At-risk measures and financial stability

Jorge E. Galán and María Rodríguez-Moreno (*)

(*) Jorge E. Galán, Financial Stability and Macroprudential Policy Department, Banco de España; address: Alcalá 48 - 28014 Madrid, Spain; e-mail: jorge.galan@bde.es. María Rodríguez-Moreno, Macrofinancial Analysis and Monetary Policy Department, Banco de España; address: Alcalá 48 - 28014 Madrid, Spain; e-mail: maria.rodriguezmoreno@bde.es. We thank Roberto Blanco, Gergely Gánics, Rafael Repullo and the anonymous referee for their useful comments and suggestions.

Abstract

Financial stability is aimed at preventing and mitigating systemic risk, which is largely associated to the tail risk of macrofinancial variables. In this context, policy makers need to consider not only the most likely (central tendency) future path of macrofinancial variables, but also the distribution of all possible outcomes about that path, and focus on the downside risk. Against this background, the so-called *at-risk* methods provide a useful framework for the assessment of financial stability by the recognition of non-linear effects on the distribution of macrofinancial variables. We describe the use of quantile regressions for this purpose and illustrate two empirical applications related to the house prices and the GDP, from which useful insights for policymakers are derived.

1 Introduction

Forecasting is an essential activity for policy makers to conduct the most suitable policy which will in turn achieve its desired objectives. Traditionally, these estimates speak about the central moment of the variable under analysis (e.g., GDP, inflation, house price, among others), that is, its future expected value given the current set of information. However, policy makers need to consider not only the most likely future path for the economy, but also the distribution of all possible outcomes about that path [Greenspan (2004)]. For that aim, in the last years, policy makers have incorporated to their analytical toolkits econometric techniques such as quantile regression, which provide a surveillance framework to identify imminent and medium term threats.

Quantile regression is a statistical technique developed by Koenker and Bassett (1978) intended to estimate the conditional quantile functions of a variable which link the future performance at the τ^{th} quantile of the distribution to the current set of information. This technique provides a useful tool for the identification of the possible differential behaviour of the distribution of a variable of interest instead of focusing on the conditional mean, which may mask distributional effects.

Quantile regression 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 given low probability, say 5%. In economics, this idea is attractive to study the distributional effects of a particular shock 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) show that this methodology provides more accurate forecasts of GDP downside risk than traditional VAR and FAVAR models. More recently, Adrian et al. (2019) show that this methodology unmasks heterogeneous effects of financial conditions over the GDP growth distribution. The authors evidence the usefulness of this method for disentangling heterogeneous effects of financial conditions on the GDP growth distribution. They 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.

Certainly, the methodology offers a flexible method to model the linkages between the financial sector and the real economy with important implications for financial stability. Some recent studies have extended the application of quantile regressions to financial stability issues. Giglio et al. (2016) use this approach to show that a broad set of systemic risk measures skew the industrial production growth distribution in the US and Europe. Aikman et al. (2018) also apply a quantile regression to study the effect of two macrofinancial indices related to leverage and assets valuation on the GDP growth distribution in the UK. Lang et al. (2019) apply quantile regressions to check the early warning properties of cyclical risk measures on the tail of the GDP growth distribution. Lang and Forletta (2019) use this method to measure the impact of cyclical systemic risk on bank profits, finding that high levels of cyclical systemic risk lead to large downside risks to return on assets three to five years ahead.

All these studies have evidenced that models focusing on the conditional mean provide an incomplete picture of the distributions of macrofinancial variables, which tend to be large skewed, mainly towards the left-tail (see for instance Chart 4, which represents the conditional quantile distribution of the Spanish real house price in three different periods of time). The impact of shocks on the low quantiles of a distribution (e.g., the 5th percentile) are measures of downside risk and the models identifying it known as “at-risk” models. In general, the use of quantile estimations of GDP growth, house prices and other macrofinancial variables offer a useful approach to assess financial stability due to the importance of the linkages between the financial sector and real economic activity.

In this article we describe the methodology to estimate “at-risk” measures and present some applications developed at Banco de España. To that aim we first present the “at-risk” methodology. We next show an application to house price-at-risk (HaR) where we forecast the distribution of the Spanish house price. Then, we present an application to growth-at-risk (GaR) and the impact of the macroprudential policy in a panel of 27 European Union (EU) countries.

The rest of the paper is organized in four additional sections. Section 2 describes the quantile regressions methodology. Section 3 presents the application of the HaR and Section 4 contains the empirical application to GaR and the impact of macroprudential policy. Finally, Section 5 concludes the paper and discusses the usefulness of the quantile regression approach for policymakers.

2 The quantile regression approach

2.1 Basics of quantile regression

The estimation of quantile regressions presents some parallel to classical linear regression methods. Linear regression methods are based on minimizing sums of squared residuals to estimate conditional mean functions. See for instance Chart 1, which depicts the association between one-year ahead real house price growth and real GDP growth based on Ordinary Least Squares (OLS). It can be seen that in these methods, the fitted line (conditional mean function) minimizes the sum of the squares of the distance (i.e., residuals) to each observed point. OLS regression provides measures of changes in the conditional mean and thus, the estimates speak about responses at the mean of the dependent variable to changes in a set of variables. However, the conditional mean gives an incomplete picture for a set of distributions in the same way that the mean provides an incomplete picture of a single distribution [Koenker (2005)]. Moreover, the impact on the central tendency of a dependent variable is not the only quantity of economic interest since we can be not only interested in shifts in the location of a distribution but also in changes in the shape of that distribution.

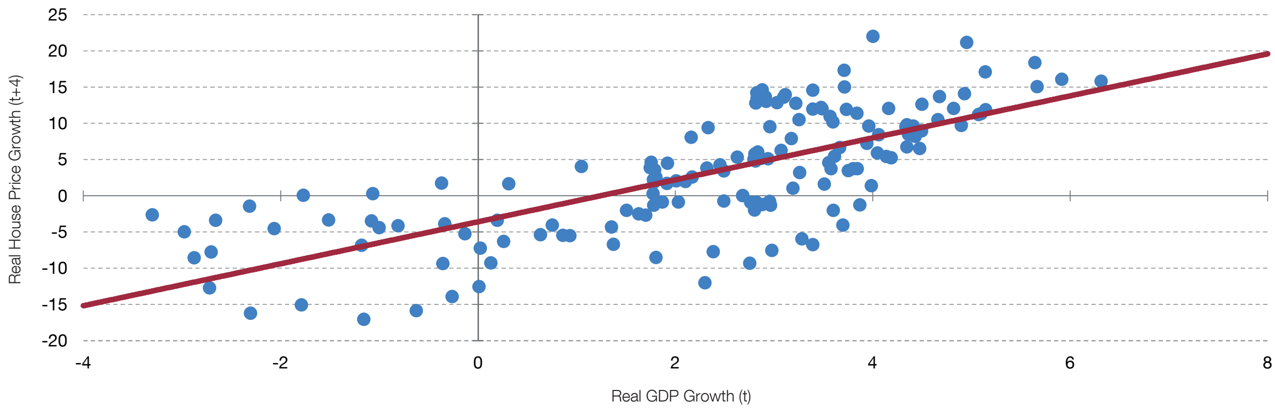
Koenker and Bassett (1978) overcome the above mentioned problems through the concept of quantile regression, which are intended to identify how changes in a set of conditioning variables affect the shape of the distribution of a dependent variable. In particular, quantile regression measures responses of a specific quantile of the variable of interest when a conditioning variable changes. To such aim, quantile regression methods estimate the conditional quantile function at certain quantile τ, on minimizing sums of the weighted absolute value of residuals, where weights depend on the quantile of interest. Chart 2 depicts the association between one-year ahead real house price growth and real GDP growth based on quantile regression methods for the 10th, 50th and 90th quantile. In this case, conditional quantile function at quantile τ is settled to ensure a proportion of τ positive residuals (i.e., fitted values above the observed points) and a proportion of $(1 - \tau)$ negative residuals.

Algebraically, the quantile regression estimator can be defined as:

$$\hat{Q}_{y_t|X_t}(\tau \mid X_t) = X_t\hat{\beta}_\tau \qquad [1]$$

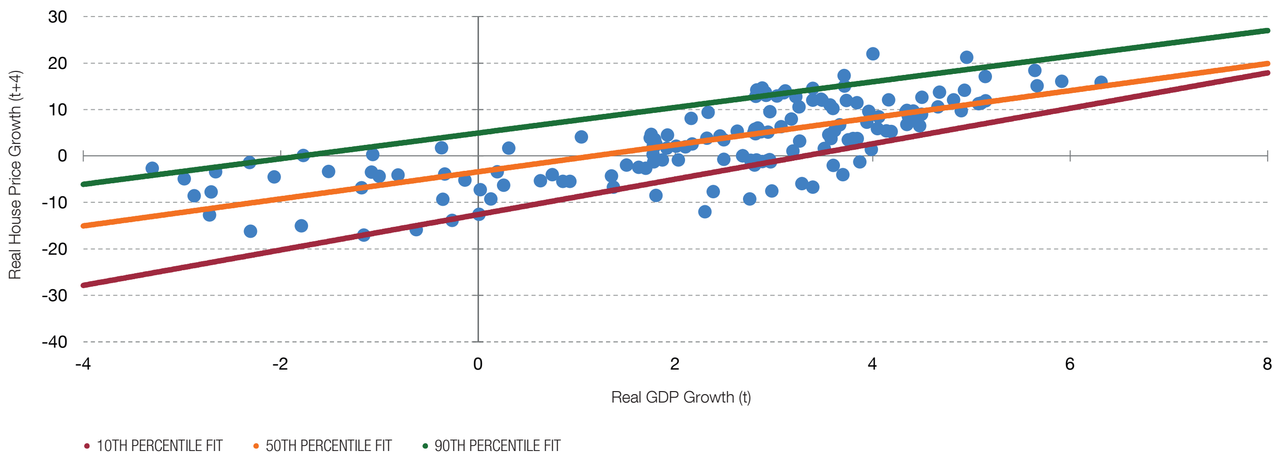
where, $\hat{Q}$ is the estimated quantile function, y_t is the dependent variable, X_t is a vector of explanatory variables, and τ is a given quantile. Koenker and Bassett (1978)

Chart 1
LINEAR REGRESSION



SOURCE: Authors' calculation.

Chart 2
QUANTILE REGRESSION



SOURCE: Authors' calculation.

show that $\hat{Q}_{y_{t|X_t}}(\tau \mid X_t)$ is a consistent linear estimator of the quantile function of y_t conditional on X_t. The regression slope β_τ is chosen to minimize the quantile weighted absolute value of errors such that the linear conditional quantile function, can be estimated by solving:

$$\hat{\beta}_\tau = \arg\min_{\beta_\tau} \sum_{t=1}^{T} \rho_\tau (y_t - X_t \beta_\tau) \qquad [2]$$

$$\rho_\tau = \tau * \mathbf{1}_{(y_t \geq x_t\beta)} \left| y_t - X_t\beta_\tau \right| + (1-\tau) * \mathbf{1}_{(y_t < x_t\beta)} \left| y_t - X_t\beta_\tau \right| \quad [3]$$

where τ_τ represents weights that depend on the quantile, **1** is an indicator function signaling whether the estimated errors are positive or negative, depending on whether fitted values are above/below the observed points.

2.2 Quantile regressions in a panel framework

Quantile regression models allow using panel data. However, if the time dimension (T) is small relative to the cross-sectional dimension (N), or if T and N are of similar size, estimates of the common parameter β 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 α_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 α_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. A related literature has also developed quantile panel data methods with correlated random effects [see Graham and Powell (2012), Arellano and Bonhomme (2016)]. In general, these estimators do not permit an arbitrary relationship between the treatment variables and the individual effects.[1]

Finally, 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.[2]

1 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 quantiles fixed effects estimators that provide consistent estimates for small T and for quantile panel data estimators with instrumental variables.

2 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.

On the other hand, unobserved fixed effects can be included as in linear regression when the time dimension is large with respect to the cross-sectional dimension [Koenker and Geling (2001)]. Certainly, the fixed effects estimator in panel quantile regressions is the equivalent to the LSDV estimator used in linear regression when T is large in absolute terms and relative to N [Kato et al. (2012)]. In this case, the large sample properties of these estimates are the same of standard quantile regressions and the application is straightforward as it proceeds in a quantile-by-quantile fashion by allowing for a different fixed effect at each quantile [Koenker (2005)].

2.3 Model performance

In order to assess the goodness of fit of the models in sample, one may use the pseudo-R2 ($\tilde{R}^2$) 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 R2. 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:

$$\tilde{R}^2(\tau) = 1 - \frac{\sum_{t=1}^{T} \rho_\tau (Y_{t+h} - X_t \hat{\beta}(\tau))}{\sum_{t=1}^{T} \rho_\tau (Y_{t+h})} \quad [4]$$

In addition, there are a broad set of tests that enable us to check the evaluation of the forecast and its properties such as the unconditional coverage (UC) test of Kupiec (1995), the conditional coverage (CC) test of Christoffersen (1998), and the dynamic quantile (DQ) test of Engle and Manganelli (2004). For this, define an indicator variable ($I_{t,\tau}$) that takes value 1 whenever the realization y_{t+h} is below the conditional quantile regressor $\hat{Q}_{y_{t+h|X_t}}(\tau \mid X_t)$:

$$I_{t,\tau} = \mathbf{1}\left(y_{t+h} \leq \hat{Q}_{y_{t+h|X_t}}(\tau \mid X_t)\right). \quad [5]$$

If $\hat{Q}_{y_{t+h|X_t}}(\tau \mid X_t)$ is the conditional quantile of y_{t+h}, given X_t, the on average, the indicator variable should be close to τ for accurate models.

Under the UC we want to test whether, on average, the conditional quantiles provide the correct coverage of the lower τ percentile of the forecast distribution. Thus, the hypothesis that $E[I_{t,\tau}] = \tau$ should be tested against the alternative $E[I_{t,\tau}] \neq \tau$, given independence. The UC test of Kupiec (1995) is a likelihood ratio test of that hypothesis. Christoffersen (1998) develops an independence test, employing a two-state Markov process, and combines this with the UC test to develop a joint likelihood ratio conditional coverage test, that examines whether the conditional quantile estimates display correct conditional coverage at each point in time. Thus, the CC test examines simultaneously whether the violations appear independently and the unconditional coverage is τ. The DQ test is also a joint test of the independence of violations and correct coverage. It employs a regression-based model of the violation-related variable “hits”, defined as $\mathbf{1}\left(y_{t+h} \leq \hat{Q}_{y_{t+h|X_t}}(\tau \mid X_t)\right) - \tau$, which will, on average, be zero if unconditional coverage is correct. A regression-type test is then employed to examine whether the “hits” are related to lagged “hits”, lagged forecasts, or other relevant regressors, over time. The DQ test is well known to be more powerful than the CC test [see e.g. Berkowitz, Christofferson and Pelletier (2011)]. Komunjer (2013) surveys a set of additional tools for the evaluation of conditional quantile predictions.

2.4 Predictive densities

A potential way to estimate the predictive density of the variable of interest is to estimate the conditional quantile curve for each quantile using the methodologies described in Sections 2.1 or 2.2, respectively, depending on the structure of the data. However, this approach presents some finite sample problems such as quantile crossings and extreme quantile. In the former case, the resulting fits may not respect a logical monotonicity requirement since each quantile is independently estimated, and thus, the forecasted τ quantile might not be necessarily lower than the forecasted ($\tau + 1$) quantile. In the latter case, fitting the conditional quantiles curves to extreme left and right quantiles requires a large data sample to ensure a reasonable fit. Recall that according to equations [2] and [3], the estimation of an extreme left quantile, as 5%, imposes a proportion of 5% positive residuals and thus, a large dataset is highly recommend to avoid that the estimation relies on a handful of points.

To overcome these problems, the full predictive density can be estimated using a two-steps procedure. Firstly, we estimate the conditional quantile curves for a limited number of quantiles (e.g., 10, 25, 50, 75 and 90 percentiles). Then, we can use these predicted values that shape the conditional distribution to estimate the probability density function. The econometric literature has proposed several approaches to carry out this last step. In this study we use a parametric (Skewed t-distribution density) and a non-parametric (Kernel-based density) method to estimate the density functions. Similar to findings by Adrian et al. (2019) we find that results are robust to the use of either method. For illustrative purposes we use the parametric fitting in the house prices-at-risk application and the non-parametric method in the growth-at-risk application (see details of the derivation of the densities with each method in Annex 1).

3 Predicting House Prices

In this section we show an application of the “at-risk” methodology to the real house price. Recently, different surveillance institutions have developed their own House Price-at-Risk (HaR) measures, whose primary objective is to identify the accumulation of downside risks in the housing market. The development of these tools is key for policy makers due to the tight relationship between house price dynamics and macroeconomics and financial stability. The HaR measure consists of forecasting extreme realizations in the left tail of the conditional distribution of the real house prices (commonly the 5th percentile) to identify in advance risks of large price falls.

For example, IMF (2019) developed their HaR model for a sample of 22 major advanced economies and 10 emerging market economies where the set of conditioning variables include a financial condition index, real GDP growth, credit growth and an overvaluation measure. The ECB (2020) presents a HaR model at euro area level using as explanatory variables the lag of house price growth, an overvaluation measure, systemic risk indicator, consumer confidence indicator, financial market conditions indicator, government bond spread, slope of yield curve, euro area non-financial corporate bond spread, and an interaction of overvaluation and a financial conditions index.

Contrary to the above works who developed their model on a panel setting (as in Section 2.2), in this application we focus on the forecasting of the Spanish real house price (RHPI)[3], and thus, we follow the methodology described in Section 2.1. Firstly, we define our variable of interest as:

$$y_{i,t+h} = \ln\left(\frac{RHPI_{t+h}}{RHPI_t}\right) / \left(\frac{h}{4}\right); h = 1, \ldots, 8. \qquad [6]$$

where $y_{i,t+h}$ is the quarterly average growth of the RHPI over the horizon h. The model employs quarterly data from 1981Q1 to 2019Q4.

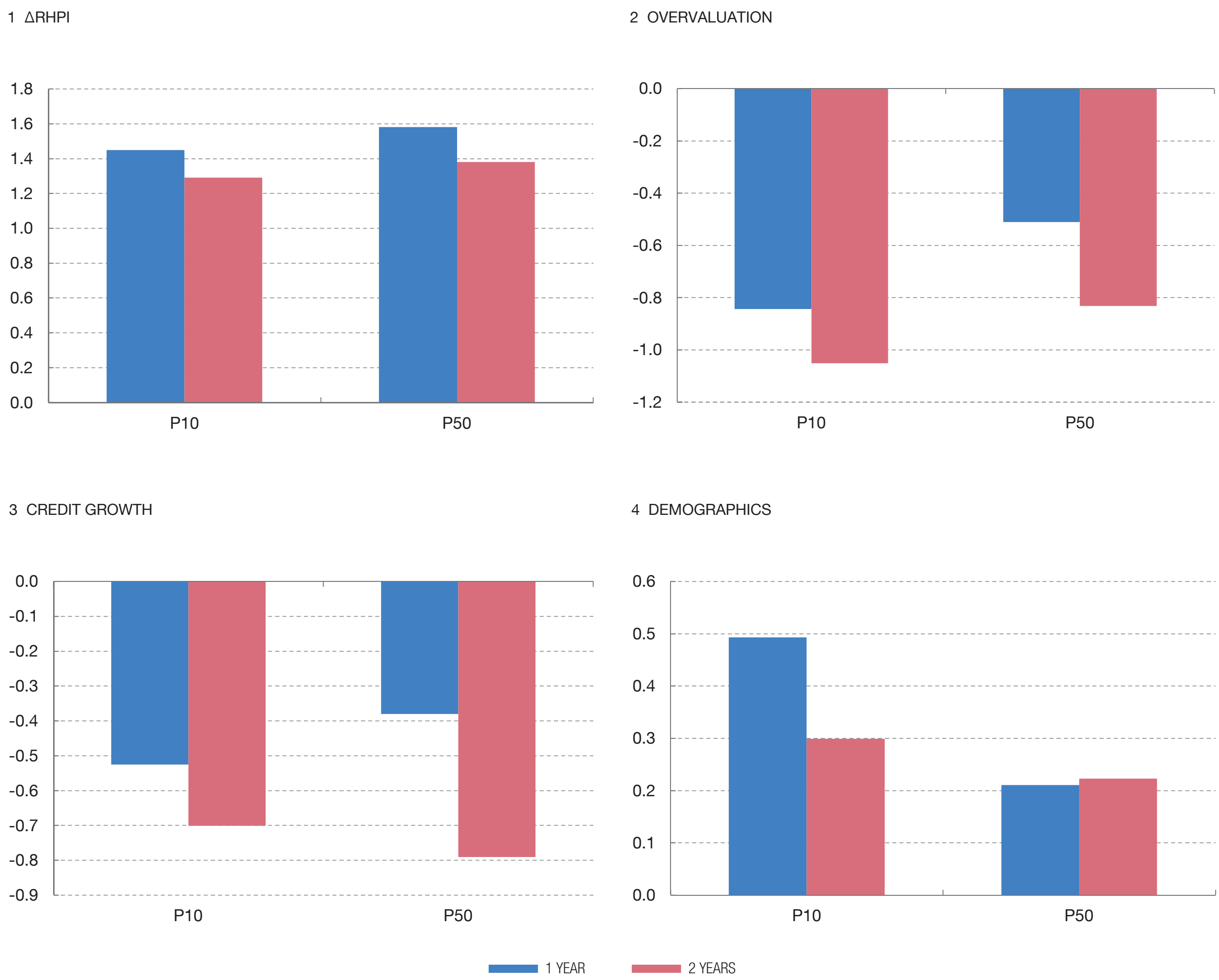
We next estimate the conditional quantile function as in equation [1] where we use as a conditional variables: i) lag of house price growth; ii) overvaluation measure defined as the deviation between the observed price and the estimated long run equilibrium price[4]; iii) the credit growth defined as the deviation between the ratio of household credit to the GDP and their long run trend[5]; iv) year-on-year growth of the population between 30 and 54 years old. Note that, due to the limited number of observations in the sample, we restrict the number of explanatory variables. In addition, we abstract from estimating the conditional quantile function in the extreme quantiles and thus, we shape the density distribution of $y_{i,t+h}$ based on the forecast of the 10, 25, 50, 75 and 90 percentiles. The validity of the model is analyzed through the implementation of the DQ test as described in Section 2.3. for the model at 1 year and 2-years horizons at the 10th quantile. The results indicate that the model satisfy basic requirements of a good quantile estimate such as unbiasedness, independent hits, and independence of the quantile estimates.

3 To construct the nominal House Price Index (HPI) we use two different data sources: 1) Ministerio de Fomento from 1980 to 2006; ii) Instituto Nacional de Estadística (INE) since 2007.

4 The overvaluation is constructed following Martínez-Pagés and Maza (2003).

5 The credit growth is constructed following Jordà and Taylor (2016).

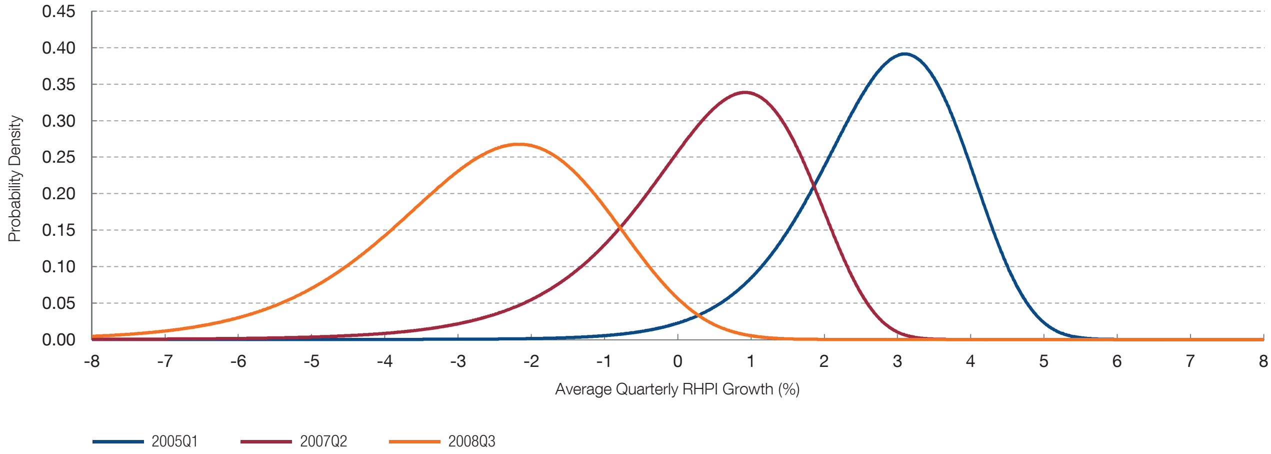
Chart 3
SENSITIVITY OF REAL HOUSE PRICE GROWTH



SOURCE: Authors' calculation.
NOTE: This chart shows the beta coefficients of equation [2] for quantiles 10 (Q10) and 50 (Q50) to changes in the standardized explanatory variables for 1 and 2 year horizons.

Chart 3 shows the sensitivity of the quarterly average growth of the RHPI for the 10 and 50 percentile in 1 and 2 year horizons, in response to a one standard deviation change in the explanatory variables. As one might expect, the coefficient of those variables related to the risk accumulation in the housing market (overvaluation and credit growth) is negative, meaning that the higher the risk accumulation, the higher the likelihood of future drops in the housing market. Indeed, their impacts at the left tail of the distribution – p10 – are stronger in longer horizons (i.e., the magnitude of the coefficient is higher for the 2-year horizon). In addition, their impact seems to be stronger at low percentiles of the distribution. We also observe that the population growth has a positive effect on the future developments of the house market and that this effect is stronger in the extreme realizations (10 percentile), as it is the case

Chart 4
1-YEAR AHEAD FORECASTING DENSITY FUNCTION



SOURCE: Authors' calculation.
NOTE: This chart depicts the 1-year ahead forecasting density function in three different periods: 2005Q1, 2007Q2 and 2008Q3.

with the overvaluation. Finally, we observe that past movements in the housing prices significantly affect the whole distribution of the forecasted housing prices rather than specific percentiles.

Once we have identified the conditional quantile function for the different quantiles and horizons, we next fit, for each horizon, the skewed t-distribution by means of equation [A1.2]. In this application we show the 1-year ahead forecasting density function in three different periods of time. For that aim, we use the conditional quantile functions estimated above using the full sample period. However, one may note that the conditional future growth density forecast depends on two sources of information: i) beta coefficients defining the quantile function; ii) the set of regressors from with the quantiles are computed upon. We take this approach to avoid regressions on very limited number of observations and thus, the only source of heterogeneity in this exercise comes from the heterogeneity in the set of regressors.[6,7]

Chart 4 depicts the forecasting density function in three periods of time: i) 2005Q1; ii) 2007Q2; and iii) 2008Q3. We can see how this powerful tool would have shown to the policy makers the increase in the downside risk. In 2005Q1, real house prices in Spain were growing at 3.3% y-o-y but the downside risk was very limited on that

6 This approach implies that there are no structural breaks in the sample and the quantile estimator is asymptotically consistent, assuming that the estimated beta coefficients will converge to the true “a-temporal” value, as the sample size increases.

7 One might add as an additional source of heterogeneity the use of *real-time* versus the *revised* macrofinancial variables, since real-time data that was available at the time, might be less informative of the downside risks than later revisions of the data. In this work we employ revised macrofinancial variables and thus we are aware that our density forecast might overestimates the information that the policymaker would have had at certain period of time.

Table 1
HOUSE PRICE-AT-RISK

This table contains the 1-year ahead forecasting RHPI growth at 5th percentile (HaR) in three periods of time: 2005Q1, 2007Q2; 2008Q3. For the estimation of the density forecasting we use two alternative approaches related to the estimation of the beta coefficients: i) full sample period (1980-2019); ii) information available in t (1989-t) for each of the three considered periods.

	2005Q1	2007Q2	2008Q3
Full sample	0.828	-2.171	-5.495
Information available in t	0.857	-2.052	-5.504

SOURCE: Authors' calculation.

horizon. However, 2007Q2 depicts a very different picture. We observe a large movement of the full distribution to the left, meaning that downside risk was substantially increasing but also that even in positive scenarios, the growth in the housing market would be weak. The forecasting density function predicted by the 2008Q3 presents a worse picture for 1-year horizon since positive outcomes were highly unlikely to happen.

In order to check whether the use of the full sample betas introduce distortions on the snapshot that policy makers would have seen at that time, we repeat the exercise re-estimating equation [1] using the information available at each point in time. Table 1 shows the evolution of the HaR (i.e., forecasting RHPI growth at 5th percentile) using both methodologies. According to the results reported in Table 1, we do not observe large differences in the HaR under both approaches. According to these results, in 2005Q1, the HaR was 0.83% meaning that in an adverse scenario (so adverse that the probability of an even more negative scenario is only 5%), RHPI would increase by 3.3% over a 1-year horizon (0.83% on average each quarter for the next 4 quarters). However, in 2007Q2 and 2008Q3 the downside risks are completely different and HaR was –2.17% and –5.49%, respectively, meaning that in an adverse scenario, RHPI would decrease by 8.7% and 22%, respectively, over a 1 year horizon.

4 Growth-at-risk and macroprudential policy

Most of previous studies have identified benefits of macroprudential policy 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)]. However, the few studies measuring the impact of macroprudential policy on GDP growth, have identified negative effects. Kim and Mehrotra (2018) identify a negative impact of macroprudential policy on output after analysing an aggregation of many different instruments in Asian economies. Richter et al. (2019) find that borrower-based measures have negative effects on output growth over a four-year horizon. Noss and Toffano (2016) and Bedayo et al. (2020) identify a negative impact of tightening capital measures on GDP growth in the short-run. In general, these negative effects have been associated to the costs of macroprudential policy.

Those studies have focused on the impact of macroprudential policy on the conditional mean of GDP growth. However, if macroprudential policy effectively reduces systemic risk, we could expect that these benefits are observed in a reduction of the downside risk of GDP growth. Against this background, quantile regressions offer a flexible framework to assess the impact of macroprudential policies on growth-at-risk. This idea has been recently explored by some authors. Duprey and Ueberfeldt (2020) study the interaction between macroprudential and monetary policy in Canada. Aikman et al. (2019) forecast the GDP growth distribution conditional on banks' capital. Brandao-Marques et al. (2020) study the complementarity between macroprudential, monetary policy and foreign exchange interventions. Finally, Galán (2020) provides an analysis of the marginal effect of macroprudential policy on different quantiles of the GDP growth.

In this section, we extend the latter exercise in order to illustrate the usefulness of growth-at-risk models for taking macroprudential policy decisions and evaluating its impact. We estimate a panel quantile regression model of future GDP growth up to 16 quarters ahead on macroprudential policy, cyclical systemic risk, financial stress and their interactions. We use a sample of 27 EU countries with quarterly data from 1970Q1 to 2019Q4. The main data source is the European Central Bank (ECB). Besides annual GDP growth, the set of variables comprises the Systemic Risk Indicator (SRI), the Country-Level Index of Financial Stress (CLIFS) and a Macroprudential Policy Index (MPI). The SRI is a composite index introduced by Lang et al. (2019), that aggregates five cyclical systemic risk variables using weights that optimize the early-warning performance of the indicator from 4 to 12 quarters ahead of systemic crises [see Lang et al. (2019)].[8] Thus, this index would allow characterizing the GDP growth distribution in the mid-term. The CLIFS is an index proposed by Duprey et al. (2015) that aggregates several variables of volatility and tail risk in the equity, sovereign and exchange rate markets. Thus, this index is intended to capture signals of materialised systemic risk, which allow characterizing the GDP growth distributions at short horizons. The MPI is an index that aggregates a broad set of macroprudential measures in different categories over time, and that distinguishes the direction of the policies, providing a measure of the net macroprudential position of a given country. We construct the index using the ECB

8 The variables composing the SRI are the 2-year average change in the credit-to-GDP ratio, the 2-year average growth of house prices, the 2-year average change in the debt-service ratio, the 2-year average growth of equity prices, and the current account balance as a percentage of GDP.

Table 2
PERFORMANCE OF DIFFERENT SPECIFICATIONS OF QUANTILE REGRESSIONS OF CONDITIONAL GDP GROWTH

The table presents the pseudo-R2 obtained from quantile estimations of GDP growth 4 and 12 quarters ahead at five percentiles. 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 for each percentile and horizon.

	h=4					h=12				
Percentile	5	25	50	75	95	5	25	50	75	95
GDP	0.15	0.12	0.09	0.10	0.12	0.13	0.10	0.07	0.09	0.11
CLIFS	0.27	0.17	0.13	0.15	0.18	0.15	0.11	0.07	0.09	0.11
SRI	0.32	0.23	0.19	0.21	0.24	0.29	0.24	0.18	0.21	0.24
MPI	0.36	0.27	0.22	0.24	0.28	0.42	0.34	0.29	0.32	0.37

SOURCE: Authors' calculation.

Macroprudential Database introduced by Budnik and Kleibl (2018).[9] In Annex 2 we present details on the computation of the MPI and its characteristics. Finally, 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 from 1 to 16 quarters ahead, as follows:

$$y_{i,t+h} = \ln\left(\frac{GDP_{i,t+h}}{GDP_{i,t}}\right) / \left(\frac{h}{4}\right); h = 1, \ldots, 16 \qquad [7]$$

The proposed panel quantile regression model is the following:

$$\hat{Q}_{y_{i,t+h}|x_{it},\alpha_i}\left(\tau \mid X_{it},\alpha_i\right) = \widehat{\alpha_{i\tau}} + \hat{\beta}_{1\tau}y_{it} + \hat{\beta}_{2\tau}CLIFS_{it} + \hat{\beta}_{3\tau}SRI_{it} + \hat{\beta}_{4\tau}MPI_{it} + \hat{\beta}_{5\tau}SRI * MPI_{it}$$
$$+\hat{\beta}_{6\tau}CLIFS_{it} * MPI_{it} + \hat{\beta}_{7\tau}SRI_{it} * CLIFS_{it}; \qquad \tau = 5, 10, \ldots 90, 95; \qquad [8]$$

where $y_{i,t+h}$ is the annualized GDP growth of country i at t + h quarters ahead as defined in equation [7]; $_{i}$ represents the unobserved country-effects; y_{it} is the contemporaneous GDP annual growth rate; CLIFS is the index of financial stress; SRI is the composite cyclical systemic risk index; MPI represents the macroprudential policy index; and τ represents the 19 estimated quantiles from the 5th to the 95th percentile.

Departing from the specification in equation [8], we present in Table 2 the performance of different specifications in terms of the pseudo-R2 (equation [4]) for relevant percentiles and two horizons (4 and 12-quarters ahead). This is carried out by adding

9 This database is a large repository of regulatory measures implemented by EU authorities over a long time span. It distinguishes between macro and microprudential measures, the type of instrument, and its direction. Only those measures classified as having a macroprudential objective are retained for this exercise. This includes tightening and loosening measures but excludes decisions where the level or the scope of the instrument remains unchanged.

one additional explanatory variable at a time starting with the contemporaneous GDP growth rate and without considering the interaction terms. We observe that the specifications including the four variables improve the goodness of fit of the model. Nonetheless, the marginal gain varies across quantiles and horizons. In particular, the CLIFS index improves the fit of the model, mainly, at a short-horizon; while the SRI improves more the performance at the longer horizon. Overall, the best fit in all the cases is at the tails, and mainly at the 5th percentile, which represents growth-at-risk.

Certainly, we identify large differences in the estimated effects of SRI, CLIFS and MPI on the left-tail with respect to those estimated in the median. Using the model without interaction terms, Chart 5 shows the response of growth-at-risk and median growth to a one standard deviation increase in the SRI, the CLIFS, and the implementation of one macroprudential measure. We also plot the 95% confidence bands obtained using bootstrapping. We observe that the magnitude and the path of the response of growth-at-risk differs from the one of median growth. In particular, an increase of cyclical systemic risk affects negatively growth-at-risk during a long horizon, while the effect on median growth would be positive during the first 6 quarters. Nonetheless, the effect on the median turns negative and more persistent at longer horizons. These results indicate that the build-up of cyclical risk may feed economic expansions in the short-run but at the expense of higher downside risk in the mid-term.

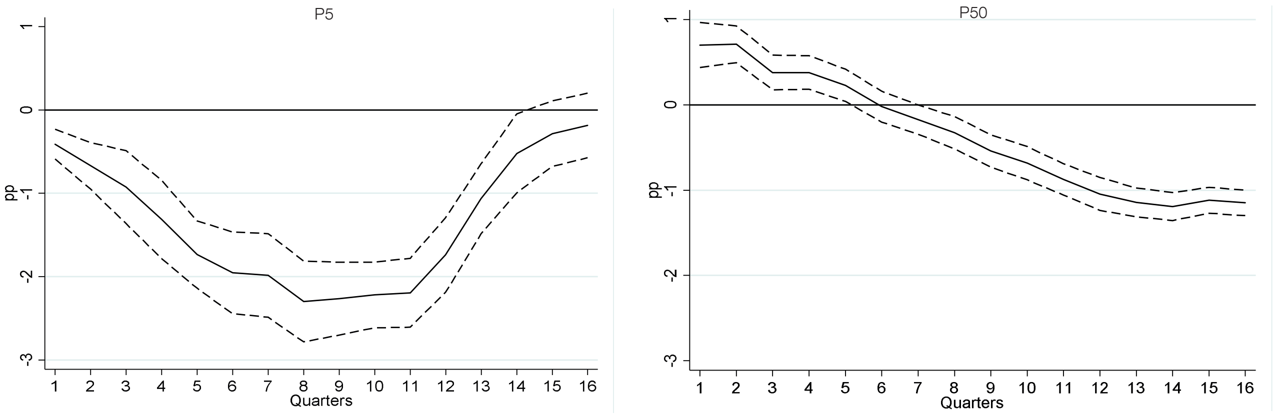
Similarly, an increase of 1s.d. in financial stress has a negative impact on growth-at-risk, but it materializes faster and is less persistent than the impact of cyclical risk. In this case, the negative effect on growth-at-risk reaches its maximum impact around 4 quarters after the shock and dilutes rapidly. This confirms that the effect of financial stress is more contemporaneous given that it is associated to the materialization of risk. The impact on median GDP growth is also negative but its magnitude is one-third than that on growth-at-risk. These results confirm the relevance of disentangling contemporaneous variables of financial risk from those capturing the building-up of cyclical systemic risk.

The response of GDP growth to the implementation of macroprudential policy is also heterogeneous across quantiles and over time. In particular, tightening macroprudential policy has a negative impact on median GDP growth, which confirms the previous findings in studies using conditional mean models. However, the impact on growth-at-risk is positive and the magnitude is larger in the mid-term. In terms of policy, these results suggest that taking early tightening decisions of macroprudential policy would reduce the downside risk of GDP growth through an increase in the resilience of the financial system. In this context, it would be possible to compare the benefits of macroprudential policy on growth-at-risk with the costs associated to reductions in median growth. This would allow policy makers to perform a cost-benefit analysis of macroprudential policy in terms of the same unit of measure, which is beyond the scope of this article [see Brandao-Marques et al. (2020), for a proposal to perform a cost-benefit analysis under this framework through the use of loss functions].

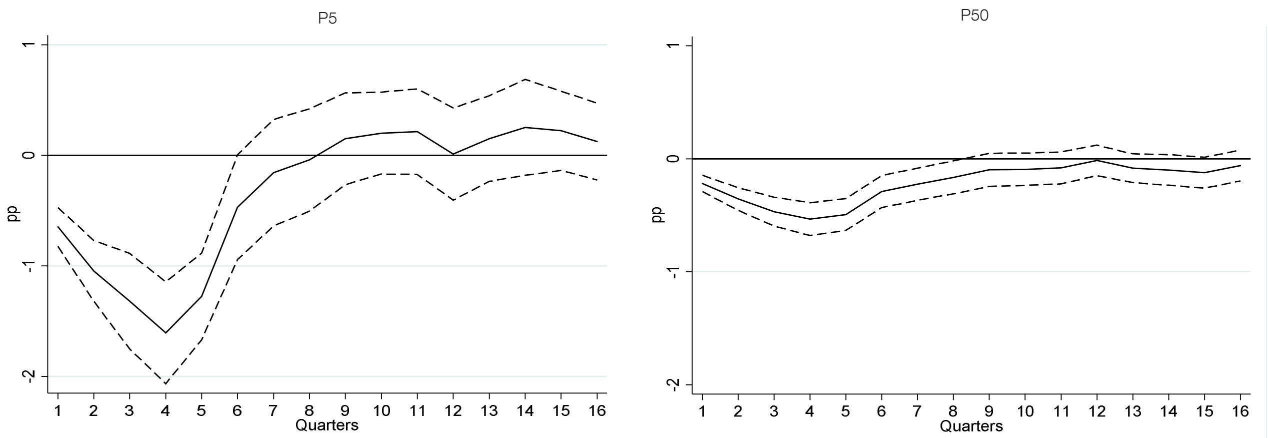
Chart 5

RESPONSE OF GROWTH-AT-RISK AND MEDIAN GROWTH FROM 1 TO 16 QUARTERS AHEAD TO CHANGES IN SRI, CLIFS AND MPI

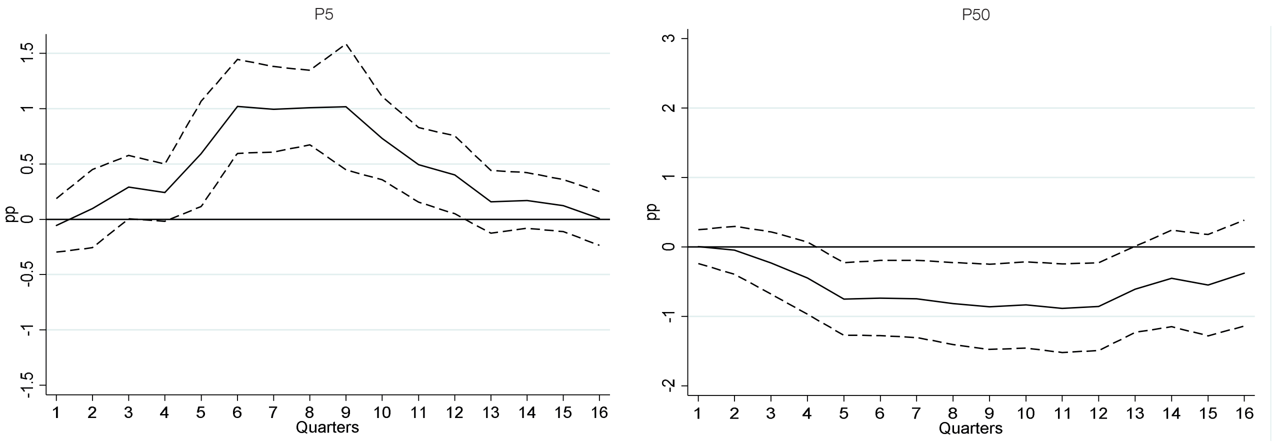
1 INCREASE OF 1 STD. DEV IN CYCLICAL SYSTEMIC RISK



2 INCREASE OF 1 STD. DEV IN FINANCIAL STRESS



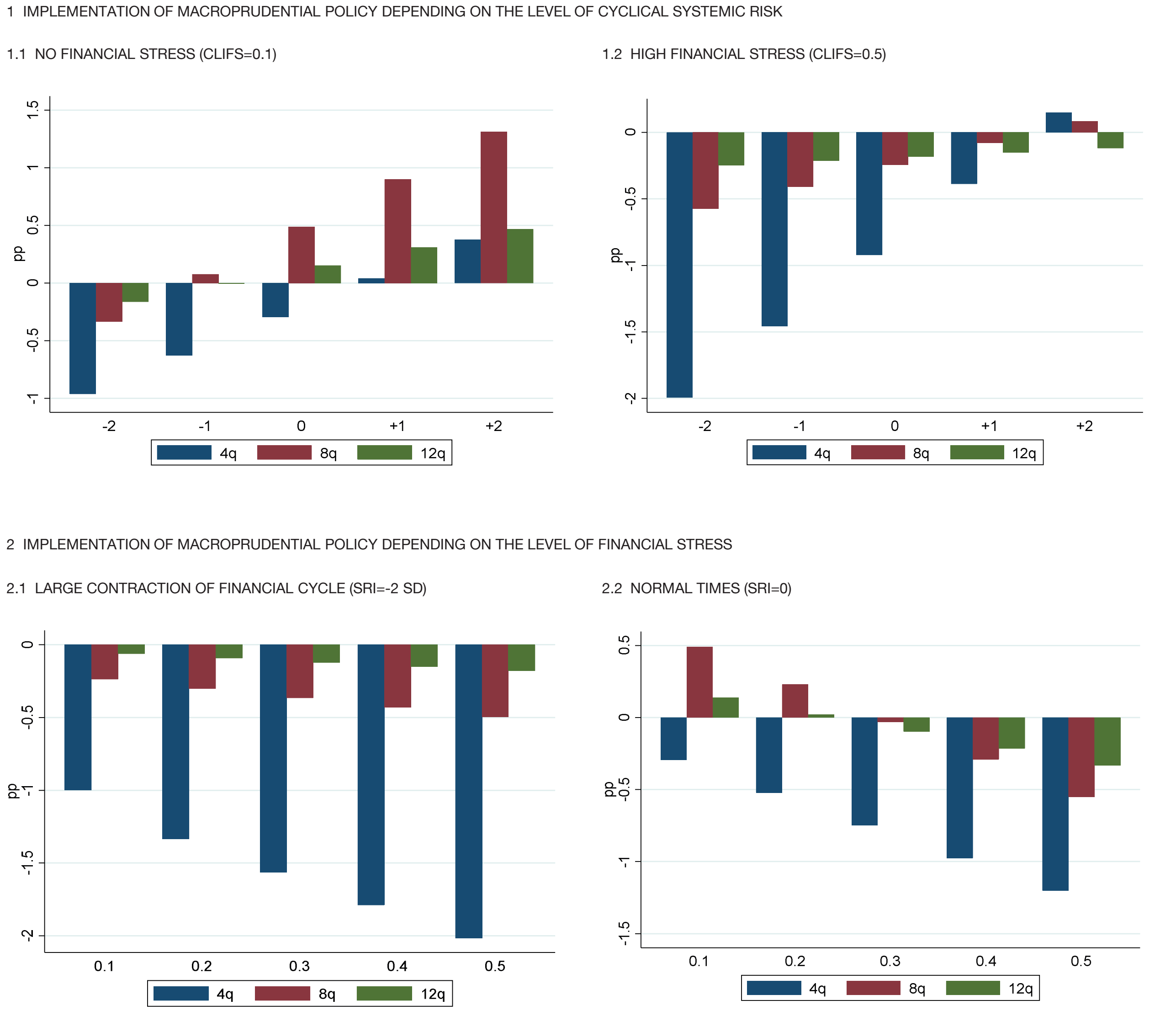
3 TIGHTENING OF A MACROPRUDENTIAL MEASURE



SOURCE: Authors' calculation.
NOTES: The continuous lines represent the estimated coefficients of the MPI in quantile regression at the 5th and 50th percentiles of the conditional GDP growth distribution from 1 to 16 quarters ahead. The dashed lines represent the 95% confidence bands obtained using bootstrapped standard errors with 500 replications.

Chart 6

MARGINAL EFFECT OF MACROPRUDENTIAL POLICY ON GROWTH-AT-RISK 4, 8 AND 12 QUARTERS AHEAD CONDITIONAL ON DIFFERENT LEVELS OF CYCLICAL SYSTEMIC RISK AND FINANCIAL STRESS



SOURCE: Authors' calculation.
NOTES: The bars represent the estimated marginal effect of tightening MPI on the 5th percentile of GDP growth at different horizons (4, 8, and 12 quarters ahead of the implementation of a policy). In panels 1.1 and 1.2, the horizontal axes represent a value of the SRI equal to -2, -1, 0, 1, and 2 standard deviations from 0, which represents a normal times situation. In panels 2.1 and 2.2, the horizontal axes represent the values of the CLIFS, where 0.1 is the median value in tranquil periods and 0.5 is the median value reached during systemic events.

Nonetheless, the impact of macroprudential policy on GDP growth may depend on the position in the financial cycle, its amplitude, and the degree of financial stress. In order to account for these interactions, we estimate the full specification in equation [8]. In Chart 6 we plot the marginal effect of the tightening of macroprudential policy on growth-at-risk conditional on different levels of cyclical systemic risk and financial stress at three different horizons. Positive values represent the benefits of tightening macroprudential policy (or the cost of loosening), while negative values represent the benefits of loosening macroprudential policy (or the cost of tightening). In Panel 1.1, we observe that the positive impact of tightening macroprudential policy during expansions (i.e., increases in the SRI) is greater when disequilibria are larger and that the impact is more evident in the mid-term. Conversely, loosening macroprudential policy has a positive impact on growth-at-risk during periods of contractions in the financial cycle (i.e. reduction in the SRI). These benefits are mainly observed at short-horizons and they become larger when contractions are more severe. In a neutral situation (normal times), the effects are mixed but it still seems that tightening macroprudential policy improves growth-at-risk after 8 quarters.

Under severe financial stress events (Panel 1.2), the benefits of loosening macroprudential policy on growth-at-risk are quite important in the short-term and larger under contractionary phases of the financial cycle. Under the occurrence of these type of events, tightening macroprudential policy is not convenient, even if they are observed during expansionary phases of the financial cycle. Nonetheless, the magnitude of the stress event is also relevant. In Panel 2.1 we observe that under a large contraction, the benefits of loosening macroprudencial policy are important in the short-run at any level of stress, but they can double when moving from a tranquil situation to a very stressed scenario. In normal times (Panel 2.2), the benefits of loosening are lower but the possibility to loosen macroprudential policy if a high stress event materializes would be particularly beneficial.

A more complete picture of the impact of macroprudential policy on the GDP growth distribution can be observed by mapping the quantile estimates at the most relevant horizons identified above into probability density functions. Departing from a baseline “normal times” scenario (i.e. SRI=0, CLIFS=0.1, and MPI at average values), in Chart 7 we show that both the location and the shape of the GDP growth distribution change after a shock either in cyclical risk or financial stress, and that they are also affected by the implementation of a macroprudential policy in the expected direction.

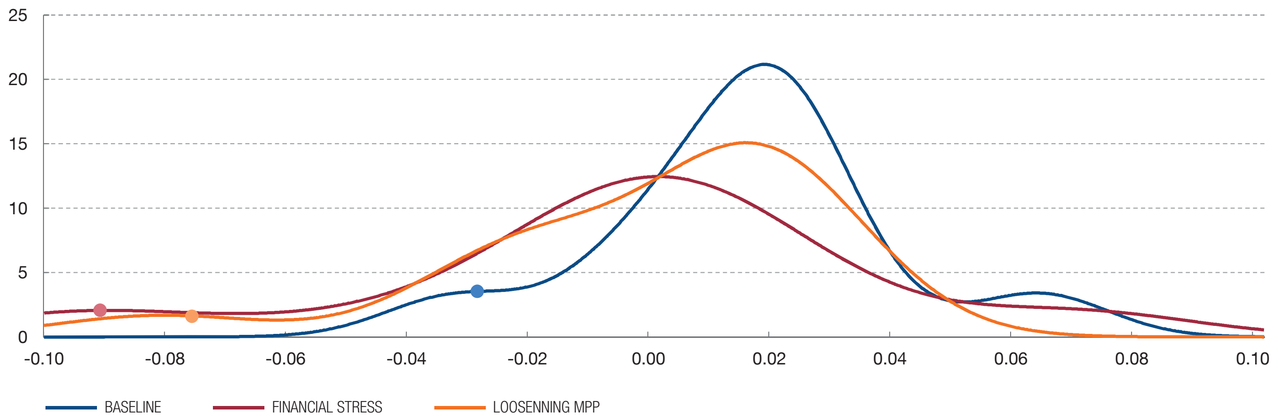
In Panel 1 we observe that a sudden high increase in financial stress, similar to the one observed during the first months of the last global financial crisis and close to the observed in some countries during the first months after the recent COVID-19 shock (CLIFS=0.5), leads to an asymmetric change in the location and shape of the 4-quarters ahead GDP growth distribution. The distribution moves towards left and becomes highly left-skewed. Thus, while median growth drops around 2.5 pp, growth-at-risk decreases 6 pp. Under this scenario, loosening macroprudential policy would improve growth-at-risk in around 1.5 pp.

The effect of a large contraction of the financial cycle, such as the one observed during the last global financial crises in most of countries (–2s.d. change in SRI) is presented in Panel 2. In this case, the change in the 4-quarters ahead GDP growth distribution is mainly observed in the left-tail with a decrease of 4 pp in growth-at-

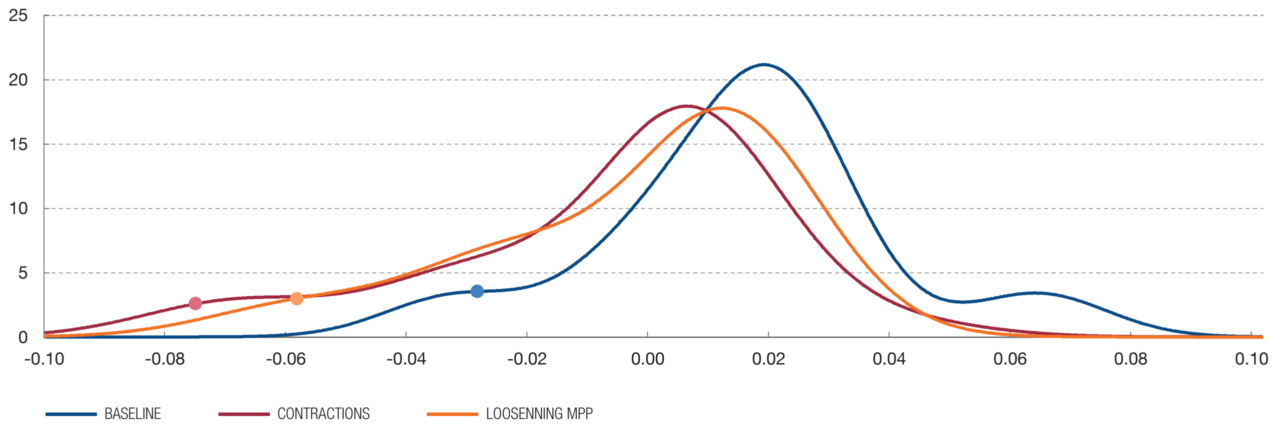
Chart 7

CONDITIONAL GDP GROWTH DISTRIBUTION 4 AND 8 QUARTERS AHEAD UNDER DIFFERENT SCENARIOS

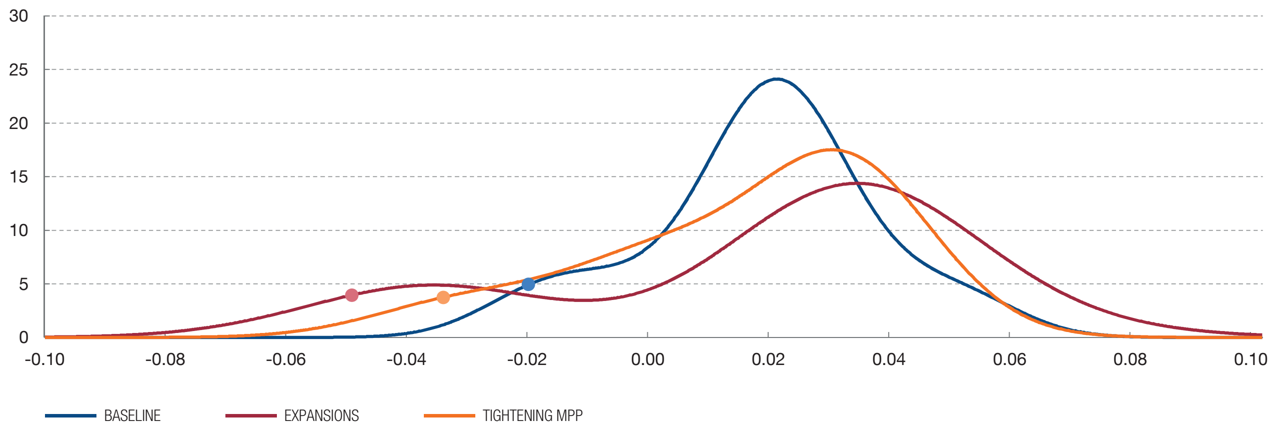
1 LOOSENING DURING FINANCIAL STRESS PERIODS (H=4)



2 LOOSENING DURING CONTRACTIONS (H=4)



3 TIGHTENING DURING EXPANSIONS (H=8)



SOURCE: Authors' calculation.
NOTE: The charts present the estimated GDP growth distributions at the specified horizons after mapping the fitted values of 19 quantile regressions from the 5th to the 95th percentiles into a probability density function using the Kernel-based method described in Annex 1. The black densities represent the baseline cases; the red densities denote the distribution in a situation of high financial stress (CLIFS = 0.5; Panel 1), large contraction (SRI=-2s.d; Panel 2), and large expansion (SRI=+2s.d; Panel 3); and blue densities represent the distribution after tightening (Panels 1, 2) or loosening (Panel 3) a macroprudential measure.

risk. Loosening macroprudential policy in this scenario improves growth-at-risk in around 1.2 pp, although the effect on the median and the right tail is less evident.

Finally, in Panel 3 we show how the GDP growth distribution changes after an expansion of the financial cycle, and the impact of tightening macroprudential policy in this scenario. We map the quantile estimates of GDP growth 8 quarters ahead since the maximum impact of tightening macroprudential policy is evidenced around this horizon. We observe that an expansion of a similar magnitude to that observed in most of countries during the run-up to the last global financial crisis (+2s.d. change in SRI), moves the location of the distribution towards right at the same time that the distribution becomes heavily left-skewed. In particular, growth-at-risk decreases around 3 pp, suggesting that higher GDP growth rates in an expansionary phase becomes at the cost of higher downside risk. Nonetheless, tightening macroprudential policy under this scenario is highly beneficial. We observe that its implementation reduces risk by flattening both tails, while median growth is almost unaltered. In particular, tightening macroprudential policy improves growth-at-risk around 1.7 pp, 8 quarters after its implementation.

Overall, cyclical risk and the materialization of financial stress have important asymmetric effects on the GDP growth distribution, which are especially negative on the left tail, thereby increasing risk for financial stability. Under these scenarios, the benefits of macroprudential policy are evident in terms of improving growth-at-risk. The results are consistent when assessing specific instruments. In Annex 3, we present an assessment of the impact of the capital requirements over the cycle, which also provides a more direct identification of elasticities.

5 Conclusions

Financial stability is aimed at preventing and mitigating systemic risk, which is largely associated to the tail risk of macrofinancial variables. In this context, policy makers need models that allow considering the effects of financial risk and financial stability policies on the whole distribution of these variables, and particularly on the left tail of the distribution, rather than only on the central tendency. The so-called at-risk methods provide a useful framework for the assessment of financial stability by the recognition of non-linear effects on the distribution of macrofinancial variables. In this context, quantile regressions offer a flexible method for this purpose.

We describe the use of the method and illustrate two empirical applications from which useful insights for policymakers are derived. Overall, at-risk-models offer a practical framework to estimate the impact of financial conditions and macroprudential policies on macrofinancial variables directly linked to financial stability; thereby becoming a very relevant tool for policy decisions.

REFERENCES

Adrian, T., N. Boyarchenko, and D. Giannone (2019). "Vulnerable Growth", *American Economic Review,* 109(4), pp. 1263-1289.

Aikman, D., J. Bridges, S. Burgess, R. Galletly, I. Levina, C. O'Neill and A. Varadi (2018). *Measuring Risks to Financial Stability,* Staff Working Paper 738, Bank of England.

Aikman, D., J. Bridges, H. S. Haciouglu, C. O'Neill and A. Raja (2019). *Credit, capital and crises: a GDP-at-risk approach,* Staff Working Paper 724, Bank of England.

Akinci, O., and J. Olmstead-Rumsey (2018). "How Effective Are Macroprudential Policies? An Empirical Investigation", *Journal of Financial Intermediation,* 33(C), pp. 33-57.

Alam, Z., A. Alter, J. Eiseman, G. Gelos, H. Kang, M. Narita, E. Nier, and N. Wang (2019). *Digging Deeper - Evidence on the Effects of Macroprudential Policies from a New Database,* IMF Working Paper WP/19/66, International Monetary Fund.

Altunbas, Y., M. Binici, and L. Gambacorta (2018). "Macroprudential policy and bank risk", *Journal of International Money and Finance,* 81, pp. 203-220.

Arellano, M., and S. Bonhomme (2016). "Nonlinear Panel Data Estimation via Quantile Regressions", *Econometrics Journal,* 19, pp. 61-94.

Azzalini, A., and A. Capitanio (2003). "Distributions Generated by Perturbations of Symmetry with Emphasis on a Multivariate Skew t Distribution", *Journal of the Royal Statistical Society: Series B,* 65, pp. 367-89.

Bedayo, M., Á. Estrada, and J. Saurina (2020). "Bank capital, lending booms, and busts. Evidence from Spain over the last 150 years", *Latin American Journal of Central Banking,* 10003.

Berkowitz, J., P. F. Christofferson, and D. Pelletier (2011). "Evaluating Value-at-Risk models with desk-level data", *Management Science,* 57 (12), pp. 2213-2227.

Boar, C., L. Gambacorta, G. Lombardo, and L. Pereira da Silva (2017). "What are the effects of macroprudential policies on macroeconomic performance?", *BIS Quarterly Review,* September, pp. 71-88.

Brandao-Marques, L., G. Gelos, M. Narita, and E. Nier (2020). *Leaning Against the Wind: A Cost-Benefit Analysis for an Integrated Policy Framework,* IMF Working Paper WP/20/123, International Monetary Fund.

Budnik, K., and J. Kleibl (2018). *Macroprudential regulation in the European Union in 1995-2014: introducing a new data set on policy actions of a macroprudential nature,* Working Paper Series 2123, European Central Bank.

Canay, I. A. (2011). "A simple approach to quantile regression for panel data", *The Econometrics Journal,* 14(3), pp. 368-386.

Cecchetti, S., and H. Li (2008). *Measuring the impact of asset price booms using quantile vector autoregressions,* Working Paper, Department of Economics, Brandeis University, USA.

Cerutti, E., S. Claessens, and L. Laeven (2017). "The use and effectiveness of macroprudential policies: New evidence", *Journal of Financial Stability,* 28, pp. 203-224.

Christoffersen, P. (1998). "Evaluating interval forecasts", *International Economic Review,* 39, pp. 841-862.

Claessens, S., S. Ghosh, and R. Mihet (2013). "Macro-prudential policies to mitigate financial system vulnerabilities", *Journal of International Money and Finance,* 39, pp. 153-185.

De Nicolo, G., and M. Lucchetta (2017). "Forecasting Tail Risks", *Journal of Applied Econometrics,* 32, pp. 159-170.

Dell'Ariccia, G., D. Igan, and L. Laeven (2016). "Credit booms and macro-financial stability", *Economic Policy,* 31, pp. 299-355.

Duprey, T., B. Klaus, and T. A. Peltonen (2015). *Dating systemic financial stress episodes in the EU countries,* ECB Working Paper No. 1873.

Duprey, T., and A. Ueberfeldt (2020). *Managing GDP Tail Risk,* Staff Working Paper 202/03, Bank of Canada.

Engle, R., and S. Manganelli (2004). "CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles", *Journal of Business & Economic Statistics,* 22(4), pp. 367-381.

Escanciano, J. C., and C. Goh (2014). "Specification analysis of linear quantile models", *Journal of Econometrics,* 178(3), pp. 495-507.

European Central Bank (2020). *Financial Stability Review,* May.

European Systemic Risk Board (2015). *Annual Report 2014,* Frankfurt am Main, July.

Financial Stability Board, International Monetary Fund, and Bank for International Settlements (2011). *Macroprudential Policy Tools and Frameworks,* Progress Report to G20, October.

Galán, J. E. (2020). *The benefits are at the tail: uncovering the impact of macroprudential policy on growth-at-risk,* Working Papers, No. 2007, Banco de España.

Gálvez, J., and J. Mencía (2014). *Distributional linkages between European sovereign bond and bank assets returns,* CEMFI Working Paper No. 1407, CEMFI.

Giglio, S., B. Kelly, and S. Pruitt (2016). "Systemic Risk and the Macroeconomy: An Empirical Evaluation", *Journal of Financial Economics,* 119(3), pp 457-471.

Graham, B. S., and J. L. Powell (2012). "Identification and estimation of average partial effects in 'irregular' correlated random coefficient panel data models", *Econometrica,* 80(5), pp. 2105-2152.

Greenspan, A. (2004). "Risk and uncertainty in monetary policy", *American Economic Review,* 94(2), pp. 33-40.

International Monetary Fund (2019). *Global Financial Stability Report,* March.

Jiménez, G., S. Ongena, J. L. Peydró, and J. Saurina (2017). "Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments", *Journal of Political Economy,* 125(6), pp. 2126-2177.

Jones, M. C., and M. J. Faddy (2003). "A skew extension of the t-distribution, with applications", *Journal of the Royal Statistical Society: Series B (Statistical Methodology),* 65, pp. 159-174.

Jordà, Ò., and A. M. Taylor (2016). "The time for austerity: estimating the average treatment effect of fiscal policy", *Economic Journal,* vol. 126(590), pp. 219-255.

Jorion, P. (2001). *Value at Risk - The New Benchmark for Managing Financial Risk,* McGraw-Hill, Chicago.

Kato, K., A. F. Galvão, and G. Montes-Rojas (2012). "Asymptotics for Panel Quantile Regression Models with Individual Effects", *Journal of Econometrics,* 170, pp. 76-91.

Kim, S., and A. Mehrotra (2018). "Effects of Monetary and Macroprudential Policies - Evidence from Four Inflation Targeting Economies", *Journal of Money, Credit and Banking,* 50(5), pp. 967-992.

Koenker, R. (2004). "Quantile regression for longitudinal data", *Journal of Multivariate Analysis,* 91, pp. 74-89.

— (2005). *Quantile Regression,* Cambridge University Press, Cambridge.

Koenker, R., and J. A. F. Machado (1999). "Goodness of Fit and Related Inference Processes for Quantile Regression", *Journal of the American Statistical Association,* 94(448), pp. 1296-1310.

Koenker, R., and G. Bassett (1978). "Regression Quantiles", *Econometrica,* 46(1), pp. 33-50.

Koenker, R., and O. Geiling (2001). "Reappraising medfly longetivity: A quantile regression approach", *Journal of American Statistic Association,* 96, pp. 458-468.

Komunjer, I. (2013). "Quantile Prediction", in *Handbook of Economic Forecasting,* edited by Graham Elliott and Allan Timmermann, Amsterdam, Elsevier.

Kupiec, P. (1995). "Techniques for verifying the accuracy of risk measurement models", *Journal of Derivatives,* 2, pp. 173-184.

Lang, J. H., C. Izzo, S. Fahr, and J. Ruzicka (2019). *Anticipating the bust: a new cyclical systemic risk indicator to assess the likelihood and severity of financial crises,* Occasional Paper Series 219, European Central Bank.

Lang, J. H., and M. Forletta (2020). *Cyclical systemic risk and downside risks to bank profitability,* Occasional Paper Series 2405, European Central Bank.

Machado, J. A. F., and J. M. C. Santos SIlva (2019). "Quantiles via moments", *Journal of Econometrics,* 213(1), pp. 145-173.

Martínez-Pagés, J., and L. Á. Maza (2003). *Analysis of house prices in Spain,* Working Papers, No. 0307, Banco de España.

Noss, J., and P. Toffano (2016). "Estimating the impact of changes in aggregate bank capital requirements on lending and growth during an upswing", *Journal of Banking and Finance,* 62, pp. 15-27.

Powell, D. (2016). *Quantile Regression with Nonadditive Fixed Effects,* Quantile Treatment Effects, RAND Labor and Population Working Paper.

Richter, B., M. Schularik, and I. Shim (2019). "The Costs of Macroprudential Policy", *Journal of International Economics,* 118, pp. 263-282.

Skewed t-distribution density

Relative to the t-distribution, the skewed t-distribution adds the shape parameter which regulates the skewing effect of the PDF and CDF. One might use the skewed t-distribution developed by Azzalini and Capitanio (2003) to smooth the quantile function and estimate the probability density function:

$$f\left(y_{t+h};\mu,\sigma,\alpha,\nu\right)=\frac{2}{\sigma}t\left(\frac{y_{t+h}-\mu}{\sigma};\nu\right)T\left(\alpha\frac{y_{t+h}-\mu}{\sigma}\sqrt{\frac{\nu+1}{\nu+\frac{y_{t+h}-\mu}{\sigma}}};\nu+1\right), \qquad \text{[A1.1]}$$

where t(·) and T(·) refers to the PDF and CDF of the Student-t, respectively. The four parameters of the distribution pin down the location μ, scale σ, fatness ν, and shape α.

Thus, we can fit the skewed-t distribution by choosing the four parameters that minimize the squared distance between our estimated quantile function $\hat{Q}_{y_{t+h|X_t}}\left(\tau\,|\,X_t\right)$ from equation [1] and the quantile function of the skewed-t distribution $F^{-1}\left(\tau;\mu;\sigma;\alpha;\nu\right)$ from equation [A1.1] to match the chosen quantiles to shape the distribution as follows:

$$\left\{\hat{\mu},\hat{\sigma},\hat{\alpha},\hat{\nu}\right\}=\arg\min_{\mu,\sigma,\alpha,\nu}\sum_{\tau}\left(\hat{Q}_{y_{t+h|X_t}}\left(\tau\,|\,X_t\right)-F^{-1}\left(\tau;\mu;\sigma;\alpha;\nu\right)\right)^2, \qquad \text{[A1.2]}$$

where $\hat{\mu}\in\mathbb{R},\widehat{\sigma}\in\mathbb{R}^{+},\hat{\alpha}\in\mathbb{R},\text{and}\,\hat{\nu}\in\mathbb{Z}^{+}$. Very similar fits can be obtained using the skewed-t distribution described in Jones and Faddy (2003).

Kernel-based density

A parametric fitting although practical, introduces strong assumptions on the density function. A non-parametric fit using Kernel-based methods provides a smooth and monotone CDF while allowing for more flexibility [Escanciano and Goh (2014)]. In particular, we focus here on the weighted Kernel interpolation method in Gálvez and Mencía (2014), where the Kernel CDF would be represented by:

$$\sum_{j=1}^{p}w_j\Phi\left(\frac{x-q\left(\theta_j\right)}{B}\right), \qquad \text{[A1.3]}$$

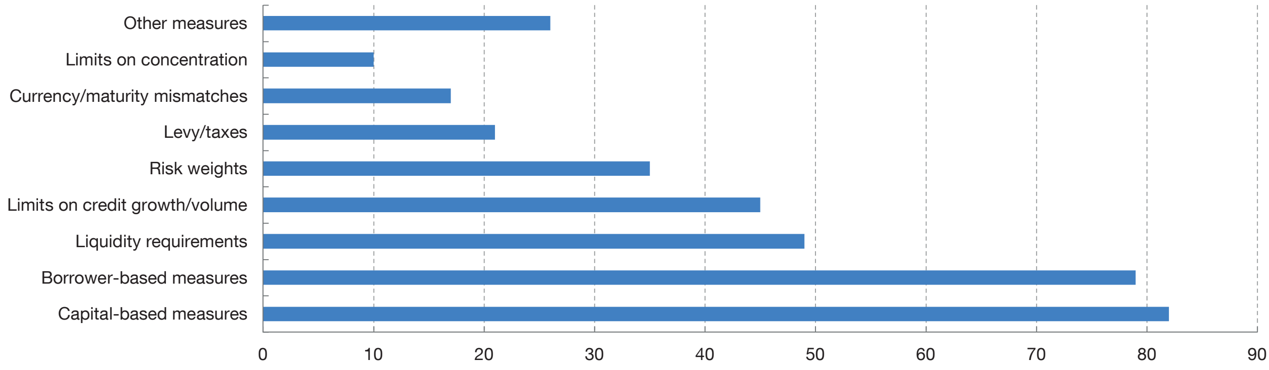
where $\Phi(\cdot)$ is the standard Gaussian cdf; p is the number of estimated quantiles, θ_j represents the quantile j; B is the smoothing parameter; and, w represents the weights $(w_1, w_2, ..., w_p)'$ that minimize the squared distance between the quantile level and its associated cdf. The bandwidth is computed as $B = 1.06 \min(\hat{s}, \hat{r}) p^{-1/5}$, where $\hat{s}$ is the standard deviation and $\hat{r}$ is the interquartile range of the quantile functions. After differentiating the Kernel cdf, the following conditional density is obtained:

$$\frac{1}{B}\sum_{j=1}^{p} \hat{w}_j \phi\left(\frac{x - q(\theta_j)}{B}\right), \quad [A1.4]$$

where $\phi(\cdot)$ is the standard normal density function.

Chart A2.1

IMPLEMENTED MACROPRUDENTIAL MEASURES IN THE EU COUNTRIES 1970-2018 BY CATEGORY



SOURCES: ECB Macroprudential Database and own elaboration.
NOTE: The horizontal axis represents the number of macroprudential measures implemented by EU countries from 1970 to 2018 in each category, excluding those where the level or scope of the measure remains unchanged.

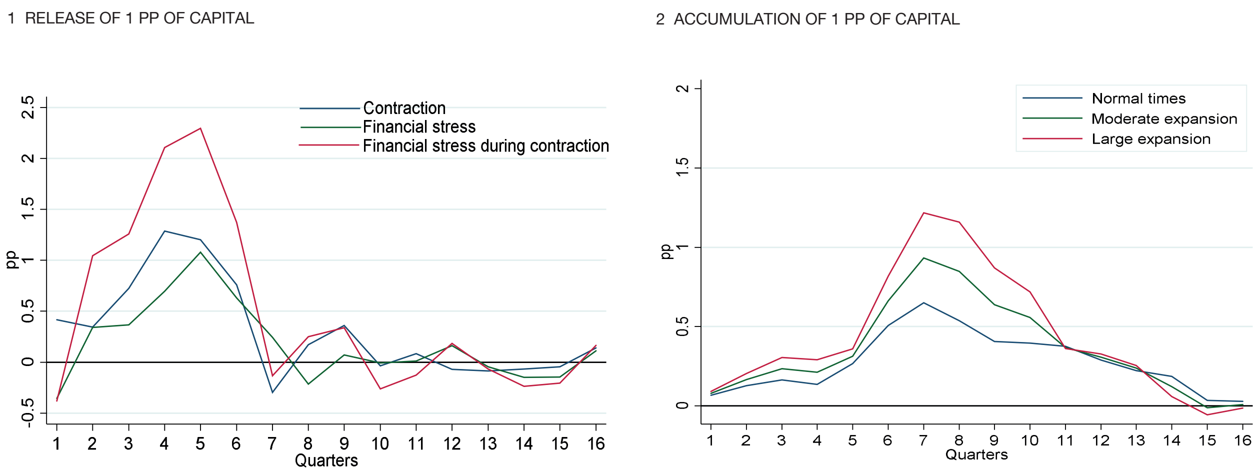
Using the information reported in the ECB Macroprudential Database introduced by Budnik and Kleibl (2018) we construct the MPI as a simple sum of the scores on 9 different categories of macroprudential policies for each country. The categories include capital-based measures (i.e., capital requirements, loan-loss provisions and capital buffers), borrower-based measures, liquidity requirements, limits on credit growth, risk weights, taxes, limits to mismatches on currency and maturity, and limits to concentration. The index is computed as follows:

$$MPI_{it} = \sum_{j=1}^{J} SP_{jit} \;;\; SP_{jit} = SP_{jit-1} + \Delta SP_{jit}, \qquad [A2.1]$$

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 1 when a macroprudential measure is either activated or tightened, while it subtracts 1 when a measure is either deactivated or loosened within that category. The intention of the index is not to capture the intensity of the measures or their change over time. The advantage of the index constructed in this way compared to the use of dummy variables is that it allows evaluating the effectiveness when more than one measure is in place, and then accounting for net tighten or loosen conditions. This approach has been followed also by other authors aggregating macroprudential measures with minor variations [Boar et al. (2017), Cerutti et al. (2017), Kim and Mehrotra (2018), Duprey and Ueberfeldt (2020), Alam et al. (2019)].

Chart A3.1

RESPONSE OF GROWTH-AT-RISK TO A 1 PP CHANGE IN CAPITAL REQUIREMENTS UNDER DIFFERENT SCENARIOS



SOURCE: Authors' calculation.

NOTE: The continuous lines represent the estimated response of growth-at-risk from 1 to 16 quarters after a shock equal to a 1 pp change in the solvency ratio under different scenarios: contraction (SRI=-2s.d.), financial stress (CLIFS = 0.5), financial stress during contraction (SRI=-2s.d. and CLIFS=0.5), normal times (SRI=0), moderate expansion (SRI=+1s.d.), and large expansion (SRI=+2s.d.); while holding other variables constant.

The growth-at-risk tool would also be useful for measuring the impact of specific instruments and possibly guiding their calibration. To illustrate this, we extend the previous exercise to assess the effects of capital requirements. We estimate the model in equation [8] but replacing the MPI by the banks' solvency ratio defined in terms of CET1 capital over risk-weighted assets, which is the main metrics for this type of requirements and buffers.

In Chart A3.1, we plot the response of growth-at-risk to a 1 pp change in capital requirements under different scenarios. We observe that releasing capital would produce rapid but low persistent benefits on growth-at-risk, but that the magnitude of the impact depends on the scenario. Under a large contraction of the financial cycle (SRI=-2s.d.), releasing 1 pp of capital leads to a rapid improvement in growth-at-risk, which is evident even from the next quarter. In a high financial stress scenario (CLIFS=0.5), the improvement seems to be slower but the economic impact would be similar 5 quarters after the release. Finally, in a combined scenario of large contraction and high financial stress, the benefits of releasing 1 pp of capital on growth-at-risk would be larger, reaching more than 2 pp.

Conversely, accumulating capital in good times has benefits during an upswing of the financial cycle. These benefits are clearer in the mid-term suggesting the need of increasing capital early enough in the cycle. Although, the benefits increase with the magnitude of the expansion, under a situation close to the equilibrium (SRI=0), the impact of accumulating capital is still positive.

Overall, these findings support the countercyclical use of capital-based measures, whose benefits in reducing the tail risk of GDP growth are evident not only when releasing capital during contractions, but also when accumulating capital during expansions. Moreover, the positive effects of increasing capital during normal times and releasing it during stress events, also support the use of instruments, such as the countercyclical capital buffer before disequilibria in the financial cycle is observed, and as an effective instrument to mitigate the negative consequences of unexpected events.