19th June 2023

To whom it may concern:

I confirm that Álvaro Fernández-Gallardo Romero is the author of the submitted paper entitled: “**The Transmission of Macroprudential Policy in the Tails: Evidence from a Narrative Approach**”.

Sincerely,

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The Transmission of Macroprudential Policy in the Tails: Evidence from a Narrative Approach*

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Abstract

We estimate the causal effects of macroprudential policies on the entire distribution of GDP growth by incorporating a narrative-identification strategy within a quantile-regression framework. Exploiting a dataset covering a range of macroprudential policy actions across advanced European economies, we identify unanticipated and exogenous macroprudential policy 'shocks' and employ them within a quantile-regression setup. While macroprudential policy has near-zero effects on the centre of the GDP-growth distribution, we find that tighter macroprudential policy brings benefits by reducing the variance of future GDP growth, significantly and robustly boosting the left tail while simultaneously reducing the right. Assessing a range of potential channels through which these effects could materialise, we find that macroprudential policy operates through opposing tails of GDP and credit. Tighter macroprudential policy reduces the right tail of the future credit-growth distribution (both household and corporate) which, in turn, is particularly important for mitigating the left tail of GDP growth (i.e., GDP-at-risk).

Key Words: Growth-at-Risk; Macroprudential Policy; Narrative Identification; Quantile Local Projections.
JEL Codes: E32, E58, G28.

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1 Introduction

Macroprudential policies are now an increasingly important part of policymakers' toolkits. Targeted at maintaining financial stability, a key aim of macroprudential policy is to reduce 'tail risks'—i.e., minimise the potential economic costs of negative shocks by bolstering the resilience of the financial sector. However, building this resilience may not always be costless. So, while macroprudential policies can contain risks and contribute to macroeconomic stability, they may also have macroeconomic costs by constraining economic growth.

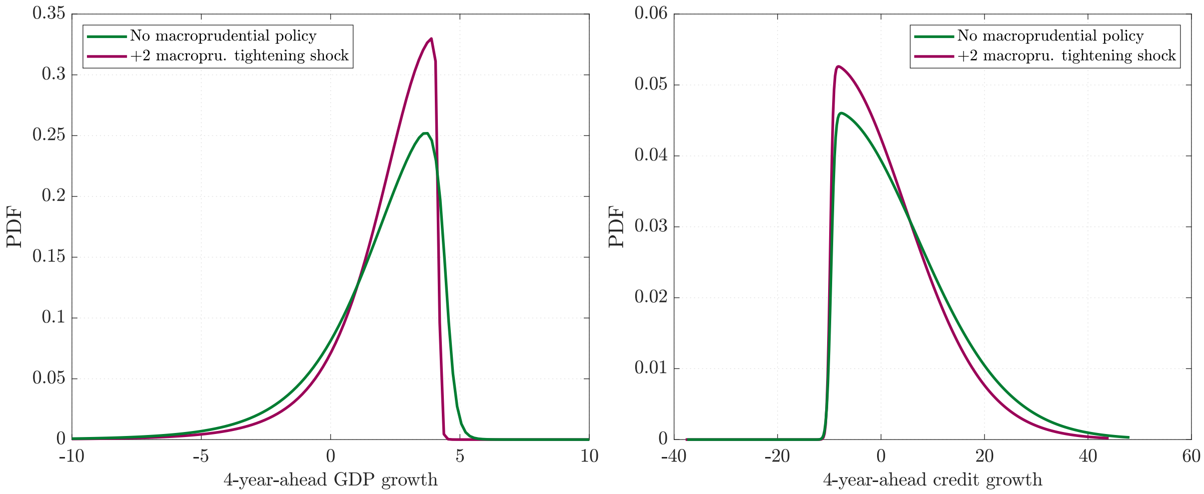
In order to gauge these costs and benefits, it is important to attain accurate estimates of the causal effects of macroprudential policies on the entire distribution of potential macroeconomic outcomes. While the development of quantile-regression techniques to estimate growth-at-risk—i.e., the size of potential '1-in-x bad outcomes'—offer policymakers a greater understanding of the drivers of tail risks when monitoring financial stability (see, e.g., Adrian, Boyarchenko, and Giannone, 2019; Aikman, Bridges, Hoke, O'Neill, and Raja, 2019; Adrian, Grinberg, Liang, Malik, and Yu, 2022; Lloyd, Manuel, and Panchev, 2023), identifying the causal effects of macroprudential policies presents a number of important empirical challenges. Crucially, as with other macroeconomic policies, macroprudential policy is not 'randomly assigned' and may be anticipated by economic agents. So a simple comparison of future economic outcomes under different policies is unlikely to uncover reliable estimates of causal effects.

In this paper, our key contribution is to estimate the causal effects of macroprudential policies on the entire GDP-growth distribution by incorporating a narrative-identification strategy within a quantile-regression framework. Narrative identification methods have been used to uncover the effects of monetary policy (Romer and Romer, 1989) and fiscal policy (Romer and Romer, 2010; Cloyne, Martinez, Mumtaz, and Surico, 2022), and have recently been employed in the macroprudential-policy literature (Richter, Schularick, and Shim, 2019; Rojas, Vegh, and Vuletin, 2022; Fernández-Gallardo, 2023). We build on this work by looking beyond the effects of specific prudential instruments and beyond just mean outcomes for GDP, considering the tails of the GDP-growth distribution. To do so, we exploit a dataset covering a range of macroprudential policy actions across advanced European economies (Budnik and Kleibl, 2018). This dataset includes a wealth of information on each policy action, including announcement and enforcement dates and whether it has a counter-cyclical design—information that is key for our narrative identification. Moreover, our dataset also allows us to account for policy anticipation, by disentangling announcement and enforcement dates for each policy action, an approach mirroring that previously employed in the fiscal-policy literature (Mertens and Ravn, 2012). Alongside this, we build on recent advances to the identification of dynamic causal effects within quantile-regression settings (Lloyd and Manuel, 2023) by controlling for factors that potential feature in macroprudential policymakers' reaction function through a 'one-step' approach. By combining this insight with the macroprudential policy data, we can effectively pin down unanticipated and exogenous macroprudential policy 'shocks' to be employed within a quantile-regression model to investigate causal effects across the distribution.

Applying these methods, we document how macroprudential policy affects different parts of the conditional distribution of future domestic GDP growth. We find that tighter macroprudential policy significantly and robustly boosts the left-tail of GDP growth (i.e., reduces downside tail risk or 'GDP-at-Risk'), while reducing the right-tail (i.e., reducing upside tail risk), with broadly zero effect on the centre of the distribution. The left-hand side of Figure 1 presents this visually, demonstrating how the 4-year-ahead predictive distribution of GDP growth shifts in response to a tightening in macroprudential policy, when all other control variables are set to their cross-country and cross-time average. Intuitively, macroprudential policy reduces the risk of large economic downturns in 'bad' states of the world, although restricts economic growth in 'good' states—in turn, reducing the variance of future GDP growth.

Armed with this result, we then consider the channels through which macroprudential policies affect the GDP-growth distribution. We first consider transmission channels through credit in the economy. Using our quantile-regression framework, we demonstrate that tighter macroprudential policy reduces credit growth, where this effect is particularly large at the right tail of the credit-growth distribution. This highlights that macroprudential policy is particularly effective at mitigating excessive credit 'booms', which we show to be a significant driver of GDP-at-Risk. This builds on previous work suggesting that macroprudential policy is effective at reducing credit growth (Cerutti, Claessens, and Laeven, 2017a) and that lower credit growth in turn is effective at reducing risks to financial stability (Schularick and Taylor, 2012). We highlight how this 'credit-at-risk' channel operates through opposing tails: tighter macroprudential policy reduces the right-tail of the credit-growth distribution which, in turn, is particularly important for mitigating left-tail GDP-growth risk. The right-hand side of Figure 1 presents this logic, illustrating how a tightening in macroprudential policy impacts the distribution of credit growth over a 4-year period.

Figure 1: Illustration of main results: The effect of a macroprudential policy tightening shock on the distributions of 4-year-ahead GDP and credit growth



Notes: Green lines show distributions of 4-year-ahead GDP and credit growth when all control variables are set to their cross-country and cross-time average values, and the macroprudential policy index is 0. The maroon lines show the same distribution when the macroprudential policy index is +2, which corresponds to a macroprudential policy tightening shock, with all other variables kept at their average values. Distributions approximated by fitting skew-t to quantile-regression estimates at $\tau = [0.1, 0.25, 0.5, 0.75, 0.9]$.

We also consider whether macroprudential policy affects the composition of credit. We find that tighter macroprudential policy is effective at preventing both household and business credit booms. Given previous literature showing that household credit booms, but not business credit booms, are associated with systemic financial crises (Müller and Verner, 2021), this points to some potential unintended consequences associated with macroprudential policy and the distribution of credit—in line with our main empirical findings around reductions in the right-tail of the GDP-growth distribution. Finally, we find limited evidence of significant transmission through asset-price channels.

Related Literature. Our paper relates to three main strands of literature.

First, our work builds on studies applying quantile-regression techniques to assess the drivers of macroeconomic tail risks (e.g., Adrian et al., 2019, 2022; Lloyd et al., 2023). While some papers have sought to assess the association between macroprudential policy and tail risks to GDP-growth (Aikman et al., 2019; Galán, 2020; Franta and Gambacorta, 2020), we build on recent developments in macroprudential policy measurement and quantile identification to plausibly identify causal impacts. The dataset we use is crucial in this regard, allowing us to overcome concerns over both endogeneity and anticipation effects. We complement this narrative approach with additional robustness exercises to demonstrate that our results are broadly unchanged when additionally controlling for macroeconomic forecasts made at the time of macroprudential policy decisions (similar in spirit to the identification strategy of Romer and Romer (2004) to estimate monetary policy effects). Here we build on recent work on the identification of dynamic causal effects with confounding factors in a quantile-regression setting in Lloyd and Manuel (2023). This work demonstrates that previous attempts to identify the effects of macroprudential policies within a quantile regression by first estimating a series of 'policy shocks' (Gelos et al., 2022; Brandão-Marques et al., 2021) suffer from a form of omitted-variable bias, which we avoid by employing an alternate 'one-step' quantile regression estimator with variables that potentially feature in the policy reaction function as controls.

Second, we contribute to a more general literature on macroprudential policy identification. We employ a narrative-identification strategy to identify the effects of macroprudential policy, in line with a range of recent papers (Richter et al., 2019; Rojas et al., 2022; Fernández-Gallardo, 2023). We build on this by looking beyond the effects of specific instruments (such as loan-to-value requirements) and beyond just mean outcomes. While previous literature has employed narrative methods to separately estimate potential costs (e.g., reductions in economic growth) and benefits (e.g., reduced probability of financial crises) of macroprudential policies, by using quantile-regression techniques we are able to simultaneously assess costs and benefits by examining the effects of macroprudential policy across the entire distribution of GDP-outcomes. In the context of cost-benefit analyses frameworks for macroprudential policy (e.g., Suarez, 2022), our results suggest that tighter macroprudential policy can, on net, be beneficial by mitigating downside risks to GDP growth without reducing expected (i.e., mean) growth.

Third, we contribute to a range of work assessing the transmission channels of macroprudential policy to the macroeconomy through the financial system. A key finding in the previous literature is that macroprudential policy can be effective at reducing rapid credit growth (Claessens, Ghosh, and Mihet, 2013; Cerutti, Claessens, and Laeven, 2017a; Forbes, 2021; Acharya, Bergant, Crosignani, Eisert, and Mccann, 2022), and in turn is effective at reducing the probability of financial crises (Belkhir, Naceur, Candelon, and Wijnandts, 2022; Fernández-Gallardo, 2023). We argue that this 'credit-at-risk' transmission mechanism operates through opposing tails: tighter macroprudential policy lifts the left tail of GDP growth by compressing the right tail of credit. We find limited evidence of other significant channels (e.g., via asset prices) through which macroprudential policy affects the conditional distribution of GDP growth.

Outline. The remainder of this paper is structured as follows. Section 2 describes our empirical specification, data and identification approach. Section 3 presents our baseline results for the effects of macroprudential policy on the distribution of future GDP growth. Section 4 investigates the role of different transmission channels. Section 5 concludes.

2 Empirical Specification, Data and Identification

In this section, we present our overarching empirical framework. In particular, we describe our narrative measure of macroprudential policy and explain how we tackle the challenge of identifying macroprudential policy shocks—which form a key part of our contributions to the growth-at-risk literature.

2.1 Empirical Specification

As in previous growth-at-risk work, we employ a quantile-regression framework (Koenker and Bassett, 1978) to study how changes in a set of conditioning variables—in our case, specifically, macroprudential policy—are associated with the distribution of future GDP growth, and (later on) credit growth and asset prices. We present our approach within a panel setting, where time is denoted by $t = 1, ..., T$ and the countries for whom we estimate the conditional distribution of GDP are labelled with $i = 1, ..., N$.

We specify the following local-projection model (Jordà, 2005) for the conditional quantile function Q of h-period-ahead annual average GDP growth, which we denote by: $\Delta^h y_{i,t+h} \equiv (y_{i,t+h} - y_{i,t})/(h/4)$ for $h = 1, ..., H$:

$$Q_{\Delta^h y_{i,t+h}}(\tau|\Delta MaPP_{i,t}, \mathbf{x}_{i,t}) = \boldsymbol{\alpha}_i^h(\tau) + \Delta MaPP_{i,t}\beta^h(\tau) + \mathbf{x}_{i,t}'\boldsymbol{\theta}^h(\tau), \quad \tau \in (0,1) \tag{1}$$

where Q computes quantiles τ of the distribution of $\Delta^h y_{i,t+h}$ given covariates: the in the narrative-based macroprudential policy indicator $\Delta MaPP_{i,t}$, a scalar with associated parameter $\beta^h(\tau)$, and the $K \times 1$ vector of covariates $\mathbf{x}_{i,t}$, with associated parameter vector $\boldsymbol{\theta}^h(\tau)$.

In equation (1), $\boldsymbol{\alpha}_i^h(\tau)$ represents country- and quantile-specific fixed effects, which control for time-invariant unobserved heterogeneity. For our baseline specification, we estimate these fixed effects following the approach of Kato et al. (2012), who show that for panel quantile regressions like ours, with many time periods compared to the number of cross-sectional units (i.e., $T \gg N$), this fixed-effects estimator is consistent and asymptotically normal.[1]

In our baseline specification, we include the following controls in $\mathbf{x}_{i,t}$: the annual growth of real credit; the annual growth of real house prices; the annual growth of general CPI prices; contemporaneous and lagged values of the dependent variable; and the US VIX. These span both domestic and foreign drivers of the GDP-growth distribution, over and above macroprudential policy. The US VIX, in particular, helps to account for global factors affecting the distribution of GDP growth (Lloyd et al., 2023). We include both the contemporaneous and first lags of each of our controls in our baseline specification. In robustness analyses, we carry out extensive tests on the sensitivity of our results to alternative controls.

Our baseline sample runs from 1990Q1 to 2017Q4, at quarterly frequency for 12 advanced economies. The selection of this sample is determined by the availability of narrative-based macroprudential policy series $MaPP_{i,t}$ that we explain subsequently in Section 2.2.

With this specification, and armed with the discussion of identification in Section 2.3, our coefficient of interest $\beta^h(\tau)$ can be interpreted as the *causal* response of the τ-th conditional quantile of GDP growth at horizon h to a tightening in macroprudential policy that is activated at time t. Throughout, we focus the majority of our presentation on the 10th, 50th and 90th percentiles of GDP growth. We choose those quantiles to estimate the impact of a macroprudential policy shock not only on the median, but also on the tails of the GDP growth distribution, which constitute measures of the macroeconomic downside and upside risk, respectively. Therefore, those percentiles represent how bad (good) growth may be under adverse (favourable) circumstances.

2.2 Measure of Macroprudential Policy Stance

We construct our macroprudential policy index $MaPP_{i,t}$ by using the Macroprudential Policies Evaluation Database (MaPPED). This database contains around 480 policy actions taken between 1990Q1 and 2017Q4 for the following 12 advanced economies: Belgium, Denmark, Germany, Ireland, Spain, France, Italy, Netherlands, Finland, Sweden, Portugal and the UK.[2]

Relative to other macroprudential policy databases such as the IMF's Integrated Macropru-

[1] In robustness analysis, we also present results using country- and quantile-specific fixed effects estimated following the approach of Machado and Santos Silva (2019).

[2] The MaPPED database includes policy actions before 1995 provided those policies were still in force in 1995. Nevertheless, there are two main reasons to believe that the vast majority, if not all, of the policies implemented between 1990 and 1994 are still included in the sample. First, deactivations of macroprudential policies represent a very small percentage of total policy actions, only 2%. Second, within the MaPPED database, policies that are eventually deactivated have an average duration of around 14 years. So it is unlikely that during the first four years of the sample, 1990-1994, policies were enforced and deactivated prior to 1995.

dential Policy (iMaPP) Database (Alam, Alter, Eiseman, Gelos, Kang, Narita, Nier, and Wang, 2019) and the International Banking Research Network's Prudential Policy Database (Cerutti, Correa, Fiorentino, and Segalla, 2017b), MaPPED has several advantages for our purposes. In particular, it provides information on the life-cycle implementation of each policy instrument, including activation, recalibration and deactivation dates. This allows us to track the impact of each policy not only when it is first activated, but also when it is recalibrated or deactivated. Moreover, the survey designed for MaPPED ensures that policy tools and actions are reported in the same manner across countries. Therefore, MaPPED allows for comparability of policy actions across countries, avoiding potential biases from unstandardised open-text questionnaires. Furthermore, MaPPED includes a wealth of information on each policy action, including announcement and enforcement dates, stance (loosening, tightening, or ambiguous), and whether it has a countercyclical design. The latter feature is key to our identification strategy, as we explain in detail in Section 2.3 below.[3]

We follow Fernández-Gallardo and Paya (2020) by constructing a macroprudential policy index $MaPP_{i,t}$ for each country in the sample. In particular, we use the announcement date of the policy to assign a value to each policy action, giving a positive value to tightening actions, a negative value to loosening actions, and a value of zero to policy actions with ambiguous impacts or no announced policy action in a given period. We also assign different weights to different policy actions based on perceived importance. We follow the weighting scheme proposed by Meuleman and Vander Vennet (2020). Under this scheme, activations and deactivations are given the highest weights. Second-tier actions, including changes in the existing level or scope of the policy are given a lower weight. Finally, maintaining the existing level is given the lowest weight. Appendix A details the weights assigned to the different policy actions.

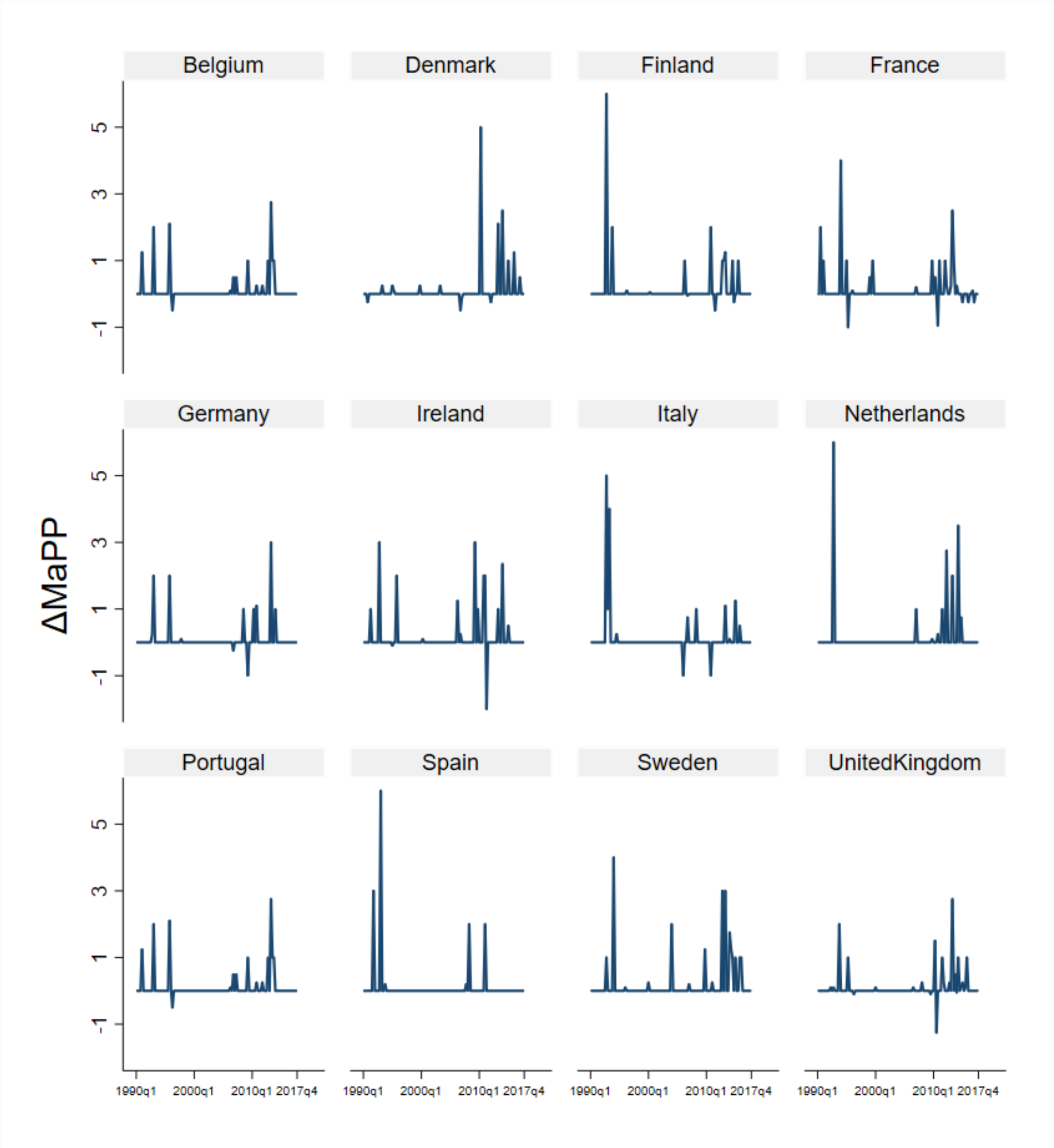
The resulting index can be interpreted as a composite measure of the overall macroprudential policy stance in each of the selected advanced economies. We plot the changes in our macroprudential policy index over time for each country in the sample in Figure 2.

2.3 Identification of Macroprudential Policy Shocks

Studying the impact of macroprudential policy changes on the GDP-growth distribution is the primary object of interest of this paper. Therefore, a crucial issue is how to pin down the non-systematic component of macroprudential policy to identify causal effects. We refer to

[3]We refer the reader to Budnik and Kleibl (2018) for detailed information on the advantages of MaPPED over other existing macroprudential policy databases.

Figure 2: Changes in the Macroprudential Policy Index over Time



Notes: Plot of $\Delta MaPP_{i,t}$ over time for each advanced-economy in our sample. Period is 1990Q1-2017Q4.

the non-systematic component of macroprudential policy actions—policy actions that do not systematically respond to short- to medium-term economic fluctuations—as macroprudential policy shocks.

Overall, we face two empirical challenges to identify unanticipated macroprudential policy shocks. First, some macroprudential policies are endogenous, as they are activated or adjusted in response to current or future economic conditions. Those policies are likely contaminated by reverse causality and therefore are invalid to recover causal effects. Second, implementation lags can possess an empirical challenge to disentangle the relationship between macroprudential policy and the GDP growth distribution. In particular, prudential policy actions subject to a delay between the passing of the legislation and the implementation of the legislation may be partially anticipated, implying that economic agents can endogenously react to such prudential policy news. Those policies with and without implementation lags can therefore have very different effects on macroeconomic variables, as shown by Mertens and Ravn (2012) in the fiscal policy context.

In the baseline, we address the first threat to identification, endogeneity, using the narrative-identification approach proposed by Fernández-Gallardo (2023) within our quantile regression framework. In particular, we use the narrative information provided in MaPPED to identify the systematic component of macroprudential policy actions. Then, we re-construct our $MaPP_{i,t}$ indicator for each country in the sample following the steps explained in Section 2.2 above, excluding those policy actions with a specific countercyclical design, as those interventions are primarily aimed at short- to medium-term stabilisation rather than implemented to address structural vulnerabilities in the financial system. Therefore, we argue that, after excluding countercyclically-motivated policies, the remaining policy actions are legitimate observations to identify causal effects because such policies are likely to be free of contemporaneous influences and are therefore less likely to be systematically correlated with other underlying factors affecting the GDP growth distribution in the medium-run.

An alternate approach frequently employed in the literature is to identify 'as good as random' moves in macroprudential policies by controlling for variables that plausibly feature in a macroprudential 'reaction function'. The underlying identifying assumption in this approach is 'selection-on-observables': conditioning on a set of observable factors, changes in macroprudential policy are exogenous with respect to all other drivers of future outturns in the outcome variable of interest. Although not typically explained in this way in the macroprudential policy literature, this is the assumption underpinning identification via propensity scores (Forbes et al., 2015; Richter et al., 2019), as well as via the estimation of policy shocks as the residuals from a reaction function (Ahnert et al., 2021; Chari et al., 2022; Gelos et al., 2022).

There are well-known challenges with this approach, most notably that it may be infeasible in practice to correctly identify and then control for all the variables that potentially feature in the policy reaction function, especially in the face of limited dimensionality in finite samples. An advantage of our approach is that we directly utilise detailed information on policies from narrative records to effectively exclude those with a specific counter-cyclical design. Note that this approach does not preclude identification by additionally controlling for potential confounding factors —indeed to ensure our approach is 'doubly robust' we can further control for variables which plausibly simultaneously drive macroprudential policy decisions and macroeconomic outcomes. And so in the spirit of Romer and Romer (2004), we explore the sensitivity of our baseline results to the inclusion of forecasted GDP growth as an additional control. This allows us to account for the information set that policymakers have available on the future state of the economy when the policy is announced.[4]

To operationalise this robustness exercise we build on recent work on estimating dynamic causal effects in a quantile-regression setting in Lloyd and Manuel (2023). A common approach in the literature is to first estimate policy shocks as a residual from a regression of the policy reaction function, and then to employ these shocks within a second-stage regression (typically a local projection). Recent approaches to estimate the effects of macroprudential policies within a quantile regression framework have followed this approach (Gelos et al., 2022; Brandão-Marques et al., 2021). In OLS settings, this 'two-step' approach can yield coefficient estimates that have a causal interpretation under 'selection-on-observables', albeit with incorrect standard error estimates. But in quantile regression, coefficient estimates suffer from a form of quantile-regression omitted-variable bias and generally yield biased estimates of causal effects. We therefore employ an alternate 'one-step' quantile regression estimator of the outcome variable on the macroprudential policy variable which includes potential reaction function variables as controls.

In the robustness section, we deal with a second threat to identification: anticipation due to policy news. Here we use the information provided by MaPPED on the announcement and enforcement date of each policy action in the sample. This is a key advantage of MaPPED

[4]The key insight of Romer and Romer (2004) is that forecasts of the outcome variable at the time of policy decisions alone can act as a sufficient statistic to control for all potential confounding factors that simultaneously drive policy and outcomes (see comment by Cochrane, 2004).

relative to other databases, allowing us to identify policies that are subject to implementation lag and therefore may be anticipated by economic agents. This approach mirrors that previously employed in the fiscal policy literature (Mertens and Ravn, 2012).

We argue this approach—employing narrative methods within a one-step quantile regression that potentially controls for any residual endogeneity—is crucial to plausibly identify the causal effects of macroprudential policy on conditional quantiles of GDP-growth.

3 Empirical Results: Macroprudential Policy and GDP

3.1 Baseline Specification

Figure 3 presents the impulse response of quantiles of the conditional GDP-growth distribution (for $\tau = 0.1, 0.5, 0.9$) to changes in our narrative macroprudential policy index across different horizons h. Table 1 presents the corresponding coefficient point estimates and standard errors. Our results highlight notable asymmetries in the effects of macroprudential policies on quantiles of the GDP-growth distribution.

Table 1: Coefficient estimates for $\beta^h(\tau)$ from baseline specification: regression of GDP growth on narrative measure macroprudential policy and controls

	$h = 4$	$h = 8$	$h = 12$	$h = 16$
$\tau = 0.1$	0.02	0.15**	0.25***	0.32***
	(0.04)	(0.08)	(0.09)	(0.08)
$\tau = 0.5$	0.03ˆ	0.05ˆ	0.02	0.06ˆ
	(0.03)	(0.04)	(0.05)	(0.06)
$\tau = 0.9$	-0.00	-0.05ˆ	-0.07ˆ	-0.14***
	(0.03)	(0.04)	(0.05)	(0.05)

Notes: This table presents coefficient estimates reflecting the association between the τ-th percentile of annual average real GDP growth at horizon $h = 1, 2, ..., 16$ and a tightening macroprudential policy activation. Coefficient estimates for the fixed effects and controls are not reported. Sample period is 1990Q1-2017Q4, for 12 advanced economies. Standard errors are based on block bootstrap with 1000 replications and are shown in parenthesis with: ˆ $p < 0.32$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Comparing panels (a) and (c) with panel (b), we find that macroprudential policies affect the tails of the GDP-growth distribution disproportionately more than at the median. In fact, panel (b) indicates that the impact of tighter macroprudential policy on median GDP growth is small and statistically insignificant across horizons.

Nevertheless, macroprudential policy does have significant impacts on the tails of GDP growth. Comparing panels (a) and (c) indicates that tighter macroprudential policies have opposing effects to the downside (i.e., the $\tau = 0.1$ left tail) and upside (i.e., the $\tau = 0.9$ right tail). In particular, while a tightening macroprudential policy shock has an insignificant effect at the median across different horizons, it has a positive (negative) effect on the left (right) tail of the GDP growth distribution that persist over the long-term. Effects in both tails are statistically significant after 2-3 years. However, our estimates reveal that the quantitative upside impact on the left tail is larger in magnitude than the downside impact on the left tail, suggesting that tighter macroprudential policy alters the skew of the GDP-growth distribution.

These results suggest that the benefits of macroprudential policy on GDP growth are most clear at the left tail of the GDP-growth distribution—consistent with previous studies of growth-at-risk and macroprudential policy (Galán, 2020; Franta and Gambacorta, 2020). Otherwise put, our results show that tighter macroprudential policy can improve 'growth-at-risk'—a now standard measure of how bad growth can be under adverse circumstances typically associated with systemic distress (Adrian et al., 2019). Therefore, our results imply that macroprudential policy can be effective at dampening downside risks to economic growth, even without significant impacts at the centre of the distribution, potentially making the growth outlook more resilient to negative future economic shocks.

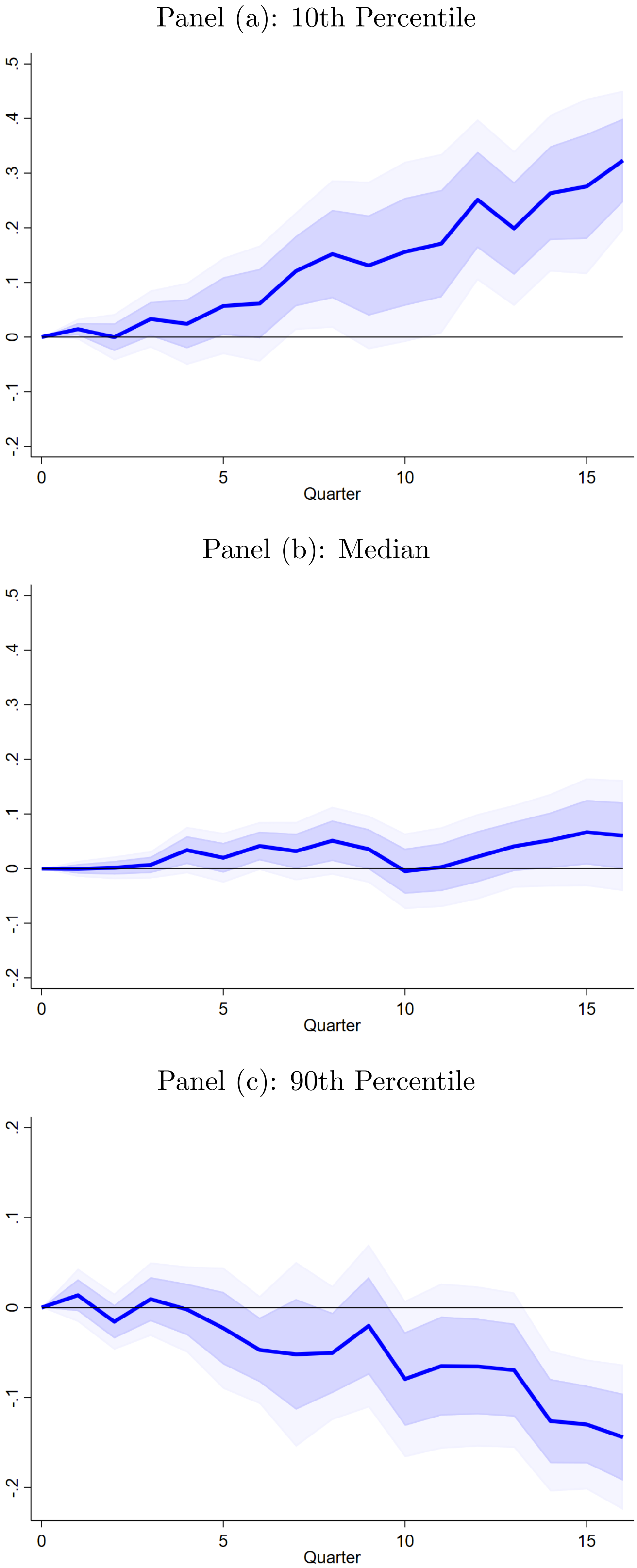
3.2 Robustness Analyses

In this sub-section, we summarise the key findings from a battery of robustness exercises.

Lags in Policy Implementation. One of the advantages of the MaPPED database is that, unlike other databases, it contains information on both the announcement and the enforcement date of each policy action in the sample. In MaPPED, the announcement date refers to the date when a law, regulation or recommendation becomes enacted, i.e. the date of approval of the legislation (by parliament or government). The enforcement date corresponds to the time when a law, regulation or recommendation legally becomes effective, i.e. when a certain threshold regarding capital or liquidity requirements and buffers has to be met. We exploit this information to compute the implementation lag for each policy action in the sample as the period that goes from the announcement to the enforcement of the policy. We define policies with implementation lag as those policies for which there is a delay between the announcement and the enforcement date of at least 90 days.[5] This 90-day threshold follows from Mertens and Ravn

[5] Around 20% of the policy actions included in MaPPED database suffer from implementation lag according to this definition.

Figure 3: Impulse Response of Quantiles of the GDP-Growth Distribution to Macroprudential Policy Tightenings



Notes: Estimated change in the τ-th percentile of annual average real GDP growth at horizon $h = 1, 2, ..., 16$, following a tightening macroprudential policy activation. Sample period is 1990Q1-2017Q4, for 12 advanced economies. Shaded areas denote the 90% (light blue) and 68% (dark blue) confidence intervals based on bootstrap with 1000 replications.

(2012).[6] Consequently, we are able to identify which policies are subject to implementation lag and therefore are anticipated. We reconstruct the narrative index using policies with no implementation lag and estimate the baseline specification using quarterly changes in the new index as our policy shock. Our benchmark results and their economic implications are qualitatively the same. We note that the estimation uncertainty is, however, larger than in the full sample where all policies are included.[7] In particular, the main difference regarding our benchmark result is that now the impact of macroprudential policy on GDP-growth quantiles is smaller at near-term horizons and takes longer to become statistically significant. This robustness exercise confirms, therefore, that the identification of macroprudential policy shocks in the baseline specification was not systematically contaminated by policies with implementation lag.

Accounting for Expectations. Our benchmark results can be interpreted as the causal effect of macroprudential policy on the GDP growth and distribution, provided that the policies included in the narrative measure of the $MaPP_{i,t}$ are not systematically correlated with short- to medium-term economic and financial fluctuations. In order to empirically test further this assumption, and in the spirit of Romer and Romer (2004), we expand our baseline specification including changes in the expected output growth over the following two quarters as an additional control. In that way, we account for the information set that policymakers have available when the policy is announced. We therefore include the expected output growth to summarise all unobserved factors that can simultaneously affect future GDP growth and policy decisions. Formally, we estimate equation (1), but augmented the set of controls $\mathbf{x}_{i,t}$ with changes in expected growth over the following two quarters. All other controls from the baseline are maintained. We note that if our narrative macroprudential policy index was not exogenous with respect to expectations in the baseline, then the addition of expected output growth as additional control should imply a significant change in the response of the GDP growth distribution following a macroprudential policy activation. However, we find that results with and without the expected economic outlook in the set of controls are qualitatively similar. This result therefore supports

[6] Mertens and Ravn (2012) examine the impact of changes in tax liability on the US. In particular, they explicitly differentiate between tax changes that are unexpected –tax changes whose delay between announcement and enforcement is lower than 90 days– and those that are announced in advance –policy changes which a delay between announcement and enforcement longer than 90 days–. They find that when a tax cut is announced but not yet implemented, it leads to a decrease in economic activity. On the other hand, when a tax cut is implemented, regardless of whether it was previously announced or not, it leads to an overall increase in economic activity. Their findings therefore show that the anticipation of policy changes can have a significant role in shaping the business cycle.

[7] The larger uncertainty in this specification can be explained by the lower variation in $MaPP_{i,t}$ when we only use policies without implementation lag to construct the index.

that the narrative identification performed in our empirical setting has been successful at the time of identifying plausibly exogenous variations in macroprudential policy.

Alternative Controls. We also assess the robustness of our findings to a range of alternative control specifications. First, we augmented our specification including a measure of financial conditions index (FCI) in our set of controls—that used by Adrian et al. (2022) and Lloyd et al. (2023). We find that, after controlling for such financial conditions, the results are qualitatively the same. Second, we augmented our specification to include controls for monetary policy—following recent research by Loria et al. (2022) who show that monetary policy has heterogeneous effects on the GDP-growth distribution.[8] This specification also helps to control for potential interlinkages between both monetary and macroprudential policies (e.g., Kim and Mehrotra, 2018; Altavilla et al., 2020; Coman and Lloyd, 2022). Therefore, this robustness analysis aims to show that our baseline results hold after controlling for the stance of monetary policy. In particular, we augment the baseline specification including the short-term interest rate as an additional control. We find similar results with and without the monetary policy instrument in the control set.

Alternative Country Fixed Effects. In the baseline, we use Kato et al. (2012) country fixed effects, which is easily estimated by including units-quantile-specific dummies in the quantile regression. Such an estimator is consistent and asymptotically normal when both the number of observations (N) and periods (T) tend to infinitive. However, such an estimator can be inconsistent in empirical applications where N is relatively large compare to T. Even though in our empirical application ($T \gg N$), in this robustness, we aim to explore whether our results are sensitive to the specific way in which fixed effects were estimated in our benchmark specification. We therefore re-estimate equation 3 using the Machado and Santos Silva (2019) country-fixed effects. They propose a quantiles-via-moments estimator whose estimation is performed using two-fixed-effects regressions and computing a univariate quantile. We find that our baseline results and their economic implications are not sensitive to the particular way in which country-fixed effects are estimated.

[8] In particular, they find that the 10th percentile of the predictive growth distributions responds about three times more than the median to a monetary policy shock.

4 Exploring the Transmission Channels

So far, we have shown that macroprudential policy has causal positive (negative) effects on the left (right) tail of the GDP-growth distribution. In this section, we turn to analysing how macroprudential policy transmits in this way to the GDP-growth distribution, exploring the mechanisms behind these results. Why does macroprudential policy have positive effects on the lower end of the GDP growth distribution? Why do these policies have the opposite effect on the upper end of the GDP growth distribution? To do so, we first investigate the impact of macroprudential policy on intermediate variables, like credit growth, and then link the effects of these intermediate variables to the GDP-growth distribution.

4.1 Quantity of Credit: Credit-at-Risk Channel

Recent literature has consistently found that financial booms, particularly credit booms, often precede financial crises (Schularick and Taylor, 2012; Jordà et al., 2015; Richter et al., 2021). Therefore, the prevention and mitigation of credit booms is a reasonable candidate for the main channel through which macroprudential policy can reduce left-tail events. Quantile regressions offer a ideal framework to explore this mechanism in detail.

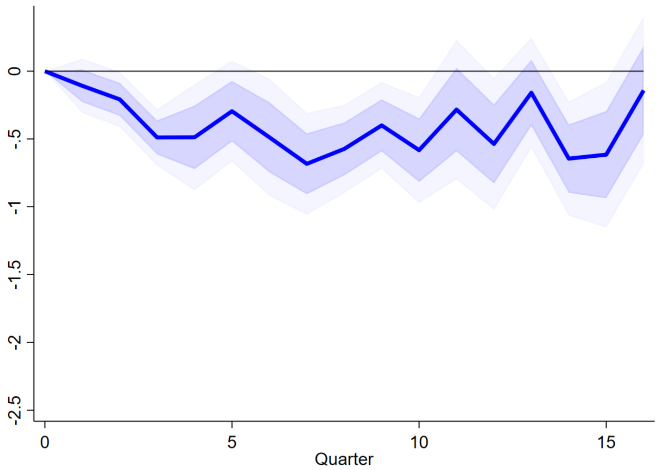
Our approach consists of two steps. First, we show that macroprudential policy is particularly effective at mitigating excessive credit growth—i.e., we find that tightening macroprudential policy push particularly down the 90th percentile of the credit distribution. Our second step then shows that the upper tail of the credit distribution—i.e., the 90th percentile of credit growth, is strongly and systematically negatively related with the left-tail of the GDP growth distribution. This second step allows us to show that credit growth in a credit boom state systematically boost vulnerabilities in the economy.

We start by estimating the responses of different future credit quantiles through local projections, using average annual real credit as the dependent variable, following a tightening macroprudential policy activation. Hence, $\Delta y_{i,t+h}$ now refers to the annual average real private credit growth over h quarters. Therefore, we formally explore whether macroprudential policies have an asymmetric impact on the credit growth distribution.

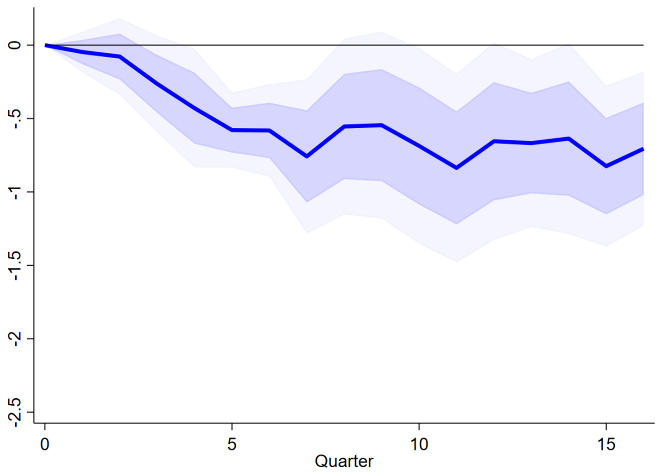
We plot the impulse responses of the credit quantiles after a contractionary policy shock in Figure 4, with corresponding point estimates and standard errors shown in Table 2. We focus again on the 10th, 50th and 90th percentiles. The main takeaway from Figure 4 is that there is

Figure 4: Impulse Response of Quantiles of the Credit-Growth Distribution to Macroprudential Policy Tightenings

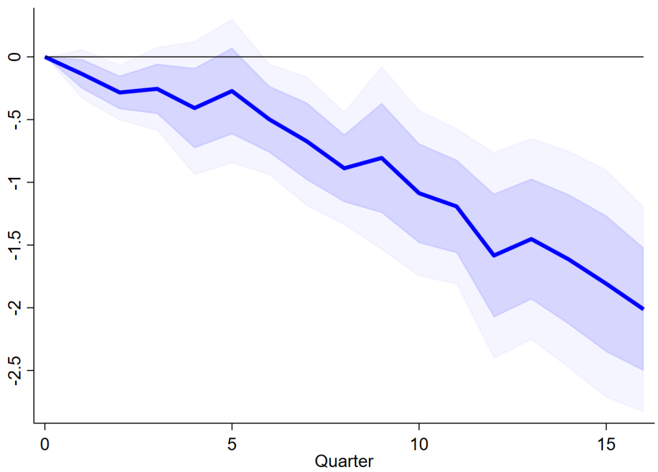
Panel (a): 10th Percentile



Panel (b): Median



Panel (c): 90th Percentile



Notes: Estimated change in the τ-th percentile of annual average real credit growth at horizon $h = 1, 2, ..., 16$, following a tightening macroprudential policy activation. Sample period is 1990Q1-2017Q4. Shaded areas denote the 90% (light blue) and 68% (dark blue) confidence intervals based on bootstrap with 1000 replications.

Table 2: Coefficient estimates for $\beta^h(\tau)$ from regression of credit growth on narrative measure of macroprudential policy and controls

	$h = 4$	$h = 8$	$h = 12$	$h = 16$
$\tau = 0.1$	-0.49**	-0.57***	-0.54**	-0.14
	(0.23)	(0.19)	(0.29)	(0.32)
$\tau = 0.5$	-0.43**	-0.55ˆ	-0.65ˆ	-0.71**
	(0.24)	(0.36)	(0.40)	(0.31)
$\tau = 0.9$	-0.41ˆ	-0.89***	-1.58***	-2.01***
	(0.32)	(0.27)	(0.49)	(0.49)

Notes: This table presents coefficient estimates reflecting the association between the τ-th percentile of annual average real credit growth at horizon $h = 1, 2, ..., 16$ and a tightening macroprudential policy activation. Coefficient estimates of fixed effects and controls not reported. Sample period is 1990Q1-2017Q4, for 12 advanced economies. Standard errors are based on block bootstrap with 1000 replications and are shown in parenthesis with: ˆ $p < 0.32$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

a clear asymmetry in the response of credit after a macroprudential policy shock. In particular, the 90th percentile responds more than the median, which in turn moves more than the 10th percentile. We find that a tightening prudential shock pushes down the right tail more strongly than other parts of the distribution.

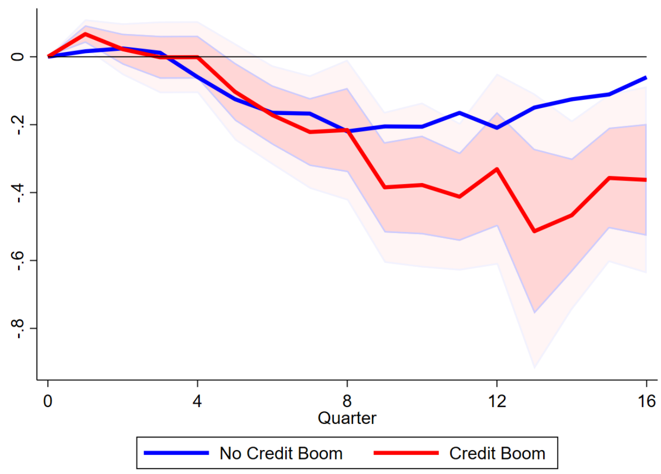
In our second step, we formally explore the role that credit plays in shaping future growth-at-risk by estimating the following state-dependent quantile local projections:

$$\begin{aligned} Q_{\Delta y_{i,t+h}}(\tau|\Delta Credit_{i,t}, \mathbb{1}^{Boom}_{i,t}, X_{i,t}) =& \boldsymbol{\alpha}^h_i(\tau) + \Delta Credit_{i,t}\beta^h(\tau) + \Delta Credit_{i,t} \times \mathbb{1}^{Boom}_{i,t}\gamma^h(\tau) \\ &+ \mathbf{x}'_{i,t}\boldsymbol{\vartheta}^h(\tau), \quad \tau \in (0, 1) \end{aligned} \tag{2}$$

where α^h_i refers to country- and quantile-specific fixed effects and $h = 1, 2, ..., H$, with $H = 16$. We focus on the 10th percentile to capture the non-linear impact of credit growth on GDP-at-Risk, i.e., $\tau = 0.1$. The set of controls $\mathbf{x}_{i,t}$ also includes now changes in our macroprudential policy index and the boom indicator. We create an indicator variable $\mathbb{1}^{Boom}_{i,t}$ based on the distribution of 2-year credit growth in our within-country year panel. In particular, we define the credit boom indicator as follows:

$$\mathbb{1}^{Boom}_{i,t} = \begin{cases} 1 & \text{if} \quad \Delta_8 Credit_{i,t} > \Delta_8 Credit_{i,90th} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Figure 5: State-Dependent Impulse Response of 10th percentile of the GDP-Growth Distribution to +1std in credit growth



Notes: Estimated change in the 10th percentile of annual average real GDP growth at horizon $h = 1, 2, ..., 16$, following a +1std in credit growth. State dependency: credit booms versus non-credit booms periods. Sample period is 1990Q1-2017Q4. Shaded areas denote the 68% (light red) and 90% (dark red) confidence interval based on bootstrap with 1000 replications.

We note that this distribution-based credit boom definition is consistent with the existing literature on credit boom measurement (see, e.g., Greenwood, Hanson, Shleifer, and Sørensen, 2022). Under this specification, $\beta^h(\tau)$ captures the association between real credit growth and the growth-at-risk in non-boom periods. $\gamma^h(\tau)$, in turn, tracks how the response of the 10th percentile of real annual GDP growth following a +1std in credit-growth differs in boom versus non-boom periods. Therefore, $\beta^h(\tau) + \gamma^h(\tau)$ allow us to compute the average impact of real credit growth on future growth-at-risk when the economy is already in a credit-boom.

Figure 5 presents the main results from our empirical exercise. We note that overall credit growth is associated with a significant reduction in the left-tail of annual average domestic growth. This result holds in both boom and non-boom periods. However, this negative effect is particularly strong when the economy is already experiencing a credit-boom, suggesting that credit growth is especially associated with a deterioration in the growth-at-risk over the medium term in financial boom episodes. Our empirical finding therefore suggests that the prevention and mitigation of credit booms plays a major role in explaining why macroprudential policy is effective in defusing downside economic risks.

4.2 Composition of Credit

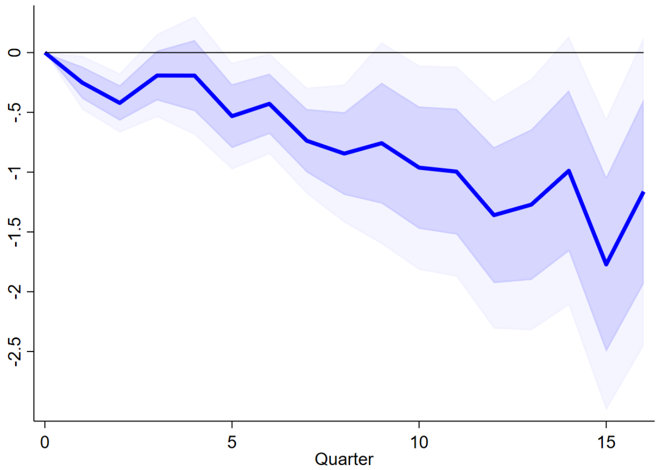
We now investigate the transmission of macorprudential policy through its affect on the composition of credit. In particular, we are interested in assessing whether macroprudential policies are particularly effective at preventing 'bad' credit booms.

To do so, we separate total credit, our baseline dependent variable, into household and business credit. The former is commonly considered as less productive credit, as most of this credit often ends up in consumption. Instead, the latter has been widely associated with productive credit, as this credit normally is used to increase the production capacity and therefore the supply side of the economy. Our credit classification is motivated by the recent work of Müller and Verner (2021). They use a novel database on sectoral credit distribution for 116 countries between 1940-2017 and show that lending to households and the non-tradable sector, rather than to the tradable sector, contributes to macroeconomic boom-bust cycles. In particular, they show that household credit is heavily associated with unsustainable demand booms, high financial fragility and resource missallocation across sectors. On top of that, they ultimately find that such household lending booms also predict elevated financial crisis risk and productivity slowdowns. In contrast, tradable-sector credit expansions are followed by stable output and productivity growth without a higher risk of a financial crisis. This empirical evidence is consistent with theoretical evidence that has revealed an important distinction between credit booms that tend to increase the productive capacity of the economy and those that tend to boost demand for final consumption goods (e.g., Kalantzis, 2015; Schmitt-Grohé and Uribe, 2016; Ozhan, 2020; Mian et al., 2020).

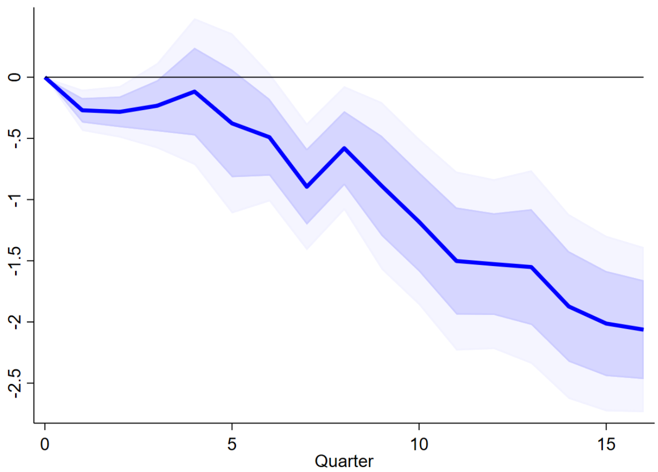
We use quantile local projections to estimate how real household and business credit change following a tightening macroprudential policy shock. We focus on the 90th percentile of the credit distribution to explore the effectiveness of macroprudential policy to prevent bad versus good credit booms. The set of controls is the same as in the benchmark specification, which had total credit as the dependent variable.

Figure 6: Impulse Response of 90th percentile of the Credit-Growth Distribution to Macroprudential Policy Tightenings

Panel (a): Household Credit



Panel (b): Business Credit



Notes: Estimated change in the 90th percentile of annual average real household and business credit at horizon $h = 1, 2, ..., 16$, following a tightening macroprudential policy activation. Sample period is 1990Q1-2017Q4. Shaded areas denote the 90% (light blue) and 68% (dark blue) confidence interval based on bootstrap with 1000 replications.

Table 3: Coefficient estimates for $\beta^h(\tau)$ from regression of household and business credit growth on narrative measure of macroprudential policy and baseline controls at 90th percentile

	$h = 4$	$h = 8$	$h = 12$	$h = 16$
Household Credit	-0.19	-0.84**	-1.36**	-1.16
	0.30	0.35	0.57	0.77
Business Credit	-0.12	-0.58**	-1.53***	-2.06***
	0.36	0.30	0.42	0.40

Notes: This table presents coefficient estimates reflecting the association between he 90th percentile of annual average real household and business credit growth at horizon $h = 1, 2, ..., 16$ and a tightening macroprudential policy activation. Coefficient estimates of fixed effects and controls not reported. Sample period is 1990Q1-2017Q4, for 12 advanced economies. Standard errors are based on block bootstrap with 1000 replications and are shown in parenthesis with: ˆ $p < 0.32$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We present the response of the upper end of household versus business credit distribution following a macroprudential policy shock in Figure 6, and the coefficient estimates in Table 3. The main conclusion from Figure 6 is that macroprudential policy does prevent and mitigate both household credit and business credit booms. Recall that we have previously stated that the existing literature has shown that household credit booms are systematically associated with systemic financial crises, while business credit booms overall are not. We therefore argue that while macroprudential policy has benefits for the left-tail of the GDP growth distribution by preventing credit booms that often end up in systemic financial crises, it may also present some economic costs by preventing good credit booms that are systematically associated with future productivity gains, thereby limiting the right-tail of GDP growth.

4.3 House Prices

Asset-price dynamics and in particular housing price bubbles have been shown to be systematically associated with future severe financial crises, especially when fuelled by credit expansions (Jordà et al., 2015; Richter et al., 2021). Therefore, it is natural to formally explore the extent to which changes in house prices following a tightening macroprudential policy activation are consistent with the observed post-policy growth vulnerabilities dynamics. To do so, we estimate the responses of different future house-price quantiles through local projections, using average annual real house price as our new dependent variable. Therefore, $\Delta y_{i,t+h}$ now denotes the annual average real house-price growth over h quarters. This specification allow us to formally explore whether macroprudential policies have a heterogeneous impact on the house-price distribution, and if so, to what extent the house-price channel can explain the positive effects we found on the left-tail of the GDP-growth distribution following a tightening macroprudential policy shock.

Figure 7 presents the impulse response of quantiles of the conditional house-price growth distribution (for $\tau = 0.1, 0.5, 0.9$) to changes in our narrative macroprudential policy index across different horizons h. Table 4 presents the corresponding coefficient point estimates and standard errors. Our results point to a small negative impact of macroprudential policy on quantiles of the house-price growth distribution. However, the estimation uncertainty is very large, and the effect is not statistically significant at any quantile. The main implication from this empirical evidence is that the positive impact on growth-at-risk following a tightening macroprudential policy activation—shown in Section 3—cannot be explained by house-price dynamics after a tightening prudential policy activation. That is, there is no evidence that changes in house-price following a tightening macroprudential policy activation can generate the observed post-policy growth vulnerability dynamics.

Table 4: Coefficient estimates for $\beta^h(\tau)$ from regression of house-price growth on narrative measure of macroprudential policy and controls

	$h=4$	$h=8$	$h=12$	$h=16$
$\tau = 0.1$	-0.11	-0.11	-0.15	-0.02
	(0.12)	(0.16)	(0.24)	(0.33)
$\tau = 0.5$	-0.08ˆ	-0.24ˆ	-0.31ˆ	-0.18
	(0.07)	(0.17)	(0.24)	(0.29)
$\tau = 0.9$	0.03	0.05	-0.05	-0.06
	(0.14)	(0.18)	(0.23)	(0.34)

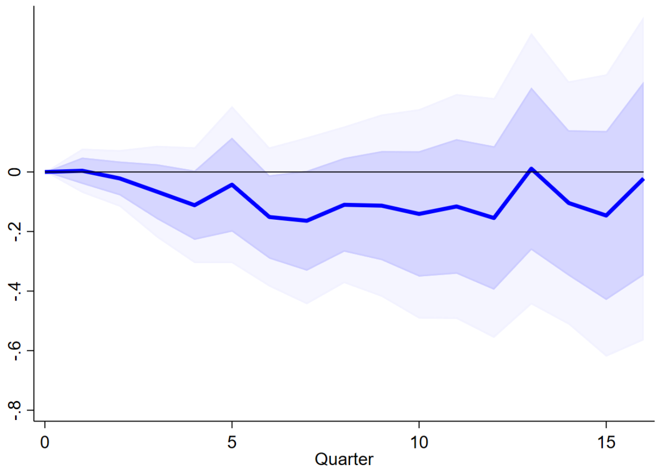
Notes: This table presents coefficient estimates reflecting the association between the τ-th percentile of annual average real house prices growth at horizon $h = 1, 2, ..., 16$ and a tightening macroprudential policy activation. Coefficient estimates of fixed effects and controls not reported. Sample period is 1990Q1-2017Q4, for 12 advanced economies. Standard errors are based on block bootstrap with 1000 replications and are shown in parenthesis with: ˆ $p < 0.32$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.4 Financial Conditions

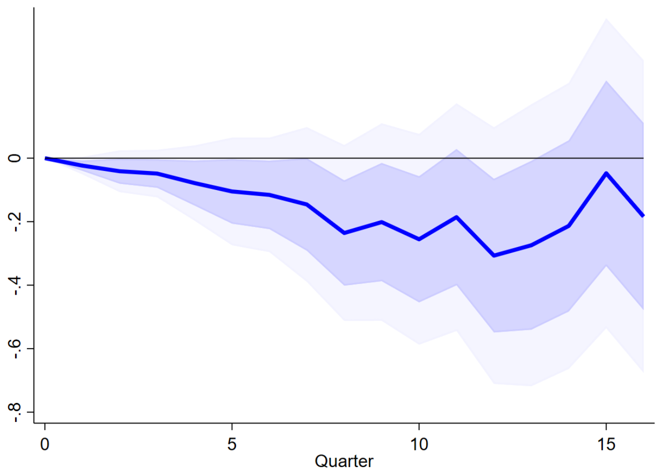
Financial conditions have been shown to play an important role to explain observed growth vulnerability dynamics (Adrian et al., 2019, 2022). We therefore study whether the financial conditions channel can be, on top of the credit-channel, a key driver of the positive effects that macroprudential policy exercises on the left-tail of the GDP-growth distribution. To do so, we follow Adrian et al. (2019, 2022) and use a domestic financial condition index (FCI) to measure

Figure 7: Impulse Response of Quantiles of the House-Price Distribution to Macroprudential Policy Tightenings

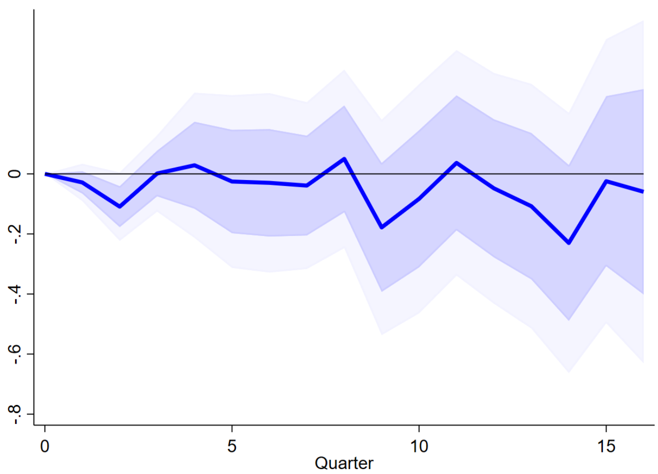
Panel (a): 10th Percentile



Panel (b): Median



Panel (c): 90th Percentile



Notes: Estimated change in the τ-th percentile of annual average real house prices growth at horizon $h = 1, 2, ..., 16$, following a tightening macroprudential policy activation. Sample period is 1990Q1-2017Q4. Shaded areas denote the 90% (light blue) and 68% (dark blue) confidence intervals based on bootstrap with 1000 replications.

financial conditions in the economy.[9] We then explore the extent to which macroprudential policy have an asymmetric impact in future financial conditions quantiles using local projections. We therefore now use the annual change in the financial condition index as our dependent variable in this specification, i.e., $\Delta y_{i,t+h}$ is the annual change in the financial condition index over h quarters.

We plot the impulse responses of financial conditions quantiles after a contractionary policy shock in Figure 8, with corresponding point estimates and standard errors shown in Table 5. We focus again on the 10th, 50th and 90th percentiles. The main takeaway from Figure 8 is that there is a significant drop in asset-prices over the midterm in response to a tightening macroprudential policy shock. However, we do not find evidence of asymmetries in the impact of such policies across the asset-price distribution. Moreover, the effects are, albeit significant, not large enough in magnitude to argue that the asset-price channel can be behind our baseline growth-at-risk results in section 3. We therefore find limited evidence of other significant channels (e.g., via asset prices) through which macroprudential policy affects the conditional distribution of GDP growth and conclude that the credit-channel plays a major role explaining the heterogeneous impact of macroprudential policy on the GDP-growth distribution.

Table 5: Coefficient estimates for $\beta^h(\tau)$ from regression of financial conditions change on narrative measure of macroprudential policy and controls

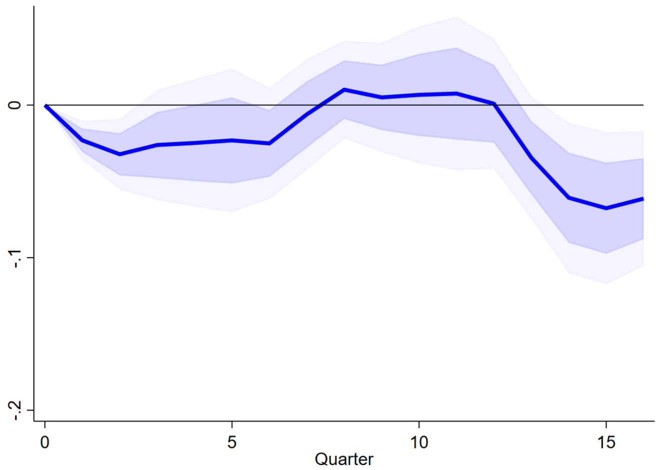
	$h = 4$	$h = 8$	$h = 12$	$h = 16$
$\tau = 0.1$	-0.02ˆ	0.01	0.00	-0.06**
	(0.02)	(0.02)	(0.03)	(0.03)
$\tau = 0.5$	-0.02**	-0.00	-0.04***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.02)
$\tau = 0.9$	-0.00	-0.02	-0.07***	-0.09**
	(0.03)	(0.03)	(0.03)	(0.05)

Notes: This table presents coefficient estimates reflecting the association between the τ-th percentile of annual average financial conditions change at horizon $h = 1, 2, ..., 16$ and a tightening macroprudential policy activation. Coefficient estimates of fixed effects and controls not reported. Sample period is 1990Q1-2017Q4, for 12 advanced economies. Standard errors are based on block bootstrap with 1000 replications and are shown in parenthesis with: ˆ $p < 0.32$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

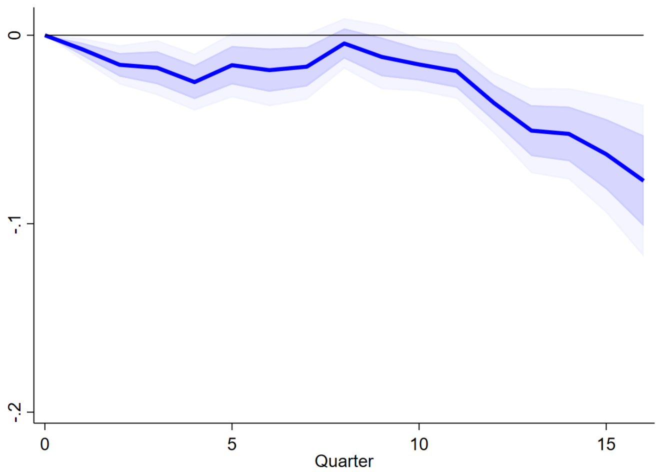
[9] The financial conditions index provides a weekly estimate of domestic financial conditions in money markets, debt and equity markets, and the traditional and shadow banking systems. Adrian et al. (2019) show that conditional quantile function is most sensitive to the overall financial conditions index than other standard measures of financial conditions such as equity volatility, term spread or credit spread.

Figure 8: Impulse Response of Quantiles of the Financial Conditions Index (FCI) Distribution to Macroprudential Policy Tightenings

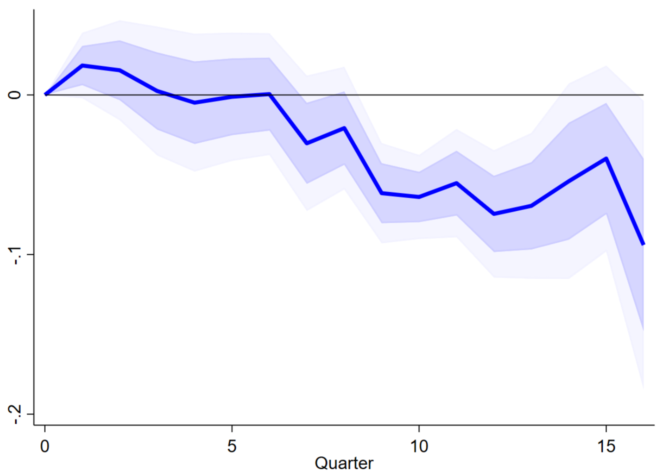
Panel (a): 10th Percentile



Panel (b): Median



Panel (c): 90th Percentile



Notes: Estimated change in the τ-th percentile of annual average financial conditions change at horizon $h = 1, 2, ..., 16$, following a tightening macroprudential policy activation. Sample period is 1990Q1-2017Q4. Shaded areas denote the 90% (light blue) and 68% (dark blue) confidence intervals based on bootstrap with 1000 replications.

5 Conclusion

In this paper, we have estimated the effects of macroprudential policies on the entire distribution of GDP growth by incorporating a narrative identification strategy within a quantile-regression framework. Exploiting a dataset covering a range of macroprudential policy actions across advanced economies, we identify unanticipated and exogenous narrative macroprudential policy 'shocks' and employ them within a quantile-regression setup to investigate causal effects across the distribution. While macroprudential policy has near-zero effects on the centre of the GDP-growth distribution, we find that tighter macroprudential policy brings benefits, by significantly and robustly boosting the left tail of future GDP growth, while simultaneously reducing the right tail. Assessing a range of potential channels through which these effects could materialise, we find that macroprudential policy operates through opposing tails of GDP and credit. Tighter macroprudential policy reduces the right tail of the future credit-growth distribution (both household and corporate) which, in turn, is important for mitigating left-tail GDP-growth risk.

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Appendix

A Weighting Scheme and Data Sources

Table A1: Weighting Scheme for Different Macroprudential Policy Actions in Narrative Measure

Type of Policy Action	Weight	Strengthening / Loosening	Sign	Final Weight
Activation	1	Tightening	+	1
		Other/ambiguous impact		0
		Loosening	-	-1
Change in the Level	0.25	Tightening	+	0.25
		Other/ambiguous impact		0
		Loosening	-	-0.25
Change in the Scope	0.10	Tightening	+	0.10
		Other/ambiguous impact		0
		Loosening	-	-0.10
Maintaning the Existing Level and Scope	0.05	Tightening	+	0.05
		Other/ambiguous impact		0
		Loosening	-	-0.05
Deactivation	Dependent on the life-cycle of the tool (cumulative index drops to zero)			

Notes: Description of the weights used to construct the cumulative index for each policy instrument based on Meuleman and Vander Vennet (2020).

Table A2: List of Data Sources

Variables	Source
Gross Domestic Product (GDP)	OECD database
Consumer Price Index (CPI)	Federal Bank Reserve of St.Louis (FRED)
Total Credit to the Private Non-Financial Sector	Bank for International Settlements (BIS)
Total Credit to Households	Bank for International Settlements (BIS)
Total Credit to non-financial corporations	Bank for International Settlements (BIS)
House Prices	Bank for International Settlements (BIS)
VIX	Datastream
GDP forecast	OECD database
3-Month or 90-day Rates and Yields: Interbank Rates	IFS + FRED
Financial Crises	ECB/ESRB EU crises database
Macroprudential Policy Index ($MaPP$)	Authors' estimation using MaPPED database

B Sensitivity Checks

In this appendix, we present our findings from all the robustness exercises described in Section 3.2.

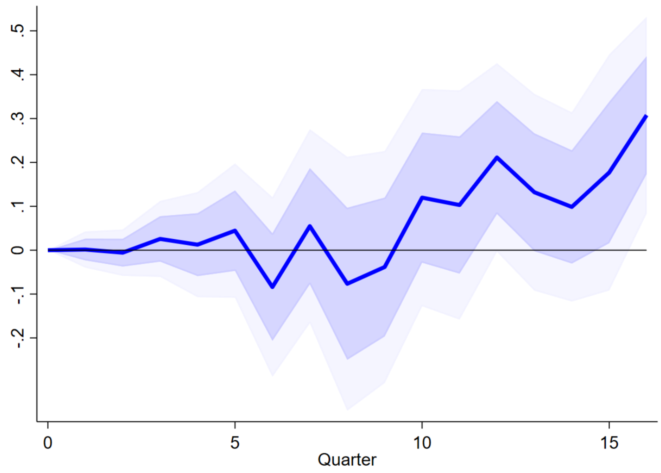
Table B.1: Baseline and Robustness estimation results: GDP-growth distribution

			$\tau = 0.1$			
	Baseline	No Implementation Lag	Expectation Data	FCI	Monetary Policy	Alternative CFE
$h = 4$	0.02	0.01	0.04	0.01	0.01	0.01
	(0.04)	(0.07)	(0.04)	(0.06)	(0.04)	(0.04)
$h = 8$	0.15**	-0.08	0.15**	0.14**	0.11**	0.10^
	(0.08)	(0.17)	(0.08)	(0.07)	(0.06)	(0.08)
$h = 12$	0.25***	0.21^	0.24**	0.18**	0.20***	0.21**
	(0.09)	(0.13)	(0.10)	(0.07)	(0.06)	(0.11)
$h = 16$	0.32***	0.31**	0.31***	0.19**	0.25***	0.25**
	(0.08)	(0.13)	(0.08)	(0.08)	(0.08)	(0.14)
			$\tau = 0.5$			
	Baseline	No Implementation Lag	Expectation Data	FCI	Monetary Policy	Alternative CFE
$h = 4$	0.03^	0.01	0.04**	0.00	0.01	0.02
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
$h = 8$	0.05^	0.05^	0.06**	0.01	0.03	0.02
	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)	(0.05)
$h = 12$	0.02	0.00	0.03	-0.01	-0.01	0.01
	(0.05)	(0.09)	(0.04)	(0.05)	(0.04)	(0.05)
$h = 16$	0.06^	0.09	0.05	0.05	0.02	0.04
	(0.06)	(0.11)	(0.05)	(0.06)	(0.05)	(0.07)
			$\tau = 0.9$			
	Baseline	No Implementation Lag	Expectation Data	FCI	Monetary Policy	Alternative CFE
$h = 4$	-0.00	-0.00	-0.00	0.01	-0.01	0.03
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.07)
$h = 8$	-0.05^	-0.08^	-0.06^	-0.02	-0.05^	-0.04
	(0.04)	(0.07)	(0.04)	(0.05)	(0.04)	(0.05)
$h = 12$	-0.07^	-0.06^	-0.07^	-0.14**	-0.09^	-0.11**
	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)
$h = 16$	-0.14***	-0.05	-0.09^	-0.13***	-0.12**	-0.11**
	(0.05)	(0.08)	(0.07)	0.05	(0.06)	(0.06)

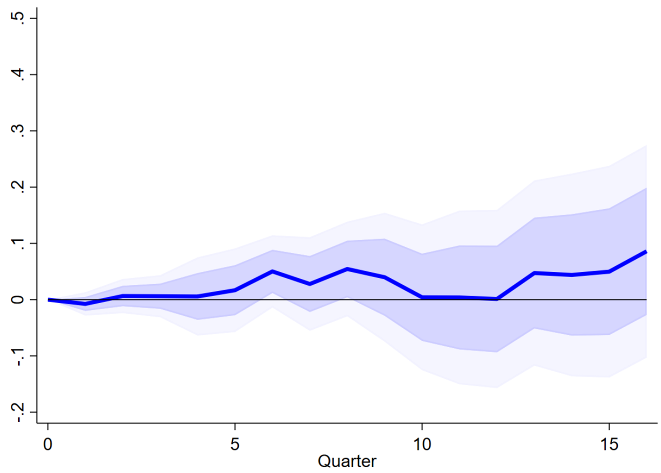
Notes: This table presents coefficient estimates reflecting the change in the τ-th percentile of annual average real output growth at horizon $h = 1, 2, ..., 16$, following a tightening macroprudential policy activation. Coefficient estimates of fixed effects and controls not reported. Sample period is 1990Q1-2017Q4. Standard errors are based on bootstrap with 1000 replications and show in parenthesis. ^ $p < 0.32$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B.1: **Lags in Policy Implementation**. Impulse Response of Quantiles of the GDP-Growth Distribution to Macroprudential Policy Tightenings.

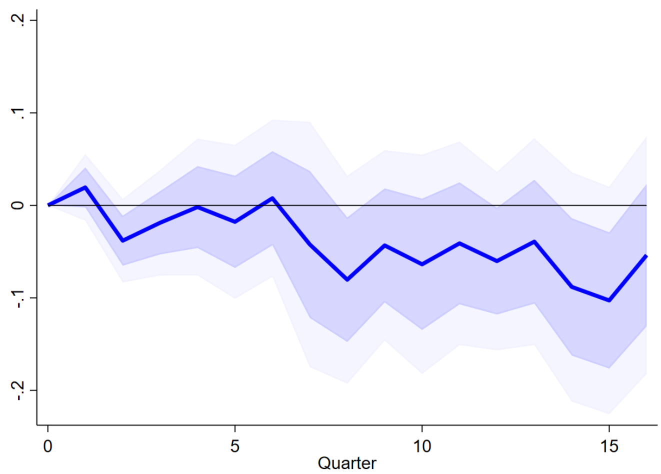
Panel (a): 10th Percentile



Panel (b): Median



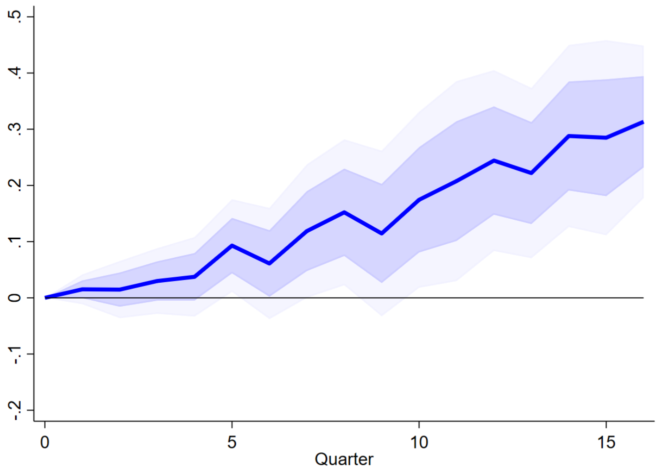
Panel (c): 90th Percentile



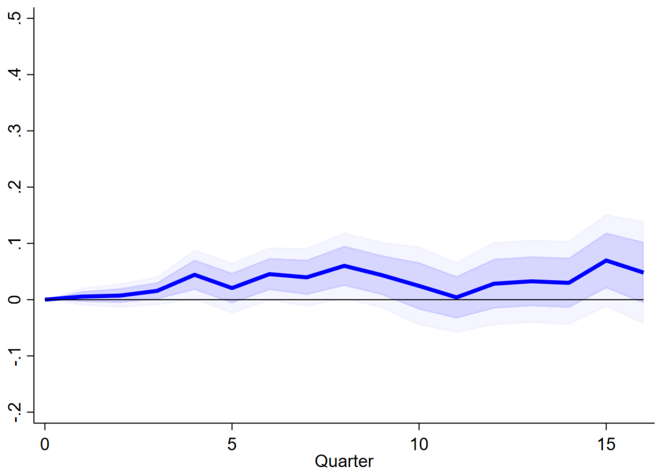
Notes: Excluding policies with implementation lag according to the 90 days threshold of Mertens and Ravn (2012). Estimated change in the τ-th percentile of annual average real GDP growth at horizon $h = 1, 2, ..., 16$, following a tightening macroprudential policy activation. Sample period is 1990Q1-2017Q4. Shaded areas denote the 90% (light blue) and 68% (dark blue) confidence interval based on bootstrap 1000 replications.

Figure B.2: **Accounting for expectations**. Impulse Response of Quantiles of the GDP-Growth Distribution to Macroprudential Policy Tightenings.

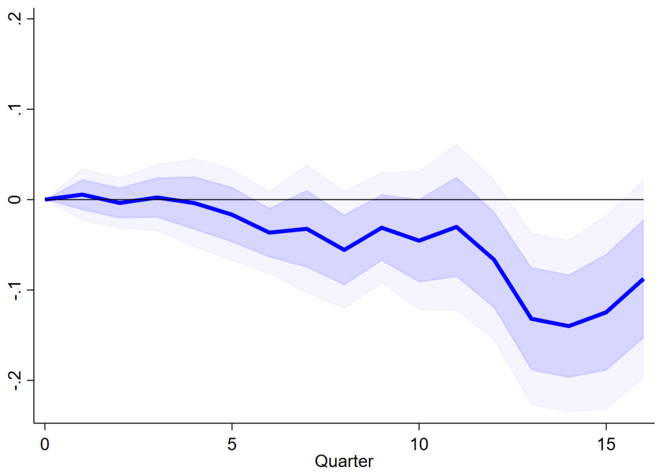
Panel (a): 10th Percentile



Panel (b): Median



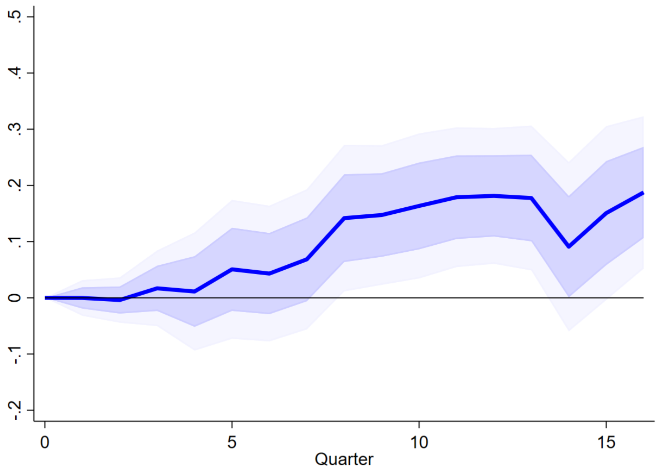
Panel (c): 90th Percentile



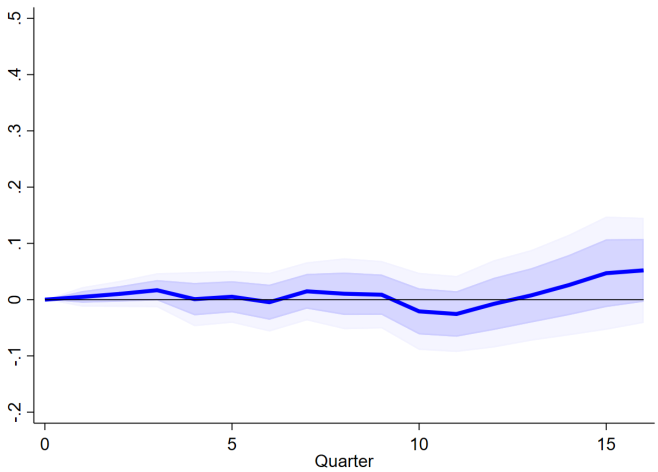
Notes: GDP growth forecast as an additional control. Estimated change in the τ-th percentile of annual average real GDP growth at horizon $h = 1, 2, ..., 16$, following a tightening macroprudential policy activation. Sample period is 1990Q1-2017Q4. Shaded areas denote the 90% (light blue) and 68% (dark blue) confidence interval based on bootstrap 1000 replications.

Figure B.3: **Alternative Controls: Financial Conditions Index (FCI)**. Impulse Response of Quantiles of the GDP-Growth Distribution to Macroprudential Policy Tightenings.

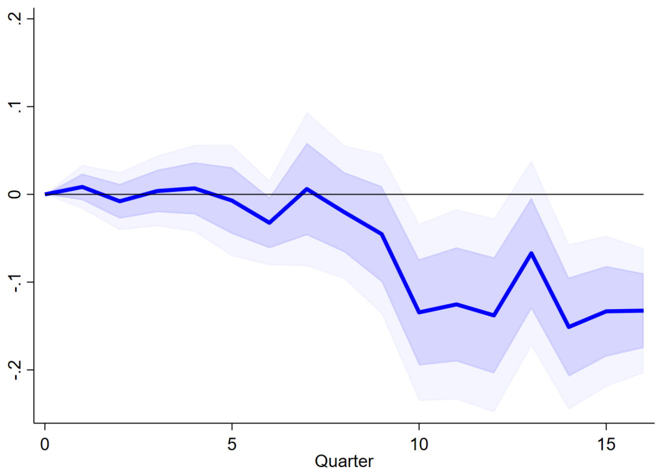
Panel (a): 10th Percentile



Panel (b): Median



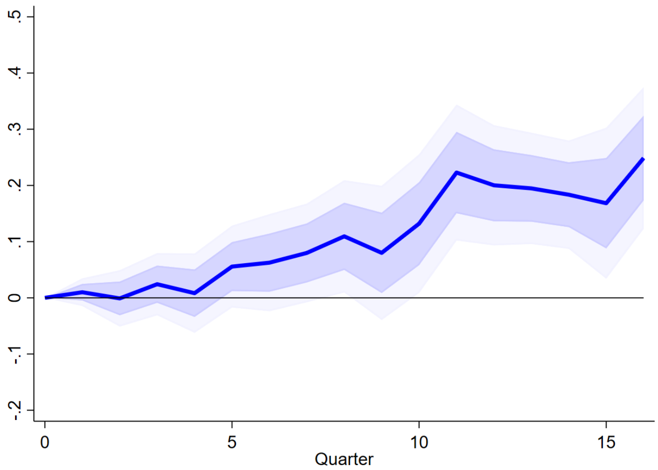
Panel (c): 90th Percentile



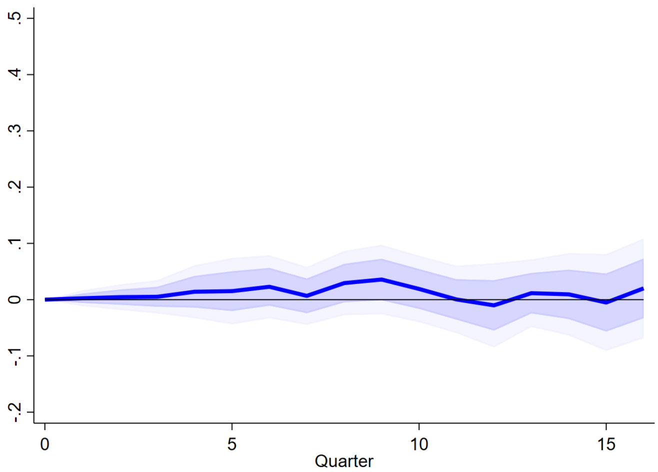
Notes: Control-augmented quantile local projections: Financial Condition Index (FCI). Estimated change in the τ-th percentile of annual average real GDP growth at horizon $h = 1, 2, ..., 16$, following a tightening macroprudential policy activation. Sample period is 1990Q1-2017Q4. Shaded areas denote the 90% (light blue) and 68% (dark blue) confidence interval based on bootstrap 1000 replications.

Figure B.4: **Alternative Controls: Monetary Policy**. Impulse Response of Quantiles of the GDP-Growth Distribution to Macroprudential Policy Tightenings.

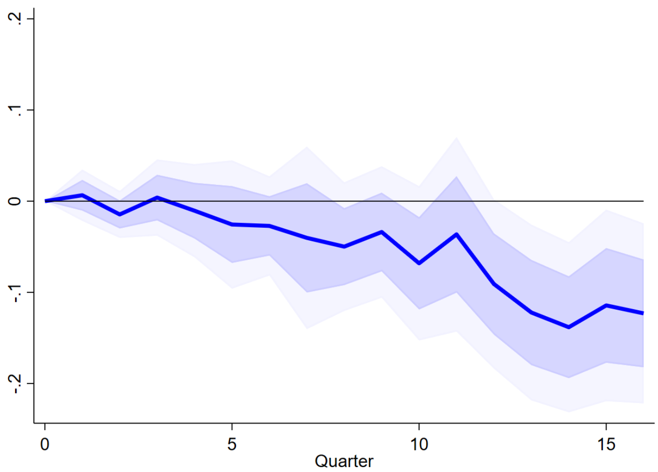
Panel (a): 10th Percentile



Panel (b): Median



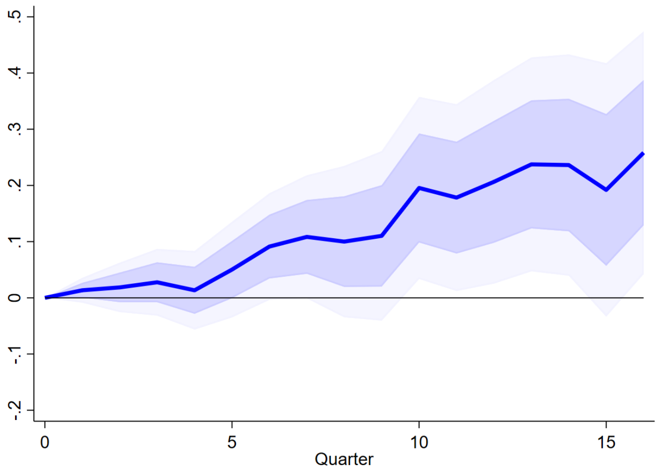
Panel (c): 90th Percentile



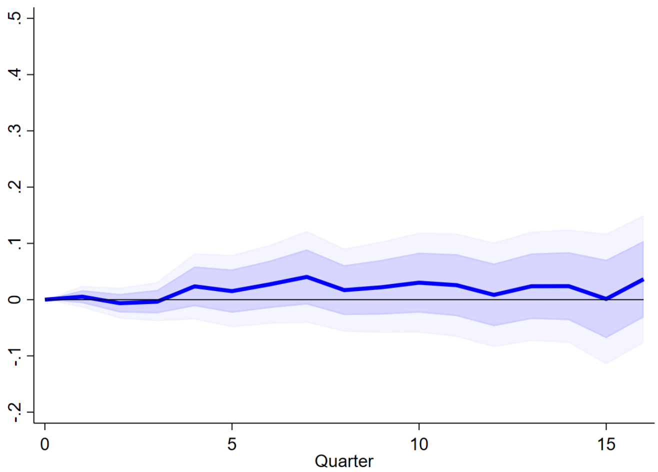
Notes: Control-augmented quantile local projections: Short-term interest rate. Estimated change in the τ-th percentile of annual average real GDP growth at horizon $h = 1, 2, ..., 16$, following a tightening macroprudential policy activation. Sample period is 1990Q1-2017Q4. Shaded areas denote the 90% (light blue) and 68% (dark blue) confidence interval based on bootstrap 1000 replications.

Figure B.5: **Alternative country fixed-effects**. Impulse Response of Quantiles of the GDP-Growth Distribution to Macroprudential Policy Tightenings.

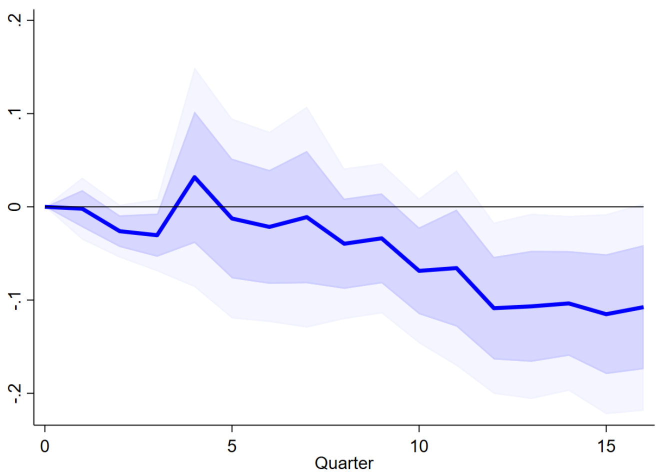
Panel (a): 10th Percentile



Panel (b): Median



Panel (c): 90th Percentile



Notes: Machado and Santos Silva (2019) country fixed-effects. Estimated change in the τ-th percentile of annual average real GDP growth at horizon $h = 1, 2, ..., 16$, following a tightening macroprudential policy activation. Sample period is 1990Q1-2017Q4. Shaded areas denote the 90% (light blue) and 68% (dark blue) confidence interval based on bootstrap 1000 replications.