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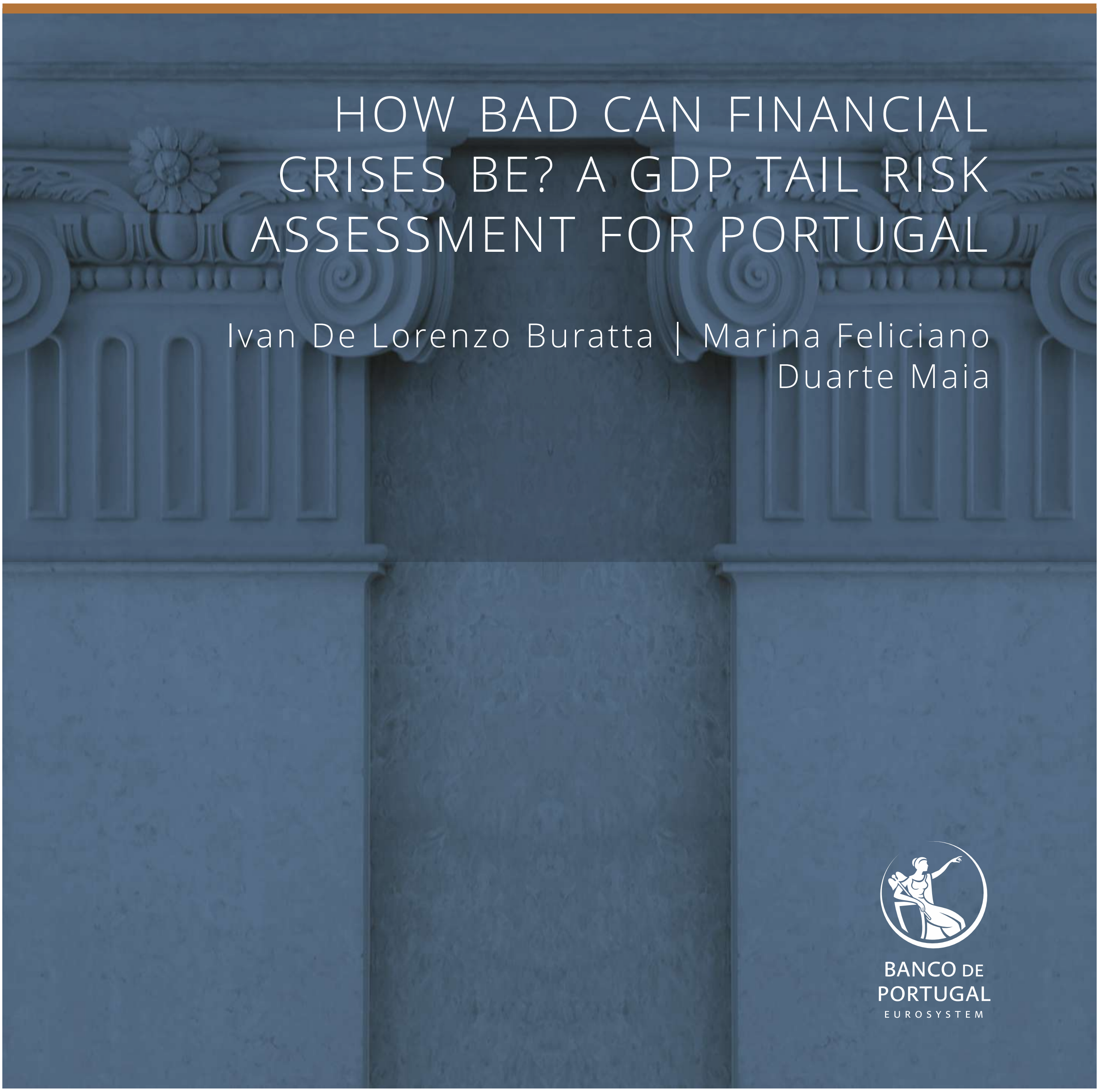

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How Bad Can Financial Crises Be? A GDP Tail Risk Assessment for Portugal

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Abstract
By monitoring the evolution of risks to economic activity over time, we quantify the likelihood and severity of future negative economic growth. Following the *Growth-at-risk* approach, we explore the non-linear relationship between the current financial situation and the distribution of future GDP growth for Portugal. We find that both financial vulnerability and risk have a negative effect on the left tail of the one-year-ahead GDP growth distribution. Financial vulnerability has the largest impact on GDP growth at the medium to long term horizon while financial risk is only significant at the short term horizon. The GDP-at-risk measure signals economic recessions, no matter whether fueled by financial stress or imbalances, reaching negative values before 2008 and stagnating at low levels before the European Sovereign Debt Crisis. To provide policymakers with better tools to signal an increase in the likelihood of a crisis, we compute a set of complementary risk measures. Among those analyzed, the distance between the tails of the conditional distribution of GDP growth complements GDP-at-risk in anticipating economic recessions since it signals the Great Financial Crisis with a clear downward trend before 2008. The moments of the GDP growth distribution have some power in signalling recessions, as they identify changes in the characteristics of the distribution. Finally, we argue that the expected shortfall and longrise can complement the GDP-at-risk measure since they encompass information which is not limited to a single percentile of the distribution.

JEL: C53, E01, E17, E27, E32, E44, G01

Keywords: Macroprudential policy, quantile regression, downside risk, macrofinancial linkages, financial stability, GDP-at-risk.

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1. Introduction

Exploring the relationship between the financial system and the business cycle has been one of the core topics in macroeconomics since the Great Financial Crisis (GFC) in 2008. A relevant strand of literature focuses in particular on the non-linear nature of this relationship, stressing how financial distress can cause deep and long-lasting economic recessions which diverge strongly from the regular business cycle behavior. *Growth-at-risk* studies fall into this branch of research: a quantile regression approach used to study the whole distribution of future GDP growth as a function of current economic and financial situation, focusing on its lowest realizations.[1] The analysis of the left tail dynamics can give warning information about the possible extreme (negative) realizations of GDP growth in the future. The seminal paper by Adrian *et al.* (2019) is the main reference of the *Growth-at-risk* framework: not only do they find for the US that financial conditions' deterioration is associated with higher conditional volatility and lower conditional mean of GDP growth, but they also study a set of complementary metrics to measure growth vulnerability. Downside entropy and expected shortfall, in particular, can provide policy-relevant warning signals and confirm the non-linear relationship between financial conditions and future macroeconomic developments.

Several other papers extend Adrian *et al.* (2019) work in different dimensions. Aikman *et al.* (2018) explore the performance of the *Growth-at-risk* framework for the UK. They find that leverage and asset price have relevant warning properties and negatively affect the left tail of the GDP growth distribution. Alessandri *et al.* (2019) and Busetti *et al.* (2020) draw similar conclusions for Italy. The tightening of credit conditions, the slowdown in trade flows, and the rise of economic uncertainty worsen the lowest (potential) realizations of GDP growth, even if the model loses some explanatory power in out-of-sample (or pseudo real-time, as we will call it henceforth) forecasting exercises. Loria *et al.* (2019) show for the US how monetary policy, credit conditions, and productivity shocks have a stronger effect on lower quantiles. Adrian *et al.* (2018), Aikman *et al.* (2019) and Galán (2020) explore panel quantile regressions. The first study stresses how the effect of financial conditions on GDP growth distribution varies over a 12-quarter projection horizon. The last two studies focus on the role of macroprudential policy in mitigating the left-tail risk in GDP growth. Galán (2020) also highlights the costs of macroprudential intervention, arguing that tightening macroprudential measures have a negative impact on the median and the right tail of the GDP growth distribution.

This work assesses the impact of the financial situation on GDP growth in Portugal at different projection horizons. We followed Adrian *et al.* (2019) methodology to study the conditional distribution of future GDP growth and build

1. The *Growth-at-risk* measure refers to a specific percentile in the left tail of the distribution of a variable of interest. Although the most common target in the literature happens to be GDP growth, this approach can be applied to several other variables such as banks' own funds ratio (Lang and Forletta 2020), house prices (Alter and Mahoney 2020) and inflation (López-Salido and Loria 2020).

risk measures to be used for policy purposes. We find that an increase in both the Systemic Risk Indicator (SRI) and the financial stress index (CLIFS, Country-Level Index of Financial Stress) have a negative effect on the left tail of the one-year-ahead GDP growth distribution. As expected, systemic risk has the largest impact on GDP growth at medium to long term horizon while financial stress is only significant at the short term horizon. GDP-at-risk, defined as the 10^{th} percentile of the GDP growth distribution, provides an adequate risk signal of economic recessions. This result is robust regardless of the nature of the downturn in our sample. Controlling for financial vulnerability and imbalances, the model can capture signals of both the GFC and the European Sovereign Debt Crisis (ESDC): the measure, estimated one year and three years ahead, falls to negative values before 2008 and remains low between 2009 and mid-2010. GDP-at-risk is thus informative of the risk of extreme (negative) realizations of GDP growth in the future. This result can be relevant from a policymaker's perspective, especially for macroprudential policies implementation purposes, as they need to act at the beginning of the systemic risk build-up.

We compute a set of complementary risk measures since focusing only on the 10^{th} percentile of the estimated GDP growth distribution may be too restrictive. Among those analyzed, the distance between the 10^{th} and the 90^{th} percentile of the one-year-ahead conditional distribution of GDP growth is a useful tool to complement GDP-at-risk in anticipating economic recessions since it shows a clear downward trend before 2008 and signals the ESDC remaining stably low between the two crises. Standard deviation, kurtosis and skewness dynamics of the one-year-ahead conditional distribution of GDP growth have some power in signalling that a recession is imminent, as they identify changes in the characteristics of the distribution. We argue that the expected shortfall and longrise can complement GDP-at-risk measure since they collect information which is not limited to the 10^{th} percentile of the estimated GDP growth distribution. In 2008, the probability of observing negative future GDP growth signals the likelihood of adverse economic situation for 2009 to be approximately 50%.

Regarding the GFC, we show how GDP-at-risk, the expected shortfall, the probability of observing negative future GDP growth, kurtosis and skewness can capture future systemic risk to economic performances even using only 2007 information. One year before the beginning of the crisis, our measure predicts risks for economic activity and higher uncertainty surrounding future GDP growth, mainly stemming from the accumulation of higher financial vulnerabilities. However, one-year anticipation could not be enough for financial stability objectives since macroprudential tools such as capital buffer need time to build up.

We also show that neither the credit-to-GDP ratio nor the total own funds ratio improve our baseline model performance substantially. The marginal effect of credit-to-GDP inflates the impact of the other variables, remaining constant across percentiles and horizons. The total own funds ratio is only significant at longer horizons and, in general, reduce the explanatory power of financial indexes.

The rest of the paper is organized as follows: section 2 explains the methodology used and provides a brief description of the data, section 3 presents the results for the baseline model, the GDP-at-risk measure and the proposed complementary risk measures. Section 4 shows some robustness checks made on the proposed model and section 5 concludes.

2. Methodology and Data

Quantile regressions (Koenker and Bassett 1978) and local projections (Òscar Jordà 2005) are combined to assess the link between the measures of financial risk and vulnerabilities and the distribution of the variable of interest at different projection horizons. The quantile regressions allow us to estimate the whole distribution of the variable of interest and the local projections enable the estimation of the same distribution h quarters ahead. We follow a two-steps approach as it is commonly used in the literature. In the first step (step 1), we estimate the marginal effect of each explanatory variable on the evolution of the dependent variable, h quarters ahead, for a specific percentile q, as follows:

$$\hat{\mathcal{Q}}_{Y_{t+h}}(q|X_t) = \hat{\alpha}^{q,h} + \hat{\beta}^{q,h} X_t \tag{1}$$

where Y_{t+h} is the dependent variable or variable of interest projected h quarters ahead, q is the percentile, X_t is a vector of explanatory variables, $\hat{\alpha}^{q,h}$ represents the model estimated constant and $\hat{\beta}^{q,h}$ is a vector of parameters that represents the estimated marginal effect of the explanatory variables on the dependent variable.

The unknown parameters are estimated through an optimization problem where the quantile weighted sum of the absolute value of the residuals is minimized. Koenker and Bassett (1978) show that the resultant estimators are consistent.[2] Equation (1) is, then, estimated for each percentile between 1% and 99% in steps of 1 percentage point and for a projection horizon that ranges between 1 and 12 quarters. We estimate in total 99 (q) times 12 (h) models considering GDP growth as the variable of interest. As in Adrian *et al.* (2019) and De Santis and Van der Veken (2020), the second step (step 2) entails fitting a distribution for each projection horizon to smooth the approximated quantile function. While Adrian *et al.* (2019) use a parametric distribution, the skewed *t*-distribution, we use a non-parametric kernel distribution in order to capture potential multimodality in the conditional GDP growth distribution – as argued by Adrian *et al.* (2021) – and to obtain a distribution closer to the estimated quantiles. A gaussian kernel with optimized bandwidth was used following Bowman and Azzalini (1997). Differently from the papers mentioned above, we also fit each percentile of the probability density to its regression counterpart to increase accuracy. Finally, once

2. For a comprehensive discussion on quantile estimators' consistency and relative conditions see Koenker (2005).

the conditional distribution is obtained, several risk measures can be computed from it.

In terms of estimation, two approaches can be followed: in-sample and pseudo real-time estimation. In the first exercise, the marginal effects, and consequently the conditional distribution and respective risk measures, are obtained from a model estimated using all the available observations. The sample includes data from the first quarter of 1991 to the fourth quarter of 2019. In the second exercise, the model is estimated using dynamic samples of observations that start in 2005Q1.[3] The sample is updated in each period by adding one additional observation, meaning that only known information up to that moment is used to obtain the estimates of the parameters in the relevant quantile regression. The aim is to simulate a real-time exercise and mimic the environment faced by policymakers when taking a decision on the level of risk prevailing: this approach is designed to replicate data availability, keeping in mind that for most of the series we will rely on final data vintages, ignoring the periodic revisions of the series. Our main focus will be on the results from this second exercise since it allows the analysis of the proposed measures in the context in which they could be used, that is, for policy purposes. However, the comparison with the results from the in-sample exercise can provide insights regarding the way the model "learns" from past events.

The model (henceforth baseline model) we chose to study the interaction between the financial situation and GDP growth at the various projection horizons considers as dependent variable the year-on-year rate of change of real GDP (henceforth GDP growth) projected h quarters ahead. As explanatory variables, we included the contemporaneous GDP growth, to avoid potential endogeneity issues, the systemic risk indicator [4] (SRI) and the financial stress indicator (CLIFS). SRI is a composite indicator proposed by Lang *et al.* (2019) which contains information regarding domestic credit, residential real estate markets, external imbalances, and private sector debt burden and can be thought as a measure of vulnerability. The SRI, as proposed by Lang *et al.* (2019), also includes information on equity prices to cover "potential mispricing of risk", but due to the low liquidity of the Portuguese capital market and its reduced size we opted for the version without this sub-indicator. This is one of the most used early warning indicators of systemic risk in the context of the euro area macroprudential policy analysis. Given the lag between the first signs of accumulated vulnerabilities and the potential materialization of an economic crisis, the conditional distribution of GDP growth is expected to be significantly more affected over the medium and long term by changes in SRI. CLIFS (Duprey *et al.* (2017)) is an index that aims at identifying, in a timely fashion, stress in equity, bond and foreign exchange markets. This indicator

3. Given the nature of the exercise, a training sample period must be considered in the estimation. Since the time span of the data available is reduced, the pseudo real-time exercise is set to start in 2005Q1.

4. For SRI, we are able to account for revisions to earlier data releases: when a new observation enters the dynamic sample in the pseudo real-time exercise, the whole series will be updated.

provides contemporaneous information about financial market turmoil and it can be considered as a measure of systemic financial stress. It is therefore expected to be more important in explaining the behavior of the conditional distribution of GDP growth over the short term, reflecting the effects of the conditions in the financial markets at each moment.

Thus, the baseline model is defined as follows:

$$\hat{Q}_{GDP_{t+h}}\left(q|GDP_t, SRI_t, CLIFS_t\right) = \\ \hat{\alpha}^{q,h} + \hat{\beta}^{q,h}_{GDP}GDP_t + \hat{\beta}^{q,h}_{SRI}SRI_t + \hat{\beta}^{q,h}_{CLIFS}CLIFS_t. \quad (2)$$

In the "robustness analysis section" (section 4) and in the appendix, we discuss the results from alternative models. These alternative models differ from the baseline model in what concerns the explanatory variables. The additional variables considered (as detailed below) are: the credit-to-GDP ratio, the economic sentiment indicator, the total own funds ratio and a set of principal components extracted from a large dataset of over 50 series. It is important to mention that given the short time span available for the variables considered, we had to choose a parsimonious model in terms of explanatory variables to guarantee the properties of the quantile estimator.

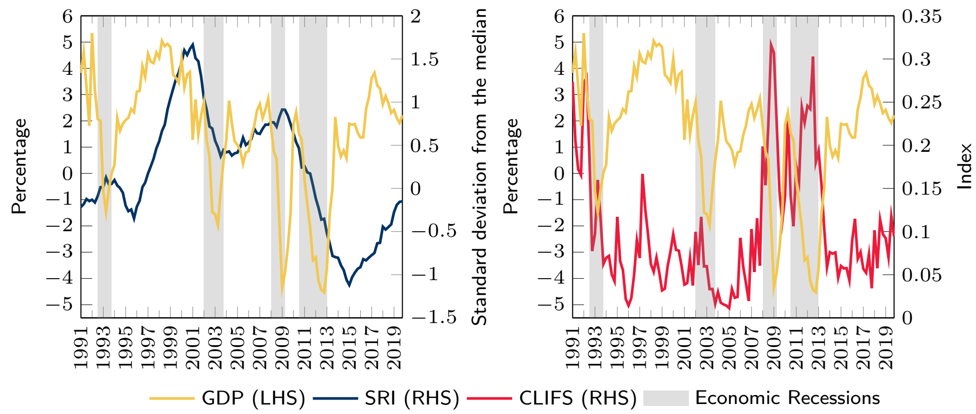
Table 1 provides the category captured by each variable and the source and available sample of each time series collected.

Variable	**Category**	**Sample**	**Source**
Real GDP (GDP)		1978Q1 - 2019Q4	INE/BdP
Systemic risk indicator (SRI)	Vulnerability	1991Q1 - 2019Q4	BdP
Country-level index of financial stress (CLIFS)	Risk	1977Q2 - 2019Q4	ECB
Credit-to-GDP ratio (C2GDP)	Vulnerability	1960Q4 - 2019Q4	BIS
Economic sentiment indicator (ICE)	Economic situation	1989Q1 - 2019Q4	INE
Total own funds ratio (TOFR^g)	Resilience	1995Q4 - 2019Q4	BdP
Principal Components (PC_1, PC_2, PC_3, PC_4)	Vulnerability/Risk	1995Q2 - 2019Q4	

Note: The GDP is the y-o-y rate of change. For the TOFR^g linear interpolation was used to fill some gaps in the data. More detailed information about the principal component is available in the appendix.

Table 1. Summary of Data

The use of multivariate quantile regression can be motivated by (i) comparing the evolution of our variable of interest over time and (ii) analyzing univariate quantile regressions computed at the 10^{th}, 50^{th} (median) and 90^{th} percentiles. Figure 1 shows the times series of GDP growth compared with SRI and CLIFS.



Note: Dates for the economic recessions as defined in Rua (2017). CLIFS is a unit-free index for which, at each point in time, the most extreme (smallest) values – corresponding to the highest (lowest) levels of stress – are characterized by the 99^{th} (1^{st}) percentile (Duprey *et al.* (2017)).

Figure 1: Times series of data used in our baseline model

We can observe how peaks in SRI and CLIFS are followed by extreme negative outcomes of GDP growth. As we will also show in the sections 3 and 4, GDP growth reacts to our explanatory variables with different lags: SRI anticipates the extreme low GDP growth realizations earlier than CLIFS.

To assess the relevance of the variables at explaining the GDP growth h quarters ahead we use univariate quantile regression models defined as:

$$\hat{Q}_{GDP_{t+h}}(q|x_t) = \hat{\alpha}^{q,h} + \hat{\beta}^{q,h} x_t \tag{3}$$

where x_t is a single explanatory variable and all the rest has the same definition provided previously. Figure 2 reports univariate quantile regressions of GDP growth at the 10^{th}, 50^{th} and 90^{th} percentiles for both $h = 4$ and $h = 12$. Overall we observe that for SRI and CLIFS the slope and level at the tails (10^{th} and 90^{th} percentiles) are different from the ones at the median (50^{th} percentile), suggesting heterogeneous effects of these variables on GDP growth distribution. For SRI we have a strong negative effect on the left tail at the shorter horizon ($h = 4$) and a significant increase in the negative slope for a medium to long term horizon ($h = 12$), for the 90^{th} percentile. For CLIFS we have different results, with a large decrease in the slope at the 10^{th} percentile from $h = 4$ to $h = 12$, while the estimated marginal effects are still negative at all the selected percentiles. This results point out that the effect of our explanatory variables on GDP growth is non-linear: using the standard OLS could lead to misleading interpretation in terms of the relationship between financial system and the real economy.

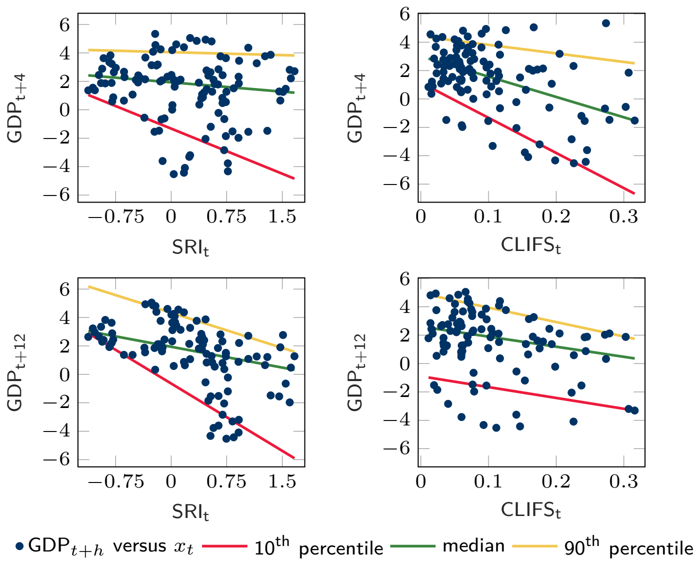


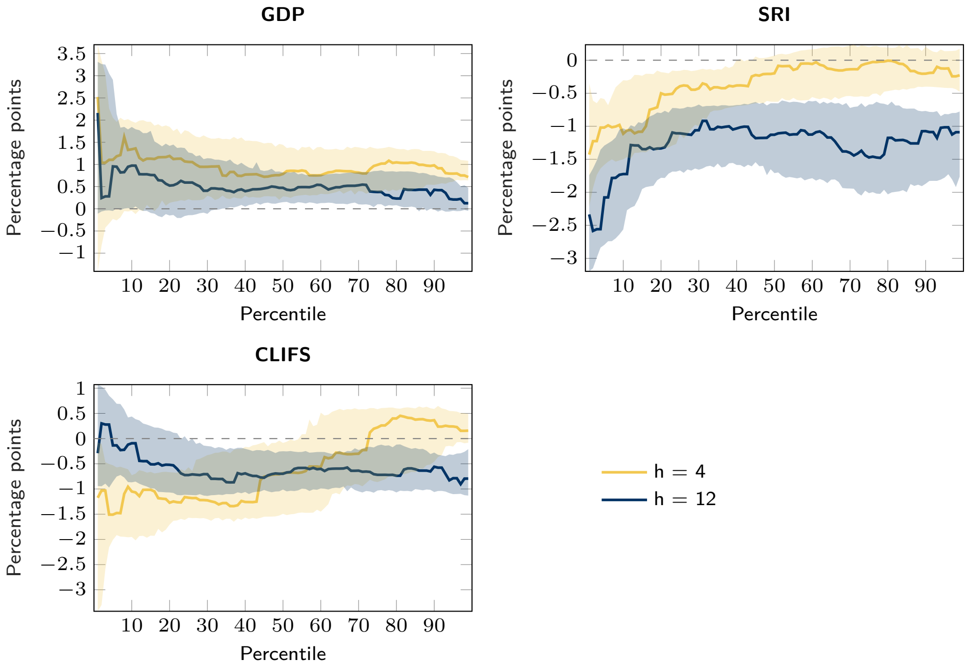
Figure 2: Univariate quantile regressions

3. Results

3.1. In sample exercise: marginal effects

We start by analyzing the results of the step 1 of the two steps approach described in section 2. The use of quantile regressions and local projection allows to analyse the results according to two dimensions: (i) analyse the marginal effects of the explanatory variables across percentiles for a given projection horizon; and (ii) analyse the marginal effects of the explanatory variables across projection horizons for a given percentile. To better understand the impact of each variable on the conditional GDP growth distribution, the results presented correspond to the in-sample exercise.

Figure 3 displays the estimated marginal effects of the explanatory variables across percentiles for two projection horizons, $h = 4$ equivalent to one year ahead (short term) and $h = 12$ equivalent to 3 years ahead (medium to long term). The estimates suggest that the variables linked to vulnerability and stress in the financial situation (SRI and CLIFS) have different effects across the percentiles of the conditional GDP growth distribution at $h = 4$. In the short term, adverse developments in the financial situation approximated by an increase in SRI and/or CLIFS, have a larger impact on the lower percentiles of the conditional distribution, normally associated with negative GDP growth. Both SRI and CLIFS have negative and statistically significant estimated marginal effects on all percentiles below the median. Regarding the percentiles above the median, the estimated marginal impacts are not statistically significant. Consequently, following a deterioration in



Notes: The shaded areas stand for 95% confidence intervals obtained using bootstrapping (xy-pair method) according to Davino *et al.* (2013). Estimated marginal effects are conditional on a one standard deviation increase holding constant all other regressors in the model.

Figure 3: Estimated marginal effects for one and three years ahead for different percentiles.

the financial situation and all else equal, the conditional GDP growth distribution at $h = 4$ will be characterized by a "heavier" left tail. Accordingly, extreme realizations may occur more frequently and the uncertainty linked to the projections also increases. In the medium to long term $(h = 12)$, the estimated marginal effects of SRI and CLIFS diverge mainly due to the fact that the indicators signal developments in the financial situation at different horizons as mentioned before. SRI has a negative and statistically significant estimated marginal effect across all the percentiles of the conditional distribution, but not in a uniform way. An increase in cyclical systemic risk leads to a leftward shift of the conditional GDP growth distribution. As in the short term, given that the estimated marginal impacts at the lowest percentiles have the largest magnitude, the conditional distribution has a "heavier" left tail when cyclical systemic risk increases. Moreover, the magnitudes of the estimated marginal effects are higher when compared to those at $h = 4$. Since only the left tail is significantly affected by SRI at the projection horizon $h = 4$, while the whole distributions is affected at the projection horizon $h = 12$, the build-up of systemic risk as measured by SRI can cause longer recessions (since it predicts a downfall of the whole economic outlook in the medium to long term). These conclusions are in line with the aim of the SRI, i.e. signalling the potential materialization of vulnerabilities accumulated in the medium to long term. As such, its contribution to the conditional GDP growth distribution is more relevant at the medium to long term. In what concerns CLIFS, its impact is not statistically significant for percentiles below the 30^{th} percentile and it is negative and statistically significant for the remaining percentiles. Although at the medium to long term horizon CLIFS has no negative impact on the left tail, it still has a negative marginal effect on the upper-tail percentiles, indicating that an increase in financial stress is linked to a deterioration of the economic outlook. In sum, negative realizations in the financial situation are linked to more adverse projections for economic activity and greater uncertainty. Negative financial developments potentially amplify the negative effects of an economic crisis. Lastly, contemporaneous GDP growth has a positive and somewhat stable effect on the conditional distribution at both projection horizons $(h = 4, 12)$. The estimated marginal effects are however not statistically significant across all percentiles, being statistically significant mainly at higher ones. An increase in GDP growth leads to a "heavier" right tail in both horizons.

Figure 4 shows the estimated marginal effect of each explanatory variable on the 10^{th} percentile of the conditional GDP growth distribution for different projection horizons.[5] The 10^{th} percentile was chosen since it will be used as a risk measure in the analysis below. The estimated marginal impact of SRI on the distribution's 10^{th} percentile is negative and statistically significant as of the projection horizon $h = 2$, intensifying as the projection horizons increases. This means that an increase in systemic risk is linked to an increasing risk of economic activity, strengthening in subsequent periods at all projection horizons. Concerning the CLIFS, its estimated marginal impact on the 10^{th} percentile is also negative, which means that an increase in financial stress is associated with a deterioration of economic activity across all horizons. However, it is not statistically significant at projection horizons longer than $h = 8$ and at $h = 1$. Lastly, the contemporaneous GDP growth has a positive and statistically significant marginal effect on the 10^{th} percentile only up to 3-quarters horizon.

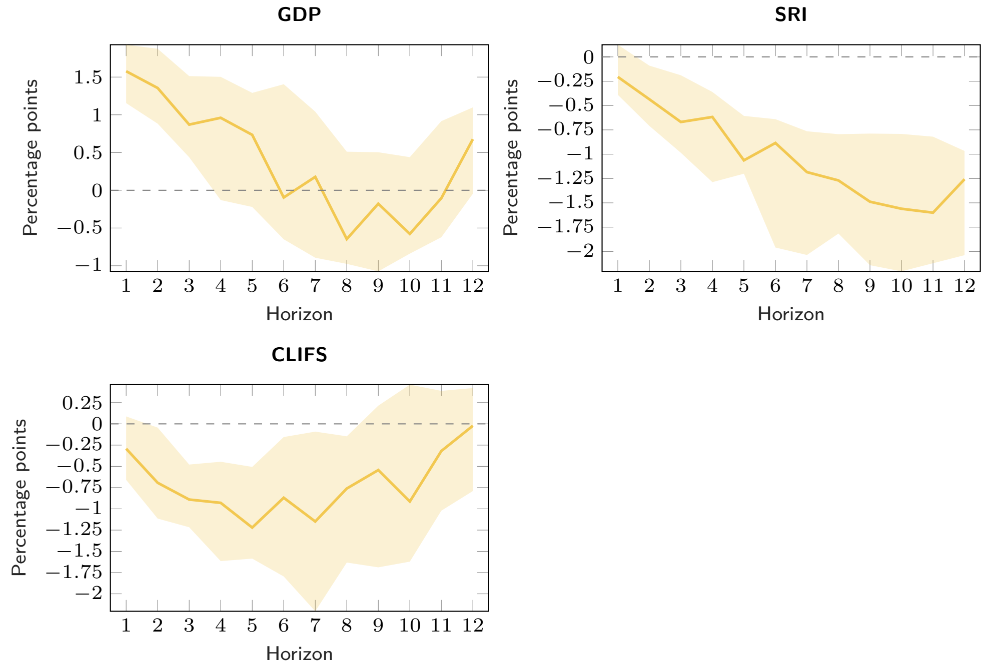
In sum, the effects of SRI and CLIFS on the conditional GDP growth distribution are heterogeneous across percentiles and seem to vary along projection horizons.

3.2. In sample and pseudo real-time exercise comparison: risk measures

3.2.1. GDP-at-risk (GaR)

In the GDP-at-risk exercise, we are interested in estimating a specific percentile of the conditional GDP growth distribution over different projection horizons.

5. This exercise is defined in the literature as "term structure" (see Adrian et al. 2018; Galán 2020). It can be interpreted as the impulse-response function of GDP growth given a unit increase of the explanatory variable.



Notes: The shaded areas stand for 95% confidence intervals obtained using bootstrapping (xy-pair method) according to Davino *et al.* (2013). Estimated marginal effects are conditional on a one standard deviation increase holding constant all other regressors in the model.

Figure 4: Estimated marginal effects for the 10^{th} percentile at different projection horizons.

Henceforth GDP-at-risk (GaR) refers to the prediction of the 10^{th} percentile of the conditional GDP growth distribution:

$$GaR_{t+h|t} \equiv \hat{Q}_{GDP_{t+h}}\left(10|GDP_t, SRI_t, CLIFS_t\right) = \\ \hat{\alpha}^{10,h} + \hat{\beta}^{10,h}_{GDP} GDP_t + \hat{\beta}^{10,h}_{SRI} SRI_t + \hat{\beta}^{10,h}_{CLIFS} CLIFS_t. \tag{4}$$

This measure should be informative of the risk of extreme (negative) realizations of GDP growth in the future. The warning properties of this measure make it potentially useful from a policymaker perspective, namely for macroprudential policy measures that need to act when systemic risk begins to rise. For this reason, the focus now is on the results obtained from the pseudo real-time approach, considering a training sample that spans between 1991Q1 and 2004Q4. $GaR^{pseudo}_{t+h|t}$ refers to the GaR estimate for period $t+h$ based on the information available until period t. We also present the results obtained using the in-sample approach with the goal of comparing with the results of the former exercise and assess how the model performs once it uses all the information available. For this case, $GaR^{in}_{t+h|t}$ refers to the GaR estimate for the period $t+h$ using all the information available to estimate the marginal effects. The only difference between the two approaches is in the sample considered for the estimation of the marginal effects.

Figure 5 compares the GDP growth observed at time t with the GaR estimated following both in-sample and pseudo real-time approaches for $h = 4$ and $h = 12$. In both approaches, GaR at time t is computed using observed values of the explanatory variables at t (see equation (4)). For example, in Figure 5, $\text{GaR}_{t+4|t}$ at 2009Q4 is the projection made for time 2010Q4 using information up to 2009Q4.

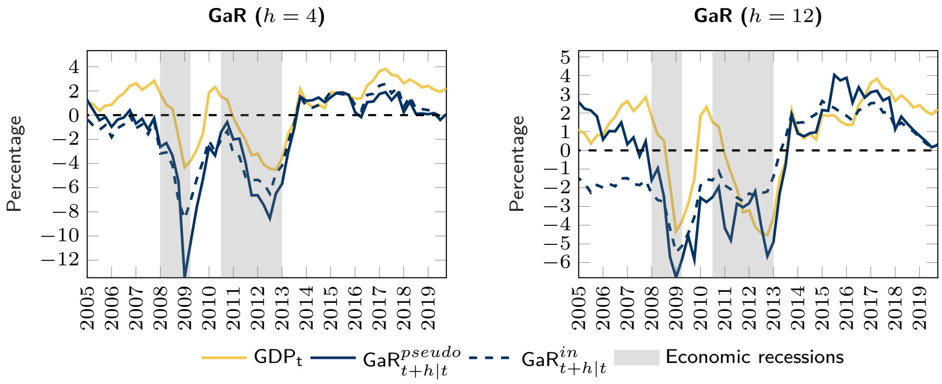
In-sample and pseudo real-time exercises provide similar results for $h = 4$, even with a relatively small sample: we can argue that the model "learns" well from past events. It is worth stressing that predicting an event that has never happened – as in the case of the GFC – is a difficult task for any model. Nevertheless, ahead of the GFC, the GaR estimated for $h = 4$ goes into negative regions, which can be interpreted as a signal of future deterioration in economic activity. The use of this indicator can provide useful information on systemic risk and vulnerability build-ups which are potentially detrimental for economic activity and integrate the macroprudential policy implementation decisions to address them. However, it must be observed that one year may not be enough to fully implement preemptive policy measures to mitigate the impact of a financial crisis and its spillover effects on economic activity.

The GaR measure estimated for 2009Q1 matches the magnitude of the trough of the observed GDP growth and remains low and negative within the period 2009-2013. This last result suggests how the model detects some systemic risk even if a recovery of GDP growth is observed between the two crises. The inclusion of CLIFS in the model, which accounts for bond market volatility, allows the GaR measure to capture the build-up of risk driven by financial imbalances in the public sector and signals the imminent ESDC.

After the two crises, both GaR measures show a significant recovery accompanying the evolution of GDP growth. At the end of our sample and before the COVID-19 pandemic onset, the GaR starts decreasing slowly, which is mainly driven by the fall in the positive contribution of the SRI, since 2015, and an increase of the negative effect of financial stress (CLIFS) after 2017.

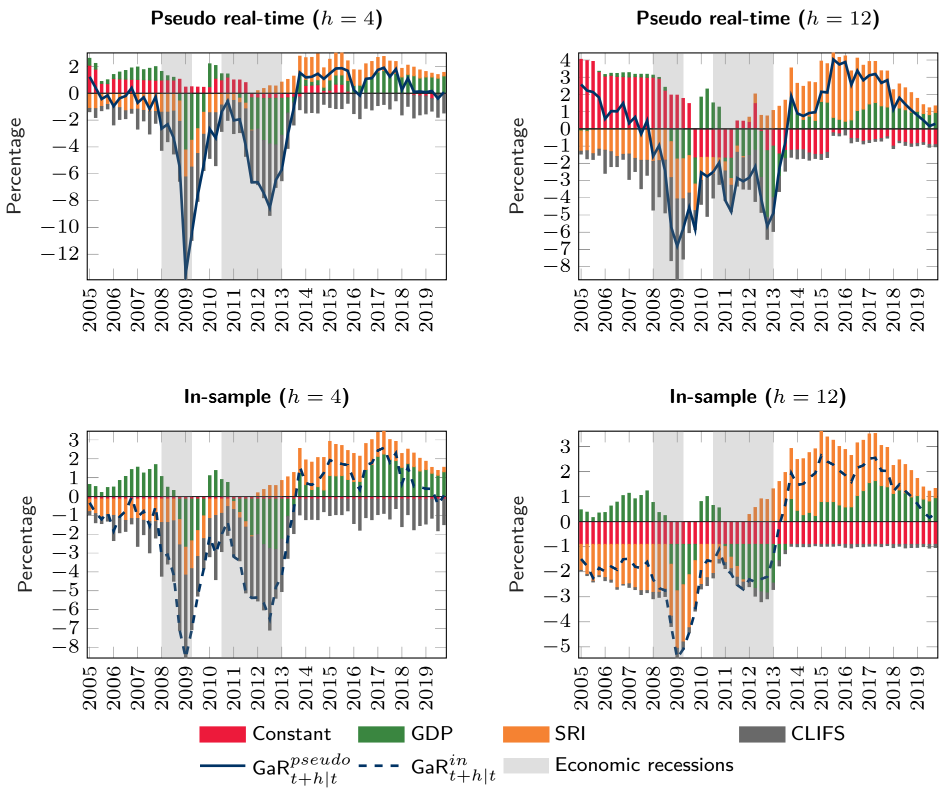
In-sample and pseudo real-time exercises provide very different but equally poor results in terms of risk-signalling for $h = 12$. This result is not unexpected, given that our model only has SRI as significant explanatory variable at $h = 12$.

Figure 6 displays the contribution of each explanatory variable for the estimated GaR, under the in-sample and the pseudo real-time exercises, respectively. We can observe how financial variables are the main drivers of GaR for both projection horizons considered. At the short-term projection horizon, the GaR measure is mainly driven by CLIFS independently of the estimation procedure chosen, signalling the negative effects of stress in the financial markets. At the medium-term projection horizon, CLIFS contributes only in the pseudo real-time exercise. SRI becomes more relevant when we move from a one-year to a three-year projection horizon, even if the quality of the overall projection is poorer at $h = 12$.



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 5: GDP-at-risk



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 6: GDP-at-risk decomposition

3.2.2. Complementary risk measures

Even though the focus of *at-risk* analysis is on the lowest percentiles of the conditional distribution, analysing the whole distribution can give additional information. In particular, it may provide insights about the nature of the changes observed in the GaR since they can be motivated by a shift of the whole distribution to the left and/or by a modification of the shape of the distribution (Figure 7). While heavier tails reveal an increase in uncertainty surrounding the economic outlook, shifts in the whole distribution can be more associated with the materialization of risks and vulnerabilities. As such, GaR may not be the only measure capable of signalling in advance risks to economic activity. Focusing only on the 10^{th} percentile of the distribution may be restrictive from policymakers' point of view: measures that explore other parts or even the whole conditional GDP growth distribution may turn out to be an appropriate complement to the analysis.

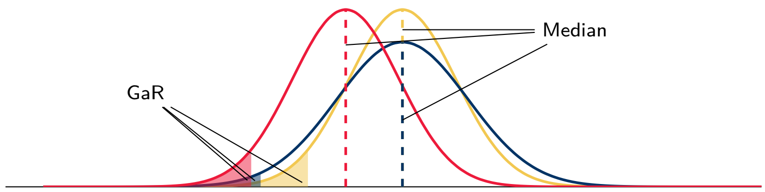


Figure 7: Example of how the shape of the distribution can affect the GaR

In this subsection, we explore additional risk measures. In order to compute the percentile differences we used the results from step 1 in the two-steps estimation approach while for the remaining measures, distribution moments, expected shortfall and longrise and probability of negative GDP growth, we used the results obtained using step 2. Given previous results in terms of statistical significance of the explanatory variables and performance of GaR, all the following measures are computed for $h = 4$, thus implying the estimation of the 4-quarters-ahead GDP growth distribution. The results for $h = 12$ are provided in the Appendix. The measures were obtained for the in-sample and pseudo real-time exercises.[6]

- *Difference between percentiles of the distribution*

The first complementary measure considered consists of percentile differences as proposed by Galán (2020). They refer to the difference between the 10^{th}

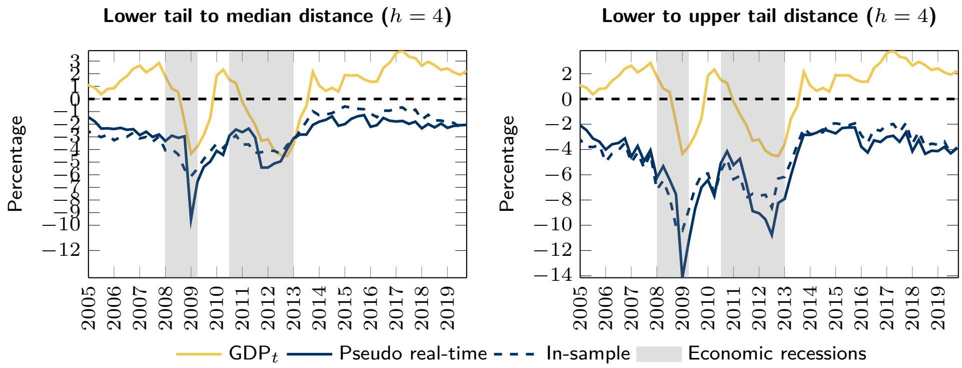
6. The GaR gap, defined as the difference between the GDP-at-risk of our baseline model and the 10^{th} percentile estimation of a model with only a constant, was also considered as a complementary risk measure. Nevertheless, the results show very similar dynamics to the GaR because the unconditional GDP-at-risk is almost constant across time.

percentile (GaR) and the 50^{th} percentile (median) and to the difference between the 10^{th} percentile and the 90^{th} percentile of the estimated conditional distribution of future GDP growth (henceforth designated as lower tail to median distance and lower to upper tail distance, respectively). These measures capture the dispersion/concentration of the distribution.[7] The goal of these measures is to determine the size of the left and right tails. An increase in the difference between these percentiles indicates not only an increase in the uncertainty surrounding future GDP growth, but also an increase in the likelihood of extreme realizations of GDP growth. Furthermore, as the 90^{th} percentile appears to be less sensitive to changes in economic and financial system situation, the lower to upper tail distance can provide more information on the deterioration of the left tail of the distribution. This measure can be interpreted as the probability of materialization of risks and vulnerabilities accumulated over the years.

Figure 8 shows how differences between percentiles evolve over time. No matter if in-sample or pseudo real-time approaches are considered, both the lower tail to median and the lower tail to upper tail distances follow closely the GaR measure (Figure 5). The increase in uncertainty is biased to the left tail of the distribution rather than distributed between the bottom and upper percentiles. This result suggests how the left tail of the 4-quarters-ahead GDP growth distribution starts decreasing faster than its median and right tail, complementing the GaR in signaling risks to economic activity and the likelihood of a crisis. Both measures do not follow much the GDP growth recovery ahead of the ESDC: the left tail continues "heavier" relatively to the median and the right tail, meaning that the measure keeps detecting systemic risk in the economy. Such a conservative value of the measure at the time of an economic recovery could have encouraged macroprudential policymakers to take preventive actions, building up a capital buffer, and thus alleviating the following ESDC crisis by releasing it. However, as argued above, a buffer build-up would take time, and one year of early warning may not be enough to implement such a measure. Analysing the behavior of the measures at the end of the sample and before the pandemic, we do not observe the same slow decrease that GaR displays, entailing that the slowdown in economic activity is more akin to a shift to the left of the whole distribution than to an increase in the "heaviness" of the left tail. After 2014, tail risk follows the median of the distribution, highlighting the lower risk environment during this period of economic recovery, which follows large economic losses and is characterised by a more active macroprudential policy.

- *Distribution moments (mean, standard deviation, kurtosis and skewness)*

7. Galán (2020), focusing on the contribution of macroprudential policies to the GaR, defines this measure as a cost-benefit indicator: positive effects of macroprudential measures on low quantiles are interpreted as benefits, while negative effects on the median are interpreted as costs of the policy interventions. This definition struggles to fit our model since we do not include any policy indicator. Nevertheless, macroprudential policies may indirectly influence our model by affecting SRI and CLIFS.



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 8: Difference between percentiles for $h = 4$

The distribution moments can give some insights related to the evolution of the distribution. Figure 9 shows how the moments of our fitted distribution change over time.

The mean is a measure of the expected (central) scenario and does not provide any warning signal ahead of crises. However, the fact that the mean seems to follow closely the behavior of GDP growth brings more relevance to the use of quantile regressions, since the usual linear regressions would not be able to provide warning signals related to eventual extreme reductions in economic activity. Considering the in-sample or the pseudo real-time exercises does not change the result.

The standard deviation, as an uncertainty measure, is able to provide information on the dispersion of the distribution. An increase in the standard deviation means that the likelihood of more extreme values of GDP growth increases as well as the uncertainty associated with future GDP growth. As for the mean, the standard deviation is indifferent to changes in the sampling approach. The results show a weak upward trend before the GFC in 2008, however the projection for 2009 using information up until 2008, already shows a high degree of uncertainty. From a policymaker point of view, even thought the observed GDP growth in 2008 is still positive, the projection one-year-ahead points to higher likelihood of more extreme realizations of GDP. Along with other indicators, this result may provide some early warning signalling for the implementation of measures to prevent contagious effects between the financial system and the real economy. Around 2010 however, given that the model “has learnt” from the GFC, the standard deviation remains relatively high despite the GDP growth recovery, signalling a still high uncertainty about GDP growth realization and the risks of observing a new recession. The standard deviation stays relatively stable between 2013 and 2018 and shows an upward trend at the end of the sample, signalling a mild increase in the likelihood of more extreme realizations of GDP. This evidence is in line with previous measures’ results, and it is mainly driven by the increasing values of SRI and CLIFS observed at the end of the sample.

Kurtosis measures the flatness of the distribution against the normal distribution. A reduction in kurtosis means that the distribution is getting flatter and as a consequence, the occurrence of extreme values of GDP growth becomes more likely. The difference between an increase in the standard deviation and a decrease in kurtosis relates to the likelihood of the central scenario. While an increase in the standard deviation, with all else equal, is associated with a higher dispersion of the possible outcomes, but without changing the shape of the distribution, a decrease in kurtosis means a change in the shape, entailing "heavier" tails. In Figure 9 we can see how kurtosis moderately declines before the GFC and signals the likelihood of the occurrence of extreme GDP growth values remaining stably low until 2014. At the end of sample, after 2018, kurtosis becomes negative and approaches the values observed before the GFC. This information, together with the behavior of the standard deviation which also slightly increases in the same period, indicates a slight rise in the likelihood of more extreme GDP growth realizations along with higher uncertainty around the central scenario. These results can be read as a possible materialization of risks and vulnerabilities, and for this reason they should be closely monitored. Nonetheless, the mild increase in standard deviation is not comparable with the path followed before the GFC.

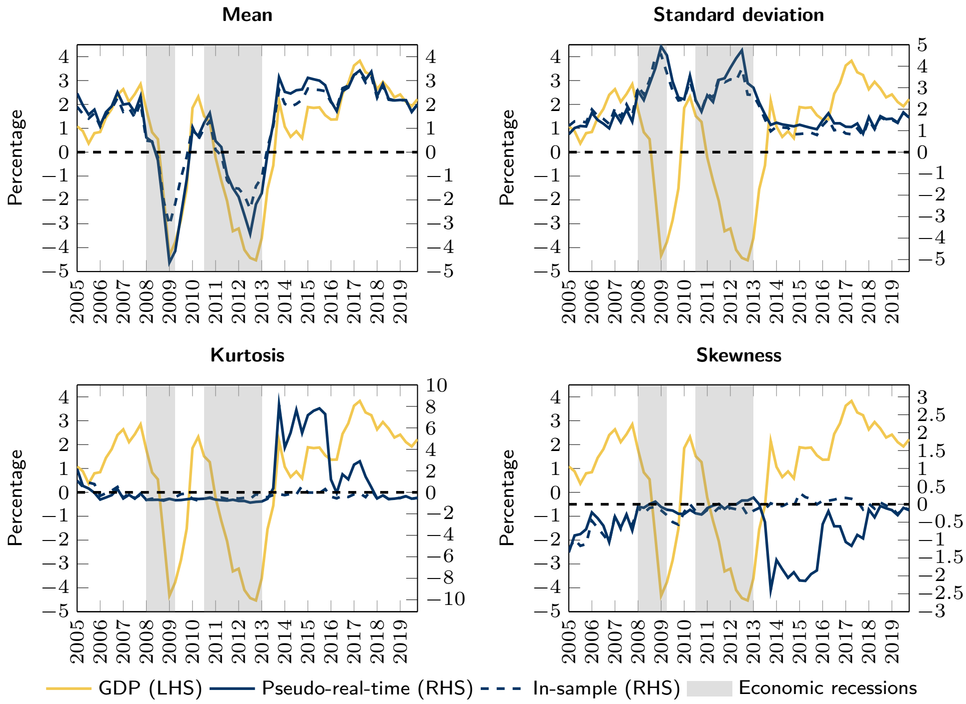
Finally, skewness is a measure of the symmetry of the distribution. When skewness is zero, the distribution is perfectly symmetric, otherwise it will be biased toward the left (positive) or right (negative). In this way, skewness is useful to indicate other types of change in the distribution. From Figure 9, it is possible to conclude that the GDP growth distribution at $h = 4$ is overall biased towards the right, meaning that the right tail is larger than the left one. As crises approach skewness moves closer to zero, indicating that the distribution gets more symmetric and that the tails became similar. This can be seen as a warning signal since more extreme (lower) outcomes become more likely. Like in the case of kurtosis, in-sample and pseudo real-time approaches exhibit very similar results from 2005 to 2014. Consistently with previous measures, at the end of the sample, skewness rapidly approaches zero again, reflecting a less concentrated distribution at the right side, and signalling a middling increase in the likelihood of lower GDP outcomes.

- *Expected shortfall and longrise*

The expected shortfall and longrise are computed following Adrian *et al.* (2019). We look at these measures to assess the tail behavior of the conditional GDP growth distribution. Formally, they are the expected values of GDP growth conditional on being at the distribution tails:

- **Expected shortfall (ESF):**

$$ESF_{t+h} = \mathbb{E}_t[Y_{t+h|X_t}|Y_{t+h} \leq GaR_{t+h|t}] = \frac{1}{0.10}\int_0^{0.1} \hat{\mathcal{F}}^{-1}_{Y_{t+h}|X_t}(q|X_t)dq$$



Note: Dates for the economic recessions as defined in Rua (2017).

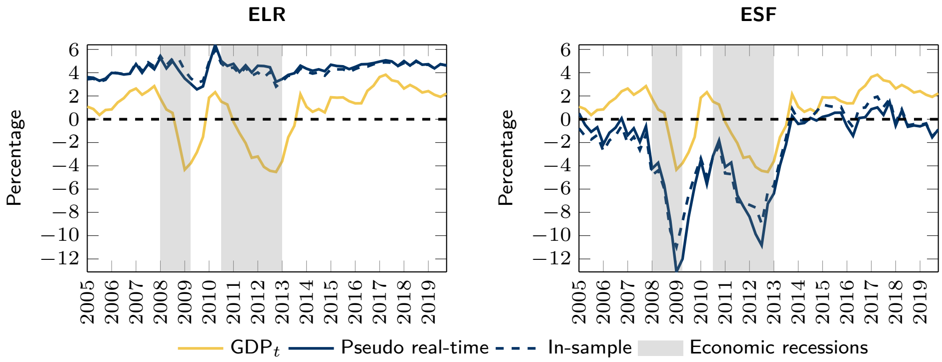
Figure 9: Moments of the distribution for $h = 4$

- **Expected longrise (ELR):**

$$ELR_{t+h} = \mathbb{E}_t[Y_{t+h|X_t}|Y_{t+h} \geq GaR_{t+h|t}] = \frac{1}{0.10}\int_{0.9}^{1} \hat{\mathcal{F}}^{-1}_{Y_{t+h}|X_t}(q|X_t)dq$$

where $\hat{\mathcal{F}}_{Y_{t+h}|X_t}(q)$ is the fitted conditional cumulative distribution. The expected shortfall can help complement the GaR in the sense that it comprises information about all the extreme possible negative outcomes of GDP growth weighted by their respective probability and does not only rely on the value of the 10^{th} percentile. Although the expected shortfall collects the overall information on the tail behavior of the conditional distribution, the results are quite similar to the ones obtained for the GaR (Figure 10).

The ELR, although usually very stable given that the higher percentiles are less sensitive to changes in economic and financial system situation as shown in subsection 3.1, can provide insights regarding whether there are shifts in the distribution versus changes in its shape. When the ELR and ESF move in opposite directions, this signals "heavier" tails. However, when the two move in the same directions, this can be understood as a shift in the distribution, which can still be complemented by "heavier" tails. After the GFC and during the ESDC there is a deterioration of both ESF and ELR, indicating a shift to the left of the distribution



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 10: Expected shortfall and longrise for $h = 4$

and, therefore, a more negative outlook for the economic activity. It should also be noted that the approximation of the realized GDP to the ELR indicates a possible reverse in the perspectives of economic activity. That is clearly observed before both crises and also around 2017. Nevertheless, the latter episode was not followed by a recession which can be related to the tightening in regulation that promoted a more resilient financial system. After 2017, the ESF starts a downward trend that follows the path of the observed GDP, and the increasing distance between them might be perceived as a rise in tail risks and the future materialization – albeit this evidence is not strong enough for active macroprudential policy intervention, but rather for continuous monitoring of risks and vulnerabilities accumulation. The results for the ESF and ELR are indifferent to changes in the sampling approach.

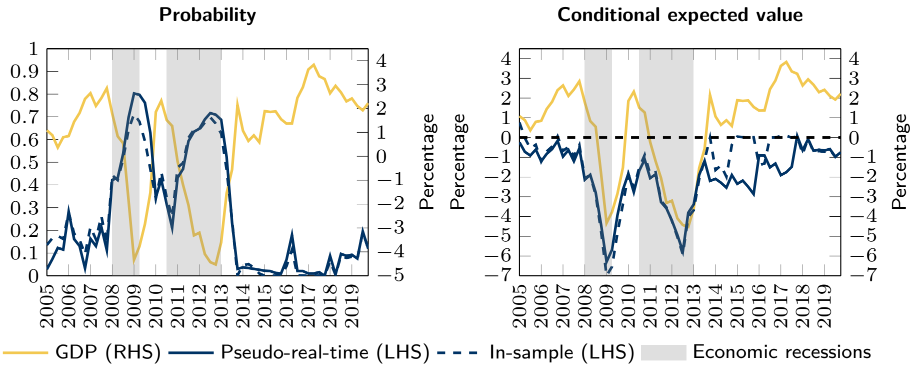
- *Probability of negative growth rate and conditional expected value*

These measures are computed following De Santis and Van der Veken (2020). Given our fitted conditional GDP growth distribution h quarters ahead, we can compute the probability of observing a negative growth rate, as follows:

$$\mathbb{P}_{t+h} = \mathcal{P}(Y_{t+h} \leq 0) = \hat{\mathcal{F}}_{Y_{t+h}|X_t}(0|X_t).$$

In addition, we compute the conditional expected value, that is, the expected value of the conditional GDP growth distribution subject to being observed a negative growth rate.

As shown in Figure 11, the probability of negative growth rate anticipates, with an upward trend, the beginning of the GFC by one year. Moreover, it is estimated a probability of approximately 50% in 2008 which strongly indicates rising risks for economic activity in a moment when the GDP growth was still positive. The estimated probability of negative growth rate reaches its peak in 2009, highlighting the still high probability of a negative GDP growth six months before the second recession starts despite the positive growth rate observed. Nonetheless, this result



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 11: Probability of negative growth rate and expected GDP growth associated for $h = 4$

seems a delayed reaction to the GFC more than a early warning signal of the ESDC. The expected shortfall for negative realizations of GDP growth is less volatile than the GaR, but seems to lose its early warning power. Nevertheless, between 2014 and 2018, despite the low probability of observing a negative GDP growth, the conditional expected value exhibits low levels. This result signals a still highly vulnerable environment, as even with low probability, the materialization has a large negative effect on GDP growth. After 2018, the probability of negative GDP growth slightly increases to levels similar to those of 2005/06. The conditional expected value stabilizes at levels closer to -1%, which are similar to those of the 2005-2008 period. Nonetheless, the volatility of the probability series is far smaller than in the pre-GFC period, and the conditional expected value is steadily following the path of the observed GDP growth. The results for the probability and respective conditional expected value after 2018 are thus reflecting the downward trend in the observed GDP growth. This argument highlights the clear distinction between the results at the end of the sample and the 2005-2008 period. Using an in-sample or a pseudo real-time approach does not affect the results.

3.3. The Great Financial Crisis: comparing the performance of different indicators

In this subsection we focus on the GFC to evaluate how GaR measures could have supported the policymaker decisions. After estimating the model, following the pseudo real-time approach, we project the GDP growth h quarters ahead using the observed value of the explanatory variables in 2007Q1:

$$\hat{Q}_{GDP_{2007Q1+h}}(q|X_{2007Q1}) = \hat{\alpha}^{q,h} + \hat{\beta}^{q,h} X_{2007Q1}, \quad h = 1, \ldots, 12 \qquad (5)$$

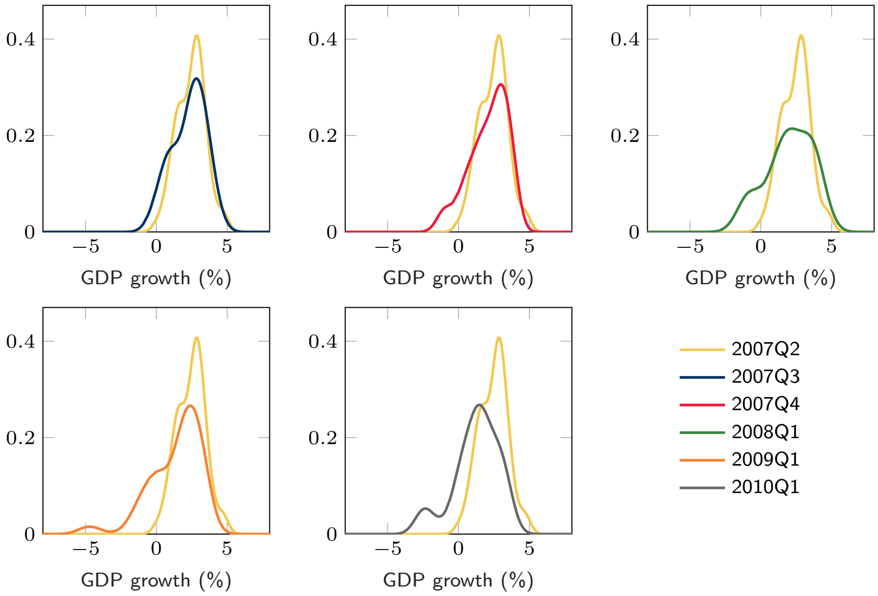


Figure 12: Estimated conditional GDP growth distribution based on information available at 2007Q1

where $\hat{\alpha}^{q,h} + \hat{\beta}^{q,h} X_{2007Q1}$ is the fitted q percentile of the conditional GDP growth distribution h quarters ahead. The projected values for GDP growth are then used to compute several of the measures discussed earlier.

Figure 12 displays how the estimated conditional distribution of future GDP growth evolves between 2007Q2 and 2010Q1. We can see from the first three figures how the estimated conditional distribution of GDP growth starts showing a "heavier" left tail two quarters before the crisis starts (2008Q1), and how the "weight" of the tail increases as we approach the beginning of the recession. With respect to 2007Q2, the model predicts the "heavier" left tail for 2009Q1, exactly the quarter in which we observe the trough of GDP growth (see the fourth figure). For 2010Q1, one year after the trough, we can see how the estimated conditional distribution of GDP growth keeps being strongly biased towards negative values, meaning that the model is still detecting risk of extreme (low) GDP growth realizations (see the fifth figure). One of the main drivers of this result is the high value displayed by SRI at the beginning of 2007 which entails a strong negative contribution to the distribution's left tail. The results described above do not change comparing in-sample and pseudo real-time approaches, confirming that the model performs well using pseudo real-time information (see Figure 26 in the appendix).

Figure 13 shows GaR and the complementary risk measures against the realized value of GDP growth, which would not have been observed by the policymaker. GaR starts decreasing before 2008 and attains negative values during the crisis. Nevertheless, the fall in GaR does not seem to fully capture the dimension of risks

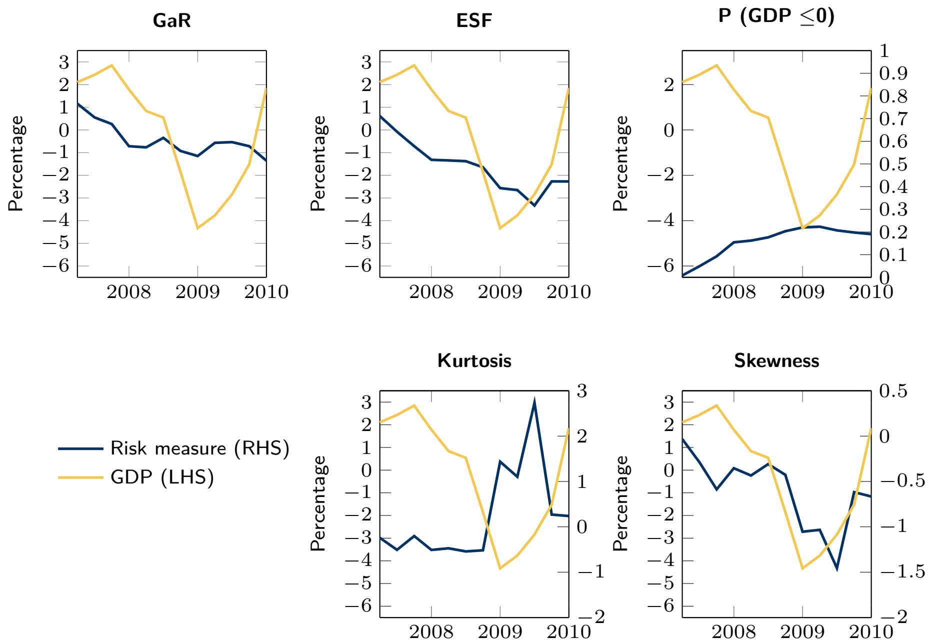


Figure 13: Estimated measures given information at 2007Q1

and vulnerabilities accumulated over the years and consequently the magnitude of the fall in GDP growth. This result suggests how important post-2007 information is for the performance of the measure. The expected shortfall dynamics is very similar to the one of GaR, however it seems to be able to better capture the magnitude of the drop in GDP growth. This is mainly due to the fact that this metric takes into account all the information in the left tail. Contrary to the GaR, the ESF can capture additional properties of the tail such as the concentration around -5% in the 2009Q1 distribution (Figure 12). The probability of negative GDP growth shows the same pre-crisis trends as GaR, but it seems to underestimate the likelihood of negative GDP growth realizations: the probability barely reaches 20%. Nonetheless, given that the projections were made with information from 2007Q1, when there was not an outstanding evidence of an upcoming crisis, the probability of observing a negative GDP growth increased from 1% in 2007Q2 to 22% in 2009Q1. Kurtosis only increases during the lowest realizations of GDP growth, indicating that the distribution is more outlier-proned. Lastly, skewness shows how the estimated conditional distribution of GDP growth becomes more and more asymmetric and biased towards the left as we approach the trough of GDP growth. The results for kurtosis and skewness are aligned with a higher probability of observing a negative GDP growth. Overall, the in-sample results are in line with the pseudo real-time approach but they seem to provide a stronger risk signal for most of the measures (see Figure 27 in the appendix).

The measures we discussed in this section provide different information regarding the distribution of future GDP growth which signal the build-up of future systemic risk to economic performances. Among those, we highlight the GaR, kurtosis, skewness, the expected shortfall and the probability of observing a negative GDP growth. The remaining measures can be found in the appendix (Figure 27), however the five above mentioned measures were the ones that provided useful information.

To sum up, one year before the crisis we would have been able to predict increasing risks for economic activity, and higher uncertainty surrounding future GDP growth mainly stemming from the accumulation of higher financial vulnerabilities. As already argued above, one year in advance can be short to fully implement preemptive measures to mitigate the contagious effects between the financial system and the real economy. This advance period would nevertheless be compatible with the decision and preparation for a capital buffer release, but this strategy cannot disregard a previous time-demanding buffer build-up. Despite the short notice, the measures would steadily signal the increasing likelihood of risk and vulnerabilities' materialization in the following years.

4. Robustness analysis

To evaluate the robustness of the model and the results provided we have performed several exercises that can be divided into three groups. In the first one, we conducted a simple analysis with univariate quantile regression models to evaluate the relevance of other variables in explaining the GDP growth at several projection horizons. The second set of exercises are related to alternative specifications of the model. [8] The third set of exercises explores the use of downside and upside entropy as "goodness of fit" measures.

4.1. Univariate quantile regressions

The Economic Sentiment Indicator (ICE, stands for *Indicador de Clima Económico* published by Statistics Portugal) is strongly connected to economic developments and agents' expectations about the future performance of the economy. In this sense, we can look at this indicator as a possible predictor of the GDP growth some quarters ahead.[9] The level of indebtedness may influence as well the economic outlook and have an amplification effect with strong and negative effects on recessions. As such, we evaluate if the credit-to-GDP ratio is a good predictor of

8. In which was also tested the use of principal component analysis (see the appendix for details).

9. Under the assumption that the ICE reflects the beliefs of economic agents about future developments of the economy, namely the GDP, and the agents make their decisions (consumption, investment, among others) based on the prospects of economic performance, we may argue that ICE could forecast the h-quarters-head GDP growth.

GDP growth and if it should be included in the model to improve the assessment of the risks to GDP growth. Lastly, we include in this analysis the banks' total own funds ratio to take into account the resilience of the banking sector.[10]

To explore the effects of the additional explanatory variables on GDP growth we estimate univariate quantile regressions of GDP growth at the 10^{th}, 50^{th} and 90^{th} percentiles for both $h = 4$ and $h = 12$ (Figure 14). We start by noticing the strong similarities between the GDP and ICE as explanatory variables. Although small differences in the observations' dispersion, the slope and levels are identical at all percentiles. This result indicates that we should avoid include both variables in the same model as it may end up on a reduction of the statistical significance of these variables and a possible bias on the estimation of the marginal effect as both variables would be accounting for the same impact on the GDP growth forecast. The banks' total own funds ratio (TOFR^g) results are far from being trivial in the analysis. At $h = 4$, we have a slight trade-off between the GDP growth given by the median and the positive effect on the left tail with the reduction of the risks to more (negative) extreme realizations of GDP growth. In the short run, with the increase of banks' own funds ratios, some negative side effects on the GDP can in fact be expected, in terms of a slowdown of its growth. Nevertheless, the resilience of the banking system increases, helping to reduce the transmission and amplification of shocks that could occur in the real economy or the financial system leading to an economic recession. For $h = 12$, the slope of the median is slightly positive, which can be interpreted as a positive effect of increasing the resilience of the banking system at a medium-to-long term.[11] Looking at the 10^{th} percentile instead, we have a strongly negative slope for $h = 12$, which indicates that an increase of banks' own funds ratio has a significant impact on the riskiness of observing large and negative GDP growth. This result can be partially explained by the expanding regulation after 2008, which entailed increases in banks' own funds ratios needed to build up the resilience of the financial system. At the same time, the economic developments were marked by a slowdown in GDP growth. It should also be noticed that for this measure we do not take into account the distance between the banks' own funds ratios and the capital requirements. Controlling for the capital requirements may change this result. Lastly, we investigate the inclusion of the credit-to-GDP ratio (C2GDP) in the model, which allows assessing the effect of the indebtedness level on the GDP growth at different horizons. The results show a negative estimated effect of credit-to-GDP ratio at all percentiles of GDP growth and for both horizons. The result also points out an increase of the GDP distribution

10. To evaluate the performance of our models we should consider as much information as possible. The longest series available on banks' own funds ratios are the total own funds and Tier 1 ratios provided by Banco de Portugal. Given the strong similarities between the two and the results they provide, we opt to present the results for the total own funds ratio.

11. This effect could also reflect a second trade-off between the expected short-term GDP growth and the expected medium-to-long term GDP growth.

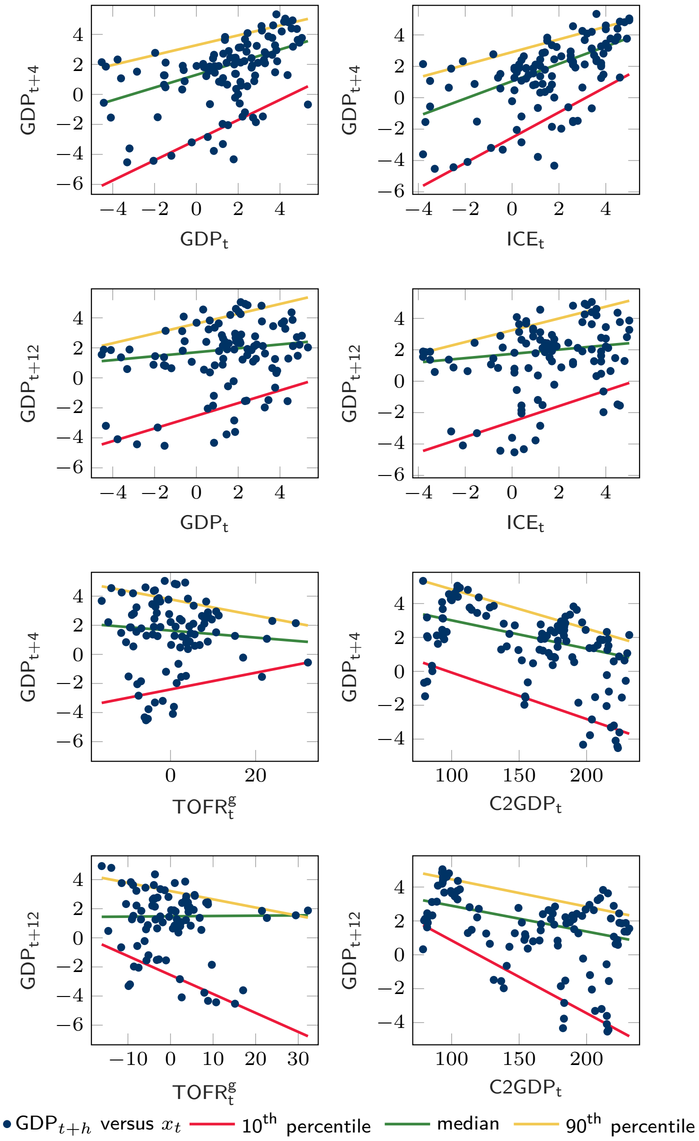


Figure 14: Univariate quantile regressions

flatness, as the slopes of the 10^{th} and the 90^{th} percentile increase with opposite sign, widening the distance between the tails of the distribution.

For the "goodness of fit" we rely on the pseudo-R^2, as suggested by Koenker and Machado (1999). This measure compares the sum of weighted deviations for the model of interest with the same sum for a model in which only a constant is included.

Pseudo-$R^2\,(q,h) \equiv R^1\,(q,h) =$

$$=1 - -\frac{\sum_{Y_{t+h}\geq\hat{Y}_{t+h}} q\cdot|Y_{t+h} - -\hat{Y}_{t+h}| + \sum_{Y_{t+h}<\hat{Y}_{t+h}} q\cdot|Y_{t+h} - -\hat{Y}_{t+h}|}{\sum_{Y_{t+h}\geq\overline{Y}_{t+h}} q\cdot|Y_{t+h} - -\overline{Y}_{t+h}| + \sum_{Y_{t+h}<\overline{Y}_{t+h}} q\cdot|Y_i - -\overline{Y}_{t+h}|}, \tag{6}$$

where $\hat{Y}_{t+h} = \hat{\alpha}^{q,h} + \hat{\beta}^{q,h}x_t$ is the fitted q percentile of the conditional GDP growth distribution h quarters ahead and $\overline{Y}_{t+h} = \hat{\alpha}^{q,h}$ is the fitted value from the model with only a constant at the same percentile. Although it is similar to the usual R^2 (it ranges between 0 and 1, with higher value corresponding to a better fit), the main difference is that, while the R^2 measures how well the model fits for the conditional mean on a set of observations, the R^1 applies the same concept but at a specific percentile. We have then a local measure of "goodness of fit", contrary to the R^2 which is a global measure of "goodness of fit" on the entire conditional distribution.

Figure 15 presents the pseudo-R^2 (or R^1) for the univariate models described above, at the 10^{th} percentile. The "goodness of fit" measure is almost the same at the two projection horizons for GDP while we observe an increase at the short horizon for ICE at the cost of a reduction at $h = 12$. Additionally, the inclusion of the contemporaneous GDP in the regression can mitigate potential endogeneity problems. For SRI, the results confirm the stronger explanatory power of this variable at longer horizons, in line with the claim that this index should anticipate by several years (on average) the hit of systemic financial crises. From a macroprudential policy perspective, the early anticipation property of this variable may be particularly useful for capital buffers, which usually need time to build up. On the contrary, CLIFS has a quick reaction to changes in financial markets (namely equity markets, bonds markets and foreign exchange markets). This makes CLIFS a short-term indicator, which is confirmed by the higher magnitude of the "goodness of fit" at $h = 4$.

4.2. Alternative explanatory variables

We decided not to include TOFR^g and C2GDP in our baseline model for distinct reasons. The TOFR^g by itself is not capable to properly fit the 10^{th} percentile of GDP growth at none of the horizons: its pseudo-R^2 value is well below that of CLIFS at $h = 4$ and that of SRI at $h = 12$. Overall, the TOFR^g has the lowest values of this metric. C2GDP exhibits one of the highest univariate pseudo-R^2 score at the longest horizon, remaining a reasonable "goodness of fit" metric at the short term horizon. Replacing GDP with this variable in the baseline model leads to very

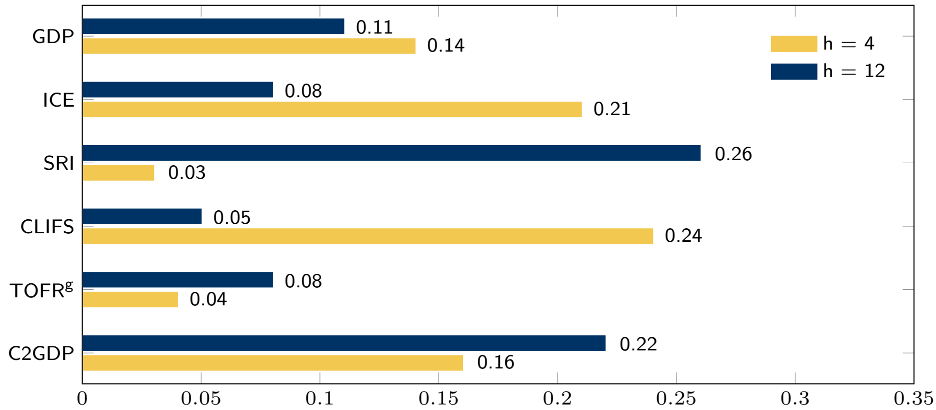


Figure 15: Pseudo-R^2 at the 10^{th} percentile of univariate models

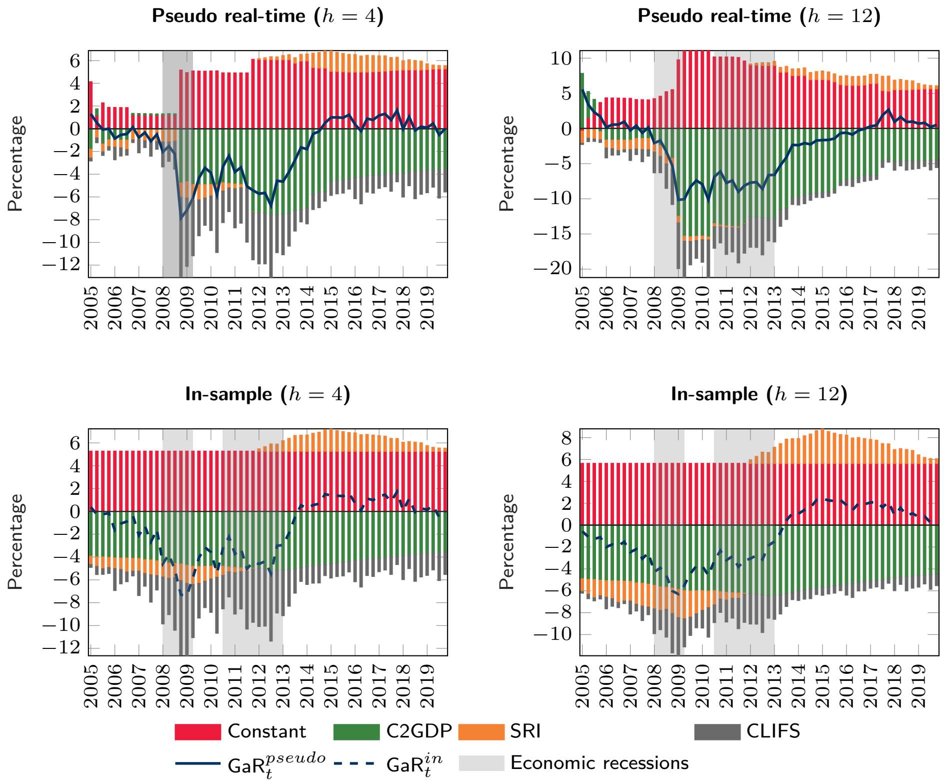
similar results for the GaR metric and the complementary measures[12], but since all variables in the model are accounting for risks and vulnerabilities we get also a strong contribution of the constant to accommodate the positive contributions that the model cannot explain. Figure 16 shows the decomposition results for the C2GDP model, i.e.:

$$\hat{Q}_{GDP_{t+h}}(10|C2GDP_t, SRI_t, CLIFS_t) = \hat{\alpha}^{10,h} + \hat{\beta}^{10,h}_{C2GDP}C2GDP_t + \hat{\beta}^{10,h}_{SRI}SRI_t + \hat{\beta}^{10,h}_{CLIFS}CLIFS_t. \quad (7)$$

The results show a very similar contribution of SRI and CLIFS to the GaR metric. The main difference is the contribution of C2GDP. While in the baseline model the contemporaneous GDP has a state-dependent contribution aligned with the cyclical component of GDP, the C2GDP contribution is mainly negative and strongly persistent. This result is in line with the hypothesis that high levels of indebtedness may amplify the magnitude and duration of economic recessions, which in the GaR is translated into a heavier, or negatively shifted, left tail of the estimated GDP distribution at different horizons. This contribution of the C2GDP is clearly compensated by the constant, with an almost symmetric contribution. Overall the GaR measures for both models are similar and confirm the robustness of the model. Consequently, we decided to keep the contemporaneous GDP in our baseline model and drop C2GDP.

Figure 17 shows pseudo-R^2 scores, at the 10^{th} percentile, for the baseline model and the C2GDP model. Although the C2GDP model outperforms the baseline model in terms of "goodness of fit" both for $h = 4$ and $h = 12$, the previous results

12. We tried to include C2GDP and the lagged GDP in the same model. The results show that we do not have any significant improvement by including both variables. The results are available upon request.



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 16: GDP-at-risk decomposition for the C2GDP model.

show that much of the C2GDP contribution to the GaR is compensated by the constant.

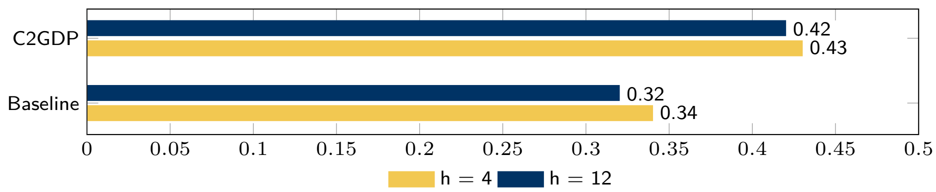
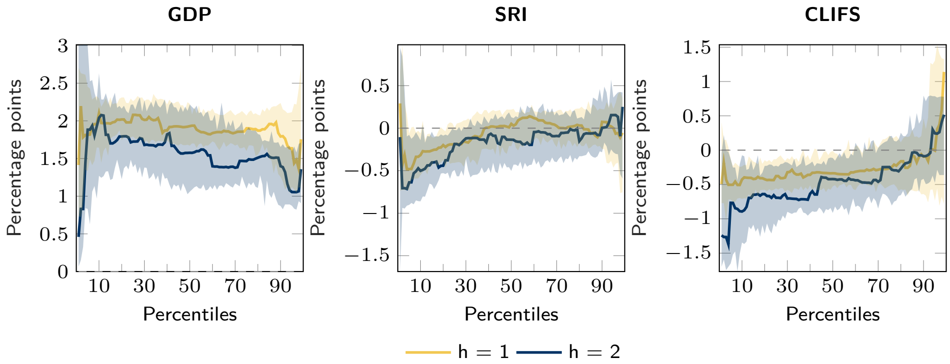


Figure 17: Pseudo-R^2 at the 10^{th} percentile of multivariate models

4.3. Alternative Horizons

We look at the estimated marginal effect of GDP at $h < 4$ to assess its statistical significance, as this variable may control for the autoregressive process. Figure 18 shows the estimated marginal effect of the explanatory variable of the baseline model for $h = 1$ and $h = 2$. At these horizons, we observe a positive and statistically



Notes: The shaded areas stand for 95% confidence intervals obtained using bootstrapping (xy-pair method) according to Davino *et al.* (2013). Estimated marginal effects are conditional on a one standard deviation increase holding constant all other regressors in the model.

Figure 18: Estimated marginal effects for one and two quarters ahead for different percentiles.

significant marginal effect for the contemporaneous GDP across all percentiles which shows that this variable is capturing the persistence of the cyclical component of GDP. The estimated marginal effect of SRI and CLIFS are aligned with the previous analysis on these variables, although at these shorter horizons both SRI and CLIFS lose preponderance in favour of the contemporaneous GDP. This result suggests that the impact of increasing financial vulnerability and stress on GDP growth takes some time to materialize and justifies the analysis for $h = 4$ and $h = 12$ presented above.

4.4. Downside and upside entropy

Entropy is another possible "goodness of fit" measure for quantile regression (Adrian *et al.* 2019). This measure compares the conditional distribution with the unconditional distribution to assess the value added by the explanatory variables at the tails. In other words, it measures, for each half of the distribution, the extra information provided by the regressors that were chosen. This is translated into the following equations:

- **Downside entropy:**

$$L^D_{t+h}(\hat{f}_{Y_{t+h}|X_t}, \hat{g}_{Y_{t+h}}) =$$

$$-\int_{-\infty}^{\hat{F}^{-1}_{Y_{t+h}|X_t}(0.5|X_t)} \left(\log \hat{g}_{Y_{t+h}}(Y) - \log \hat{f}_{Y_{t+h}|X_t}(Y|X_t)\right) \hat{f}_{Y_{t+h}|X_t}(Y|X_t) dY$$

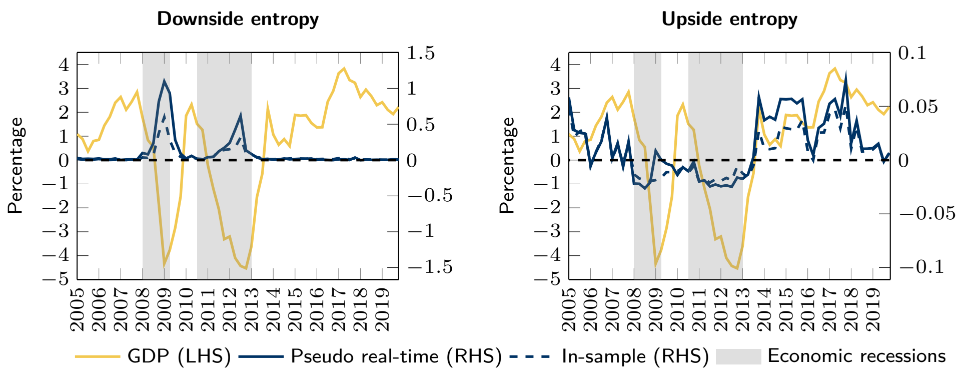
- **Upside entropy:**

$$L^U_{t+h}(\hat{f}_{Y_{t+h}|X_t}, \hat{g}_{Y_{t+h}}) =$$

$$-\int_{\hat{F}^{-1}_{Y_{t+h}|X_t}(0.5|X_t)}^{+\infty} \left(\log \hat{g}_{Y_{t+h}}(Y) - \log \hat{f}_{Y_{t+h}|X_t}(Y|X_t)\right) \hat{f}_{Y_{t+h}|X_t}(Y|X_t) dY$$

where $\hat{f}_{Y_{t+h}|X_t}$ is the conditional density obtained from the baseline model, $\hat{g}_{Y_{t+h}}$ is the unconditional density computed from a model where only a constant is included (i.e. a model entailing a GDP distribution where we expect no changes when booms or busts occur), and $\hat{F}^{-1}_{Y_{t+h}|X_t}(0.5)$ is the conditional median.

These measures give us important information about the performance of the model, since they allow us to meaningfully quantify the explanatory power at the tails of our specification. Figure 19 shows how our baseline model performs better than a model where only a constant is included, especially at the left tail of the distribution (downside entropy) between 2009 and 2014. The explanatory power at the right tail (upside entropy) has a 10-times smaller range with respect to the left tail counterpart and is close to 0 between 2009 and 2014.



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 19: Downside and upside entropy for $h = 4$

In Figure 20 we selected two particular points in time to show how the estimated conditional distribution of GDP growth outperforms the estimated unconditional distribution in the pseudo real-time approach. The shaded areas correspond to the information used for downside and upside entropy, which are computed for the last quarter of 2010 and 2012 respectively, using the information up to the last quarter of 2009. This figure also clarifies the nature of both sign and magnitude of downside and upside entropy. The left half of the conditional distribution – on which the downside entropy depends – is always above the unconditional distribution, while the right half of the conditional distribution – on which the upside entropy depends – is not always below the unconditional distribution. The area where the right half of the conditional distribution is above the unconditional distribution positively offsets the negative value of upside entropy and explains the difference in magnitude with respect to downside entropy.

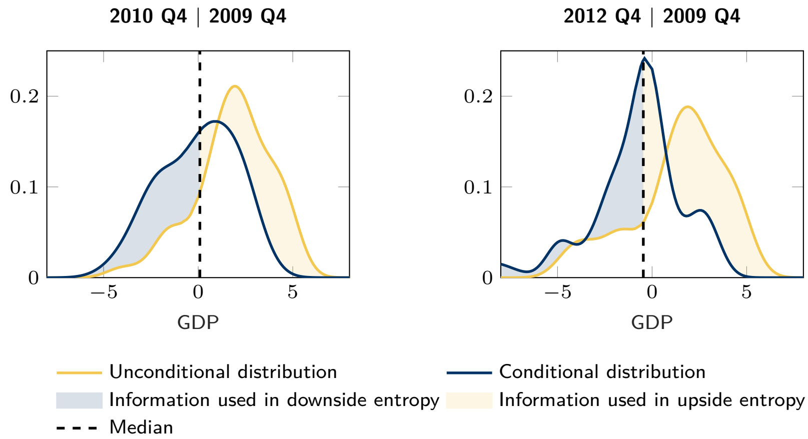


Figure 20: Unconditional versus conditional distribution

5. Conclusions

This paper aims to assess the impact of financial developments on GDP growth for Portugal, with a focus on the likelihood of low GDP growth realizations and using different measures to assess their impact. Using a quantile regression approach, we analysed the marginal effect of vulnerability and risk indicators, and we suggested risk measures to be used for macroprudential policy purposes. We find that both the Systemic Risk Indicator (SRI) and the financial stress index (CLIFS) have a negative effect on the extreme (negative) GDP growth realizations one-year-ahead. We conclude that systemic risk has the largest impact on future GDP growth at medium to long term horizon while financial stress is only significant at the short term horizon. The GaR measure, defined as the 10^{th} percentile of the GDP growth distribution, is a reliable risk-signalling tool for economic recessions, no matter whether the crisis was triggered by financial stress or financial imbalances. The use of this indicator can provide useful insight on the rising of systemic risks and vulnerabilities that could harm the economic activity and complement the assessment of the need to implement macroprudential measures to tackle them.

With the objective to provide policymakers with better tools to identify systemic risk, we compute a set of complementary risk measures, since focusing only on the 10^{th} percentile of the estimated GDP growth distribution may be limiting. The distance between the 10^{th} and the 90^{th} percentile of the estimated one-year-ahead GDP growth distribution results to be a useful tool to complement GaR in anticipating economic recessions since it shows a clear downward trend before 2008 and signals the ESDC remaining stably low between the two crises. Dispersion, flatness and symmetry dynamics of the estimated GDP growth distribution have some power in anticipating recessions. The expected shortfall can complement GaR measure since it collects information which is not limited to the 10^{th} percentile of the estimated GDP growth distribution thus encompassing the dynamics of the whole estimated GDP growth distribution. The probability of observing negative future GDP growth provides proper signals of recessions, in particular in 2008 when it estimates the likelihood of adverse economic situation for 2009 to be approximately 50%.

Focusing on the Great Financial Crisis to understand how our measures could have supported policymakers decisions, we compute projections of the risk measures only using 2007 information. We show how GaR, the expected shortfall, the probability to observe negative future GDP growth, kurtosis and skewness have good properties in detecting future systemic risk to economic performances. One year before the crisis, an increase in risks for economic activity and higher uncertainty regarding future GDP growth could have been predicted.

Overall, the risk measures we analyze show early warning properties and could potentially integrate the macroprudential toolkit, enhancing the effectiveness of those measures – like capital buffers – that must anticipate and help to mitigate the rise in systemic risk. Nevertheless, these measures seem to perform more poorly once we move from a one-year to a three-year projection horizon. A one-year anticipation may not be enough to fulfill financial stability objectives since macroprudential tools generally need more time to build up.

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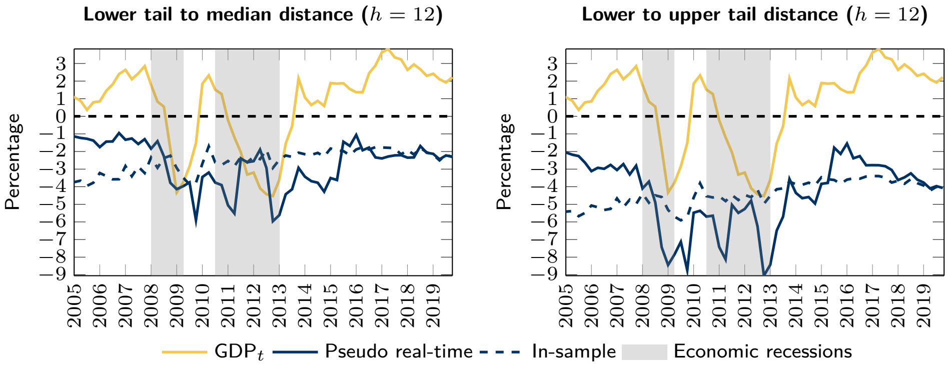
Appendix

Complementary measures: results for $h = 12$

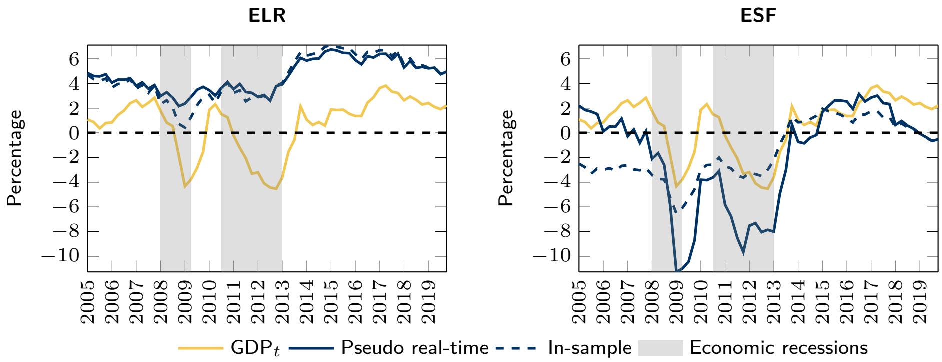
Difference between percentiles of the distribution.



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 21: Difference between percentiles for $h = 12$

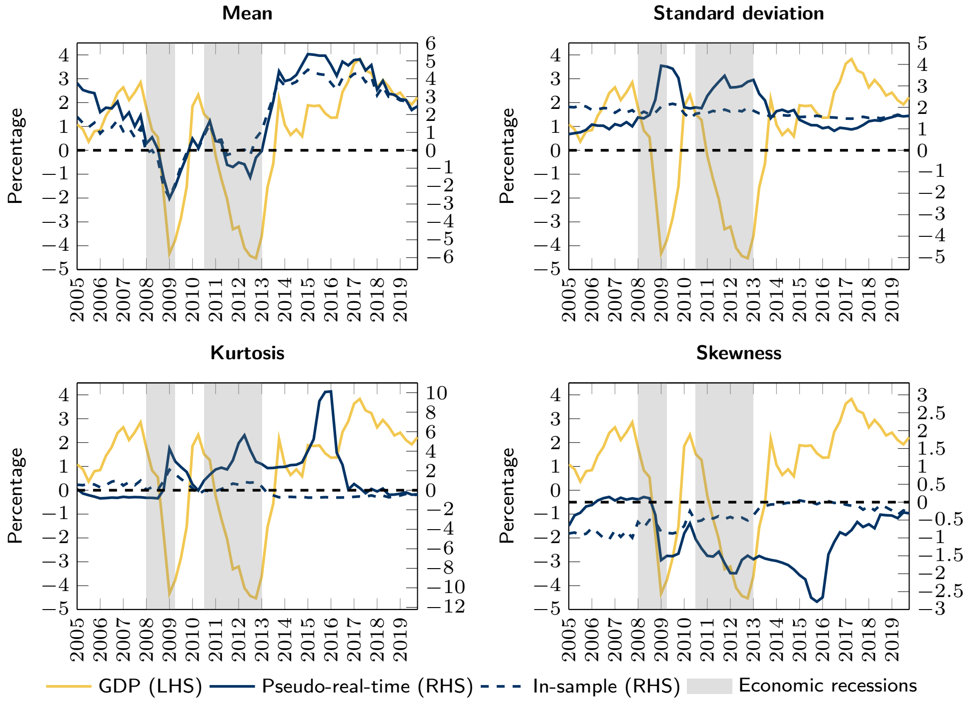
Expected shortfall and longrise.



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 22: Expected shortfall and longrise for $h = 12$

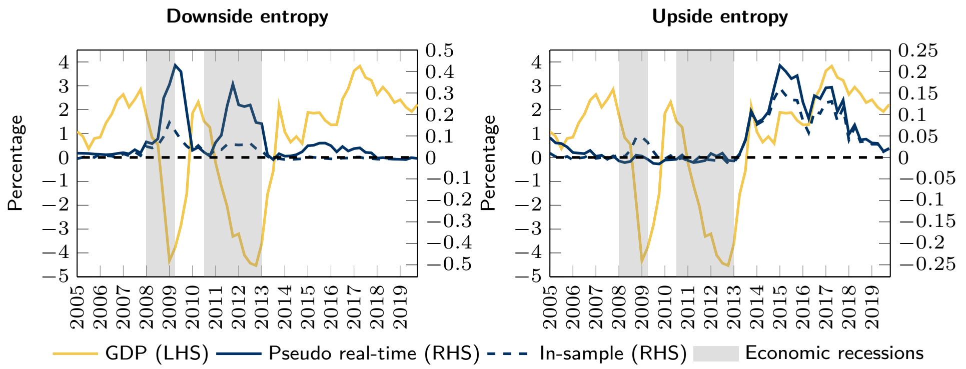
Distribution moments (mean, standard deviation, kurtosis, skewness).



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 23: Moments of the distribution for $h = 12$

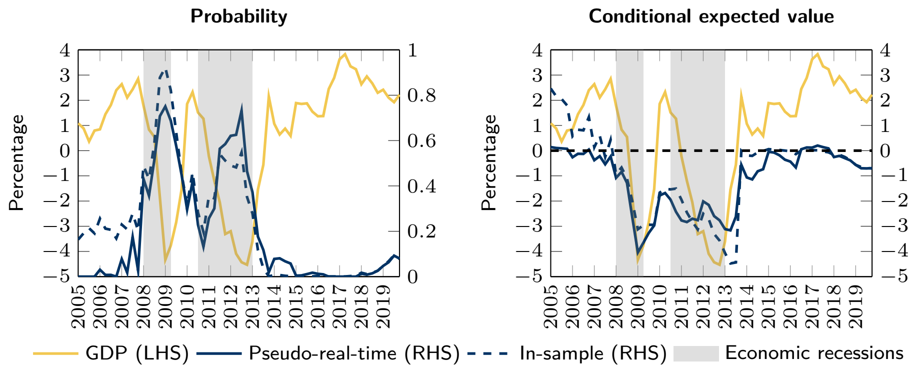
Downside and upside entropy.



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 24: Downside and upside entropy for $h = 12$

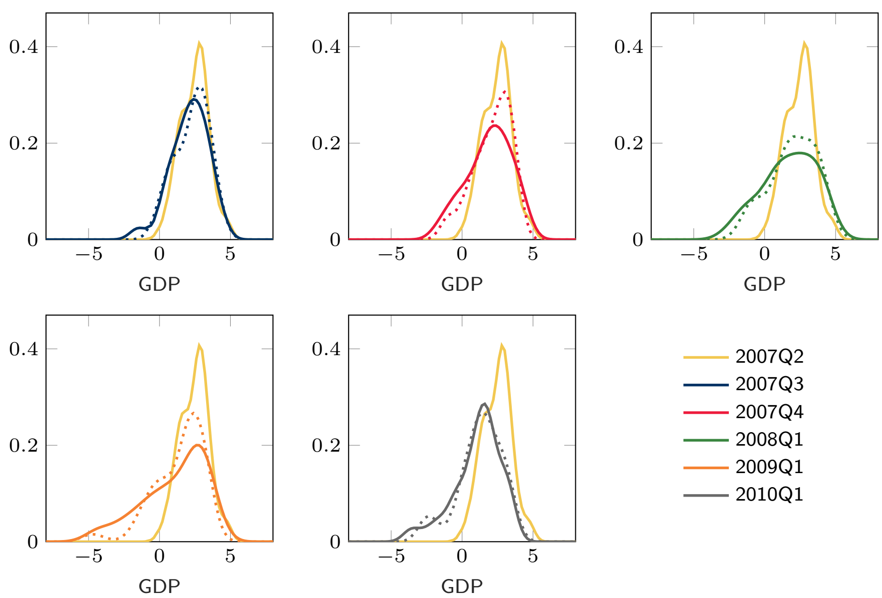
Probability of negative growth rate and conditional expected value.



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 25: Probability of negative growth rate and expected GDP growth associated for $h = 12$

The Great Financial Crisis: additional results



Note: The dotted line stands for the estimated conditional GDP distribution in pseudo real-time.

Figure 26: Estimated conditional GDP growth distribution based on information available at 2007Q1

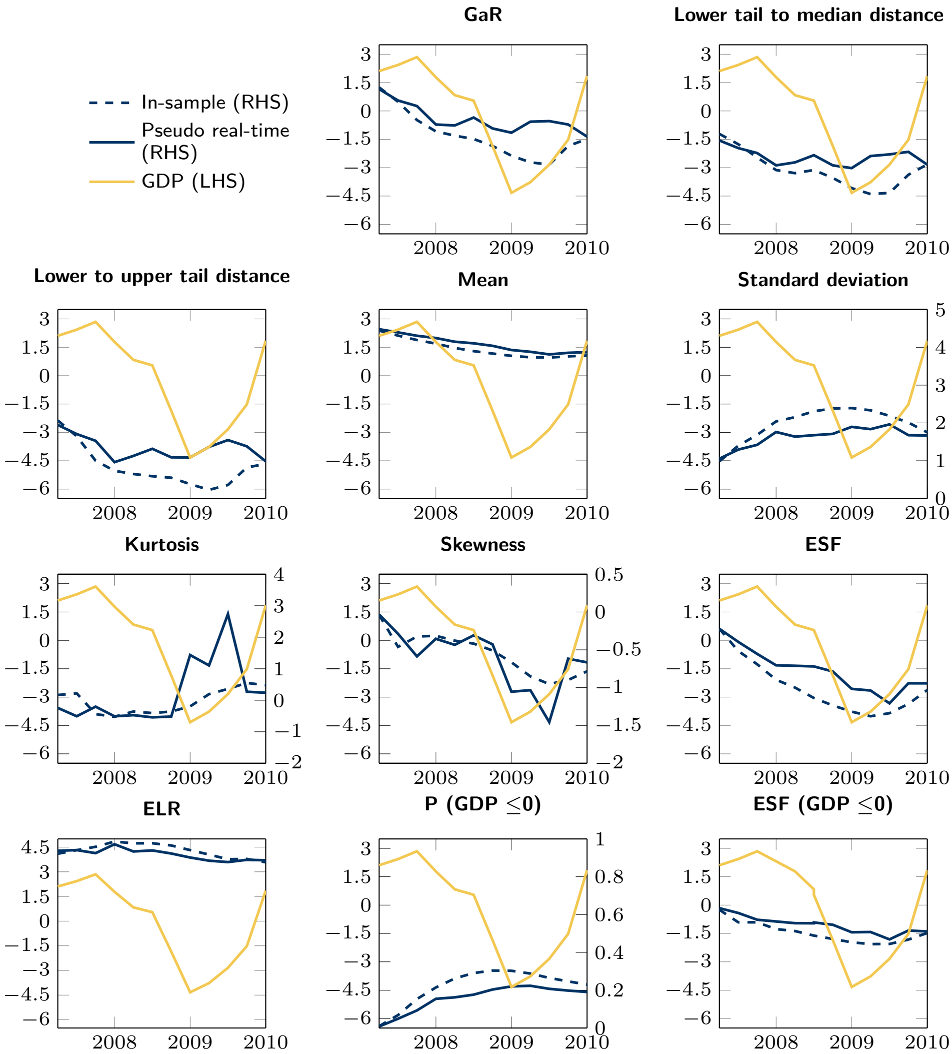


Figure 27: Estimated measures given information at 2007Q1

Principal Components Analysis

Principal Components Analysis (PCA) is one of the methodologies used to complement and enrich the GaR models. The stress in financial markets and the accumulation of vulnerabilities in the financial system may not be completely captured by the composite indicators CLIFS and SRI. As such, the quantile regressions used to estimate GaR and the other complementary measures of risk may benefit from more information. Nevertheless, as mentioned in section 2, given the small time span of the available time series there is a limit to how many variables should be included in the model. One possible way to overcome this issue is to use PCA. This technique allows to reduce the dimension of the explanatory variables

PCA block variables	Transformation	Source
Financial Risk		
Euro/ECU exchange rates – Pound sterling	y-o-y growth rate	SWD
Euro/ECU exchange rates – US dollar	y-o-y growth rate	SWD
Real effective exchange rate index	q-o-q differences	BdP
House price index	q-o-q growth rate	OCDE
Transaction value of residential property dwellings	y-o-y growth rate	OCDE
Portugal 10-year Government Benchmark bond yield	q-o-q differences	SWD
PSI Geral (Real)	y-o-y growth rate	BdP
SP500 Index (Real)	y-o-y growth rate	Thomson Reuters
Standard deviation – Euro Stoxx 50 Price Index (Real)	None	Thomson Reuters
Standard deviation – Euronext Lisbon PSI20 Index (Real)	None	Thomson Reuters
Standard deviation – SP500 Index (Real)	None	Thomson Reuters
Financial Vulnerability		
Credit-to-GDP gap	q-o-q differences	BIS
International debt securities, nonbanks, short term	None	BIS
New credit to Households	None	BdP
New loans to NFC	None	BdP
New securities issued by NFC	None	BIS
Total bank credit – Loans to HH for consumption	HP Filter $\lambda = 1600$	BdP
Total bank credit – Loans to HH for house purchase	HP Filter $\lambda = 1600$	BdP
Total bank credit – Loans to HH for other purposes	HP Filter $\lambda = 1600$	BdP
Total bank credit – Loans to NFC	HP Filter $\lambda = 1600$	BdP
Total bank credit – Securities NFC	HP Filter $\lambda = 1600$	BdP
Total own funds ratio	HP Filter $\lambda = 1600$	BdP
Total loans to NFC	HP Filter $\lambda = 1600$	BdP
Total securities issued by NFC	HP Filter $\lambda = 1600$	BdP

Table 2. Series used in PCA

by retaining the information that is most relevant to explain the general behavior of the selected variables.

With this in mind, we collected a large number of time series and applied different transformations to ensure that they were all stationary. The second step consisted in analyzing the obtained series, as some displayed high correlation. To avoid repeating the same information (or very similar one), we chose a subset of the original data set that contained variables not closely related. Finally, the series were standardized to have mean zero and unit standard deviation. Table 3 shows series included in the PCA, the respective transformation and the data source.

After performing the PCA, the first 3 or 4 components were chosen to be included as regressors in the quantile regressions. Table 4 shows the percentage of the total database that is explained by the first components.

PCA block variables	Transformation	Source
Real Economy		
Assessment of current production capacity	q-o-q differences	Eurostat
Business climate indicator	None	Eurostat
Competitive position on foreign markets inside the EU over the past three months	None	Eurostat
Competitive position on foreign markets outside the EU over the past three months	None	Eurostat
Construction confidence indicator	q-o-q differences	Eurostat
Consumer confidence indicator	q-o-q differences	Eurostat
Current level of capacity utilization (%)	q-o-q differences	Eurostat
Duration of production assured by current order-books	q-o-q differences	Eurostat
Export expectations for the months ahead	None	Eurostat
Home improvements over the next 12 months	q-o-q differences	Eurostat
Industrial production	y-o-y growth rate	Eurostat
Intention to buy a car within the next 12 months	q-o-q differences	Eurostat
Operating time ensured by current backlog, months	q-o-q differences	Eurostat
Purchase or build a home within the next 12 months	q-o-q differences	Eurostat
Retail confidence indicator	q-o-q differences	Eurostat
Standardised unemployment rate	q-o-q differences	SDW
Uncertainty Index (WUI)	None	IMF
Budget outturn	None	BdP
Private consumption – Durables (Real)	y-o-y growth rate	BdP
Private consumption – Non-durables (Real)	y-o-y growth rate	BdP
Public consumption (Real)	q-o-q differences	BdP
GFCF (Real)	y-o-y growth rate	BdP
Change in inventories (Nominal)	y-o-y growth rate	BdP
Exports of goods and services (Real)	y-o-y growth rate	BdP
Imports of goods and services (Real)	y-o-y growth rate	BdP
Private disposable income	y-o-y growth rate	BdP
Core CPI	q-o-q growth rate	SDW
M3	q-o-q growth rate	SDW
Money market 3-month interest rate	None	FRED
Total reserves	y-o-y growth rate	WB

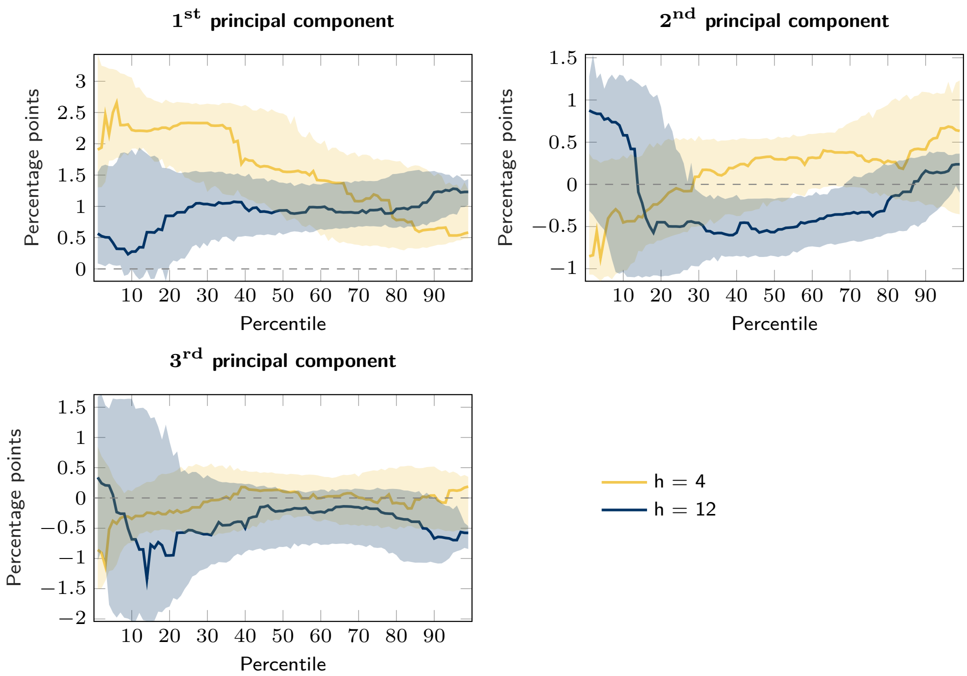
Table 3. Series used in PCA

Component	1	2	3	4
% Explained	19.25	11.7	6.62	6

Table 4. Percentage of total database explained by the first principal components

The rest of the process is as explained in the methodology section. Thus, the following quantile regressions were considered:

$$\mathcal{Q}_{GDP_{t+h}}(q|PC\_1_t, PC\_2_t, PC\_3_t) = \\ \alpha^{q,h} + \beta^{q,h}_{PC\_1} PC\_1_t + \beta^{q,h}_{PC\_2} PC\_2_t + \beta^{q,h}_{PC\_3} PC\_3_t \quad (8)$$



Note: The shaded areas correspond to 95% confidence intervals obtained using bootstrapping (xy-pair method) according to Davino *et al.* (2013). Estimated marginal effects are conditional on a one standard deviation increase holding constant all other regressors in the model.

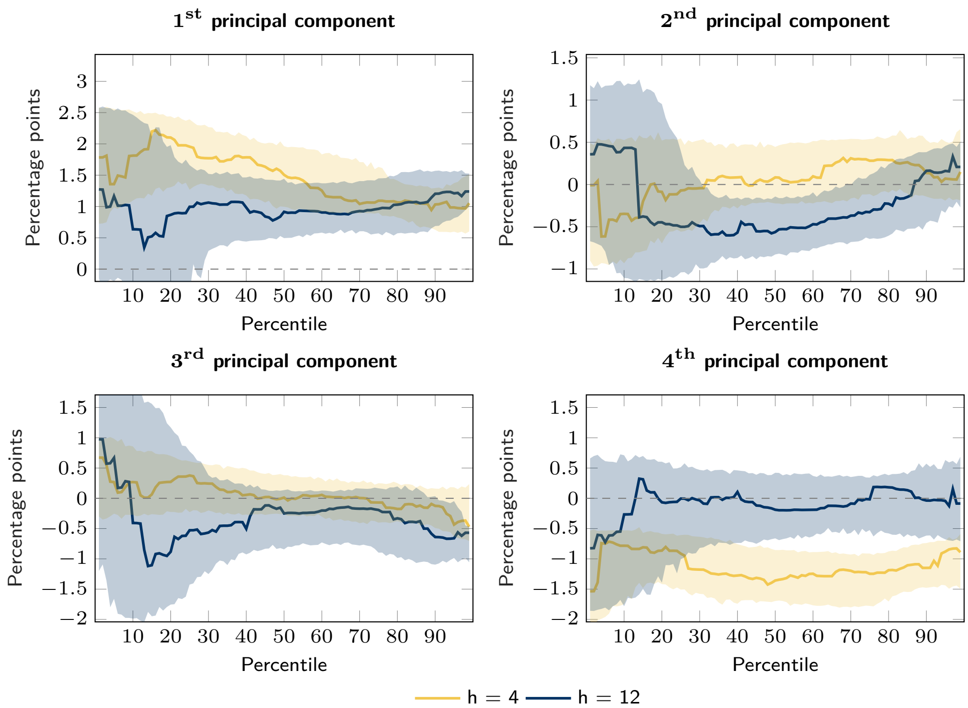
Figure 28: Estimated marginal effects for $h = 4$ and $h = 12$: PCA model with 3 components

$$\mathcal{Q}_{GDP_{t+h}}(q|PC\_1_t, PC\_2_t, PC\_3_t, PC\_4_t) =$$
$$\alpha^{q,h} + \beta^{q,h}_{PC\_1} PC\_1_t + \beta^{q,h}_{PC\_2} PC\_2_t + \beta^{q,h}_{PC\_3} PC\_3_t + \beta^{q,h}_{PC\_4} PC\_4_t \quad (9)$$

Figures 28 and 29 show the quantile regression estimated coefficients across percentiles for the two models (3- and 4-components) for $h = 4$ and $h = 12$. For the 3-components regression, only the first one for $h = 4$ is statistically significant. For the 4-components regression, the fourth component for $h = 4$ is also statistically significant. Consequently, this shows that the model based on PCA may not be the best to predict future GDP growth.

Figures 30 and 31 show the estimated GaR according to the two models considered and, as before, under the pseudo real-time exercise. Looking at this risk measure, we can conclude that the use of principal components does not improve the modeling results. Comparing to the baseline model, we lost any signal of GFC' anticipation, along with the warning between the two crises. Due to these results, the baseline model remained the preferred one in our analysis.

We also considered an alternative way of implementing PCA. Instead of considering a large data set with all the variables, we sorted them according to tree

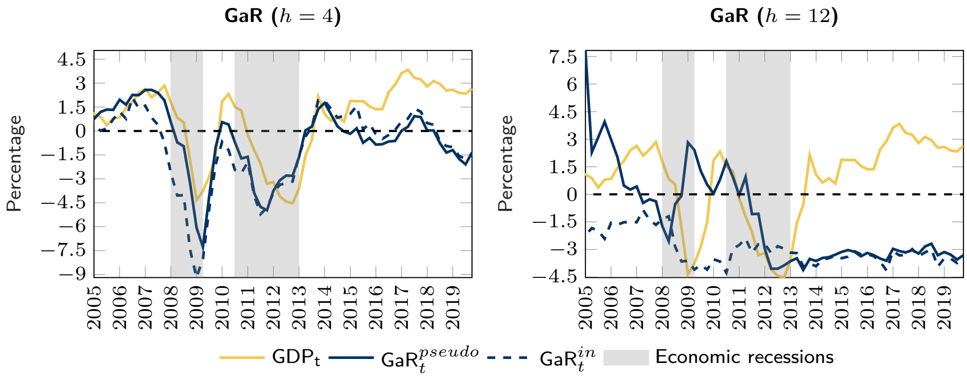


Note: The shaded areas correspond to 95% confidence intervals obtained using bootstrapping (xy-pair method) according to Davino *et al.* (2013). Estimated marginal effects are conditional on a one standard deviation increase holding constant all other regressors in the model.

Figure 29: Estimated marginal effects for $h = 4$ and $h = 12$: PCA model with 4 components

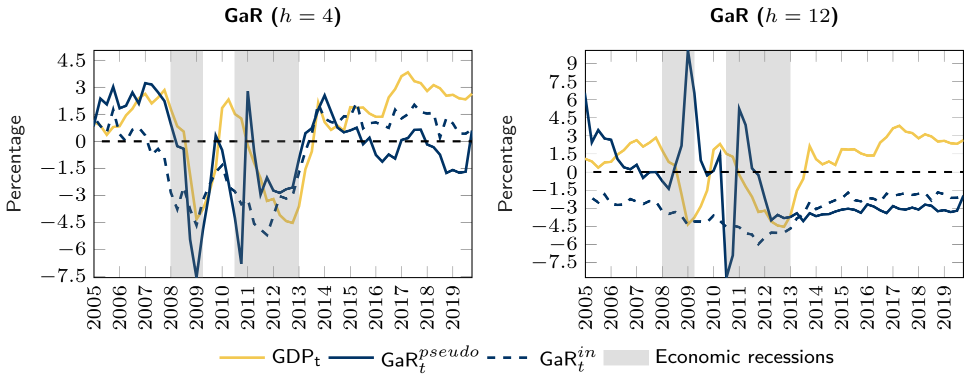
categories: real economy, financial vulnerability and financial risk (as discriminated in table 3). PCA was applied to each subset of the time series and we considered only the first component. When compared with our baseline PCA models, we found this specification to give very similar results.[13]

13. The results are available upon request.



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 30: GDP-at-risk of the model with three principal components for the in-sample and pseudo real-time.



Note: Dates for the economic recessions as defined in Rua (2017).

Figure 31: GDP-at-risk of the model with four principal components for the in-sample and pseudo real-time.

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