepsilon_2(\tau_2) \tag{1}$$

$$\vdots$$

$$Q_{\tau_I}(y_{I,t}|y_{1,t}, y_{2,t}, \ldots, y_{I-1,t}, \mathcal{F}_{t-1}) = \sum_{i=1}^{I-1} a_{0Ii}(\tau_I)y_{i,t} + \sum_{i=1}^{I}\sum_{p=1}^{P} a_{pIi}(\tau_I)y_{i,t-p} + \varepsilon_I(\tau_I)$$

---

[3]This type of a stochastic process was studied by Chavleishvili and Manganelli (2019), Ruzicka (2021a,b) and Montes-Rojas (2022). It is a special case of the VAR for VaR of White et al. (2015), who additionally allow conditional quantiles to depend on the lags of conditional quantiles.

This stochastic process can be expressed in a random coefficient representation as

$$
\begin{aligned}
y_{1,t} &= \sum_{i=1}^{I} \sum_{p=1}^{P} a_{p1i}(u_{1t}) y_{i,t-p} + \varepsilon_1(u_{1t}) \\
y_{2,t} &= a_{021}(u_{2t}) y_{1,t} + \sum_{i=1}^{I} \sum_{p=1}^{P} a_{p2i}(u_{2t}) y_{i,t-p} + \varepsilon_2(u_{2t}) \\
&\;\;\vdots \\
y_{I,t} &= \sum_{i=1}^{I-1} a_{0Ii}(u_{It}) y_{i,t} + \sum_{i=1}^{I} \sum_{p=1}^{P} a_{pIi}(u_{It}) y_{i,t-p} + \varepsilon_I(u_{It})
\end{aligned}
\tag{2}
$$

where $u_{i,t} \sim U[0,1]$, $y_{i,t}$ is non-decreasing in u_{it} a.s. for all i and t, and $\{u_{it}\}$ are independent.

The disturbances $\{u_{it}\}$ in (2) change from one period to the next and represent the realized values of τ_i in each time period.[4]

The model is identified by recursive short-run restrictions. For example, the second variable is not allowed to contemporaneously affect the distribution of the first variable, but it may affect the distribution of the third variable. This recursive ordering is analogous to the one of Sims (1980). However, note that the identification restrictions are not equivalent to a Cholesky decomposition of a covariance matrix – in fact, the quantile model above is well-defined even if the variance of Y_t doesn't exist.

In the first, simulation-based approach, we estimate the quantile regression process of all equations above over all quantile indices in (0,1) and subsequently recover the quantile treatment effects of shocks by simulation, as outlined earlier. In the second, direct estimation approach, we rely on the result of Ruzicka (2021a) who shows that for all forecast horizons $h \in \mathbb{N}_0$ and all $i, j \in \{1, 2, \ldots, I\}$ in the representation

$$
Q_\tau(y_{j,t+h} | \mathcal{F}_{t-1}, y_{1,t}, \ldots, y_{i,t}) = \beta_{0,j,0,h}(\tau) + \sum_{k=1}^{i} \beta_{k,j,0,h}(\tau) y_{k,t} + \sum_{k=1}^{I} \sum_{p=1}^{P-1} \beta_{k,j,p,h}(\tau) y_{k,t-p}
\tag{3}
$$

the slope coefficient $\beta_{i,j,0,h}(\tau)$ is the quantile treatment effect of the ith shock on variable j after h periods at quantile τ. The last equation could be estimated directly by quantile regression, separately for each forecast horizon. However, such estimates are usually rather inaccurate and difficult to interpret as they differ dramatically between neighboring forecast horizons. For

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[4]Koenker et al. (2018)[pp. 313-317, 328-329] discuss the conditional quantile and random coefficient forms of quantile autoregressive processes, their relations and role in forecasting.

that reason we use the smooth quantile local projections estimator of Ruzicka (2021a), which solves the problem by regularization, shrinking the impulse response functions towards cubic polynomials via roughness penalties. In addition, we impose a long-run equilibrium constraint which ensures the impulse response functions converge to a constant function at the final forecast horizon.[5] We set the optimal value of the roughness penalty by the Bayesian information criterion (Schwarz, 1978), as adapted for this setup by Ruzicka (2021a). Following Ruzicka (2021a), we construct the confidence intervals by the weighted bootstrap with undersmoothing (using standard exponential weights; the roughness penalty for confidence intervals is one quarter of its value for point estimates.)

We collect the quantile treatment effects at different horizons into a quantile impulse response function, using the definition of Ruzicka (2021b). The quantile impulse response function $QIR(j, i, h, \tau, s)$ is the response of the jth variable at quantile τ to the ith shock of size s after h periods, formally

$$QIR(j, i, h, \tau, s) = Q_\tau \Big[y_{j,t+h}\Big|\varepsilon_i(u_{it}) := \varepsilon_i(u_{it}) + s\Big] - Q_\tau \Big[y_{j,t+h}\Big] \tag{4}$$

$$= \frac{\partial Q_\tau[y_{j,t+h}|u_{it}]}{\partial \varepsilon_i(u_{it})} s \tag{5}$$

where the notation $\varepsilon_i(u_{it}) := \varepsilon_i(u_{it}) + s$ represents a modified version of the process, with $\varepsilon_i(u_{it})$ substituted by $\varepsilon_i(u_{it}) + s$ for all $u_{it} \in [0, 1]$. For some variables we are interested in the cumulative effect of a shock through cumulative quantile impulse response functions, given by

$$QIRC(j, i, h, \tau, s) = Q_\tau \left[\sum_{k=0}^{h} y_{j,t+k} \Bigg| \varepsilon_i(u_{it}) := \varepsilon_i(u_{it}) + s\right] - Q_\tau \left[\sum_{k=0}^{h} y_{j,t+k}\right] \tag{6}$$

$$= \frac{\partial Q_\tau \left[\sum_{k=0}^{h} y_{j,t+k} \Bigg| u_{it}\right]}{\partial \varepsilon_i(u_{it})} s \tag{7}$$

4.2   Counterfactual scenarios – linking forecasts and impulse responses

The quantile impulse response function as defined above involves an intervention at a single point in time. However, it is also possible to allow interventions in various consecutive time periods. This is more complicated, but it is useful in order to isolate the effects of sustained policy interventions. To be specific, we work with monthly data, the interventions are introduced

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[5]For our two models, the forecast horizon is up to 72 months and 12 months, respectively.

in 12 consecutive months, and the response variable is a monthly growth rate. Formally, the intervention at time $t + m$ is of size s_m, where $m \in \{0, 1, \ldots, 11\}$. We want to see the effect of the interventions on the τth quantile of $\sum_{k=0}^{11} y_{j,t+k}$, which represents the year-over-year growth rate of the response variable. Using the same notation as in (4), the effect of the sequence of interventions is

$$Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \forall m \in \{0, 1, \ldots, 11\} \colon \varepsilon_i(u_{i,t+m}) := \varepsilon_i(u_{i,t+m}) + s_m \right] - Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \right] \qquad (8)$$

It can be shown[6] that (8) equals

$$\sum_{l=0}^{11} QIRC(j, i, l, \tau, s_{11-l}) \qquad (9)$$

The sequence of external impulses can be combined with quantile forecasts into a counterfactual scenario. Such a scenario shows how quantile forecasts would have responded to policy interventions in the past. Recall that $\mathcal{F}_{t-1}$ represents the information known at time $t-1$. The forecast of the year-over-year growth rate of the ith variable is represented by

$$Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1} \right] \qquad (10)$$

Next, we introduce policy interventions over 12 consecutive months. The forecast changes to

$$Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1}, \forall m \in \{0, 1, \ldots, 11\} \colon \varepsilon_i(u_{i,t+m}) := \varepsilon_i(u_{i,t+m}) + s_m \right] \qquad (11)$$

and represents our counterfactual scenario. It turns out that[7] (11) equals (12)

$$Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1} \right] + \sum_{l=0}^{11} QIRC(j, i, l, \tau, s_{11-l}) \qquad (12)$$

which comprises the quantile forecast (the first term) and the effect of the sequence of interventions (the second term).

This form of a counterfactual scenario does not set any specific sample path and so it is different from the one in Chavleishvili et al. (2021). Fixing a sample path ex ante as in Chavleishvili

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[6]Proof A.2 in the appendix.
[7]Proof A.3 in the appendix.

et al. (2021) obviates the need to run a large number of simulations. However, since our counterfactual scenario is based on a sequence of exogenous interventions, we can calculate (9) just by summing up the cumulative quantile impulse response functions. These must be estimated beforehand, either by simulation or by direct estimation through local projections.

Finally, the counterfactual scenario gives us a way to quantify the contribution of interventions (observed or estimated) on the in-sample quantile forecasts over a specific time horizon. In our case, the interventions are monetary policy surprises. Formally, consider interventions to variable i at time $t+l$ of size s_{t+l}, where $0 \leq l \leq 11$. Then the term

$$\sum_{l=0}^{11} QIRC(j, i, l, \tau, s_{t+11-l}) \tag{13}$$

measures how the year-over-year growth rate of the jth variable would change if the interventions $s_t, s_{t+1}, \ldots, s_{t+11}$ were replaced by zero. We interpret (13) as the contribution of the interventions to the year-over-year growth rate of variable j over the time horizon $t, t+1, \ldots, t+11$.

4.3 The setup: real economy, financial variables and monetary policy

Based on the general framework described in the previous section, we outline the specific model setup for an economy with financial interactions. In brief, we estimate three models. The first one encompasses economic activity, price level, financial vulnerabilities, and financial stress. We obtain the second model by incorporating short-term rates. Finally, we replace the short-term rates by long-term rates to arrive at our third model. These models are estimated separately to ensure tractability, results from one combined model with both monetary policy series are qualitatively similar but subject to wider confidence bands.

We estimate each of the three models using the two alternative methods described earlier, that is, with a simulation-based approach as well as with a local projection approach. Both approaches rely on the same identification assumptions. Theoretically, the estimates from both methods converge to the same limit in large samples, provided our model is correctly specified. All specifications include three lags of all the included variables.

The first model combines real GDP growth and HICP inflation with variables of financial vulnerabilities and systemic stress into a four-variable model of their entire distribution. Financial vulnerabilities are captured by the SRI and financial stress is measured by the CISS. Identification is achieved through recursive short-run restrictions: Hereby real GDP growth is

placed first, HICP inflation second, the SRI third and CISS fourth. The identification strategy thus implies that the financial stress variable (placed fourth) can react contemporaneously to macroeconomic and SRI shocks, while the SRI (placed third) can only react contemporaneously to shocks to output growth and HICP inflation. In turn, real output growth only reacts with a lag to shocks of inflation, the SRI, and stress. This follows standard assumptions in the empirical literature such as Kilian (2009) and Gilchrist and Zakrajšek (2012). The estimates and the identification strategy allow us to quantify amplifications of risks for future economic activity caused by elevated levels of financial imbalances as well as financial stress. This is relevant for modelling the variables over time and for the counterfactual policy scenarios. In this four-variable model we consider impulse responses up to 72 months ahead.

The second and third model append the previous four-variable model by adding either the short-end or the long-end monetary policy surprise factors (while results based on central bank information shocks are shown in the appendix). The monetary policy series are ordered first so as to contemporaneously affect all the other variables in the system. Given that we investigate the monetary policy effects on different parts of the distribution of the response variables while having a modest sample size, we focus on impulse responses over the short-run, up to 12 months ahead. Even though we cannot comment on medium term monetary policy effects, Doh and Foerster (2022) show that monetary policy transmission lags have shortened after 2009, at least in the United States.

5 Results

With model specifications and the monetary policy shock identification fully established, this section focuses on the estimation results and their interpretation. We discuss the quantile impulse response functions in two blocks starting with those based on the model without monetary policy surprises which we show up to 72 months ahead, followed by those from the two models that include monetary policy surprises, for which we focus on short-term dynamics of up to 12 months ahead.

5.1 Impulse responses of macro-financial variables

The impulse responses of macroeconomic variables in our quantile setting follow those known from structural linear VARs in the literature. As Figure 4 shows, an impulse to real GDP leads to

a persistent increase of GDP, accompanied by an increase in inflation – with a mild overshooting – over two quarters. In turn, an impulse to inflation does not imply persistent effects for future inflation and does not affect real GDP growth in a statistically significant manner. The impulse responses of the two variables do not indicate heterogeneous dynamics across quantiles.

Figure 4: Impulse Responses of GDP, inflation, financial vulnerability, and stress (estimated by simulation)
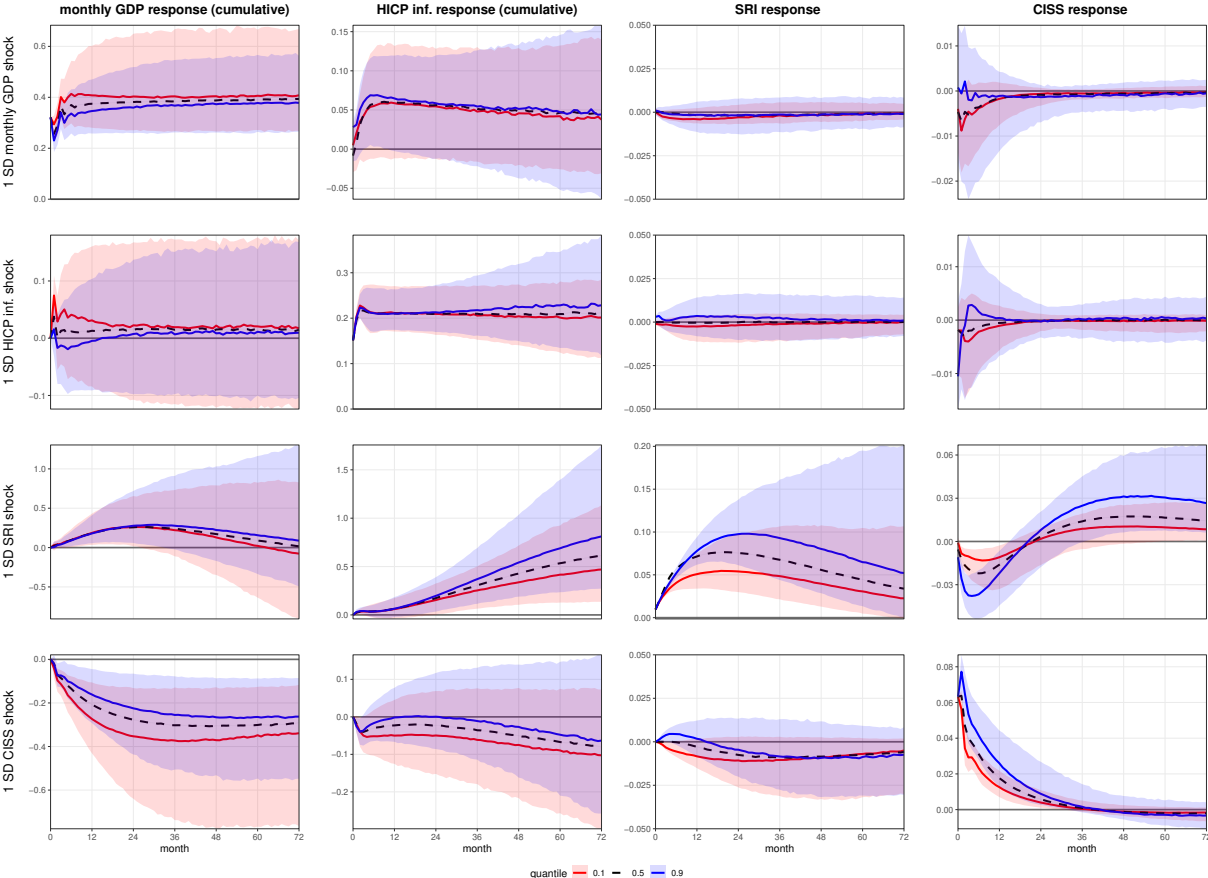
Notes: Four-variable specification without monetary policy shock. Confidence bands are at 90% and are excluded for the median response.

In turn, the financial variables provide additional information on the macroeconomic dynamics. An innovation of the SRI, reflecting an increase in financial vulnerabilities, implies a temporary upward deviation of output with a peak after 24 months, whereby the 10th percentile of the distribution reverts more quickly while the 90th percentile has a larger persistence. The effects on inflation, on the other hand, appear more persistent, especially for the upper tail of the distribution. These findings indicate that macroprudential policy targeting the SRI can be effective in boosting or slowing growth and inflation. As regards the materialisation of stress

as captured by the CISS, it exerts a strong downward adjustment for the 10th percentile of the GDP distribution, in line with the findings in the literature (Adrian et al., 2019; Chavleishvili and Manganelli, 2019; Chavleishvili and Kremer, 2021). In turn, the inflation rate adjusts in the short term but rebounds quickly, without statistically significant longer-term effects on the price level.

As regards the impulse responses of financial vulnerabilities and stress, we find that shocks to GDP and HICP inflation have only insignificant impacts on financial variables, while the corresponding impulse responses indicate that a positive SRI impulse initiates a persistent medium-term episode of increasing vulnerabilities, whereby higher quantiles increase relatively more strongly and cumulate after 24 months compared to the lower quantiles. Together with increasing financial vulnerabilities, financial stress is being dampened in the short-term, especially for higher quantiles of the CISS. However, as the vulnerabilities indicator recedes, the stress indicator reverts with financial market stress and losses. This interplay between financial vulnerabilities and financial stress reflects a key intertemporal trade-off for policymakers between short-term gains from exuberant financial conditions and higher risks of financial stress in the medium term. Shocks to the CISS have only a statistically insignificant impact on the SRI, and appear to die out after about 24 months.

The impulse responses from the two estimation approaches are qualitatively comparable with only few exceptions, such as the impact of CISS shocks on the upper part of the SRI distribution or the effect of the SRI shock on the upper part of the GDP growth distribution.

5.2 Impact of monetary policy shocks

Beyond the macro-financial interactions discussed thus far, we next assess the impact of monetary policy shocks on financial stability conditions and the real economy. For this, we employ the two monetary policy factors defined in Section 3.3, the short-end factor capturing surprises in short-term rates and linked to conventional monetary policy, and the long-end factor capturing surprises in longer rates, unrelated to surprises in short-term rates, and thus linked to unconventional monetary policy. The results for monetary policy shocks feature in this section, while the impulse responses of the central bank information shocks are shown in the appendix.

As Figures 6 and 7 show, an identified conventional monetary policy tightening shock has the expected contractionary effect on real GDP growth and HICP inflation, in line with the monetary policy literature (Bernanke and Mishkin, 1997; Clarida et al., 1999). Beyond the

Figure 5: Impulse Responses of GDP, inflation, financial vulnerability, and stress
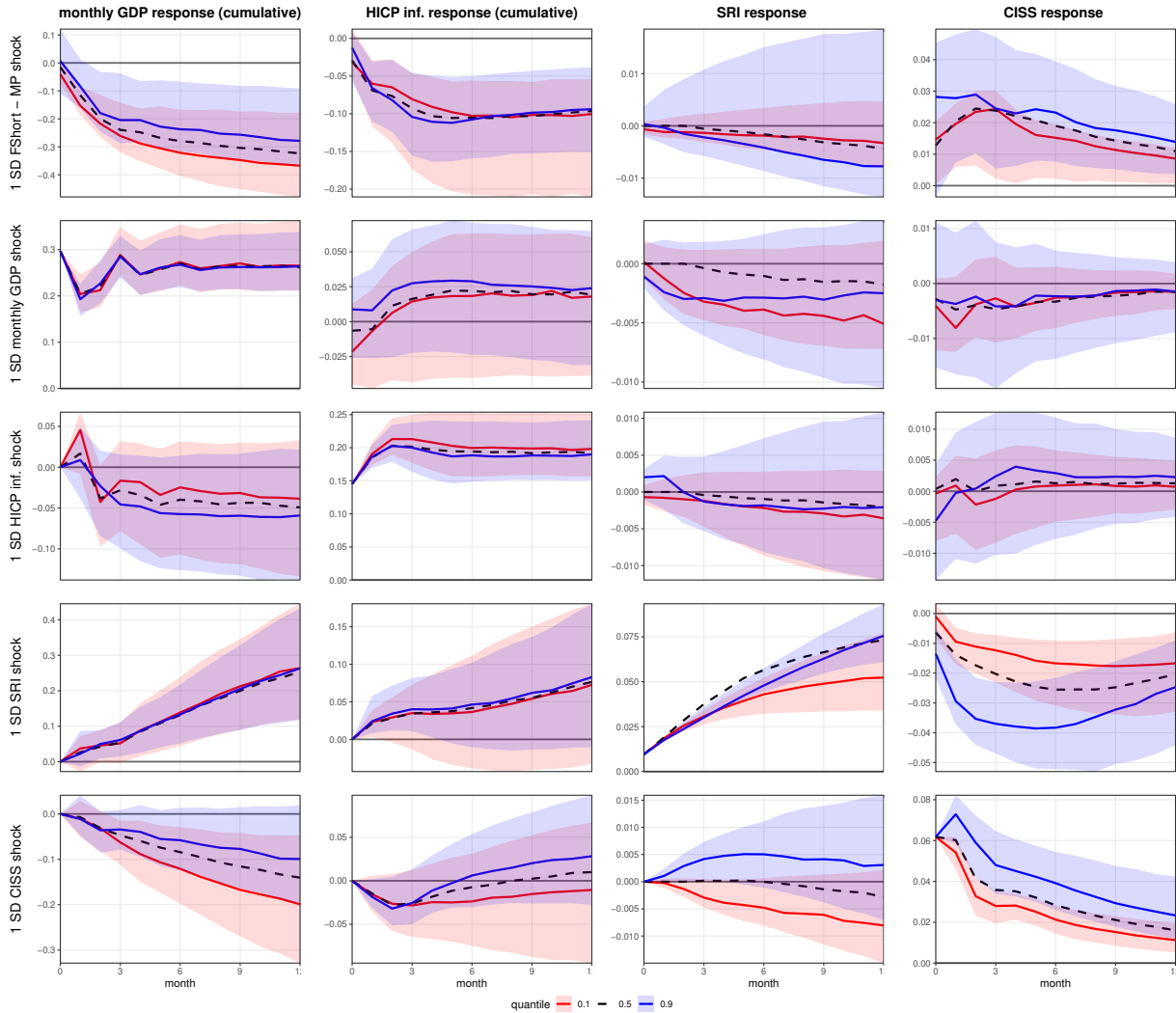(estimated by local projections)
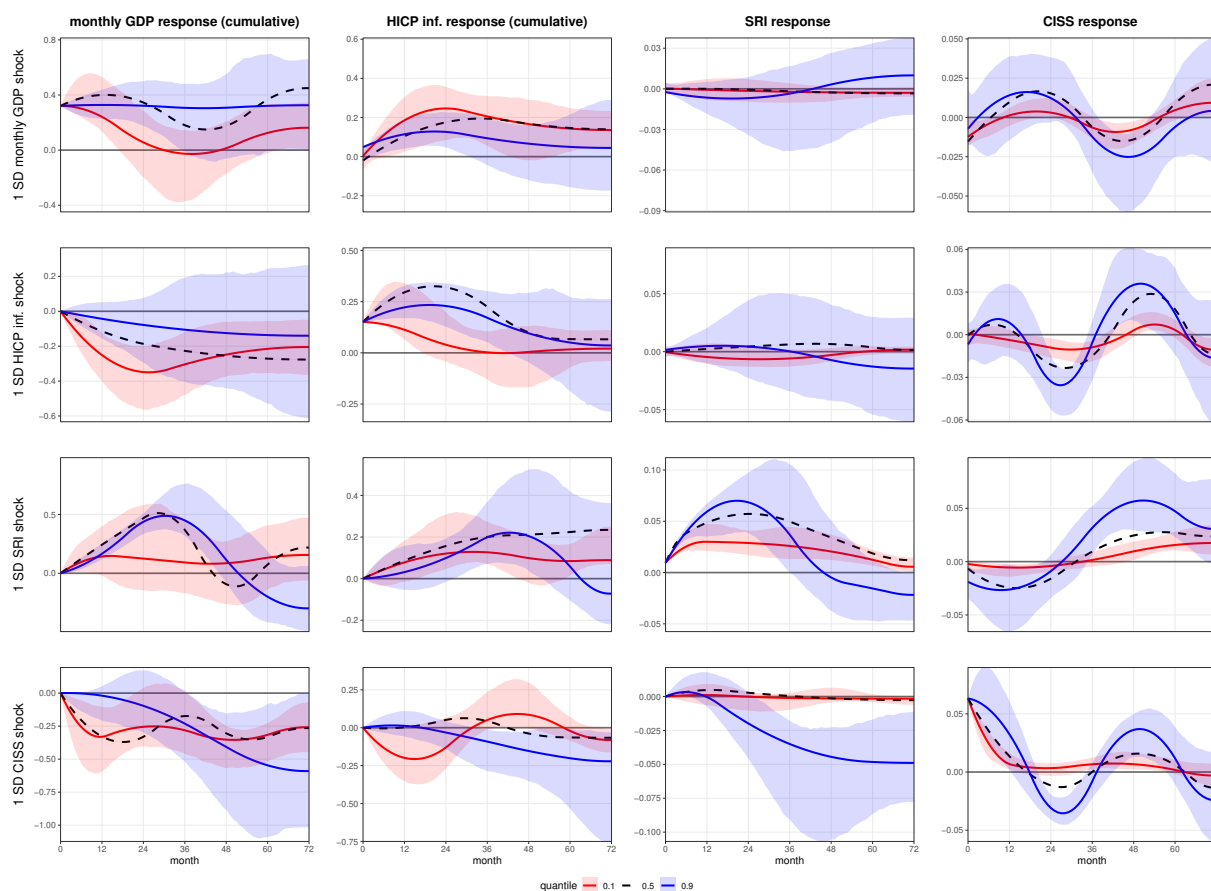
Notes: Four-variable specification without monetary policy shock. Confidence bands are at 90% and are excluded for the median response.

macroeconomic effects, a tightening shock also impacts financial stability conditions. In the short term, the shock raises financial stress measured by the CISS across all quantiles, but especially so for the upper part of the distribution. This implies that following a tightening shock, the CISS does not only increase on average, but the distribution also becomes more asymmetric with a larger right tail, permitting stronger surges in financial stress.

In turn, the impact on systemic risk and medium-term financial vulnerabilities is less clear cut. It appears that over time, the impact on the SRI is negative, indicating 'taming-the-cycle' dynamics, but the effects are statistically insignificant.

Impulse responses to an unconventional monetary policy tightening shock differ meaningfully from those following a shock to the short-end factor. Figures 8 and 9 show that the impact of a comparable one standard deviation shock on GDP growth is smaller, and statistically not

Figure 6: Impulse Responses of monetary policy tightening shock on short-term rates (estimated by simulation)
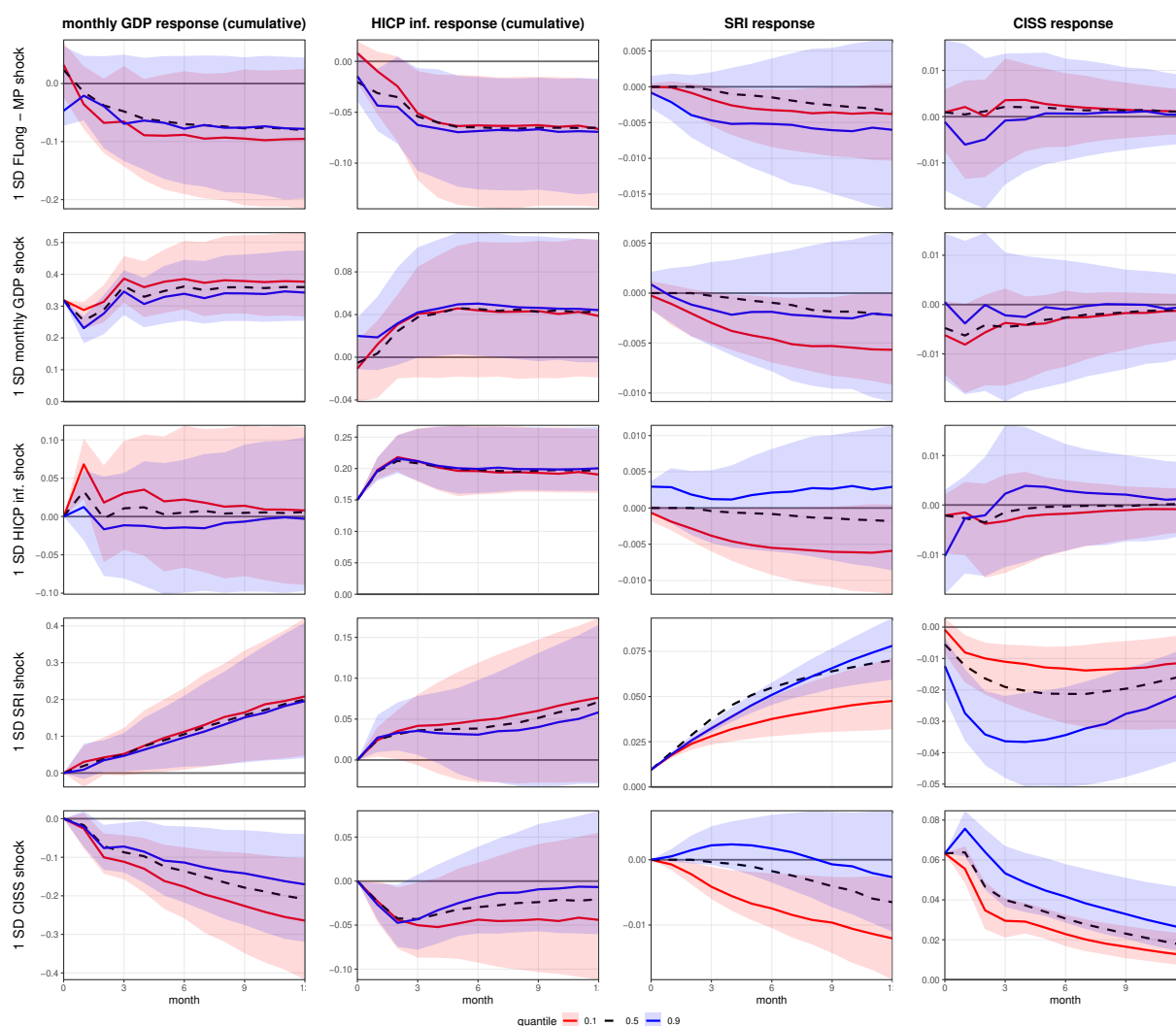

Notes: Five-variable specification with response of monetary policy shock variable excluded. Confidence bands are at 90% and are excluded for the median response.

significant, while the impact on HICP inflation is comparable and statistically significant. As for short-end shocks we find a dampening impact on financial vulnerabilities, this time marginally significant at least for the 10th percentile. The impact of long-end shocks on financial stress is found to be insignificant, unlike short-end shocks. Finally, impulse responses to monetary policy shocks generated from the two estimation approaches are generally comparable for both monetary policy factors.

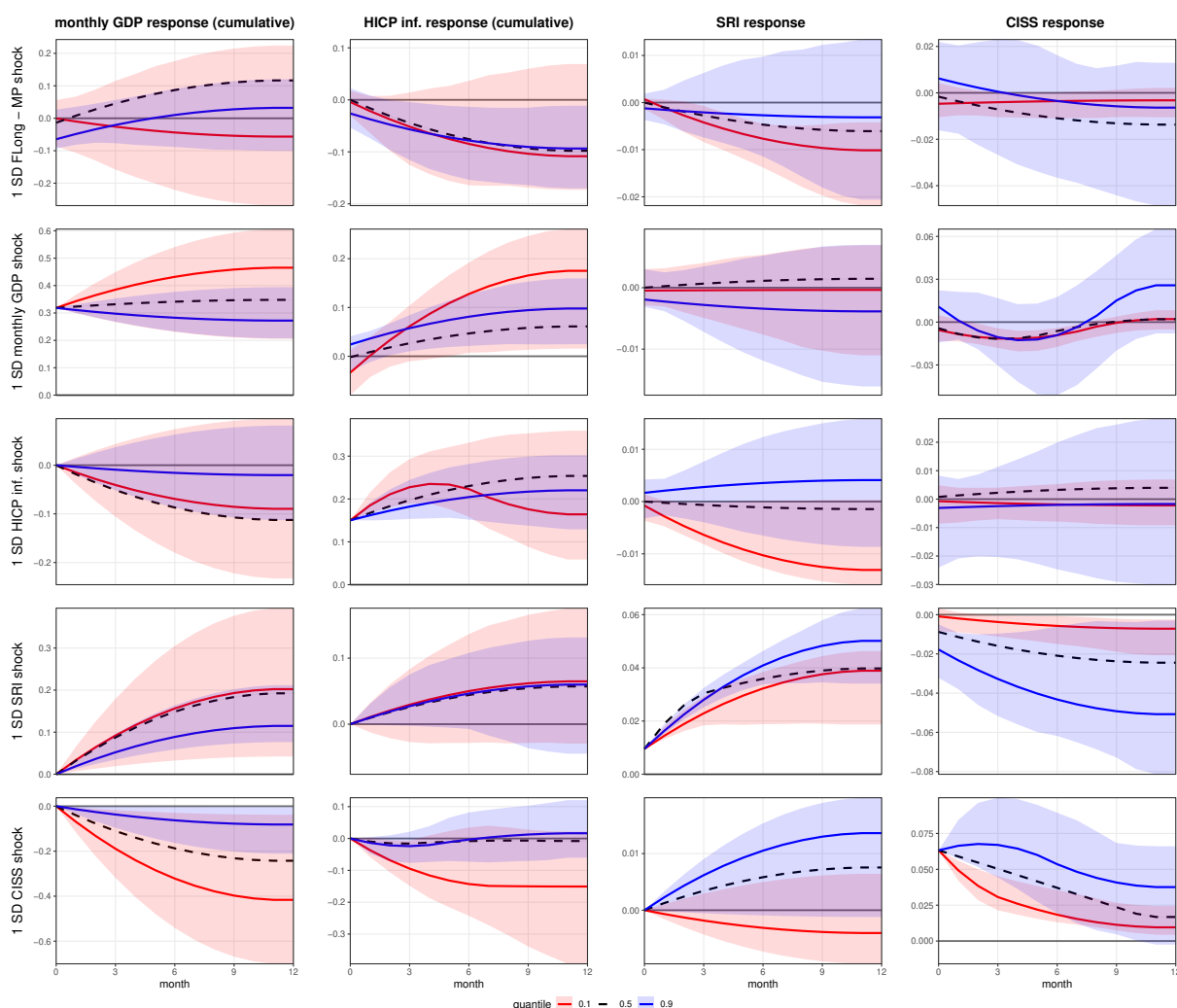Figure 7: Impulse Responses of monetary policy tightening shock on short-term rates (estimated by local projections)
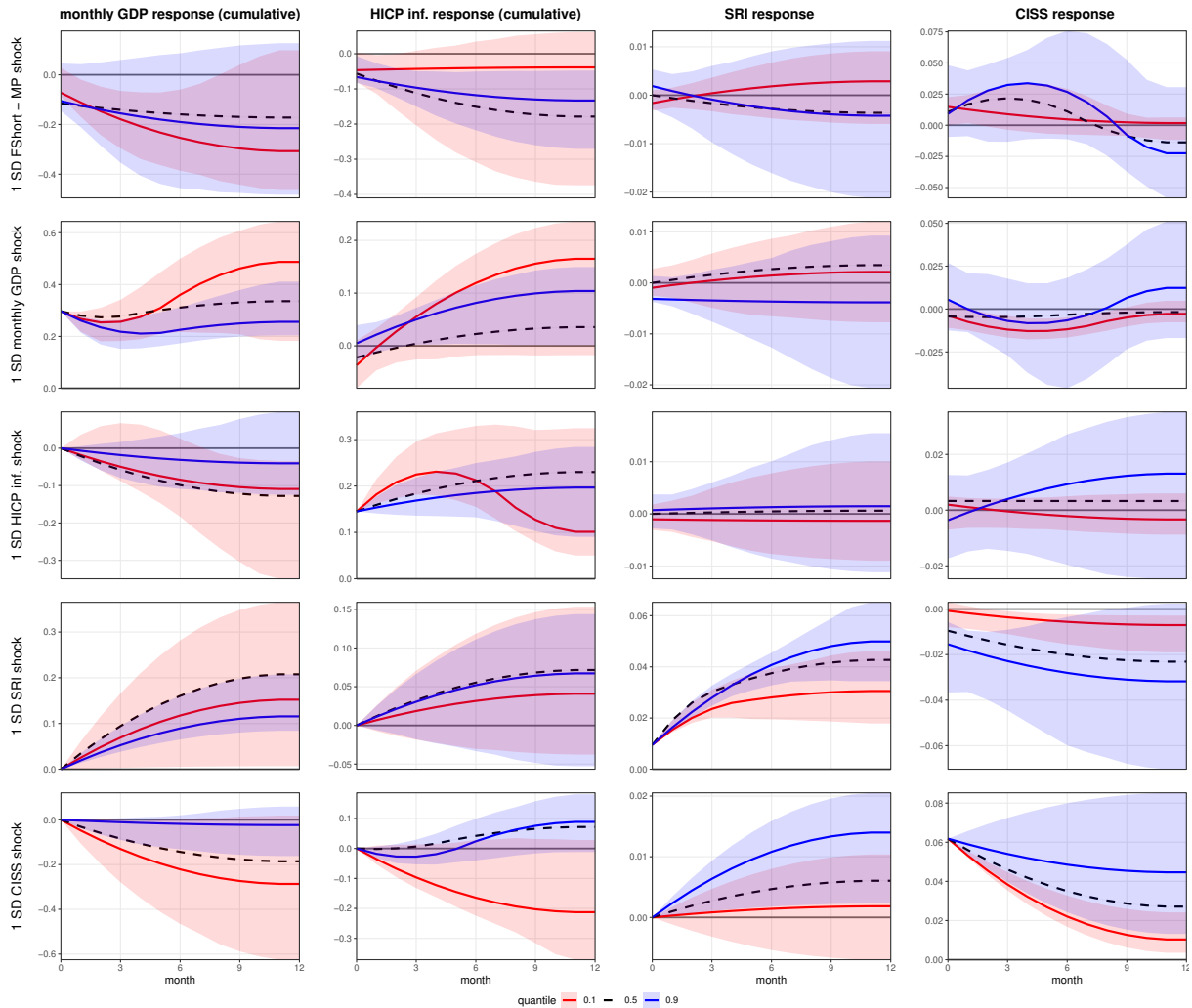
Notes: Five-variable specification with response of monetary policy shock variable excluded. Confidence bands are at 90% and are excluded for the median response.

6 Counterfactuals

6.1 Impact of monetary policy shocks on inflation and Growth-at-Risk

The empirical quantile models allow us to identify the role of monetary policy in the forecasts of macro-financial variables and to consider counterfactual analysis. Figure 10 shows the forecasts for GaR and one year ahead median annual HICP inflation together with the contribution of monetary policy shocks over time. The monetary policy contributions are constructed as the 12-month cumulative impact of the individual monetary policy surprises in each of these months

Figure 8: Impulse Responses of monetary policy tightening shock on long-term rates (estimated by simulation)

Notes: Five-variable specification with response of monetary policy shock variable excluded. Confidence bands are at 90%.

multiplied with the estimated impulse response function of the relevant horizon. They are thus conditional on the macro-financial information up to a point t, but conditional on the monetary policy surprises from t to $t + 12$.

The largest contributions of conventional monetary policy for GaR and the annual median inflation forecast (left panels), can be observed over the period 2007–2008 when it exerted large negative, i.e. tightening, contributions. When excluding these shocks, the Growth-at-Risk measure would have been positive, instead of falling into negative territory. Our counterfactual analysis indicates that the cumulative impact of conventional monetary policy shocks helped to

Figure 9: Impulse Responses of monetary policy tightening shock on long-term rates
(estimated by local projections)

Notes: Five-variable specification with response of monetary policy shock variable excluded. Confidence bands are at 90% and are excluded for the median response.

stabilize inflation over that period – it would otherwise have increased above 4% – and then bring down inflation forecasts in 2008.

The relatively large impact of monetary policy over this episode can be explained by tightening shocks in the second half of 2008 (see also Figure 3), while markets may have expected larger reductions earlier in the crisis. Beyond the Global Financial Crisis, sizable monetary policy impacts of the short-term interest rate factor appear during the aftermath of the euro area debt crisis (2013–2014) when loosening policy helped to boost growth and to uphold inflation.

While the 12-month cumulated surprises in the short-rate factor played an important role

Figure 10: Monetary policy contributions to 1-year ahead GaR and inflation for short- and long-end factor
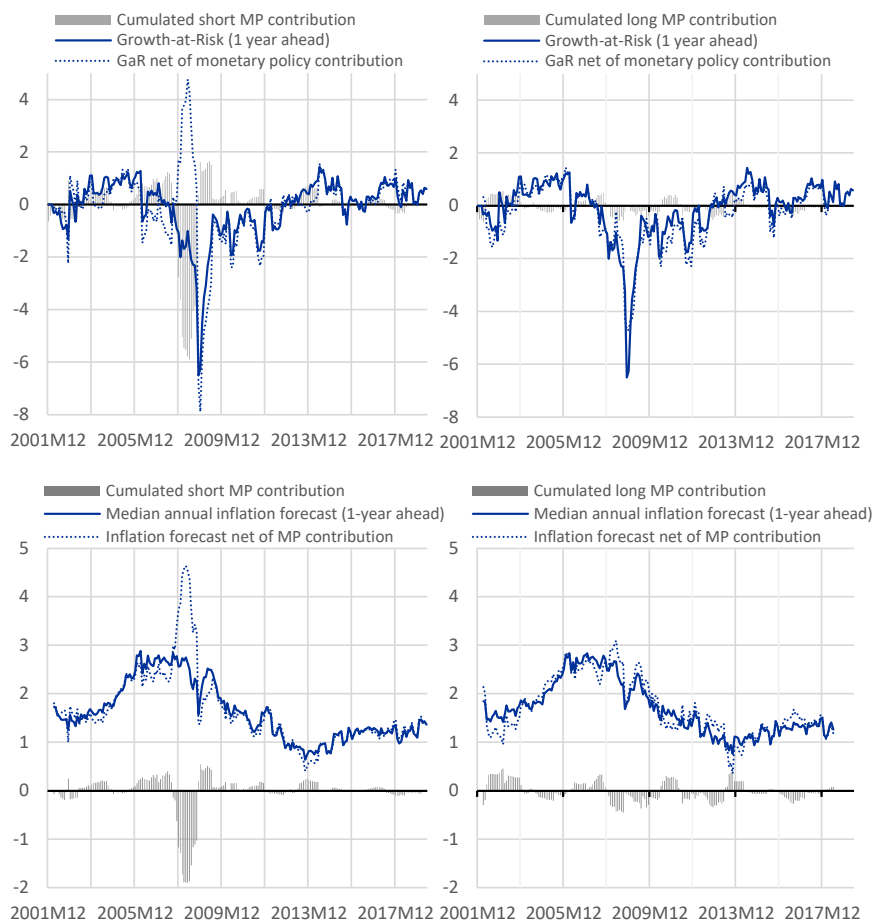
Notes: This figure shows the forecasts for one year ahead GaR and median annual HICP inflation together with the contribution of monetary policy shocks over time. The monetary policy contributions are constructed as the 12-month cumulative impact of the individual monetary policy surprises in each of these months multiplied with the estimated impulse response function of the relevant horizon. They are thus conditional on the macro-financial information up to a point t, but conditional on the monetary policy surprises from t to $t+12$.

during the Global Financial Crisis, the long-rate factor had more limited effects on GaR and median inflation forecasts, as can be seen from the right panels in Figure 10. The contributions are not only smaller in comparison to those from the short-end factor, but alternate sign more frequently. Up until 2014, effects were in the range of up to one percentage point for GaR and 0.5 percentage points for median inflation, but became more muted since then.

6.2 Monetary policy and stabilization trade-offs

The contributions of monetary policy surprises to GDP Growth-at-Risk and HICP inflation serve as a basis for assessing monetary policy trade-offs while pursuing a price stability objective. We illustrate how monetary policy could stabilize median inflation at the price stability objective of 2% and how such a stabilization compares to a policy that would stabilize GaR at its long-run mean. The sign and size of the required stabilizing policy will depend on the state of the economy in deviations from the respective inflation and GaR objective and the effectiveness with which the policy instruments can achieve these objectives. A larger policy innovation is needed if current forecasts strongly deviate from the objective or if the policy instrument is less effective in bringing the economy back to the objective.

Figure 11: Short-end monetary policy shocks needed to stabilise GaR and 1-year ahead median inflation forecasts
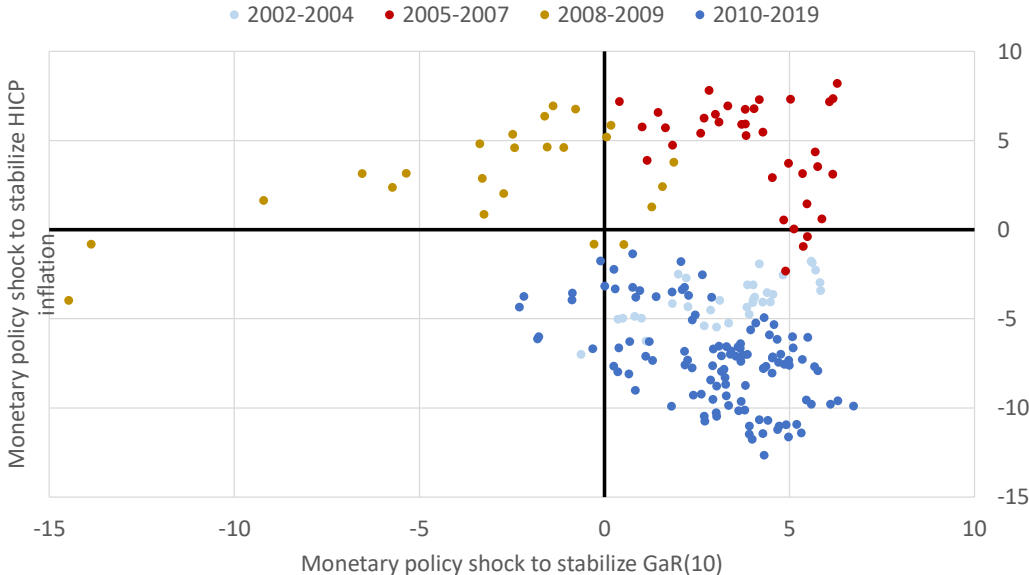
Notes: The monetary policy changes required to stabilize median HICP inflation and the 10th percentile of GDP growth are in standard deviations of the monetary policy innovations. Positive values imply a required tightening and negative values a required loosening of short-term rates.

Figure 11 illustrates the necessary size of the short-term interest rate factor to stabilize 1-year ahead forecasts of median inflation at 2% (vertical axis) and of GaR at its sample average of -1.08% (horizontal axis). Observations in the upper right quadrant indicate that a tightening of short-term rate would have helped to jointly stabilize price inflation and GaR objective. This

concerns primarily the period leading up to the Global Financial Crisis (2005–2007). In turn, observations in the lower left quadrant would have implied a loosening to bring the variables towards their objectives, but there have been only few of such instances over the sample period. For the observations in the upper left quadrant, instead, policy prescriptions would have implied a monetary policy tightening to stabilize inflation, but a loosening to raise GaR towards its target, relevant during the height of the Global Financial Crisis (2008–2009). For the observations in the bottom right quadrant, a loosening of monetary policy would have been needed to raise inflation towards its 2% objective, but a tighter policy would have helped to stabilize GaR. The numerous observations in this bottom right quadrant indicate that monetary policy faced an inflation-GaR trade-off for most of the post-crisis period. In such a trade-off situation, an additional policy instrument could complement and support monetary policy to stabilize the macroeconomy. Such policies may be fiscal or structural policies for the economic dimension, or macroprudential policy for the financial dimension.

6.3   Relative efficiency of monetary and macroprudential policy

Our estimation framework can capture an important role for macroprudential policy in complementing monetary policy in its efforts to stabilize the macroeconomy. The use of macroprudential policy would be most effective if it was complementary to monetary policy in stabilizing median inflation and GaR. To assess the relative efficiency of the two policies, we consider the policy interventions that are necessary to bring one-year ahead median inflation to 2% or to stabilize GaR at its historical average of -1.08%. In the empirical specifications, monetary policy is captured by the short- or the long-factor of risk-free interest rates, and macroprudential policy is captured by the SRI.[8] In order to make the size of the two policies comparable, we divide both measures by their historical standard deviation. The results on the relative efficiency hinge on the standard deviation of historical surprises in the short- and long-factor and in the SRI.

The cumulated impulse responses of the policy variables reveal that, to stabilize 1-year ahead GaR, a one-standard deviation of monetary policy achieves the same stabilization as 1.39 standard deviations of the SRI. When considering the long-term factor of interest rates, the relative efficiency to stabilize GaR is 0.42 which implies that macroprudential policy is more than twice as effective relative to the long-rate factor. Taken together, the short-term interest rate factor is more efficient relative to macroprudential policy and macroprudential policy is more

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[8]This implicitly assumes that macroprudential policy makers can freely adjust the level of vulnerabilities.

effective than the long term factor in stabilising GaR. When assessing the relative effectiveness in stabilizing median inflation based on the cumulative impulse responses, we find that the short factor is 1.3 times more effective than the SRI and the long-rate factor is as effective as the SRI (factor of 1.0).

The estimation indicates that the short factor is the most efficient instrument not only to stabilize GaR but also inflation. However the differences in effectiveness are larger for GaR than for inflation. When considering a potential assignment of policy instruments to policy objectives, the relative effectiveness in stabilizing one or the other variable becomes key (Fahr and Fell, 2017). Using the effectiveness of the SRI as a reference point, the short-term rate is 1.07 (=1.39/1.30) times more effective in stabilising GaR relative to inflation. In turn, the long-rate factor is only 0.42 (=0.42/1.00) times as effective to stabilize GaR relative to inflation, which implies that in relative terms the long-rate stabilizes inflation with least impact on GaR.

The relative efficiency itself does not yet provide us with the indications on the specific timing for using either of the two policies. The complementarity comes to the fore when monetary policy is constrained by a trade-off between stabilizing inflation and GaR, as captured in the top-left and bottom-right corner of Figure 11. In those situations, the adjustment of macroprudential policy can help to reduce the trade-off for monetary policy.

6.4 Monetary and macroprudential policy for stabilizing inflation and Growth-at-Risk

Having established the relative efficiency of different policy tools, we illustrate how the estimation results could inform monetary and macroprudential policy to enhance stabilization over the sample period. We assume policy objectives of 2% median inflation one year ahead and stabilization of GaR at its sample average of -1.08%. Given the relative efficiencies ,the policymaker uses monetary policy (long-end interest rate factor) and macroprudential policy (SRI). The GaR objective is non-symmetric, implying that the policymaker avoids GaR falling below the value of -1.08% while focusing solely on the objective of inflation otherwise. The policymakers thus provides a hedge against crisis outcomes.

Figure 12 displays results from this exercise. We find that relatively large monetary policy shocks would have been needed to bring inflation forecasts back to their target over the period from 2005 until the first half of 2009. In contrast, over the earlier as well as later parts of the sample period our results would have called for looser monetary policy as inflation forecasts

Figure 12: Monetary- and macroprudential policy mix for joint inflation and Growth-at-Risk targets.

Left: policy shocks. Right: forecasts conditional on policy shocks
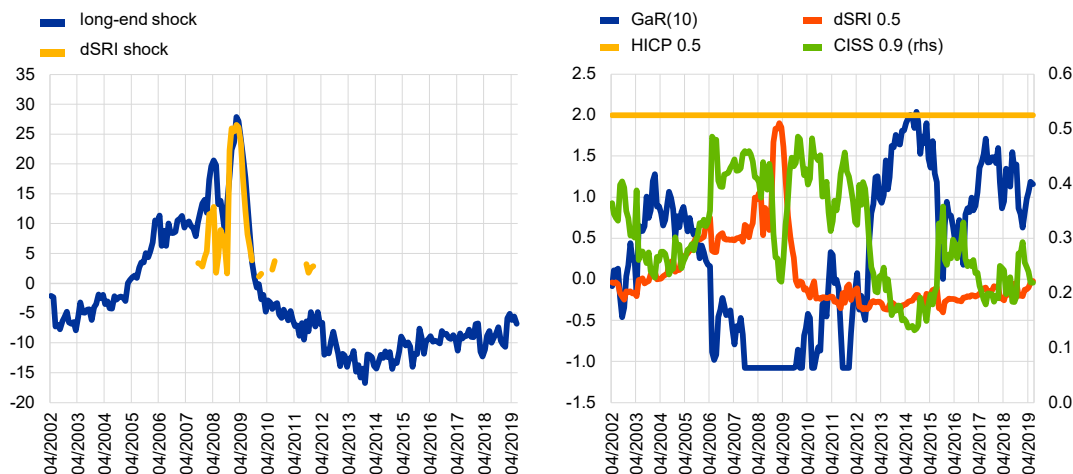
Notes: Left: This panel shows long-end and SRI shocks (in standard deviations) required to simultaneously achieve a 2% one-year ahead HICP inflation forecast while ensuring GaR above its sample average of -1.08%. Positive shocks indicate tightening for monetary policy but loosening for macroprudential policy. Right: This panel shows one-year ahead forecasts conditional on the policy shocks from the left panel. We show median forecasts for inflation and SRI, GaR and the 90th percentile forecast for the CISS.

from our models were consistently below their 2% target. Looser macroprudential policy (SRI) would have been needed starting in September 2007 and throughout the Global Financial Crisis until September 2009 and again on a few occasions during the euro area debt crisis. Forecasts implied by these policy counterfactuals show that they would have been effective in meeting their targets, while effectively limiting financial stress.

7 Conclusions

Our empirical analysis focused on the interaction of monetary policy shocks, financial stability conditions and the real economy in the euro area. The quantile vector autoregressive model, using two estimation techniques and five variables, estimates the entire distribution of real and financial variables. The setup allows for quantitatively assessing monetary policy trade-offs. One such trade-off involves two different policy goals and is captured by interactions between macro variables, such as inflation and GDP growth, and financial stability as measured by financial stress and vulnerabilities. A second trade-off is of intertemporal nature and differentiates between the potential impact of monetary policy on short-term financial stress relative to

adjustments to financial vulnerabilities in the medium term.

Our specifications consider not only the short-term interest rates as a policy tool, but also changes in the longer term rates, so as to capture effects from forward guidance and asset purchases of medium- to long-term securities. To identify monetary policy shocks, our empirical strategy considers surprises in risk-free interest rates in a narrow time window around the communication of ECB monetary policy decisions and further separates between information and monetary policy shocks.

We find that surging financial stress has a strong short-term impact on the lower tail of the GDP distribution. In turn, a build-up of financial vulnerabilities tends to be followed by subdued financial stress initially, but vulnerabilities rise again over the medium term. Furthermore, tightening conventional monetary policy reduces inflationary pressures (and real GDP growth) at the cost of increasing financial stress. Changes in the long-term interest rates induced by unconventional monetary policy, on the other hand, are equally effective in bringing down inflation but have a relatively smaller adverse impact on growth and financial stress while financial vulnerabilities mildly recede.

Our quantitative assessment of monetary policy using counterfactuals sheds light on monetary policy trade-offs. During the global financial crisis, monetary policy would have had to either tighten to stabilize inflation forecasts at 2% or loosen to prevent Growth-at-Risk to deteriorate. Our analysis thus indicates the potentially beneficial use of an alternative policy and we show how macroprudential tools - through their impact on financial vulnerabilities - can be deployed effectively in a complementary way to stabilize the financial system and macro economy.

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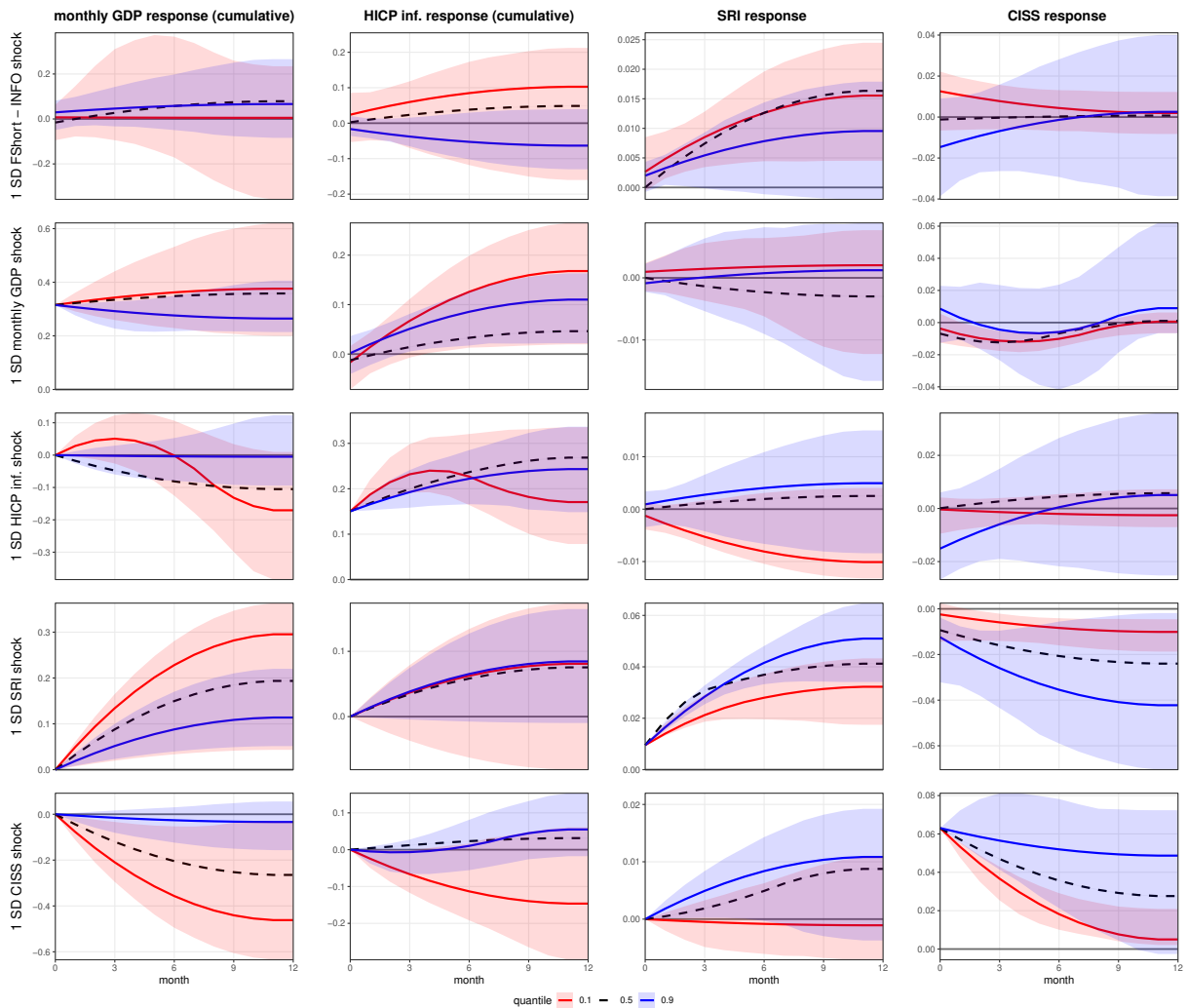
A Appendix

A.1 Additional results

Figure A.1: Impulse Responses of information shock on short-term rates
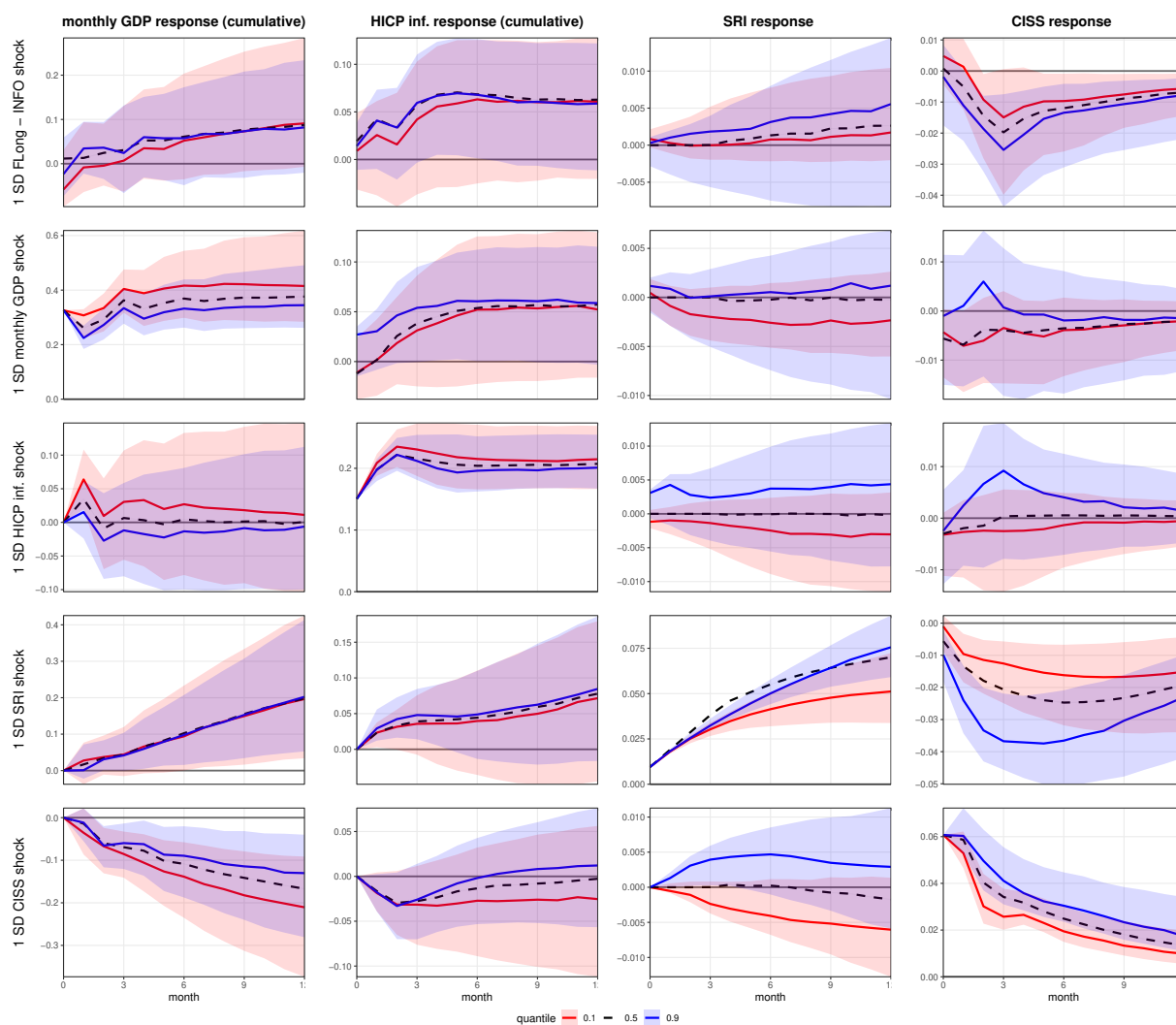(estimated by simulation)
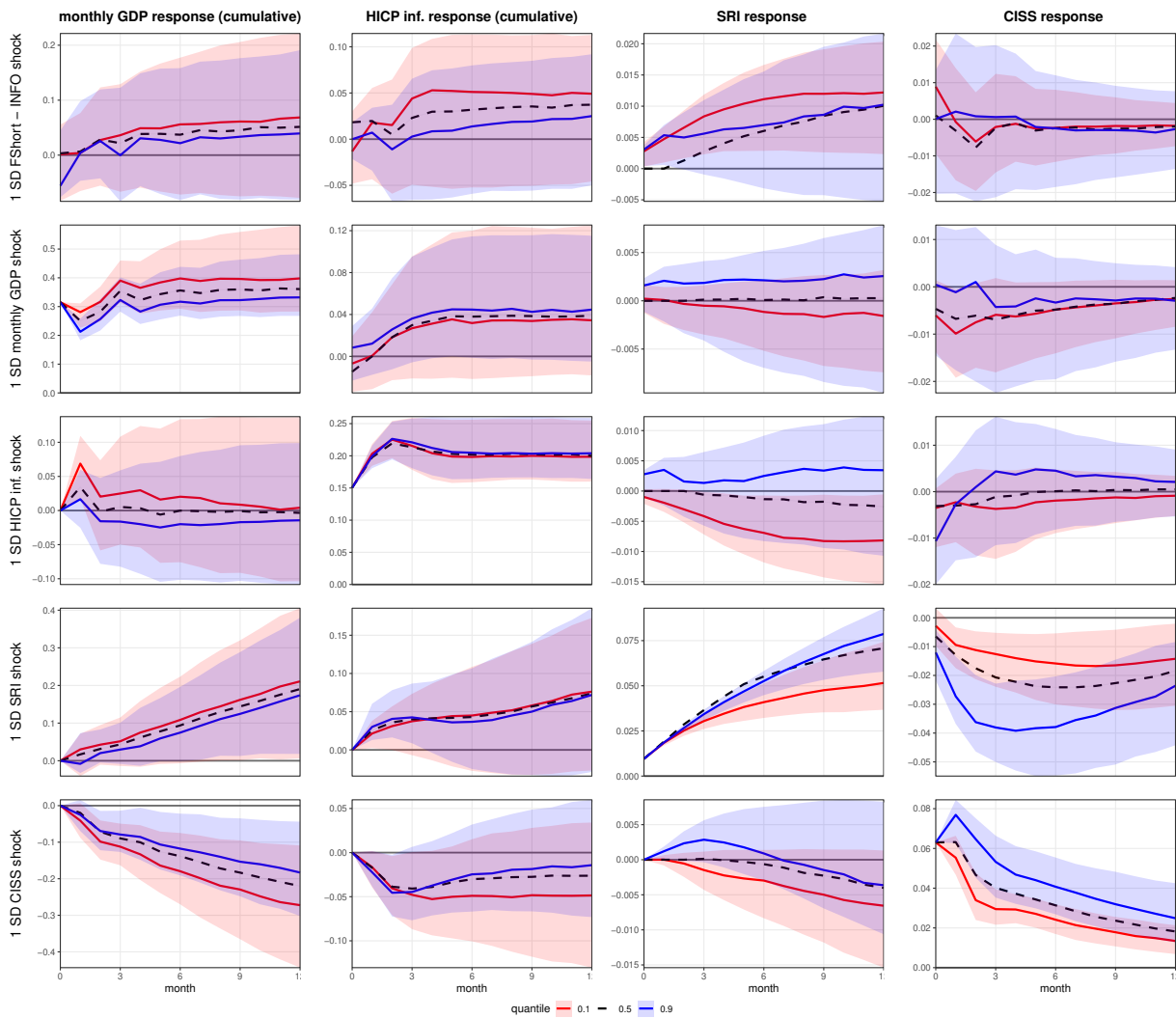
Notes: Five-variable specification with response of information shock variable excluded. Confidence bands are at 90% and are excluded for the median response.

Figure A.2: Impulse Responses of information shock on short-term rates
(estimated by local projections)

Notes: Five-variable specification with response of information shock variable excluded. Confidence bands are at 90% and are excluded for the median response.

Figure A.3: Impulse Responses of information shock on long-term rates
(estimated by simulation)

Notes: Five-variable specification with response of information shock variable excluded. Confidence bands are at 90% and are excluded for the median response.

Figure A.4: Impulse Responses of information shock on long-term rates
(estimated by local projections)
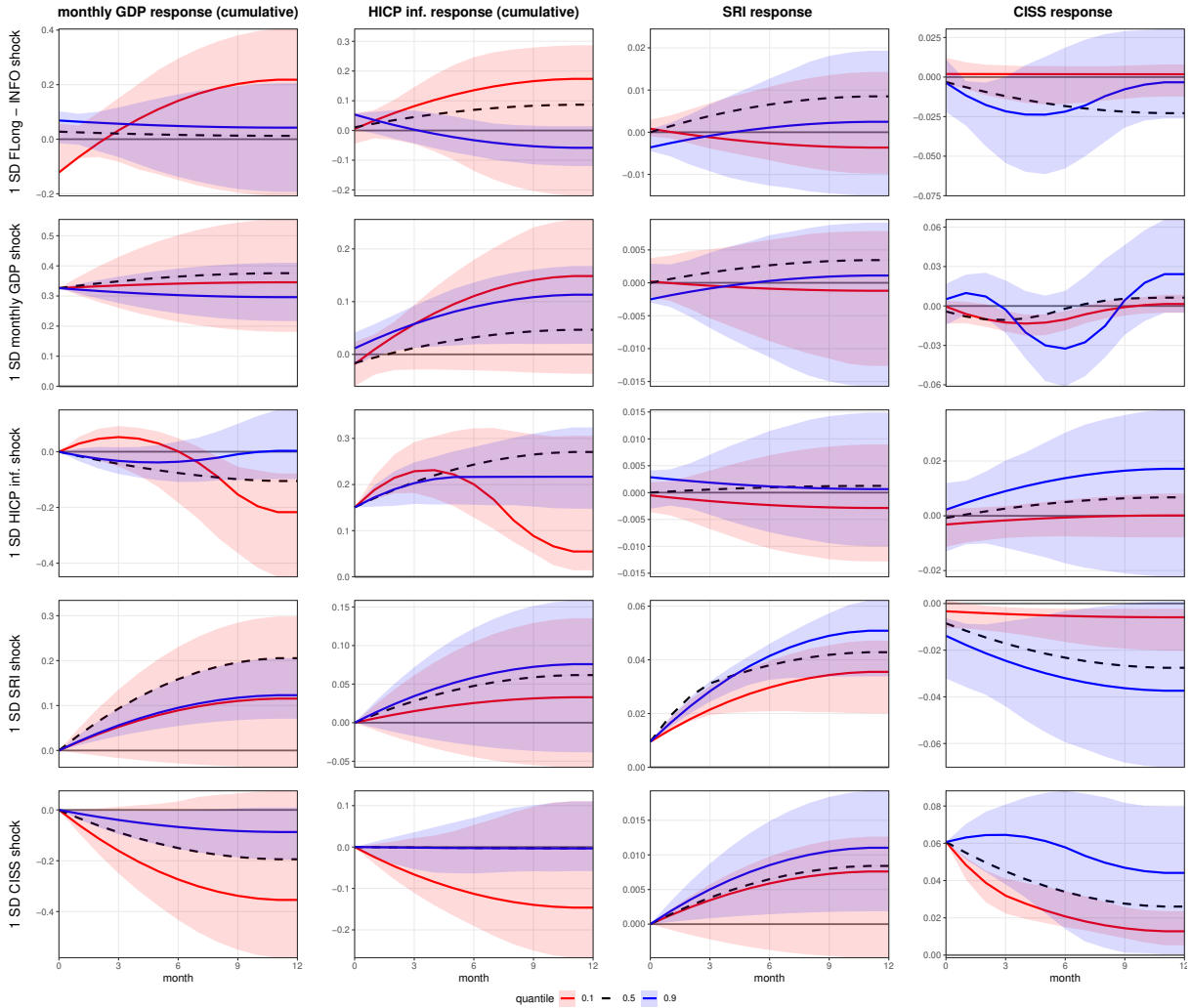
Notes: Five-variable specification with response of information shock variable excluded. Confidence bands are at 90% and are exluded for the median response.

A.2 Representing a sequence of external interventions – proof

We need to show

$$
Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \,\middle|\, \forall m \in \{0, 1, \ldots, 11\} : \varepsilon_i(u_{i,t+m}) := \varepsilon_i(u_{i,t+m}) + s_m \right] - Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \right]
$$

$$
= \sum_{l=0}^{11} QIRC(j, i, l, \tau, s_{11-l})
$$

First, we rewrite the expression as a telescoping sum. Second, we use the history independence property of quantile impulse response functions (4). Third, using the linearity of quantile impulse response functions (4), we express the difference between the two quantiles as the derivative of a conditional quantile. Finally, $u_{i,t+l}$ is independent of $y_{j,t+k}$ for $k < l$, so we can eliminate the first $l-1$ terms from the sum.

$$Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \forall m \in \{0, 1, \ldots, 11\} : \varepsilon_i(u_{i,t+m}) := \varepsilon_i(u_{i,t+m}) + s_m \right] - Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \right] \tag{14}$$

$$= \sum_{l=0}^{11} \left(Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \forall m \in \{0, 1, \ldots, l\} : \varepsilon_i(u_{i,t+m}) := \varepsilon_i(u_{i,t+m}) + s_m \right] \right. \tag{15}$$

$$\left. - Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \forall m \in \{0, 1, \ldots, l-1\} : \varepsilon_i(u_{i,t+m}) := \varepsilon_i(u_{i,t+m}) + s_m \right] \right) \tag{16}$$

$$= \sum_{l=0}^{11} \left(Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \forall u_{i,t+l} \in [0,1] : \varepsilon_i(u_{i,t+l}) := \varepsilon_i(u_{i,t+l}) + s_l \right] - Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \right] \right) \tag{17}$$

$$= \sum_{l=0}^{11} \frac{\partial Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| u_{i,t+l} \right]}{\partial \varepsilon_i(u_{i,t+l})} s_l = \sum_{l=0}^{11} \frac{\partial Q_\tau \left[\sum_{k=l}^{11} y_{j,t+k} \middle| u_{i,t+l} \right]}{\partial \varepsilon_i(u_{i,t+l})} s_l \tag{18}$$

$$= \sum_{l=0}^{11} QIRC(j, i, 11-l, \tau, s_l) = \sum_{l=0}^{11} QIRC(j, i, l, \tau, s_{11-l}) \tag{19}$$

A.3 Representing a counterfactual scenario – proof

We need to show

$$Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1}, \forall m \in \{0, 1, \ldots, 11\} \colon \varepsilon_i(u_{i,t+m}) := \varepsilon_i(u_{i,t+m}) + s_m \right] =$$
$$Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1} \right] + \sum_{l=0}^{11} QIRC(j, i, l, \tau, s_{11-l}) \tag{20}$$

First, we subtract and add the quantile forecast. The second equality follows by the same arguments as in the proof (A.2). The third equality is due to the history independence property of quantile impulse response functions (4).

$$Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1}, \forall m \in \{0, 1, \ldots, 11\} \colon \varepsilon_i(u_{i,t+m}) := \varepsilon_i(u_{i,t+m}) + s_m \right] = \tag{21}$$

$$Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1}, \forall m \in \{0, 1, \ldots, 11\} \colon \varepsilon_i(u_{i,t+m}) := \varepsilon_i(u_{i,t+m}) + s_m \right] \tag{22}$$

$$- Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1} \right] + Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1} \right] = \tag{23}$$

$$\sum_{l=0}^{11} \frac{\partial Q_\tau \left[\sum_{k=l}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1}, u_{i,t+l} \right]}{\partial \varepsilon_i(u_{i,t+l})} s_l + Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1} \right] = \tag{24}$$

$$\sum_{l=0}^{11} \frac{\partial Q_\tau \left[\sum_{k=l}^{11} y_{j,t+k} \middle| u_{i,t+l} \right]}{\partial \varepsilon_i(u_{i,t+l})} s_l + Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1} \right] = \tag{25}$$

$$Q_\tau \left[\sum_{k=0}^{11} y_{j,t+k} \middle| \mathcal{F}_{t-1} \right] + \sum_{l=0}^{11} QIRC(j, i, l, \tau, s_{11-l}) \tag{26}$$

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