# THE BENEFITS ARE AT THE TAIL: UNCOVERING THE IMPACT OF MACROPRUDENTIAL POLICY ON GROWTH-AT-RISK

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## Abstract

This paper brings together recent developments on the growth-at-risk methodology and the literature on the impact of macroprudential policy. For this purpose, I extend the recent proposals on the use of quantile regressions of GDP growth by including macrofinancial variables with early warning properties of systemic risk, and macroprudential measures. I identify heterogeneous effects of macroprudential policy on GDP growth, uncovering important benefits on the left tail of its distribution. The positive effect of macroprudential policy on reducing the downside risk of GDP is found to be larger than the negative impact on the median, suggesting a net positive effect in the mid-term. Nonetheless, I identify heterogeneous effects depending on the position in the financial cycle, the direction of the policy, the type of instrument, and the time elapsed since its implementation. In particular, tightening capital measures during expansions may take up to two years in evidencing benefits on growth-at-risk, while the positive impact of borrower-based measures is rapidly observed. This suggests the need of implementing capital measures, such as the countercyclical capital buffer, early enough in the cycle; while borrower-based measures can be tightened in more advanced stages. Conversely, in downturns the benefits of loosening capital measures are immediate, while those of borrower-based measures are limited. Overall, this study provides a useful framework to assess costs and benefits of macroprudential policy in terms of GDP growth, and to identify the term-structure of specific types of instruments.



**Keywords:** financial stability, growth-at-risk, systemic risk, macroprudential policy, quantile regressions.

**JEL classification:** C32, E32, E58, G01, G28.

## Resumen

Este estudio une los desarrollos recientes sobre la metodología de crecimiento en riesgo con la literatura sobre evaluaciones de impacto de la política macroprudencial. Para ello, extiendo el uso de regresiones cuantílicas del crecimiento del PIB con el objetivo de incluir variables macrofinancieras con propiedades de alerta temprana de riesgo sistémico y medidas macroprudenciales. Como resultado, encuentro efectos heterogéneos de la política macroprudencial sobre el crecimiento del PIB, los cuales permiten identificar beneficios importantes sobre la cola izquierda de su distribución. Este efecto positivo de la política macroprudencial en la reducción del crecimiento en riesgo es mayor que el impacto negativo sobre la mediana de la distribución, lo que sugiere un efecto neto positivo en el medio plazo. No obstante, estos efectos son heterogéneos y dependen de la posición en el ciclo financiero, la dirección de la política, el tipo de instrumento implementado y el tiempo transcurrido desde su implementación. En particular, el endurecimiento de medidas de capital durante fases expansivas del ciclo puede tardar hasta dos años en evidenciar beneficios sobre el crecimiento en riesgo, mientras que el efecto positivo de medidas de límites a los estándares crediticios se materializaría rápidamente. Esto sugiere la necesidad de implementar medidas de capital, como el colchón de capital anticíclico, con suficiente antelación respecto al desarrollo del ciclo, mientras que el endurecimiento de límites a los estándares crediticios podría implementarse en etapas más avanzadas. Por otra parte, durante episodios de crisis financieras, los beneficios de la liberación de capital son inmediatos, mientras que los de la relajación de límites a los estándares de crédito son más limitados. En general, este estudio brinda un marco de gran utilidad para la evaluación de los costes y los beneficios de la política macroprudencial en términos de crecimiento del PIB y permite identificar la estructura temporal de instrumentos específicos.

**Palabras clave:** crecimiento en riesgo, estabilidad financiera, política macroprudencial, regresiones cuantílicas, riesgo sistémico.

**Códigos JEL:** C32, E32, E58, G01, G28.

## 1. Introduction

The global financial crisis has evidenced the high costs of the accumulation of financial imbalances for the real economy. Aikman et al. (2019a) estimate that financial vulnerabilities built-up during the previous years to the great recession explain around three-quarters of the subsequent output loss in the US. Moreover, they identify that the magnitude of the negative impact could have been significantly reduced by the active use of macroprudential policies. Certainly, preventing and mitigating large negative effects of systemic risk on economic growth is the ultimate objective of macroprudential policy (ECB, 2009; ESRB, 2015).

Against this background, several recent empirical studies have assessed the effects of either individual or broad sets of macroprudential policies. Most of those studies have found important benefits in different dimensions. Claessens et al. (2013) find that macroprudential policy reduces asset prices and leverage growth by studying the effect of borrower-based measures on individual banks. Cerutti et al. (2017) identify that macroprudential measures are very effective on reducing credit growth during booming periods through a wide cross-country study. Also, using a broad sample of countries, Akinci and Olmstead-Rumsey (2018) identify that macroprudential measures are effective curbing credit growth and house prices appreciation and that, in particular, borrower-based measures are the most effective. Also, a set of studies have assessed the impact of macroprudential policy in terms of probabilities. Dell'Ariccia et al. (2016) find that macroprudential policies are effective on reducing the probability of systemic crises, Jiménez et al. (2017) identify that countercyclical capital measures increase the probability of survivor of firms, and Altunbas et al. (2018) find that macroprudential policy reduces the probability of banks' default.

However, these measures are difficult to be translated in terms of a more homogeneous and standardised measure of economic activity. In this regard, some few recent studies have assessed directly the impact of macroprudential policies on GDP growth, finding negative effects on the conditional mean. Kim and Mehrotra (2018) identify a negative impact of macroprudential policy on output after analysing an aggregation of many different instruments in Asian economies. Focusing on borrower-based measures, Richter et al. (2018) find that these instruments have negative effects on output growth over a four-year horizon and that the effects are clearer when they are tightened than when they are loosened. Regarding capital measures, Bedayo et al. (2018) identify negative effects of tightening this type of instruments on GDP growth in the short-run after studying the financial cycle in Spain over the last 150 years. These negative effects can be seen as costs of macroprudential policy. However, this would leave the analysis of the benefits in terms of different units of measure, which makes difficult a comprehensive cost-benefit analysis.

In this context, Boar et al. (2017) have shed some light on the benefits of macroprudential policy in terms of output by analysing its impact on the variance of the GDP growth distribution. The authors find that the most active countries in the use of macroprudential policy achieve a reduction in the variance of GDP growth which minimizes the likelihood of severe contractions. Thus, the reduction in the magnitude of GDP contractions that occur with certain probability could be seen as the potential benefits of macroprudential policy. This idea has been recently explored by Duprey and Ueberfeldt (2018) and Aikman et al. (2019b). The former study focuses on the complementarity between macroprudential and monetary policy, while the latter intends to forecast the GDP growth distribution conditional on the level of banks capital ratio. These two studies take advantage of the flexibility of quantile regressions to identify the impact on the left-tail of the GDP growth distribution, which can be interpreted as the downside risk of GDP.

The magnitude of a decline in GDP that occurs with a probability of 5% is known in the literature as growth-at-risk. In a recent study, Adrian et al. (2019) have evidenced the usefulness of this method for disentangling heterogeneous effects of macrofinancial variables on the GDP growth distribution. Certainly, the authors provide new evidence on the underestimation of downside GDP tail risk when using traditional models focused on the conditional mean, and on the importance of accounting for financial conditions in explaining the skewness of the GDP growth distribution at horizons of up to 1 year.[1]

Departing from that study, some extensions have been recently proposed. Adrian et al. (2018) apply a panel quantile regression to a sample of 22 advanced and emerging economies, where the distribution of GDP growth up to 8 quarters ahead is estimated conditional on inflation, a dummy identifying credit boom periods, GDP growth, and a financial conditions index. The focus of that study is to show that financial conditions not only affect the GDP growth distribution but also that its effects change over a 12-quarter projection horizon. Aikman et al. (2018) also applies a quantile regression to study the downside risk of GDP growth in the UK. The authors include two macrofinancial indices related to leverage and assets valuation, which are found to have good early warning properties of systemic crises. The authors find out that leverage imbalances and assets prices disequilibria have large negative effects on the left tail of the GDP growth distribution 4 and 12 quarters ahead. Loria et al. (2019) propose to use quantile regressions and local projections, as in Jorda (2005), in order to identify the effects of monetary policy, credit conditions, and productivity shocks on the tails of the GDP growth distribution. Applying this method to US data, the authors find that the effects of these shocks affect disproportionately more the left tail than other quantiles.

In this context, the growth-at-risk methodology offers a useful framework to assess the impact of macroprudential policies, not only due to the importance of the linkages between the financial sector and the real economy but also because mitigating the negative effects of financial imbalances on economic growth is the ultimate objective of macroprudential policy.[2] Against this background, the aim of this study is to bring together both strands of literature, on the impact assessment of macroprudential policy and growth-at-risk, in order to uncover heterogeneous effects of macroprudential policy on the GDP growth distribution that may facilitate the identification of costs and benefits in terms of the same unit of measure.

For this purpose, I extend the work in Adrian et al. (2019) by estimating quantile regressions of future GDP growth up to four years ahead on different types of macroprudential measures and macrofinancial variables related to credit, house prices, external imbalances and financial stress. I use a large sample of the 28 European Union (EU) countries from 1970 to 2018, which allows accounting for very different types of macroprudential measures while controlling for unobserved country-specific heterogeneity. This is a similar approach to that in Aikman et al. (2019b) but including the effect of a broad set of macroprudential policies rather than predicting the impact of changes in the banks' capital ratio. Thus, this study focuses on the marginal effects of macroprudential policy and the term structure of its impact rather than forecasting GDP growth. This work is also related to that presented by Duprey and Ueberfeldt (2018), who assess the effect of macroprudential measures in Canada through an index summarizing different policies.

Nonetheless, the aim of the authors is to study the interaction between macroprudential and monetary policy by assuming that macroprudential policy affects the left-tail while monetary

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[1] Although previous studies have proposed methods for the estimation of conditional predictive distributions of GDP growth (see Hamilton, 1989; Primiceri, 2005; Smith and Vahey, 2016; for two-state Markov chain, Bayesian VAR and Copula estimates, respectively), quantile regressions (Koenker and Basset, 1978) offer an easy and flexible method in terms of computation effort and requirements of assumptions. These properties have also extended its application to financial stability issues. In this context, the use of this tool by IMF (2017) has brought the topic to the policy debate.

[2] See ECB (2009) and ESRB (2015) for a definition of macroprudential policy and its objectives, as well as a description of the macroprudential framework in the European Union.

policy affects the median of the GDP growth distribution. Thus, the authors use quantile regressions as a first step of a broader analysis of shocks through a vector autoregressive (VAR) model; while in this work the impact of macroprudential policy is assessed across the entire distribution and over time in order to disentangle potential costs and benefits of these policies.

Another close study to this paper is the one by Sánchez and Röhn (2016), who include a set of macroprudential measures into a quantile regression using a panel data set of OECD countries. However, the aim of the authors is to study the effect of a broad range of policies including labour market, quality of institutions and banking supervision. Thus, the authors omit key macrofinancial controls associated to the activation of macroprudential policies such as measures of the build-up of systemic risk. The authors also focus on contemporaneous effects on the GDP growth distribution, which does not capture the impact of these policies over a mid-term span, which is key from a macroprudential policy perspective. In fact, the analysis of the impact over a mid-term horizon provides interesting insights on the speed and persistence of macroprudential policy over the GDP growth distribution. The present study also analyses the role of the financial cycle on the relationship between macroprudential policy and GDP growth, which allows differentiating between the effects of tightening and loosening policies. Finally, a more detailed analysis of the two most used types of macroprudential measures is performed, i.e. borrower-based and capital measures.

The results of this study uncover important heterogeneous effects of macroprudential policies on GDP growth. While macroprudential policy is found to have significant positive effects on reducing the downside risk of GDP, the impact on the median and the right tail of the distribution tend to be negative. These differential effects can be interpreted as benefits and costs of macroprudential policy. Moreover, the position in the financial cycle is identified to have a significant role on determining the magnitude and speed of the effects of macroprudential policy on the GDP growth distribution. In particular, tightening macroprudential policy during normal times and expansionary phases has a large positive impact on growth-at-risk in the mid-term, while loosening policies during crises has immediate positive effects on reducing the downside risk of GDP. A further inspection of the impact of specific types of instruments during normal times or expansions suggests rapid and persistent positive effects of tightening borrower-based measures on the left-tail of the GDP growth distribution, while the benefits of implementing capital measures may take around 8 quarters in being observed. Conversely, when crises materialize releasing capital has rapid positive effects, while loosening borrower-based measures has a limited impact. From a policy perspective, these results would encourage macroprudential authorities to implement capital measures early enough in the cycle, while policy actions to tighten lending standards could be implemented in advanced stages.

Overall, this study provides a useful framework to assess costs and benefits of macroprudential policies in terms of GDP growth, and to identify the term-structure of specific macroprudential instruments.

Besides this introduction, the rest of the paper is organized in four additional sections. Section 2 describes the data and presents an inspection of the main variables. Section 3 describes the methodology and presents the proposed empirical specification. Section 4 analyses the estimation results by focusing on the impact of macroprudential policies on the conditional GDP growth distribution over the cycle. Section 5 presents some robustness exercises. Finally, section 6 concludes the paper and discusses some implications for policymakers.

## 2. Data

The data set comprises quarterly time series for the 28 European Union countries from 1970Q1 to 2018Q4. This is an unbalanced panel containing 5,488 observations. The data sources of the variables are the European Central Bank (ECB) and the Bank of International Settlements (BIS). Besides the annual growth of GDP, the set of variables comprises the 2-year average change in the credit-to-GDP ratio, the 2-year average change in house prices, the current account balance, the Country-Level Index of Financial Stress (CLIFS), and a broad set of macroprudential measures collected in the ECB Macroprudential Database. A summary statistics of the macrofinancial variables is presented in Table 1. An inspection of these variables and their relationship to the GDP growth distribution is presented below.

Table 1. Summary statistics

| Variable | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|
| GDP (1y Growth) | -0.0255 | 0.0116 | 0.0273 | 0.0429 | 0.0742 |
| Credit-to-GDP (2y Av. Change) | -0.1231 | -0.0203 | 0.0349 | 0.0898 | 0.2061 |
| House prices (2y Av. Growth) | -0.1252 | 0.0126 | 0.0980 | 0.1985 | 0.3860 |
| Current account balance (% GDP) | -9.5471 | -3.1887 | 0.6368 | 1.9380 | 7.0951 |
| CLIFS | 0.0303 | 0.0594 | 0.0984 | 0.1709 | 0.3411 |

Source: ECB and BIS.

### 2.1. GDP growth and macrofinancial variables

The variable of interest ($y_{i,t+h}$) is defined as the annualized average growth rate of real GDP for every country over a time horizon *h* from 1 to 16 quarters ahead, as follows:

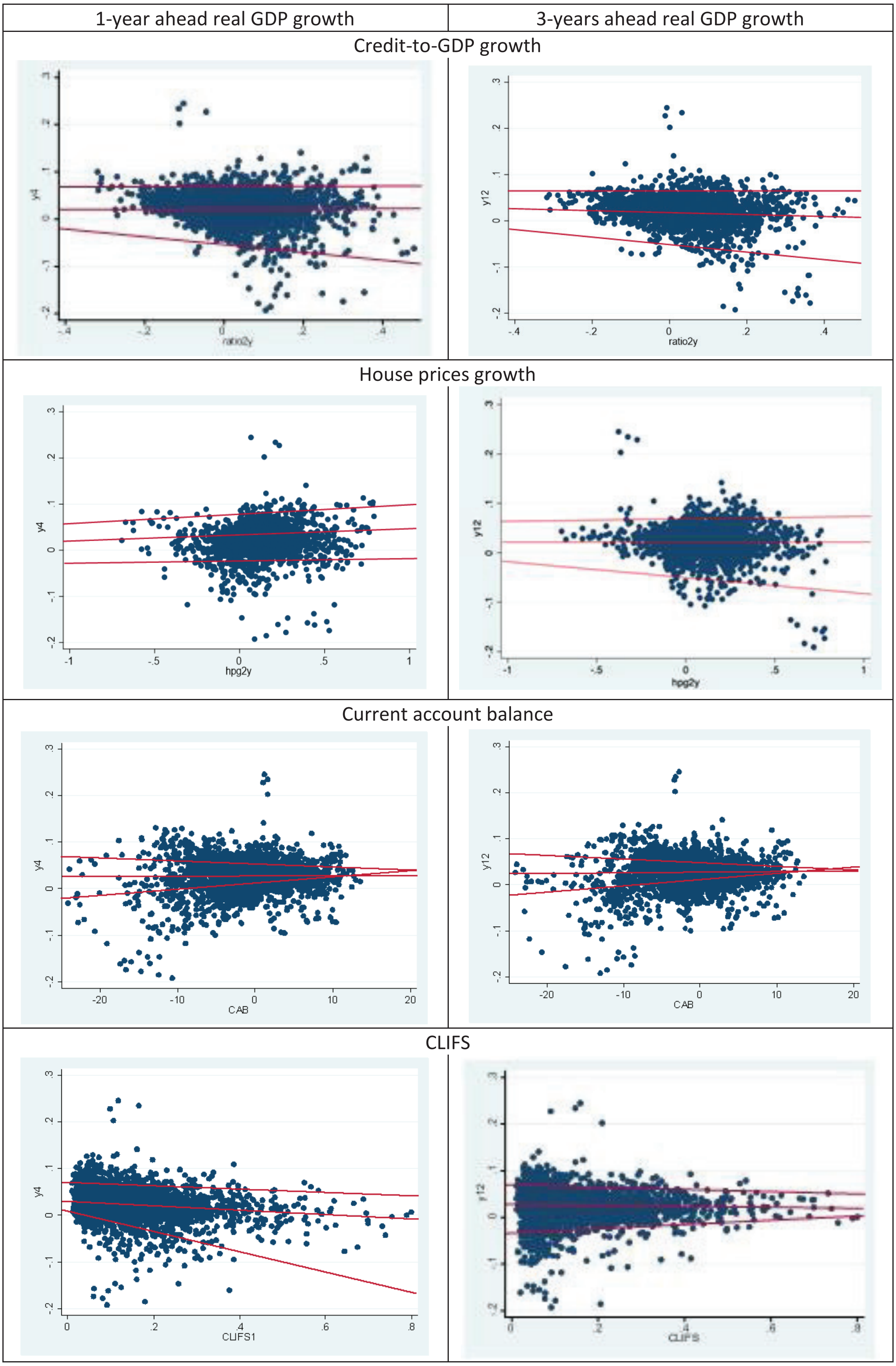
$$y_{i,t+h} = \ln\left(\frac{GDP_{i,t+h}}{GDP_{i,t+h-4}}\right); h = 1, \dots ,16 \quad (1)$$

A first inspection of this variable shows that its distribution is far from being normal due to the presence of fat tails as has been previously documented (see, Adrian et al, 2019; Loria et al, 2019). In Figure A1 in the Annex it can be observed that the left tail presents a higher density and may justify the need of a different fitting for the left tail than for the median or the mean.

The relationship between different quantiles of the GDP growth distribution and the systemic risk variables is an indication of the heterogeneous effects of these measures on the variable of interest. To explore this, I estimate simple pooled quantile regressions of GDP growth at the 5$^{th}$, 50$^{th}$ and 95$^{th}$ percentiles. Figure 1 shows the predicted values of these estimations for real GDP growth 4 and 12 quarters ahead. It is observed that not only the level but also the slope of the fitted values at the tails of the distribution are different from those at the median suggesting that quantile regressions may allow identifying heterogeneous effects of these variables on the GDP growth distribution. The fitted values for the 5$^{th}$ quantile are particularly different, evidencing that the effects at the tails are not symmetric. This is in line with the findings by Adrian et al (2019) using a financial conditions index.

There are also differences in terms of the horizon used for GDP growth. While the financial stress index evidences large differences in the fitted values of GDP growth 1-year ahead, the three cyclical systemic risk indicators exhibit larger differences 3-years ahead. This is consistent with previous studies exploring the use of early-warning systemic risk measures in quantile estimations of GDP growth (see Aikman et al., 2018; Lang et al., 2019). This also indicates the usefulness of including measures of cyclical systemic risk with good mid-term early-warning properties for characterizing GDP growth at longer horizons, which is not achievable using a financial conditions index only (see Adrian et al., 2019).

Figure 1.Univariate simple quantile regressions

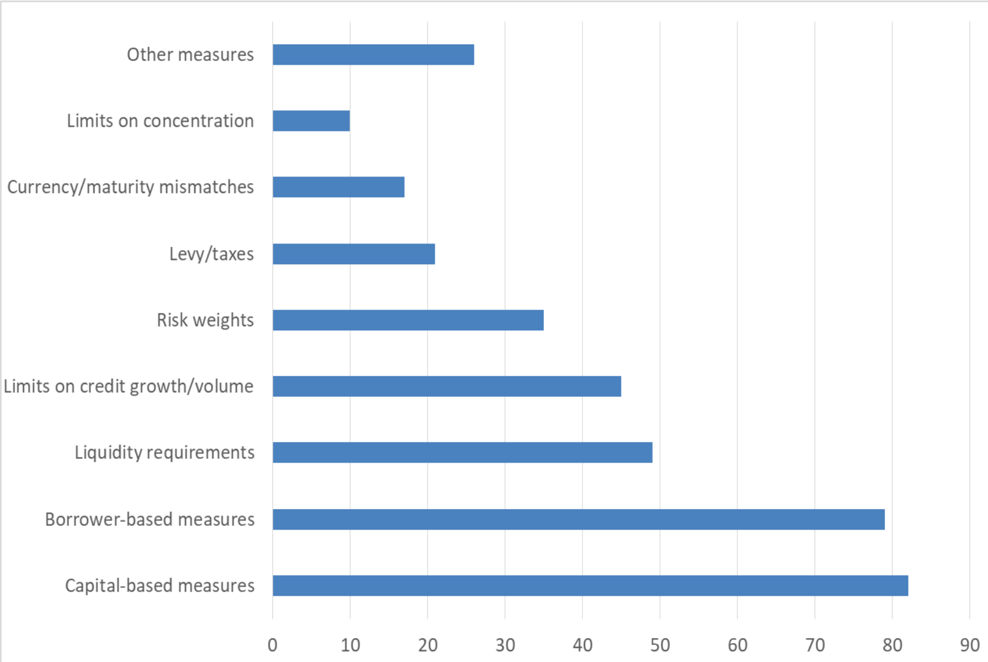



Note: The vertical axes represent the annual GDP growth one and three-years ahead. The horizontal axes represent the values of the different independent variables. The lower, middle and upper red lines represent the fitted values after estimating pooled simple quantile regressions at the 5th, 50th and 95th, respectively.

2.2. Macroprudential measures and index

The information on the implemented macroprudential measures in EU countries is collected from the recently published ECB Macroprudential Database introduced by Budnik and Kleibl (2018). This database contains very granular and detailed information on all the prudential measures taken by the 28 EU countries in different categories starting in 1951. This database represents a great repository of regulatory information over a long time span, and allows distinguishing between macro and microprudential measures, the type of instrument, and its direction, as well as detailed descriptions of each measure. Only those measures classified as having at least partly a macroprudential objective are retained for this exercise.

Figure 2. Macroprudential decisions in the EU countries 1970-2018 by category




Source: ECB Macroprudential Database. Own elaboration.
Note: The horizontal axis represent the number of macroprudential measures implemented by the 28 EU countries from 1970 to 2018 in each category, excluding those where the level or scope of the measure remains unchanged.

Figure 2 summarizes the number of macroprudential measures taken by the 28 EU countries from 1970 classified by category. This includes tightening and loosening measures but excludes decisions where the level or the scope of the instrument remains unchanged. It is observed that capital-based measures, which include capital requirements, loan-loss provisions and capital buffers, as well as borrower-based measures tackling lending standards, have been the most used type of macroprudential policy actions implemented in EU countries. These measures are followed by liquidity requirements, limits on credit growth and risk weights. Finally, taxes, limits to mismatches on currency and maturity, and limits to concentration have been less implemented by EU authorities for macroprudential purposes. The use of macroprudential policies has been heterogeneous among countries (Figure A2 in the Annex presents the distribution of macroprudential policies by country).

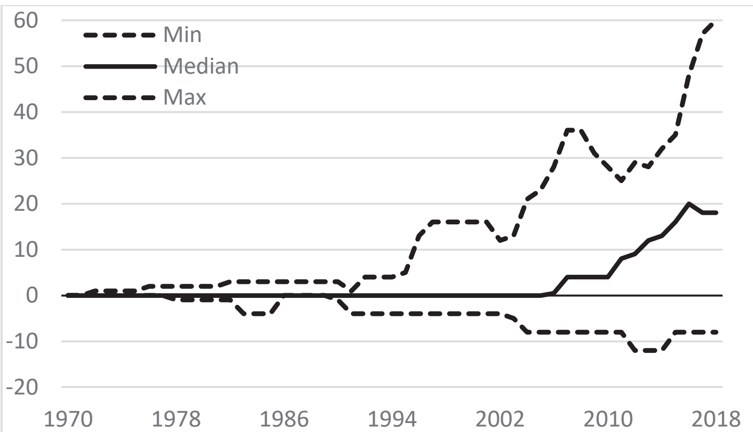
In order to analyse the use of macroprudential policies, an index that aggregates the different types of measures is constructed. In this regard, Cerutti et al. (2017) propose a way to compute a macroprudential policy index (MPI) for a large sample of countries. In this study, I follow their approach, which consists in a simple sum of the scores on different categories of macroprudential policies for each country. This approach has been followed also by other authors aggregating macroprudential measures with minor variations (Boar et al., 2017; Kim and Mehrotra, 2018; Duprey and Ueberfeldt, 2018; Alam et al., 2019). The advantage of the index constructed in this way compared to the use of dummy variables is that this index allows evaluating the effectiveness when more than one measure is in place, and then accounting for net tighten or loosen conditions (see Boar et al., 2017, for a discussion). The computation of the MPI is as follows:

$$MPI_{it} = \sum_{j=1}^{9} SP_{jit} \ ; \ SP_{jit} = SP_{jit-1} + \Delta SP_{jit} \ , \tag{2}$$

where, $MPI_{it}$ is the index for country $i$ at quarter $t$, computed as a sum of the scores $SP$ for each category $j$. In particular, the score of each category adds a value equal to 1 when a macroprudential measure is either activated or tightened within the category, while it subtract 1 when a measure is either deactivated or loosened within that category. If more than one measure is tightened or loosened in the same category and in the same quarter, then net sum of the measures is added to the score. Likewise other indexes constructed in the literature, the intention here is not to capture the intensity of the measures or their change over time, which would imply to know how binding each of the measure is in each country and introducing a lot of subjectivity that I prefer to avoid.

Figure 3 presents the evolution of the minimum, maximum and median values of the MPI in EU countries over time. It is observed that before the 90's, macroprudential policies where not very actively used. This situation starts to change during the second half of the 90's decade and has continued increasing, mainly in the last decade, due to the adoption of macroprudential policy and new toolkits of instruments in many countries as a consequence of the last financial crisis. As it could be expected, most of the policy actions have been tightening measures, but to the extent more measures are activated, then loosen policies become a possibility, as it is evidenced from the drop in the maximum and minimum values of MPI around the last financial crisis. Figure A3 in the Annex presents the number of tightening and loosening macroprudential policies over time.

Figure 3. MPI in the EU over time




Source: ECB Macroprudential Database. Own elaboration.
Note: The vertical axis represent the value of the MPI computed as in Eq. (1), where a positive value would mean that a given country is in a net tighten position, while a negative value imply that the country is in a net loosen position. The minimum, median and maximum values in the sample at every quarter from 1970 to 2018 are presented.

## 3. Methodology

### 3.1. Panel quantile regressions

Koenker and Basset (1978) proposed quantile regressions as a useful tool for the identification of differential effects on the distribution of a variable of interest instead of focusing on the conditional mean, which may mask distributional effects. Since then, the methodology has been applied in different fields. In finance the most standard application is the computation of value at risk (Jorion, 2001), which is the computation of the expected loss of a portfolio given the materialization of an extreme event that may occur with a 5% of probability. In economics, this idea is attractive to study the distributional effects over a macroeconomic variable. Cecchetti and Li (2008) use this method to study the impact of asset prices on the distribution of inflation and GDP growth, while De Niccolo and Lucchetta (2017) identify that this methodology provides more accurate forecasts of GDP downside risk than traditional VAR and FAVAR models. More related to financial stability the method has been used to assess the impact of systemic risk measures over the GDP growth distribution (Giglio et al., 2016; Aikman et al., 2018; Lang et al., 2019). More recently, Adrian et al. (2019) show that this methodology unmasks heterogeneous effects of financial conditions over the GDP growth distribution.

In general, quantile regression models allow accounting for heterogeneous covariates effects, while the availability of panel data allow including fixed effects to control for time-invariant unobserved heterogeneity. Application of quantile models with fixed effects is straightforward as it proceeds in a quantile-by-quantile fashion by allowing for a different fixed effect at each quantile (Koenker, 2005). Certainly, unobserved fixed effects can be included as in linear regression when *T* is large with respect to *N* (Koenker and Geling 2001). The large sample properties of these estimates are the same of standard quantile regressions when *T* is large both in absolute terms and relative to *N*. Thus, the quantile panel fixed effects model is represented as follows:

$$\widehat{\boldsymbol{Q}}_{y_{it}|\boldsymbol{X}_{it},\alpha_i}(\tau|\boldsymbol{X}_{it}, \alpha_i) = \widehat{\alpha}_{i\tau} + \boldsymbol{X}_{it}\widehat{\boldsymbol{\beta}}_{\tau} \quad (3)$$

$$\left(\widehat{\boldsymbol{\beta}}_{\tau}, \widehat{\alpha}_{i\tau}\right) = arg \min_{\alpha_i,\boldsymbol{\beta}_{\tau}} \sum_{i=1}^{n} \sum_{t=1}^{T-h} \rho_{\tau} \left|y_{it} - \boldsymbol{X}_{it}\boldsymbol{\beta}_{\tau} - \alpha_i\right| \quad (4)$$

$$\rho_{\tau} = \tau \cdot \mathbf{1}_{(y_{i,t} \geq \boldsymbol{X}_{it}\boldsymbol{\beta} + \alpha_i)} + (1-\tau) \cdot \mathbf{1}_{(y_{i,t} < X_{it}\boldsymbol{\beta} + \alpha_i)} \quad (5)$$

where, $\widehat{\boldsymbol{Q}}$ is the estimated quantile function; $\tau$ is a given percentile; $y_{it}$ is the dependent variable, $\boldsymbol{X}_{it}$ is a vector of explanatory variables, $\alpha_i$ represents a vector of individual unobserved effects, $\rho_{\tau}$ are weights that depend on the quantile, and $\mathbf{1}$ is an indicator function signaling whether the estimated errors are positive or negative. Koenker and Bassett (1978) show that $\widehat{\boldsymbol{Q}}_{y_{i,t}|x_{it}}(\tau|\boldsymbol{X}_{it})$ is a consistent estimator of the quantile function of $y_{it}|\boldsymbol{X}_{it}$ providing an inverse cumulative distribution function. The model is solved as an optimization problem where the weighted sum of the absolute value of the residuals is minimized, instead of the squared residuals as in linear regression.

However, if *T* is small relative to N or if *T* and *N* are of similar size, estimates of the common parameter $\beta$ may be biased or even under-identified, and an incidental parameters problem may arise. Kato et al. (2012) study how the relationship between the size of *N* and *T* is key to guarantee unbiased and asymptotic estimates in panel quantile regressions with individual effects, finding that the main problems arise when *T* is small. To solve these problems, several methods have been proposed in the literature. Koenker (2004) takes an approach where the $\alpha_i$'s are parameters to be jointly estimated with $\theta(\tau)$ for *q* different quantiles. He proposes a penalized estimator that correct for the incidental parameters problem. Canay (2011) propose a two-step estimator following the idea that $\alpha_i$ has a location shift effect on the conditional distribution that is the same across quantiles. In the first step the variable of interest is transformed by subtracting an estimated fixed effect, by first estimating a panel linear regression of the variable of interest on the regressors and averaging over *T*. The estimator is proved to be consistent and asymptotically normal as both *N* and *T* grow.[3] A related literature has also developed quantile panel data methods with correlated random effects (see Graham et al., 2015; Arellano and Bonhomme, 2016). In general, these estimators do not permit an arbitrary relationship between the treatment variables and the individual effects.[4]

Finally, very recently Machado and Santos Silva (2019) propose the estimation of quantiles via moments in order to estimate panel data models with individual effects and models with endogenous explanatory variables. The advantage of this approach is that it allows the use of methods that are only valid in the estimation of conditional means, while still providing information on how the regressors affect the entire conditional distribution. The approach is easy to implement even in very large problems and it allows the individual effects to affect the entire distribution, rather than being just location shifters.[5]

3.2. The empirical model

As described above, when *T* is large in relative terms to *N*, including additive unobserved fixed effects into a panel quantile regression provides consistent estimates. As it is described further below, the large sample constructed for this study allows following this approach. Nonetheless, in Section 5 we provide some robustness exercises using some of the recent panel quantile regression methods described above. The proposed baseline model is the following:

$$\widehat{\boldsymbol{Q}}_{y_{i,t+h}|x_{it},\alpha_i}(\tau|\boldsymbol{X}_{it},\alpha_i) = \widehat{\alpha}_{i\tau} + \hat{\beta}_{1\tau}y_{it} + \hat{\beta}_{2\tau}CLIFS_{it} + \hat{\beta}_{3\tau}credit_{it} + \hat{\beta}_{4\tau}HP_{it} + \hat{\beta}_{5\tau}CAB_{it} + \hat{\beta}_{6\tau}MPI_{it}; \qquad \tau = 5,10,\ldots 90,95; \qquad h = 1,\ldots,16 \tag{6}$$

where $y_{i,t+h}$ is the annualized GDP growth of country *i* at *t+h* quarters ahead as defined in Eq. (1); $\alpha_i$ represents the unobserved country-effects; $y_{it}$ is the contemporaneous GDP annual growth rate; $CLIFS$ is the index of financial stress; $credit$ is the 2-year average change in the credit-to-GDP ratio; $HP$ is the 2-year average growth in house prices; $CAB$ is the current account balance as a percentage of GDP; $MPI$ represents the macroprudential policy index; and $\tau$ represents the 19 estimated quantiles departing from the 5$^{th}$ to the 95$^{th}$ percentiles.

This specification extends the one proposed by Adrian et al. (2019) in two main directions. First, it adds three of the most informative mid-term early warning indicators of cyclical systemic risk (see Castro et al., 2016; Lang et al., 2019; for empirical testing), which would allow characterizing GDP growth at mid-term horizons. In fact, the financial conditions index included by Adrian et al. (2019) is only able to explain changes in the conditional GDP growth distribution at horizons between 1 and 4 quarters ahead. In this regard, Aikman et al. (2018) have found that early-

[3] There is also a related literature on non-separable panel data models. These types of models are flexible enough to provide quantile treatment effects, which are partially identified for fixed T (see Graham and Powell, 2012).

[4] Alternatively, Powell (2016) proposes a quantile regression estimator for panel data with non-additive fixed effects that accounts for an arbitrary correlation between the fixed effects and instruments. It is one of the few quantile fixed effects estimators that provides consistent estimates for small T and for quantile panel data estimators with instrumental variables.

[5] In a conditional location-scale model, the information provided by the conditional mean and the conditional scale function is equivalent to the information provided by regression quantiles in the sense that these functions completely characterize how the regressors affect the conditional distribution. This is the result that the authors use to estimate quantiles from estimates of the conditional mean and the conditional scale function.

warning cyclical systemic risk indicators perform well when assessing mid-term GDP tail risk. I also include the CLIFS, which incorporates more contemporaneous information of systemic risk and is intended to characterize the conditional GDP growth distribution at short horizons. Second, this is a panel specification, which allows taking advantage of more information, mainly regarding the use of macroprudential policies, while accounting for country-level fixed effects. At methodological level, the large number of observations of this sample makes possible to include all the variables in the baseline specification and still obtain reliable estimates with low and high quantiles.[6]

In order to assess the goodness of fit of the models, I compute the pseudo-$R^2$ ($\tilde{R}^2$) proposed by Koenker and Machado (1999). This measure is dependent on the quantile, so it is a local measure of fit of the quantile specific regression and differs from the OLS $R^2$. In particular, the measure compares the sum of weighted deviations for the model of interest with the same sum from a model in which only the intercept appears, and is defined as follows:

$$\tilde{R}^2(\tau) = 1 - \frac{\sum_{t=1}^{T} \rho_\tau (Y_{t+h} - \widehat{\alpha}_i(\tau) - \boldsymbol{X}_t \widehat{\boldsymbol{\beta}}(\tau))}{\sum_{t=1}^{T} \rho_\tau (Y_{t+h} - \widehat{\alpha}_i(\tau))}$$

Finally, after obtaining the estimates of the parameters in the panel quantile regressions, predictions of the variable of interest $y_{i,t+h}$ can be made for each country at every period. These predictions obtained for a given country and period of time can be computed at different percentiles $\tau$. In this application I compute it for 19 percentiles from 0.05 to 0.95 with steps of 0.05. The predicted values would shape the conditional distribution of $y_{i,t+h}$, allowing to estimate a probability density function. However, mapping the estimates of the quantile function into a probability density function is not straightforward. There are several methods to recover the conditional density. In principle one could obtain it by estimating a large number of quantiles or by cubic interpolation. However, these methods may produce non-monotonic conditional cumulative distribution functions. Adrian et al. (2019) propose to estimate it parametrically by fitting a skewed-t distribution to the predicted values.[7] Nonetheless, this method introduces strong assumptions on the density function. A non-parametric fit using kernel-based methods provides a smooth and monotone cumulative distribution function while allowing for more flexibility (Escanciano and Goh, 2014). In particular, I follow the weighted kernel interpolation method in Galvez and Mencia (2014).

## 4. Results

Departing from the baseline specification in Eq. (6), first I assess the performance of different specifications by estimating quantile regressions for the 5th, 25th, 50th, 75th, and 95th percentiles where one explanatory variable is added at a time, starting with the contemporaneous GDP growth rate, and then adding the CLIFS index, the credit-to-GDP growth, the house prices growth, the current account balance and the MPI. These regressions are estimated for GDP growth at two different horizons (4 and 12-quarters ahead). Table 2 presents the obtained pseudo-R2 for each specification. It is observed that the full specification improves the goodness of fit of the model for all quantiles and horizons. However, the marginal added value of including

6 A key element is the existence of enough observations above/below the quantile to assure the fit is not an artifact of a few extreme observations. Moreover, the asymptotics of quantile regressions rely on there being enough observations on both sides in order to accomplish the conditional CLT. A rough rule of thumb is: $\min\{n\tau, n(1-\tau)\} \geqslant 10p$, where $p$ is the number of explanatory variables (e.g. to estimate the 5th percentile with 5 parameters, the sample size should be greater than 1000) (see, Chernozhukov, 2005).

7 Adrian et al. (2019) prove that fitting the probability density function using a non-parametric approach do not change the results.

different variables varies across quantiles and horizons. In particular, the CLIFS index improves the fit of the model at short-horizons but it does not add value for long-horizons. This is consistent with the fact that this index is intended to capture conditions of stress in the financial sector, which usually increase when risk has already materialized and then are rapidly reflected in GDP growth. On the other hand, the early-warning variables of cyclical systemic risk are more useful in explaining GDP growth at longer horizons and mainly characterizing the tails of the distribution. This is also expected given that macrofinancial variables related to credit, house prices and external imbalances have been proved before to capture properly the build-up of systemic risk around three-years before they materialize (see Lang et al., 2019). Overall, the best fit in all the cases is at the tails of the GDP growth distribution, and mainly at low quantiles, which evidences the importance of moving away from the OLS estimation in order to model properly the dynamics of the responses of output to financial cycle movements and the effects of macroprudential policies.

Table 2. Performance of different specifications of quantile regressions of conditional GDP growth 4 and 12 quarters ahead

| | ***h*=4** | | | | | ***h*=12** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **0.05** | **0.25** | **0.50** | **0.75** | **0.95** | **0.05** | **0.25** | **0.50** | **0.75** | **0.95** |
| **GDP** | 0.103 | 0.084 | 0.116 | 0.167 | **0.204** | 0.109 | 0.084 | 0.065 | 0.133 | **0.161** |
| **CLIFS** | **0.220** | 0.119 | 0.134 | 0.171 | **0.211** | 0.121 | 0.084 | 0.065 | 0.125 | **0.142** |
| **Credit** | **0.285** | 0.125 | 0.139 | 0.136 | 0.282 | **0.294** | 0.191 | 0.116 | 0.182 | 0.232 |
| **HP** | **0.307** | 0.129 | 0.142 | 0.136 | 0.295 | **0.336** | 0.218 | 0.158 | 0.201 | 0.295 |
| **CAB** | **0.323** | 0.159 | 0.144 | 0.155 | 0.300 | **0.389** | 0.244 | 0.173 | 0.247 | 0.338 |
| **MPI** | **0.353** | 0.169 | 0.162 | 0.174 | 0.314 | **0.430** | 0.263 | 0.212 | 0.260 | 0.369 |

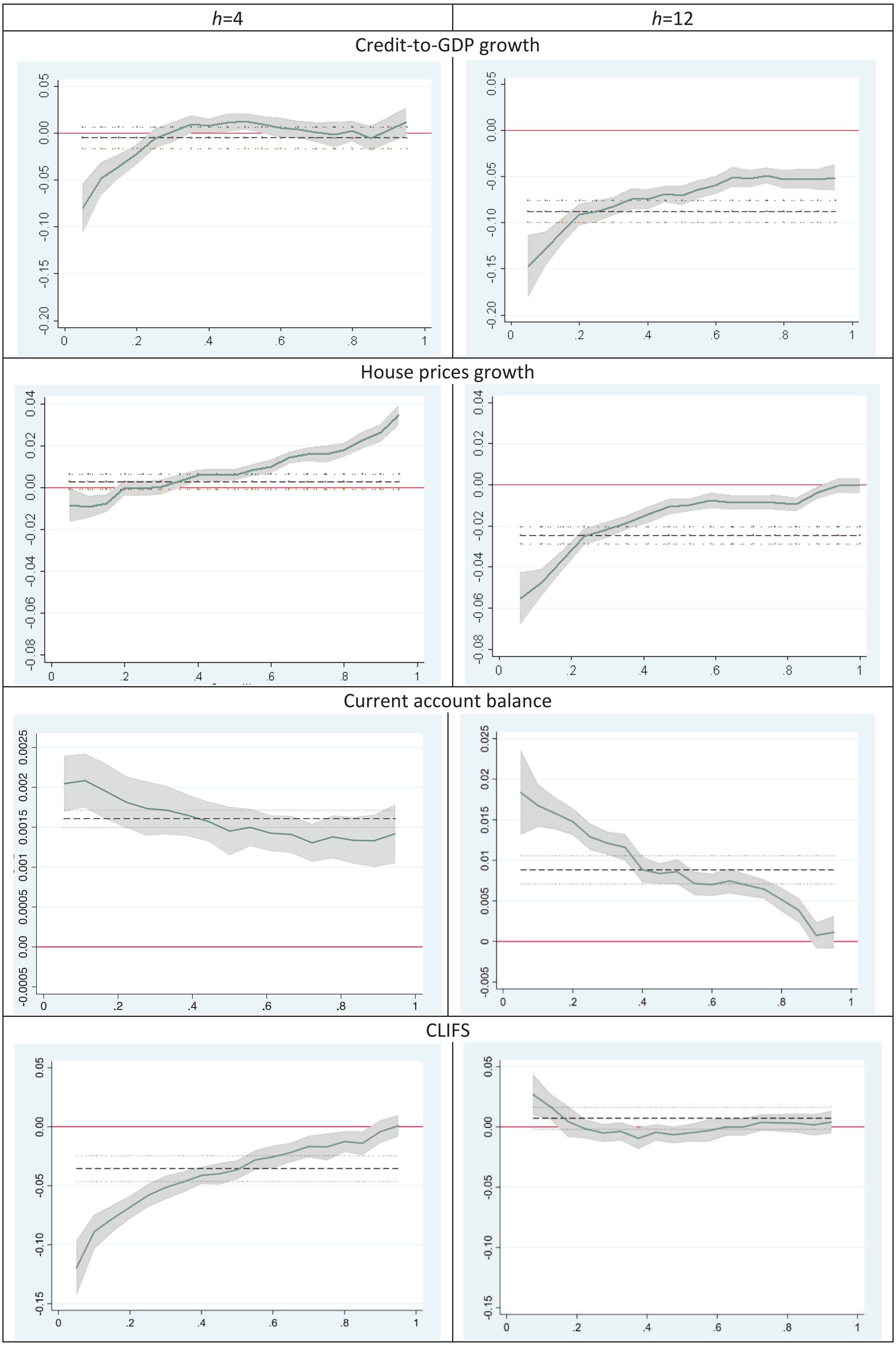
Note: The table presents the value of the pseudo-R2 obtained from quantile estimations of GDP growth 4 and 12 quarters ahead at the five percentiles in the second row. Each row represents a regression where the variable in that row is added to those in previous rows. Values in bold represent the maximum value of the pseudo –R2 in each row and horizon.

The heterogeneous effects of macrofinancial variables across quantiles of the GDP growth distribution are evident in Figure 4, where the estimated quantile regression coefficients for these variables in the baseline model are plotted along with the 95% confidence bands obtained using bootstrapping, and a comparison against the conditional mean estimation provided by an OLS model. Results are presented for the conditional GDP growth distribution 4 and 12 quarters ahead. Two main general results are observed. First, there are clear differential effects of macrofinancial variables on the GDP growth conditional distribution, and second, these effects change depending on the time horizon of GDP growth.

In particular, credit imbalances affect negatively the left tail of the GDP growth distribution both at short and long horizons. However, in the short-run, the median effect and that on the right tail of the GDP growth distribution are barely significant. This indicates that periods of high credit growth in relation to GDP, would worsen growth-at-risk in the future and that the economic effect is larger in the mid-term. Certainly, the negative impact of these type of imbalances affects the entire GDP growth distribution 12 quarters ahead by moving it to the left. Nonetheless, the effect on the right tail is about one-third of that on the left tail, indicating that the negative impact is concentrated mainly in the downside risk of GDP growth.

Similar conclusions arrive from the coefficient of house prices growth regarding the impact on the left tail of the GDP growth distribution. That is, periods of high growth of house prices affect negatively the left tail, and the effect is greater in the mid-term, suggesting that the accumulation

Figure 4. Estimated quantile regression coefficients of macrofinancial variables




Note: The vertical axes represent the values of the coefficients, the horizontal axes represent the quantiles, the continuous dark lines represents the values of the estimated coefficients at every quantile, the grey shaded areas represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications, the horizontal red line represents the value of zero, and the dark and light dashed horizontal lines represent the estimated coefficients via OLS and their 95% confidence bands.

of cyclical risk related to imbalances of real estate prices would increase growth-at-risk three-years ahead. On the other hand, the impact on the right tail is positive in the short run, reflecting the rapid effect that house prices may have on feeding economic expansions.

Regarding external imbalances, differential effects across the quantiles of the GDP growth distribution are also found, and these effects are clearer in the mid-term. In particular, a positive (negative) current account balance would lead to reduce (increase) the downside risk of GDP. That is, periods of deficit of the current account would signal the building-up of imbalances that lead to a deeper GDP contraction, although the magnitude of the economic impact on the left tail would be similar in the short- and mid-term.

The CLIFS index shows opposite results. That is, an increase in financial stress conditions would present more distributional effects on GDP growth in the short-run than in the mid-term, when the impact is diluted. This implies that the effect of financial stress is more contemporaneous but also that a deterioration of these conditions has a larger impact worsening growth-at-risk than on reducing high GDP growth scenarios. These findings are consistent with those identified by Aikman et al. (2019b) in the mid-term, who use a measure of equity volatility, and suggest the relevance of disentangling contemporaneous variables of financial risk from those capturing the building-up of systemic risk. This in contrast to Adrian et al (2019) who mix both type of variables in a financial conditions index.

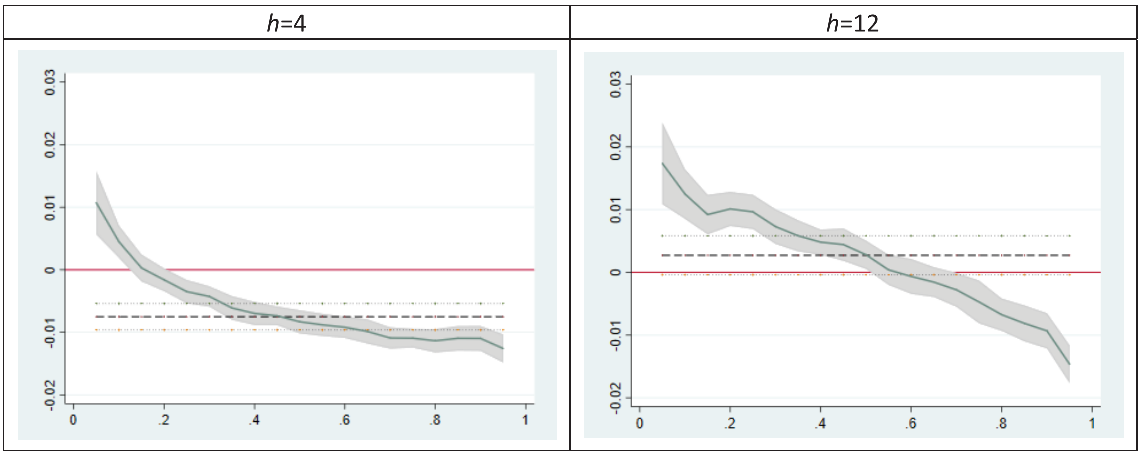
With respect to contemporaneous economic growth, results are more homogeneous across quantiles at a 4-quarters horizon, and the estimated effects are positive. This is similar to what is documented by Adrian et al. (2019). At a longer horizon, low positive effects are still observed in the median and the right tail of the distribution, while no significant effects are identified on the left tail (see Figure A4 in the Annex).

### 4.1. Macroprudential measures

Since the focus this study is not predicting crises but identifying the effects of macroprudential policies on the GDP growth conditional distribution, a detailed analysis of the impact of macroprudential measures on the conditional GDP growth distribution is presented in this subsection. As described in Section 2, the MPI aggregates the implementation of macroprudential measures and provides information on the direction of the policies (tightening or loosening), while it does not attempt to capture the intensity of the measures.

Figure 5 presents the estimated quantile regression coefficients of the MPI for the conditional GDP growth distribution 4 and 12 quarters ahead. Similar to macrofinancial variables, important differences in the estimated coefficients of MPI are observed across quantiles, and between those estimated for the tails and those from a linear regression. In particular, we observe that the greater the MPI the lower the quantile marginal effect on conditional GDP growth. In fact, the impact changes from positive in the left tail to negative in the median and the right tail of the GDP growth distribution. That is, the more tighten is macroprudential policy the lower is growth-at-risk but also the lower is the magnitude of high GDP growth scenarios. Thus, macroprudential policy would reduce both tails of the conditional GDP growth distribution making it less disperse. This is consistent with previous findings by Boar et al., (2017) on the reduction of GDP growth volatility after the implementation of macroprudential policies. Differences are also noticed depending on the horizon analysed. While the mid-term the effects are larger for the left tail and the median of the GDP growth distribution, they remain more stable in the right tail. In terms of policy, these results suggest that taking early tightening decisions of macroprudential policies would increase the positive impact on reducing downside risk.

Figure 5. Estimated quantile regression coefficients of MPI




Note: The vertical axes represent the values of the coefficients, the horizontal axes represent the quantiles, the continuous dark lines represents the values of the estimated coefficients at every quantile, the grey shaded areas represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications, the horizontal red line represents the value of zero, and the dark and light dashed horizontal lines represent the estimated coefficients via OLS and their 95% confidence bands.

Importantly, these results unmask the benefits of macroprudential policy on GDP growth, which would be concentrated in the left tail of the distribution. This benefit could be related to an increase in the resilience of the financial system leading to a reduction of downside risk. This is a very relevant result since previous literature assessing the impact of macroprudential policies on GDP growth have identified negative effects, mainly in the short-run, which are associated to the costs of these policies (Kim and Mehrotra, 2018; Richter et al., 2018). Those studies assess the impact of macroprudential policy through models that focus on the conditional mean, which is consistent with the results obtained through quantile regressions estimated for the median and with OLS regressions.

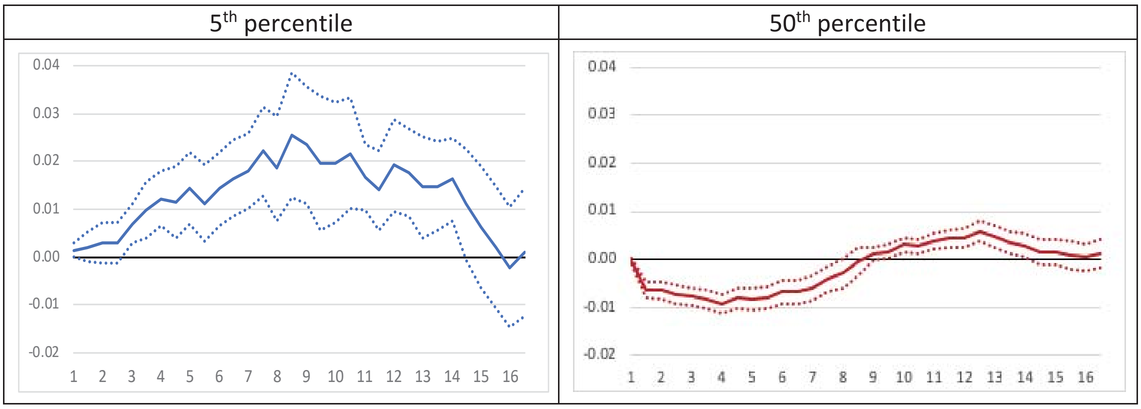
These findings suggest the need of studying more in detail the effects on the left tail and the median of the GDP growth distribution over time, which can be interpreted as benefits and costs of macroprudential policy. This is explored below.

### *4.1.1. The term structure of macroprudential policies*

As it was observed above, the impact of macroprudential policies on GDP growth differs across quantiles and between the short-run and the mid-term. Interpreting, the positive effects in low quantiles of the GDP growth distribution as benefits and the negative effects in the median as costs would allow analysing the term structure of costs and benefits of the implementation of macroprudential policies. To explore this, I extend the estimations of the 5$^{th}$, and 50$^{th}$ percentiles to horizons of GDP growth from 1 to 16 quarters ahead in steps of one quarter in order to obtain the impulse-response of macroprudential policies. Figure 6 plots the evolution over time of the impact of tightening a macroprudential measure as captured by the MPI on the mentioned GDP growth percentiles, including the corresponding 95% confidence bands estimated using bootstrapped standard errors.

It is observed that the positive effects on growth-at-risk start to be significant around 3 quarters after tightening macroprudential policy and that these effects last for almost three years, reaching a maximum impact around two years after the implementation. The estimated economic effect suggests that the increase in the magnitude of GDP growth occurring with a probability of 5% would reach around 2pp. On the other hand, the negative effect on the median

Figure 6. Estimated quantile regression coefficients of MPI on the 5th and 50th percentiles of the GDP growth distribution from 1 to 16 quarters ahead.




Notes: The blue and red lines represent the estimated coefficients of the MPI on quantile regression at the 5th and 50th percentiles on the conditional GDP growth distribution from 1 to 16 quarters ahead. The dotted lines represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications.

of the GDP growth distribution would become significant just one quarter after the policy is activated. Nonetheless, the economic effect is of lower magnitude and less persistent over time. The reduction in the median GDP growth would represent maximum 1pp around 1 year after the implementation of the policy action and it would dilute 2 years after the implementation. This is consistent with the magnitude and duration of the estimated negative impact of macroprudential policies on the conditional mean GDP growth in previous studies (Kim and Mehrotra, 2018).

In general, the positive effects on the left tail of the distribution are larger than the negative effects on the median at every time horizon. This suggests a net benefit of implementing macroprudential policies, but that this benefit may take some time to materialize. In terms of policy implementation, these results indicate that macroprudential authorities need to anticipate their decisions on the activation or tightening of macroprudential policies in order to effectively reduce growth-at-risk and compensate the mean reductions.

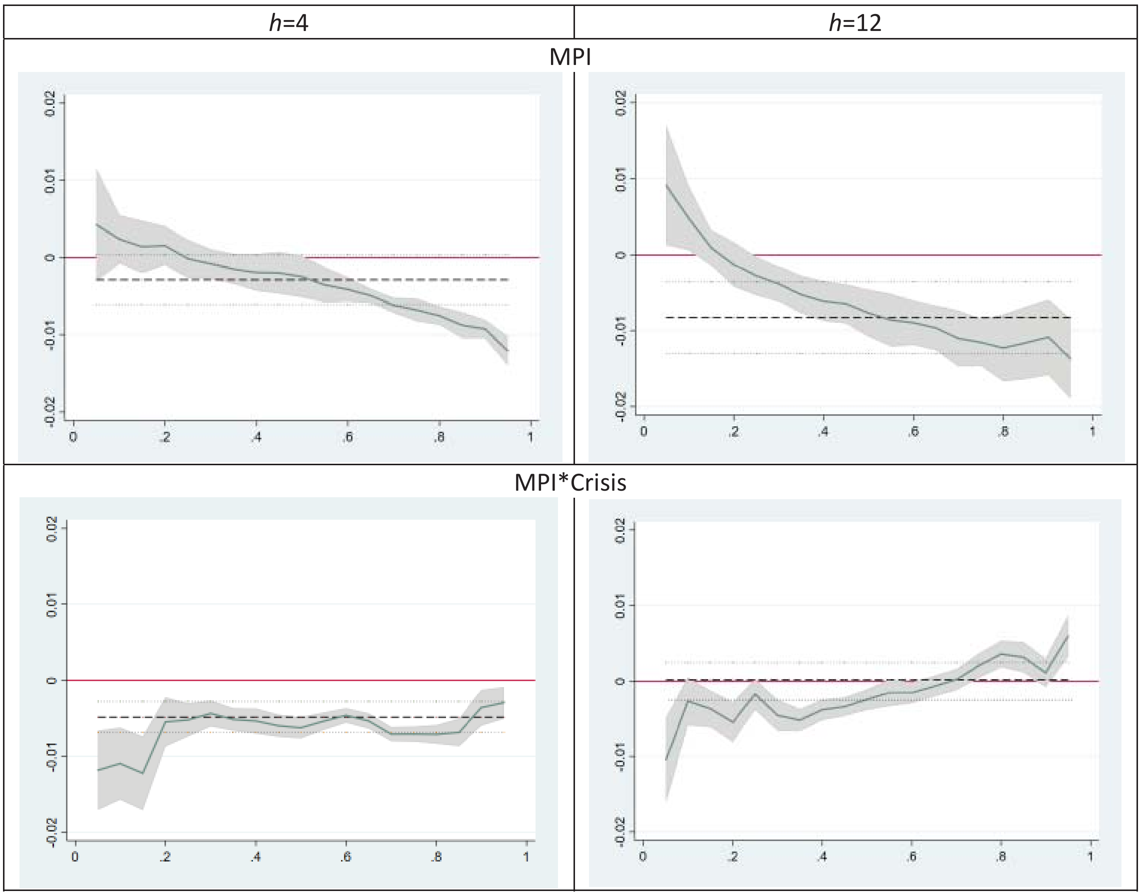
### *4.1.2. Differential effects over the cycle*

So far, I have assumed that the effects of macroprudential policies over the GDP growth distribution remain unchanged across the financial cycle, which also lead to interpret that the impact of loosening macroprudential policies would be opposite and symmetric to the impact of tightening policies. Nonetheless, in practice national authorities would tight macroprudential instruments when systemic risk is being accumulated, which is usually observed during expansionary stages of the financial cycle. On the other hand, during contractionary stages of the cycle macroprudential authorities would like to loosen or deactivate measures, which might have different economic effects over the GDP growth distribution and over time.

Certainly, previous studies have found that the timing of macroprudential policies is relevant and may produce differential effects depending on the stage of the financial cycle. Jiménez et al. (2016) find that cumulating capital buffers during credit expansions reduce the magnitude of bank credit contractions during systemic crises, but that it magnifies the negative effects on credit and firm's probability of survivor if they are cumulated during a downward phase of the cycle. Also, in an analysis of borrower-based measures, Claessens et al. (2013) and Cerutti et al. (2017) have identified that these measures are more effective during booms than in bust periods.

In order to disentangle these effects, I include a variable identifying periods of systemic crises and its interaction with macroprudential policy into the baseline model. Systemic crises periods are those identified by national authorities of the 28 EU countries as systemic events relevant from a macroprudential perspective in the ECB/ESRB crises database published in Lo Duca et al. (2017). The results obtained for the coefficients of MPI and its interaction with systemic crises are presented in Figure 7 for GDP growth 4 and 12 quarters ahead.

Figure 7. Estimated quantile regression coefficients of MPI and its interaction with crises on the conditional GDP growth distribution 4 and 12 quarters ahead.




Note: The vertical axes represent the values of the coefficients, the horizontal axes represent the quantiles, the continuous dark lines represents the values of the estimated coefficients at every quantile, the grey shaded areas represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications, the horizontal red line represents the value of zero, and the dark and light dashed horizontal lines represent the estimated coefficients via OLS and their 95% confidence bands.

It is observed that the estimated coefficient of MPI is lower than the one estimated above, and even not significant for the median and the left tail of the distribution in the short-term. However, at a longer horizon (12 quarters ahead), the impact would be positive although lower than the one presented in Figure 6 (around 1pp for the 5th percentile). This would imply that tightening macroprudential policies during normal times or expansionary periods might have a longer delay in becoming effective on reducing the downside risk of GDP growth.

Regarding the interaction term, it has a negative and significant impact along the GDP growth distribution in a 4 quarters horizon, though the effect is larger in the low quantiles. In the mid-term, the effect on the left tail of the distribution remains almost unchanged, while it becomes positive for high quantiles. These results imply that the stage of the financial cycle plays an important role on the economic impact of macroprudential policy.

In particular, during a systemic crisis there is a significant positive effect of loosening macroprudential policy (reduction in the MPI), which would affect specially the left tail of the GDP growth distribution. Thus, the total effect of loosening a macroprudential instrument during financial crises periods is positive in terms of reducing growth-at risk and these benefits are observable in the short-run, while they dilute in the mid-term (sum of both coefficients around zero for $h$=12). On the other hand, this would imply that tightening macroprudential policies during crises would have a negative effect mainly evident on the tails of the distribution. In fact, macroprudential policies are intended to be put on place during expansionary phases of the financial cycle, when cyclical systemic risks is built-up; while during contractionary phases, macroprudential policies are supposed to be deactivated or loosened. These results are found to be robust to an alternative specification where tightening and loosening measures are separated into two dummy variables flagging each of the decisions and interacted with the crises variable.[8]

To illustrate these effects along the distribution, I map the estimates of the quantile function obtained with the model adding the interaction with crises periods into a probability density function by using the Kernel-based method described in Section 3.2. This allows predicting the effect of tightening and loosening macroprudential policy in the two different stages of the cycle. Figure 8 presents the fitted distributions for the conditional GDP growth distribution 4 and 12-quarters ahead during crises and non-crises periods and compare them with the predicted distributions assuming that macroprudential policy is tightened or loosened by one measure.[9]

In the left panel, it is observed that introducing a tightening policy during normal times or expansionary phases would reduce both tails of the conditional GDP growth distribution producing a less disperse and more symmetric distribution, which is more evident at longer horizons. In particular, the positive effect on the left tail would be related to an increase of resilience, while potential effects on smoothing the cycle might explain the negative impact on the right tail. On the other hand, the right panel shows the effects of loosening macroprudential policies during crises periods, when it is observed that both tails of the distribution move to the right, both reducing downside risk and increasing the magnitude of potential expansions. In this case, these effects are more evident in the short-run and tend to dilute 12 quarters ahead, mainly for the left tail.

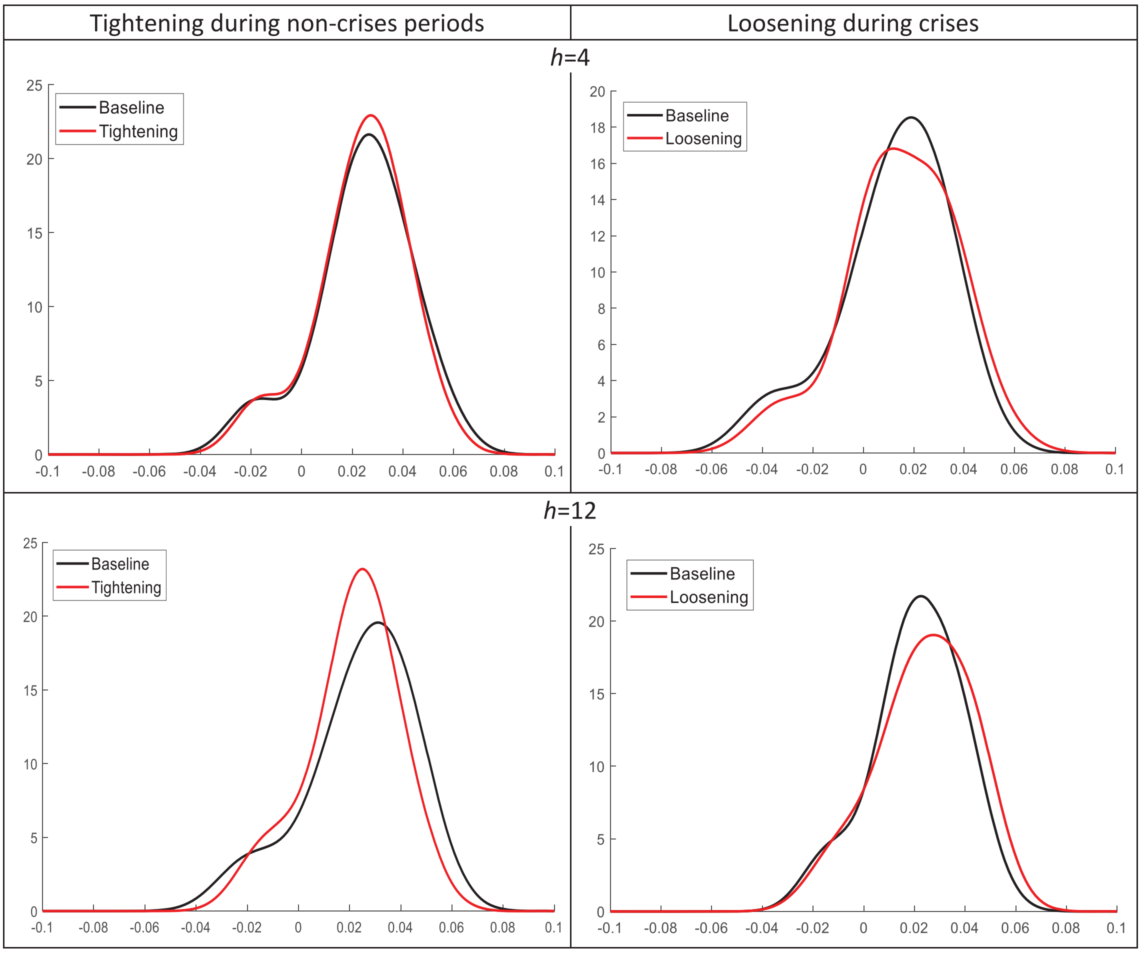
These findings support that the effects of macroprudential policy on the conditional GDP growth distribution are heterogeneous through the cycle and that the direction of policy in terms of tightening and loosening might have both positive and negative effects on downside risk depending on the position in the financial cycle. Nonetheless, the term structure seems again to play an important role on the impact of tightening and loosening policies.

Certainly, when macroprudential instruments are tightened, this is usually a gradual process and its implementation may take different stages. On the contrary, when macroprudential policy is loosened, it is usually a fast process implemented in few steps. The reason is that tightening macroprudential policy occurs to the extent systemic risk vulnerabilities are confirmed and reflected by the indicators, thereby they can be distributed along the expansionary phase of the cycle. On the other hand, crises materialize quickly forcing loosening decisions to be taken rapidly. Moreover, the characteristics of expansionary and contractionary phases of the cycle

[8] Figure A5 in the Annex presents the impulse response of the 5th and 50th percentiles of GDP growth up to 16 quarters ahead after tightening policies during non-crises periods and loosening policies during busts. An advantage of this specification is that it allows non-symmetric effects of tightening and loosening decisions during the same stage of the cycle. However, some drawbacks include that the number of loosening decisions is limited and that the dummy variables do not cumulate previous decisions as the MPI does. Thus, it does not allow to evaluate the effectiveness when more than one measure is in place, and the net tighten or loosen conditions (Boar et al., 2017).

[9] The MPI adds up 1 if a measure is tightened and subtract 1 in the case of loosening a macroprudential measure.

Figure 8. Conditional GDP growth distribution 4 and 12 quarters ahead of the implementation of tightening/loosening macroprudential policies over the cycle.




Note: The figures present the estimated GDP growth distributions at horizons equal to 4 and 12 quarters ahead, after mapping the fitted values of the quantile functions obtained with the model adding the interaction with crises into a probability density function by using the Kernel-based method described in Section 3.2. The black densities represent the fitted values filtering by crises and non-crises periods, while the red densities represent the counterfactual assuming that macroprudential policy is tightened or loosened in one measure for all countries.

are different affecting also the effectiveness of the measures and the time they last to have real effects.

### *4.1.3. Different types of macroprudential instruments*

Differential effects of the direction of macroprudential policy and over the cycle on the GDP growth distribution were disentangled above. However, the definition of macroprudential policy used is an aggregation of very different types of instruments, which might have different effects on real economy. While capital measures act indirectly through an improvement in solvency conditions of banks, thereby increasing the resilience of the banking sector; borrower-based measures act directly by assuring that lending at its origination accomplishes minimum standards, thereby limiting risk-taking.

Certainly, borrower-based and capital measures are, by far, the most used types of instruments by EU countries (see Figure 2). This is also why most of studies assessing the impact of macroprudential policies have focused on these two types of measures. In general, studies on capital measures have evidenced important differences in the effects of these instruments over the cycle (see Jiménez et al., 2017). In general, these effects have been identified to be negative on credit growth during upswings but positive during downturns. Regarding borrower-based measures, these instruments have been found to effectively curve house prices and households credit growth. These measures have also been identified to have different effects over the cycle. Claessens et al. (2013) and Cerutti et al. (2017) find that these measures are more effective during expansionary phases of the cycle. In this regard, Poghosyan (2019) identify that the effects of tightening borrower-based measures during booming periods takes more time to become effective compared to their loosening during busts.

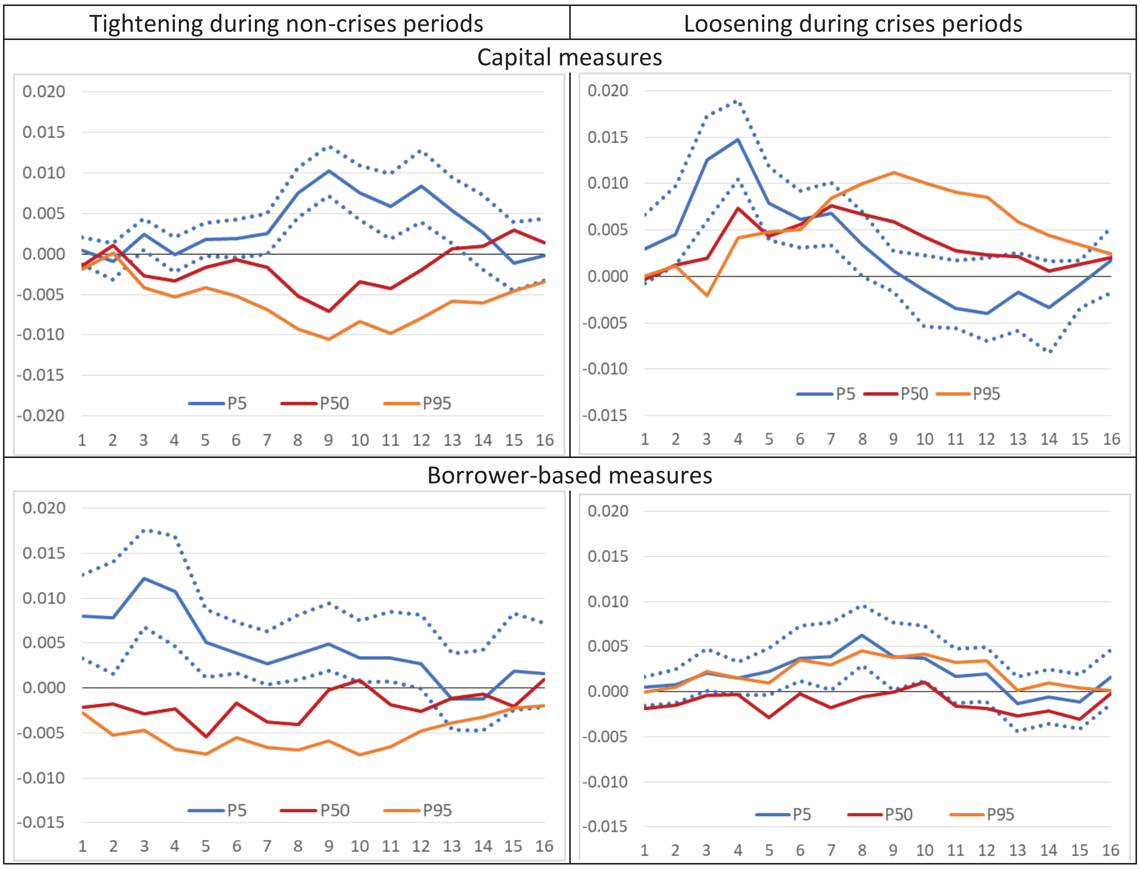
To study the potential different effects from these two types of instruments, I split the MPI into three indexes. The first two indexes are the scores $SP_j$ defined in Eq. (2) for the categories of borrower-based and capital measures. In the first case it includes capital requirements, capital buffers and loan provisions, while in the second case it encompasses all measures tied to lending standards such as caps on ratios of loan-to-value, loan-to-income, loan service-to-income, loan terms and other restrictions linked to borrower's characteristics. The third index encompasses all the rest of measures, which would control for potential misidentification of effect of other type of measures placed simultaneously. All three indexes are interacted with the crisis dummy variable in order to account for the effects of the cycle. The regressions are estimated for each of the GDP growth horizons from 1 to 16 quarters ahead.

Figure 9 presents the marginal effects of both types of measures on the GDP growth distribution over different horizons distinguishing by the direction of the policy (tightening and loosening) and the stage of the financial cycle (crises and non-crises periods). This would provide the impulse-response of macroprudential policies in these categories. In particular, the effects on the $5^{th}$, $50^{th}$ and $95^{th}$ percentiles are presented. As it was previously identified using the aggregate MPI, important differences in the impact of these specific policies across quantiles are observed. In general, the impact on growth-at-risk is different from those estimated for the median and the right tail, which are closer among them. The effects on the left tail are always positive when significant, while those on the median and the right tail are mostly negative, mainly when these measures are tightened during normal or expansionary periods. Nonetheless, important differences are also observed in the response of the quantiles of GDP growth over time.

In particular, tightening capital measures during non-crises periods has a positive impact on the downside risk of GDP growth but this benefit takes more than 2 years in becoming evident. The economic impact would reach an increase of up to 1pp of growth-at-risk over this period. This suggests that tightening capital measures would be beneficial in terms of lowering downside risk only if these measures are implemented early enough. Regarding the right tail, effects related to smoothing the cycle may explain the negative impact, which is in fact a secondary objective of countercyclical capital buffers.

On the other hand, when these measures are loosened during busts, the benefits are more immediate and larger. The estimated effect would reach an increase of around 1.5pp in growth-at-risk and this benefit would materialize during the first year after releasing or loosening capital measures. These results are consistent with previous literature. Jiménez et al. (2017) identify that, while the impact of a 1pp increase in capital buffers on credit growth would reach a 6pp reduction over expansionary phases, the impact of releasing the same amount of capital during busts would imply a 9pp lower reduction in credit growth. The authors identify similar non-linearities in terms of the probability of survivor of firms and employment. Interestingly, loosening/releasing capital measures during crises would have a positive impact on the median and the right tail of the GDP growth distribution at longer horizons, which might be associated with a stronger recovery of GDP after crises.

Figure 9. Impulse response of tightening and loosening different macroprudential instruments over the cycle at different horizons (5th, 50th and 95th percentiles)




Notes: The blue and red lines represent the estimated coefficients of the MPI on quantile regression at the 5th, 50th and 95th percentiles on the conditional GDP growth distribution from 1 to 16 quarters ahead. The dotted lines represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications.

Similarly to capital instruments, tightening borrower-based measures during non-crisis periods has relevant differential effects on the left tail of the GDP growth distribution with respect to the impact on the median and the right tail. However, tightening this type of measures would have a more immediate positive impact on the downside risk of GDP growth and its effects would last for longer. In particular, restricting lending standards implies an increase of around 1.2pp on growth-at-risk just three quarters after the implementation of such measures, and the positive effect would last for up to 3 years. These benefits seem to be larger than the costs associated to the estimated reduction on the median GDP growth. On the other hand, the impact of loosening borrower-based measures during systemic crises is more limited. It would have a positive impact of less than 0.5pp on growth-at-risk around two years after its implementation. Interestingly, in this case, there is not a clear difference between the effect in left and the right tails of the distribution, which seem to be affected in a similar way, while the impact on the median growth would be negligible.

These results corroborate some previous findings on the differential effects of the effectiveness of borrower-based measures over the cycle. Although previous approaches estimate conditional mean effects and focus mostly on the impact on credit and house prices, those studies have found large effects when these measures are tightened during expansionary phases of the cycle, and a low impact when they are loosened during contractionary phases. Claessens et al. (2013) and Cerutti, et al. (2017) document this heterogeneous impact on credit and house prices growth, while Galán and Lamas (2019) identify these differences in terms of default risk of mortgages. Poghosyan (2019) also identifies differences in the time these measures take to become effective depending on the direction of the policy and the position in the cycle.

Overall, these results have important policy implications. Although, both types of measures are effective on reducing the downside risk of GDP growth during expansionary phases of the cycle, the identified impact delay suggests that capital measures should be implemented promptly and earlier than borrower-based measures, whose benefits can be perceived more rapidly. During downturns, the benefits of loosening capital requirements or releasing capital buffers on reducing the downside risk of GDP growth are important and more immediate, while the benefits of loosening borrower-based measures are more limited. Certainly, given that risks materialize rapidly during crises, macroprudential authorities have incentives to release capital buffers suddenly with rapid effects on improving the banking sector resilience. On the other hand, it is very likely that loosening borrower-based measures during busts would not be binding given that the unfavourable macrofinancial environment incentivise banks to self-regulate by tightening their credit conditions.

## *5.* **Robustness**

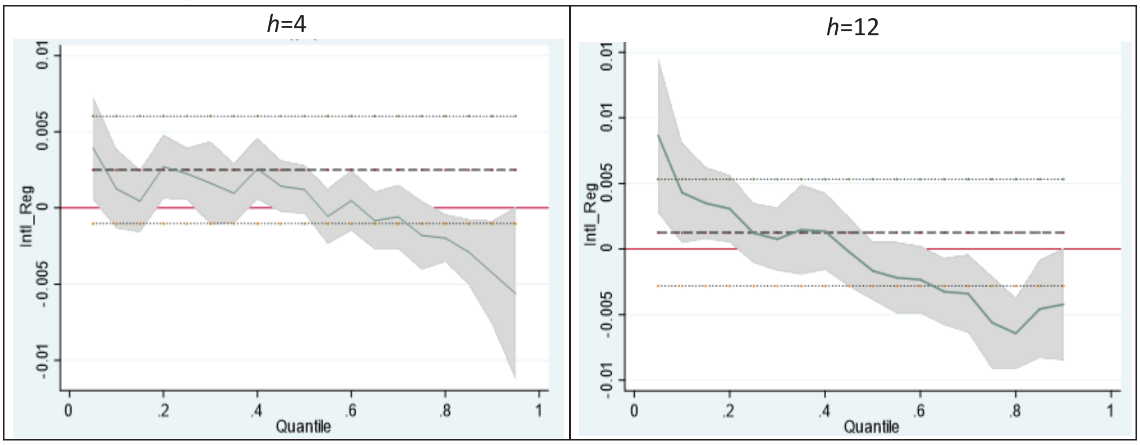
### 5.1. Endogeneity of macroprudential measures

#### *5.1.1. Macroprudential measures from international regulation*

A concern that may arise with the inclusion of macroprudential policy in the models is that it is potentially endogenous to future GDP growth. That is, although financial and business cycles have been identified to have different lengths (Claessens et al., 2012; Galati et al., 2016) and macroprudential policies are intended to respond to the former, macroprudential authorities may take decisions on these instruments using prospective information and expectations on the business cycle. In this context, macroprudential measures taken by national authorities might be dependent on those expectations, arising an endogeneity problem. In order to avoid this potential bias introduced in the results above, I include an alternative MPI built only on strictly exogenous measures. For that purpose, I keep only macroprudential measures reported in the database as coming from transpositions of international regulation. Figure A6 in the Annex presents a comparison of macroprudential measures based on national and international regulation.

Results of the quantile estimations at GDP growth horizons equal to 4 and 12 quarters are presented in Figure 10, where the previous MPI is replaced by the new version including only

Figure 10. Quantile estimates of the alternative macroprudential policy index based on international regulation (MPI*) at different horizons.




Note: The vertical axes represent the values of the coefficients, the horizontal axes represent the quantiles, the continuous dark lines represents the values of the estimated coefficients at every quantile, the grey shaded areas represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications, the horizontal red line represents the value of zero, and the dark and light dashed horizontal lines represent the estimated coefficients via OLS and their 95% confidence bands.

international regulation-based measures (MPI*). Results of the quantile estimates at both horizons are very similar to those reported for the original MPI above. In particular, the effect is positive in the 5th percentile while it is negative in the right tail of the GDP growth distribution. The positive impact is more evident at the longer horizon and the economic estimated effect is of similar magnitude. Nonetheless, the impact on the median is not significant. Interpreting these results in terms of costs and benefits suggests a larger net benefit. Overall, using only exogenous macroprudential decisions, previous results hold and seem robust to this more strict definition.

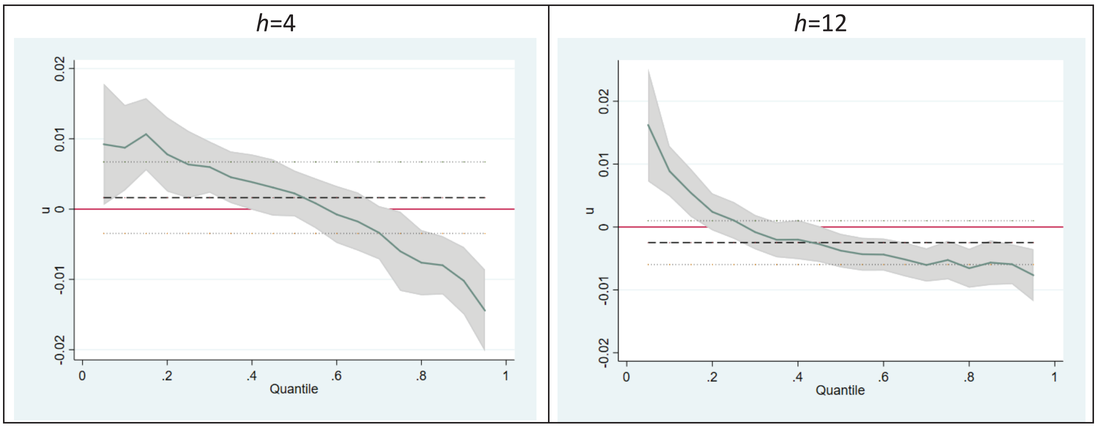
*5.1.2. Non-systematic macroprudential measures*

Another way to isolate potential endogeneity concerns could be splitting macroprudential measures into their systematic and non-systematic components. Boar et al. (2017) propose a way to separate macroprudential policy into these two components based on what has been previously attempted for monetary policy in terms of residuals of the Taylor rule (Taylor, 1993) or for fiscal policy in terms of residuals of fiscal rules linked to GDP changes (Fatás and Mihov, 2012). The authors propose to regress a macroprudential index, which is constructed in a very similar to the one used in this study, on the most common variables considered for taking macroprudential policy decisions, including credit-to-GDP growth and output growth. Therefore, following Boar et al. (2017) I replace the original MPI with the residuals ($u_{it}$) of a fixed effects regression of the MPI on the rest of variables in the baseline specification in Eq. (6) as follows:

$$MPI_{it} = \alpha_i + \beta_1 y_{it} + \beta_2 CLIFS_{it} + \beta_3 credit_{it} + \beta_4 HP_{it} + \beta_{5\tau} CAB_{it} + u_{it} \quad (3)$$

Figure 11 presents the quantile estimates for the non-systematic component of MPI at the two main GDP growth horizons analysed above. It is observed that the heterogeneous effects and their estimated magnitudes across quantiles are very similar to those obtained using the original MPI proposed above. This would imply that the impact of macroprudential policy on the GDP growth distribution is robust to accounting for only non-systematic decisions, thereby alleviating endogeneity concerns regarding factors associated to systematic macroprudential decisions in the exercises performed above.

Figure 11. Quantile estimates of the non-systematic component of macroprudential policy at different horizons.



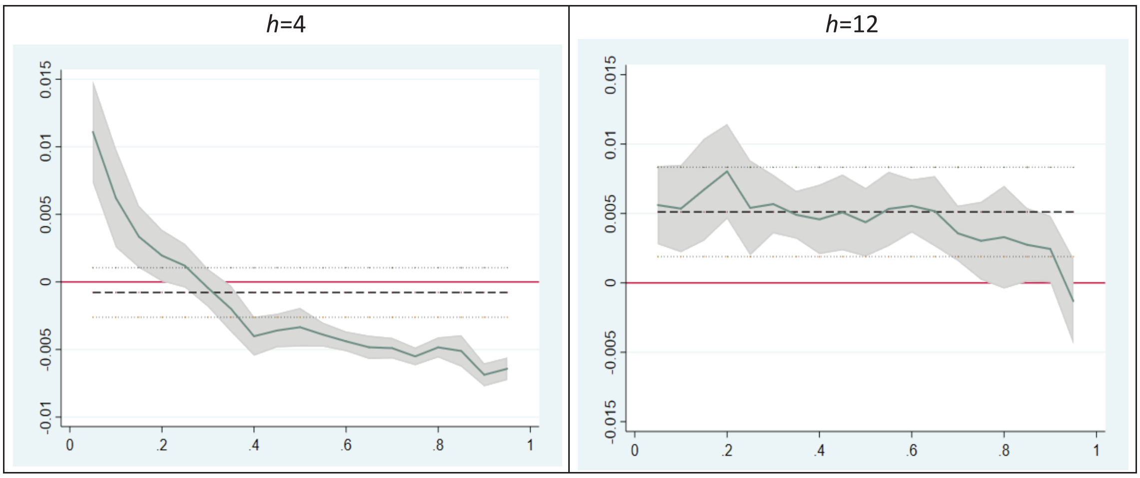

Note: The vertical axes represent the values of the coefficients, the horizontal axes represent the quantiles, the continuous dark lines represents the values of the estimated coefficients at every quantile, the grey shaded areas represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications, the horizontal red line represents the value of zero, and the dark and light dashed horizontal lines represent the estimated coefficients via OLS and their 95% confidence bands..

5.2. A continuous measure of capital requirements: the solvency ratio

The assessed macroprudential measures have identified the impact of the direction of policies (i.e. tightening or loosening) but their magnitude has been omitted from the exercise given the complexity of creating intensity measures for the different types of instruments in the sample. Nonetheless, in the case of capital measures most of the requirements and buffers are linked to the solvency ratio, which can be used as a proxy for the intensity of this type of macroprudential policies. Solvency and capital ratios are usually used for this purpose in empirical studies. In fact, Aikman et al. (2019b) include this variable directly in a growth-at-risk model to forecast GDP growth after the implementation of different CCyB rates. It is important to remark that this variable assumes that banks only increase their solvency ratio due to regulatory requirements and that macroprudential capital-based policies have a direct effect on increasing the solvency ratio. However, in practice it is possible that capital measures are not binding due to the existence of voluntary or management capital buffers. Also, endogeneity issues may arise given that banks may take decision on their level of solvency given GDP growth expectations.

Figure 12 shows the estimated coefficients across quantiles for the same GDP growth horizons assessed above. It is observed that an increase of 1pp in the solvency ratio has important differential effects on the conditional GDP growth distribution across quantiles. While the median effect is negative in the short-run, which is consistent with most of studies assessing the impact of capital and solvency ratios on the conditional mean GDP growth (Noss and Toffano, 2016; Jiménez et al., 2017), the impact on the left tail of the distribution is clearly positive identifying the benefits of the increase in the resilience of the banking sector. The negative impact on the right tail can also be interpreted as the effect on smoothing the cycle, which is a secondary objective of some capital measures such as the CCyB. In the mid-term, the differences across the distribution are less notorious, except for the right tail, where no significant effects are observed. In contrast to the results obtained above using the narrative measure, the largest positive impact of increasing capital is identified in the short-run. This may reflect the fact that this variable captures directly changes in the solvency ratio rather than the implementation of capital measures by national authorities, which would have a delay in affecting banks balances. Also, as it was aforementioned, the narrative measure identifies the tightening or loosening of conditions on banks' capital, which are not necessarily observed through changes in the solvency ratio.

Figure 12. Impact of a 1pp increase in the solvency ratio on the quantiles of the GDP growth distribution at different horizons.



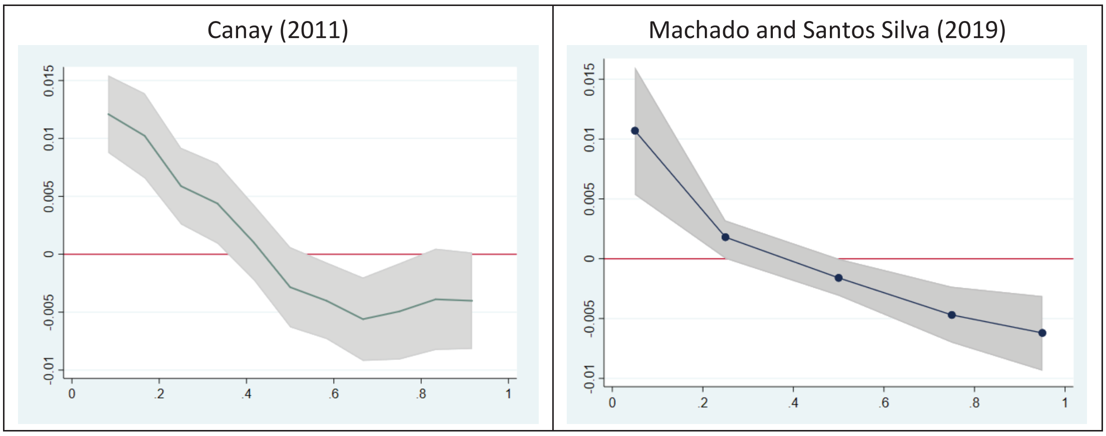

Note: The vertical axes represent the values of the coefficients, the horizontal axes represent the quantiles, the continuous dark lines represents the values of the estimated coefficients at every quantile, the grey shaded areas represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications, the horizontal red line represents the value of zero, and the dark and light dashed horizontal lines represent the estimated coefficients via OLS and their 95% confidence bands.

5.3. Alternative estimation methods: Two-steps additive fixed effects, quantiles via moments

In this study I take advantage of the panel structure with large time series observations with respect to the cross-sectional dimension in order to control for time-invariant unobserved heterogeneity by including directly fixed effects at each quantile (Koenker and Geling 2001). Nonetheless, when *T* is small in relative terms to *N*, the estimates of the common parameters may be biased or under-identified and the alternative methods described in section 3 to overcome these issues should be used for the estimations. In this section, two of the most used methods are estimated to check whether or not the obtained results could be dependent on the estimation method. In particular, I apply the two-step additive fixed effects estimator proposed by Canay (2011) and previously used from a financial stability perspective by Aikman et al. (2019b), and the quantile via moments method proposed recently by Machado and Santos Silva (2019).

Canay (2011) proposes to estimate a panel linear regression of the variable of interest on the explanatory variables and to use the prediction after averaging over *T* as an estimated fixed effect to be subtracted from the variable of interest, and then to estimate the quantile regressions using the transformed dependent variable. On the other hand, Machado and Santos Silva (2019) propose the estimation of quantiles via moments in order to estimate panel data models with individual effects. The method estimates the conditional mean and scale functions, which characterize how the regressors affect the conditional distribution, providing equivalent information to that obtained from regression quantiles. Figure 13 presents the estimated coefficients for the MPI in quantile regressions of GDP growth 12-quarters ahead (Figure A7 in the Annex presents the estimated coefficients of the macrofinancial variables). Estimation results from these two methods are consistent with those presented above, both in terms of the differences across quantiles and the economic effects. This is also observed when the exercise is replicated for different horizons.

Figure 13. Estimated coefficients of MPI under alternative fixed effects quantile methods (*h*=12)




Note: The vertical axes represent the values of the coefficients, the horizontal axes represent the quantiles, the continuous dark lines represents the values of the estimated coefficients at every quantile, the grey shaded areas represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications, the horizontal red line represents the value of zero, and the dark and light dashed horizontal lines represent the estimated coefficients via OLS and their 95% confidence bands. In the model of Machado and Santos Silva (2019) the 5th, 25th, 50th, 75th and 95th percentiles are estimated.

## 6. Conclusions

In this paper, I bring together recent developments on the impact assessment of macroprudential policies and the growth-at-risk methodology. The main purpose of the study is to identify heterogeneous effects of macroprudential policies on the GDP growth distribution at different horizons, which allow assessing the costs and benefits of macroprudential policies in terms of the same unit of measure. Certainly, most of previous studies on the impact of macroprudential policy have identified benefits in different dimensions such as curbing credit and house prices growth (Claessens et al., 2013; Cerutti et al., 2017); reducing the probability of systemic crises (Dell'Ariccia et al., 2016); increasing the probability of survivor of firms in a crisis (Jiménez et al., 2017); or decreasing the probability of banks' default (Altunbas et al., 2018), among others. However, these measures are difficult to translate in terms of a homogeneous measure of economic activity. On the other hand, the few recent studies assessing directly the impact of macroprudential policies on GDP growth usually find negative effects, which are associated to the costs of macroprudential policy (Kim and Mehrotra, 2018; Richter et al. 2018).

For this purpose, I extend the recent proposal by Adrian et al. (2019) on the use of quantile regressions of GDP growth conditional on financial conditions in three dimensions. First, by splitting the variables included in the model into: i) macrofinancial variables with mid-term early warning properties of cyclical systemic risk such as credit growth, house prices growth and external imbalances, which allow characterizing GDP growth at longer horizons; and, ii) a financial stress index that incorporates information related to the materialization of systemic risk and then more associated to GDP growth at short horizons. Second, by focusing on the assessment of the impact of the implementation of macroprudential policies on the GDP growth distribution rather than forecasting future GDP growth densities. Third, by using a panel specification, which allows taking advantage of more information, mainly regarding the use of macroprudential policies, while accounting for country-level fixed effects. I collect quarterly data on those variables for the 28 EU countries from 1970 to 2018.

Results confirm the existence of heterogeneous effects of both macrofinancial variables and macroprudential policy across the quantiles of the GDP growth distribution, which also varies over the assessed horizons. In particular, macroprudential policy is found to have a negative impact on the median of the GDP growth distribution, which is consistent with previous literature focusing on conditional mean effects. However, a significant positive impact on reducing the downside risk of GDP growth is identified. This uncovers the benefits of macroprudential policy in terms of future GDP growth, which are only evident when focusing on the left tail of the distribution.

Moreover, the positive effects on growth-at-risk are found to be larger than the negative effects on the median, suggesting a net benefit of macroprudential policy via lower severe GDP contractions. Nonetheless, the position in the financial cycle has a relevant role on determining the magnitude and speed of the effects of macroprudential policy on the GDP growth distribution. In particular, tightening macroprudential policy during normal times or expansionary phases of the financial cycle has a large impact in the mid-term, while loosening policies has a more immediate positive effect on reducing the downside risk of GDP during crises. These results may capture the reaction of macroprudential authorities over the cycle. That is, during upswings vulnerabilities tend to cumulate slowly and macroprudential authorities would take more paused tightening decisions. On the contrary, during busts risks tend to materialize quickly leading macroprudential authorities to loose measures rapidly.

Differences are also identified depending on the type of macroprudential instrument implemented. While the effects of borrower-based measures on the left-tail of the conditional GDP growth distribution are manifested very rapidly and tend to be persistent, the positive effects of capital measures present a delay of around 8 quarters in becoming evident and dilute 16 quarters after their implementation. These results have important policy implications. Although, both types of measures are found to be effective on reducing the downside risk of GDP growth, capital measures should be implemented early enough in the cycle, while borrower-based measures can be tightened also in advanced stages given that their benefits are perceived more rapidly. Conversely, during crises the benefits of loosening capital requirements or releasing capital buffers on reducing the downside risk of GDP growth are economically significant and more immediate, while those of loosening borrower-based measures are limited. Certainly, releasing capital buffers during busts allow banks to increase their resilience immediately, while withdrawing or relaxing caps on lending standards may not have real effects given that banks have incentives to self-regulate by tightening their credit conditions due to the unfavourable macrofinancial environment.

Overall, this study provides a useful framework to estimate the impact of macroprudential policies by distinguishing between costs and benefits in terms of GDP growth, and to assess the effects of specific instruments over the cycle, which is identified to be of a high relevance for policy decisions.

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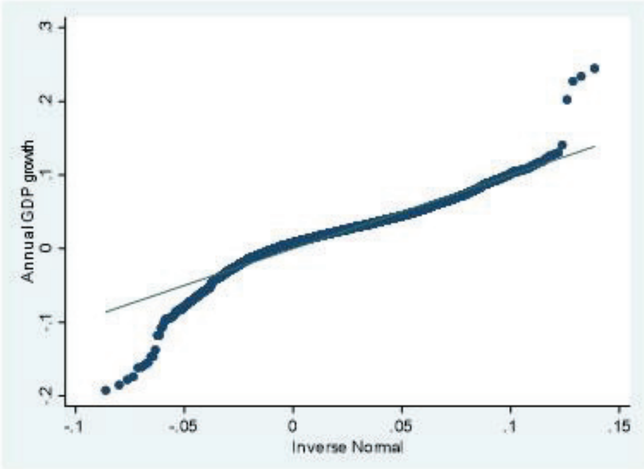
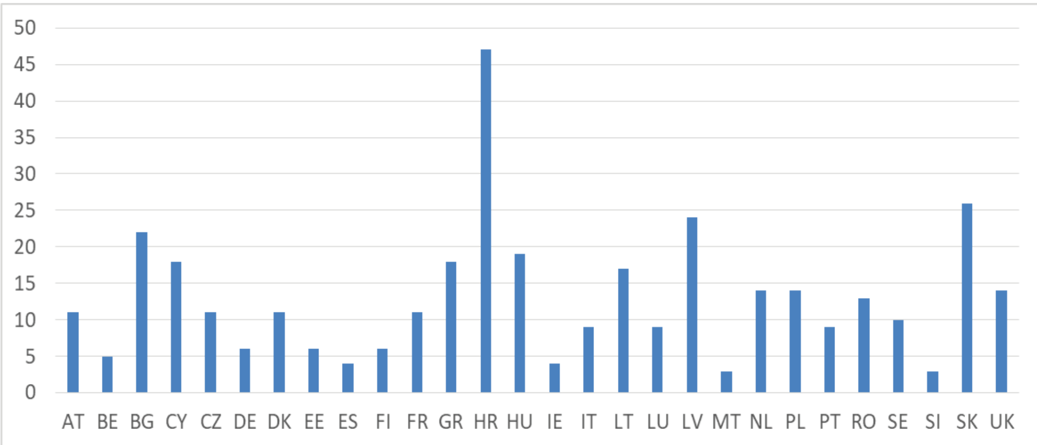
## Annex

Figure A1. Normal probability plot of annual GDP growth



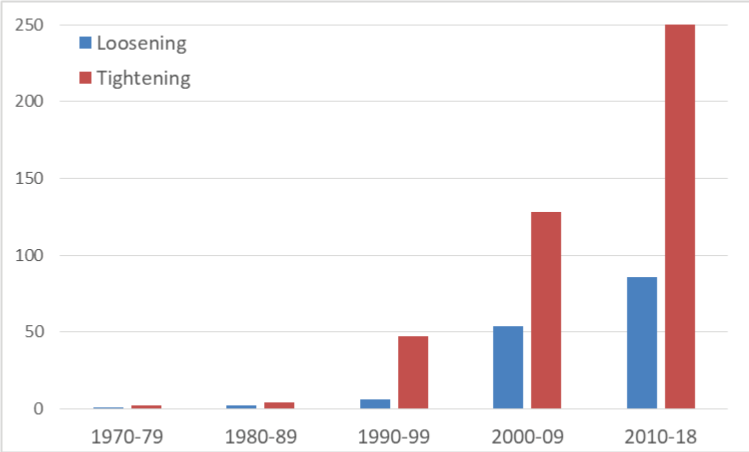

Note: The vertical axis represent the quantiles of the annual GDP growth and the horizontal axis represent the quantiles under a normal distribution. Deviations from the diagonal blue line indicate deviations from a normal distribution.

Figure A2. Number of implemented macroprudential policies by country (1970-2018)



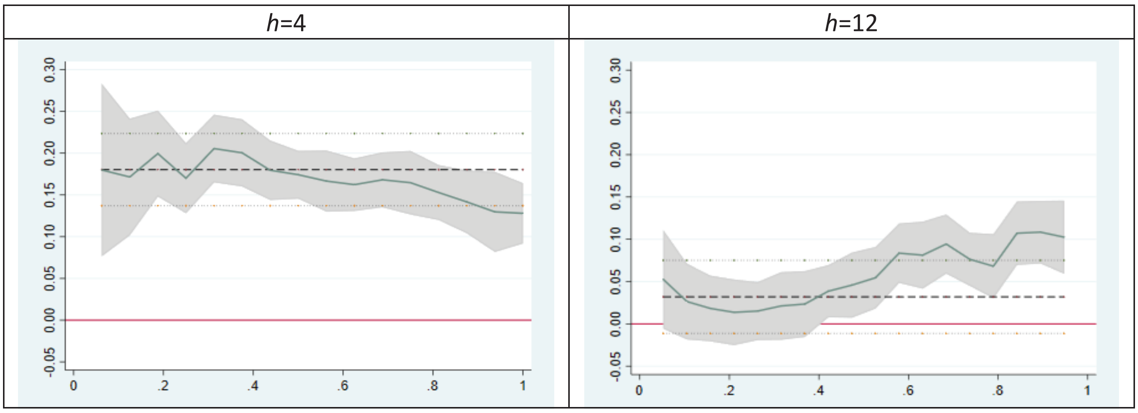

Source: ECB Macroprudential Database. Own elaboration.
Note: The vertical axis represent the number of macroprudential measures implemented from 1970 to 2018 by each country in the 9 categories described in Section 2, excluding those where the level or scope of the measure is hold unchanged.

Figure A3. Tightening and loosening macroprudential decisions in the EU over time



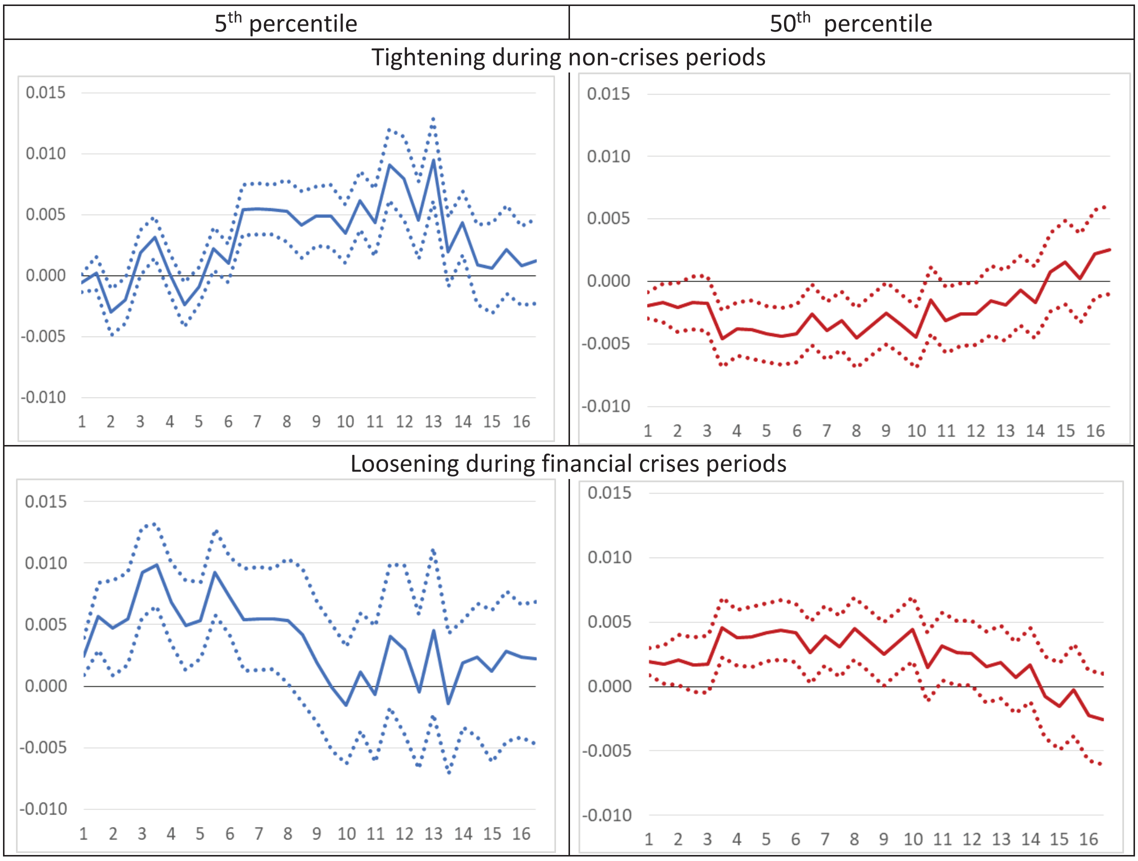

Source: ECB Macroprudential Database. Own elaboration.
Note: The vertical axis represent the number of macroprudential measures implemented by the 28 EU countries from 1970 to 2018 in the 9 categories described in Section 2, excluding those where the level or scope of the measure is hold unchanged.

Figure A4. Estimated quantile regression coefficients of contemporaneous GDP growth



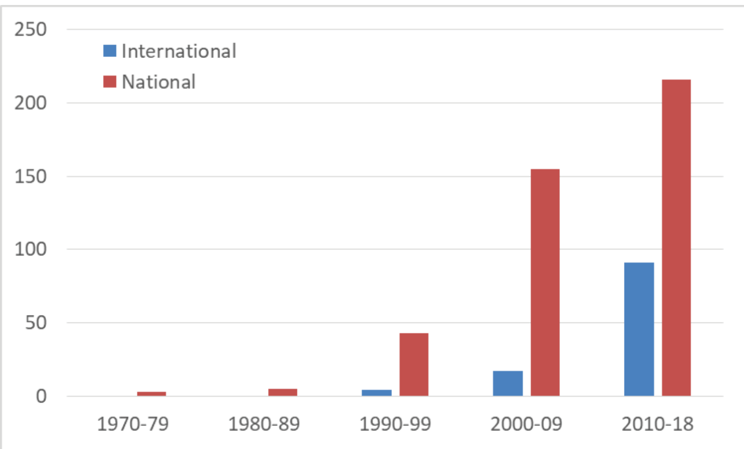

Note: The vertical axes represent the values of the coefficients, the horizontal axes represent the quantiles of the GDP growth distribution, the continuous dark green line represents the value of the estimated coefficients at every quantile, the grey shaded areas represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications, the horizontal red line represents the value of zero, and the dark and light dashed horizontal lines represent the estimated coefficients via OLS and their corresponding 95% confidence bands

Figure A5. Impulse response of tightening and loosening macroprudential measures over the cycle at different horizons (5th and 50th percentiles).



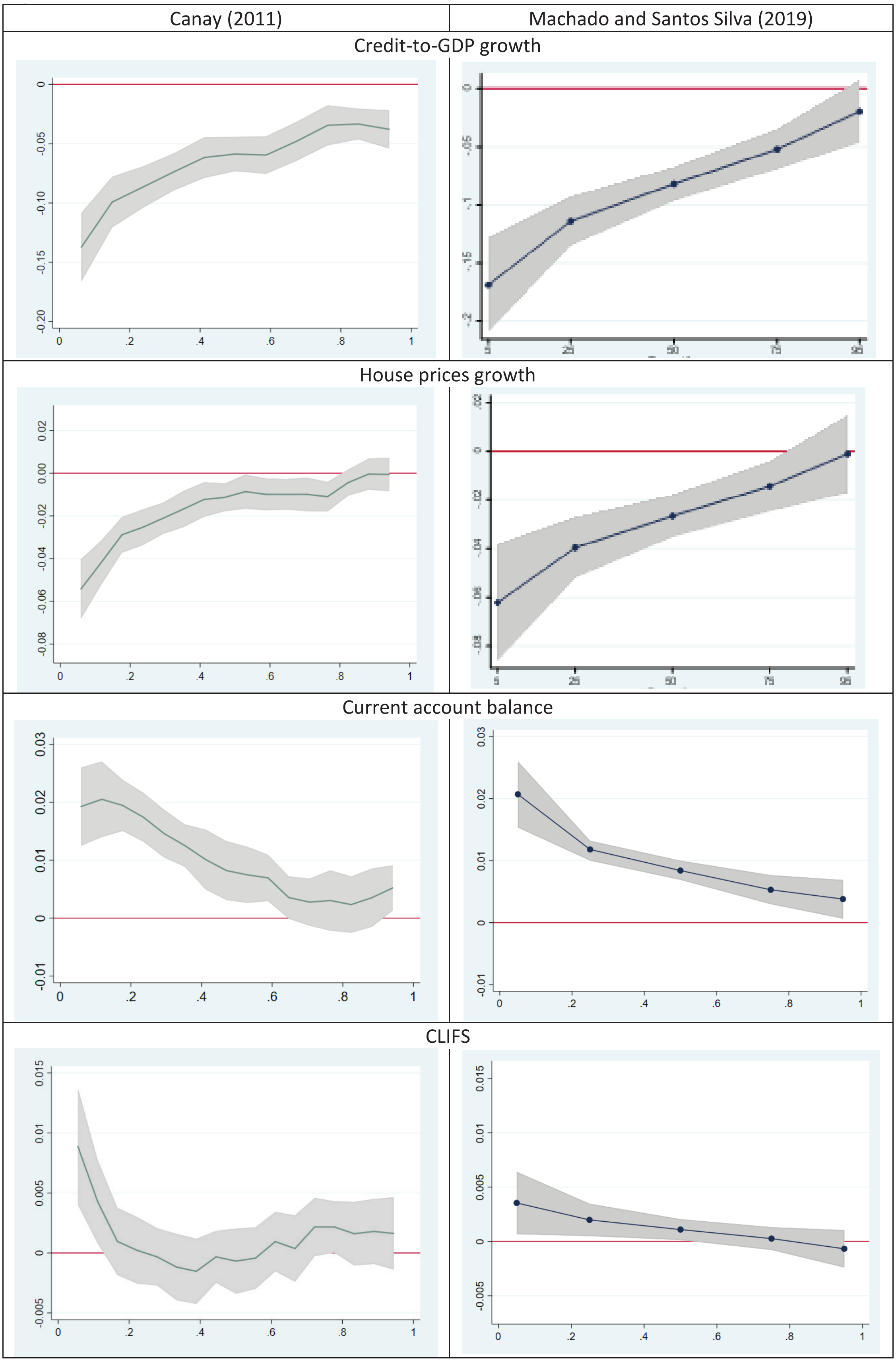

Notes: Results presented are derived from quantile regressions where the baseline specification is modified by replacing the MPI with two dummy variables capturing the direction (tightening or loosening) of a macroprudential measure implemented by each country in a given period of time. Interactions of these two variables with crises periods are also included. The solid lines represent the impulse responses of tightening and loosening macroprudential measures on the 5th and 50th percentiles of the conditional GDP growth distribution from 1 to 16 quarters ahead. The dotted lines represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications.

Figure A6. Implementation of macroprudential policies in the EU over time: international vs national regulatory-based measures




Source: ECB Macroprudential Database. Own elaboration.
Note: The vertical axis represent the number of macroprudential measures implemented by the 28 EU countries from 1970 to 2018 in the 9 categories described in Section 2, excluding those where the level or scope of the measure is hold unchanged. Macroprudential measures are separated into those being transpositions of international regulation and those taken at national level.

Figure A7. Estimated coefficients of macrofinancial variables with alternative methods (*h*=12).




Note: The vertical axes represent the values of the coefficients, the horizontal axes represent the quantiles, the continuous dark lines represents the values of the estimated coefficients at every quantile, the grey shaded areas represent the 95% confidence bands estimated via bootstrapping, the horizontal red line represents the value of zero. In the model based on Machado and Santos Silva (2019) the estimated percentiles are the 5th, 25th, 50th, 75th and 95th.

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