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Mind the Build-up: Quantifying Tail Risks for Credit Growth in Portugal

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Abstract
We quantify the effect of cyclical systemic risk and economic sentiment on non-financial corporations and households' (total) credit growth for Portugal between 1991Q1 and 2020Q2, following the *Growth-at-risk* methodology. We focus on the right-hand tail of the future credit growth distribution, as credit booms are potentially detrimental to financial stability. A set of measures of the upside tail risk in credit growth is computed to provide policymakers with more information to anticipate credit build-ups. We find that financial vulnerabilities and industrial sector economic confidence increase the upper tail risk of credit growth realizations for non-financial corporations in the short term (4 quarters horizon). At the medium to long term (12 quarters horizon), the impact of those indicators almost cancels each other out. As regards households, increasing financial vulnerabilities and consumers' economic confidence display opposite effects on the upper tail risk of credit growth, at short and medium to long terms. Credit-at-risk anticipates credit build-ups preceding financial crises and decelerations corresponding to recessions. The upper tail to median and the upper to lower tail distances identify the upper tail dynamics as the main responsible for future credit growth uncertainty. Expected longrise reinforces Credit-at-risk results while the probabilities of observing future credit growth above its mean and credit growth one standard deviation above its current value exhibit high levels before 2008 for both non-financial corporations and households, followed by deep falls during recessions which signal credit busts. For all the measures, the 2013-2018 increase in tail risk depends on the structural change in credit growth dynamics observed in the early 2000s. The most recent results highlight the predominant role of confidence indicators, further dampened in 2020 by the COVID-19 effects on the economic outlook.

Keywords: Macroprudential policy, quantile regression, upside risk, macrofinancial linkages, financial stability, credit-at-risk.

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1. Introduction

The recent experience with financial crises exposed how excessive credit growth often causes build-ups of cyclical systemic risk and is usually followed by deep credit busts that have a negative spillover effect on economic activity (Jordà *et al.* 2011; Schularick and Taylor 2012; Aikman *et al.* 2015; Alessi and Detken 2018). Credit booms during an expansion increase the likelihood of subsequent financial crisis (Jordà *et al.* 2013) and, as such, they reveal themselves as a good indicator of a financial crisis (Reinhart and Rogoff 2009; Boissay *et al.* 2016). These findings point to the need for overseeing the upside tail risks of credit growth.

The importance of monitoring upside tail risks of credit growth brings about an important research question, which constitutes the motivation for the present work: whether it is possible to signal excessive credit growth with sufficient advance so that policy measures can be adopted if needed. The tools that policymakers currently have to track developments in credit growth can be improved with complementary measures that allow adopting a more forward-looking approach. Having additional indicators with these properties would lead to less uncertainty regarding the analysis of future developments in credit growth, which may translate into a more efficient toolkit to tackle risks for financial stability.

As we intend to predict the behavior of the highest potential future realizations of credit growth, we rely on the *Growth-at-risk* approach to conduct our analysis. The *Growth-at-risk* measures are derived from quantile regression models used to study the future growth conditional distribution of a time series of interest, focusing on specific percentiles and taking advantage of the non-linear relationship between dependent and independent variables. Although the most common target in the literature happens to be GDP growth[1], this approach can be applied to several other variables such as banks' capital ratio (Lang and Forletta 2020), house prices (Alter and Mahoney 2020; Deghi *et al.* 2020) and inflation (Korobilis 2017; López-Salido and Loria 2020; Korobilis *et al.* 2021).

In this work, we explore a new strand of the literature trying to assess the impact of financial and economic indicators on non-financial corporations (NFCs) and households' (HHs) credit growth in Portugal. Chuliá *et al.* (2021) closely relates to our study, as the authors use panel quantile regressions to quantify how US financial conditions impact on funding markets of the private non financial sector (both credit and equity) in a large set of countries, mainly focusing on funding vulnerabilities. Among the main findings, the paper stresses the heterogeneous effect of the US financial condition index across quantiles – with more pronounced negative effect on the lower quantiles than on the central quantiles – and across countries. Hodula *et al.* (2019) applies panel quantile regression to explore the

1. In De Lorenzo Buratta *et al.* (2022), we contribute to the literature analysing the role that the current financial situation plays on the conditional distribution of future GDP growth for Portugal. We find that both financial vulnerability and cyclical systemic risk have a negative effect on the left tail of the one-year-ahead GDP growth distribution.

non-linear relationship between households' macroeconomic conditions and credit dynamics. The results, which are limited to a one-quarter horizon, reveal a stronger procyclicality of credit at lower quantiles for both "good and bad times".

Deviating from the standard quantile-regression framework that aims at anticipating economic recessions, we focus our analysis on the right-hand tail of the future credit growth conditional distribution. Our Credit-at-Risk (CaR) measure estimates the highest realizations of future credit growth, which, in a forward-looking perspective, are the most potentially damaging for financial stability. The methodology allows an acceptable level of agnosticism regarding the definition of excessive credit growth, as we focus on the most extreme values that credit growth can take and their likelihood. Nevertheless, some arbitrariness in defining what is perceived as excessive risk to credit growth persists. The policymaker chooses threshold percentiles - the 90^{th} in our case - even if the corresponding value may vary over time, and some level of expert judgment might still be needed. The *Growth-at-risk* approach also provides a direct way to focus on how the current economic outlook and financial situation relate to future credit growth, both at the short and medium to long term horizons. This feature is important to detect the build-up of upper tail risk before its materialization. Moreover, this methodology permits exploring the non-linear relationship that may elapse between the current economic and financial situation and future credit growth. By estimating the whole conditional distribution of future credit growth, this methodology also allows to collect additional information regarding credit growth. For instance, the level of uncertainty regarding future credit growth, the expected average credit growth that would be observed in case of extreme (tail) events, the probability of observing credit growth rising above given values and the conditional expected values. With such information, in addition to CaR, we compute a set of measures of the upside tail risk in credit growth intending to provide macroprudential policymakers with complementary indicators to monitor credit build-ups.

This paper contributes to the literature on *Growth-at-risk* applications to credit growth in several dimensions. First of all, we analyse both NFCs' and HHs' domestic credit growth, while Chuliá *et al.* (2021) only target NFCs and Hodula *et al.* (2019) focus on HHs. We use domestic indicators instead of global ones, and we include both vulnerability and confidence indicators for NFCs and HHs.[2] Compared to Hodula *et al.* (2019), we consider the heterogeneous effects across time of our explanatory variables, as we implement local projections along with the quantile

2. Chuliá *et al.* (2021) include as explanatory variables, in their baseline specification, the US financial condition indicator, a global macroeconomic factor and a global financial factor. The two global factors are estimated via Principal Component Analysis (PCA) and Kalman filter. The global financial factor includes information on real credit growth, stock returns and changes in sovereign bond yields, while the global macroeconomic factor comprises real GDP growth and inflation information, plus the global financial factor information. Hodula *et al.* (2019) include a households' macroeconomic conditions index, which is intended to approximate the perception of macroeconomic conditions by the households, and supply-side control variables, which includes a proxy for bank credit risk profile, a proxy for bank leverage and a proxy for bank profitability.

regressions. We update this strand of the literature by shifting the focus of the analysis to the upper tail of the future credit growth distribution, instead of the lower tail. Moreover, we do not limit our study to the estimation of a few percentiles of the future credit growth distribution as – to our knowledge – this work represents the first attempt in this context to compute complementary measures that encompass information of the whole credit growth conditional distribution. These measures aim at providing a more comprehensive understanding of the upside tail risk in credit growth and, in this way, improving macroprudential surveillance.

We find that rising financial vulnerabilities and high levels of confidence from the industrial sector increase the upside tail risk of NFCs' credit growth in the short term (4 quarters horizon). At the medium to long term (12 quarters horizon), these indicators have opposite effects on future credit growth tail risk of almost the same magnitude if an increase of one standard deviation is considered. The confidence indicator has a positive contribution for the upper tail risk. In terms of tail risk assessment, the estimated CaR measure signals the sharp increase in credit growth observed before the Great Financial Crisis (GFC), captures the increase in credit growth realized in 2011 and then anticipates the upward trend in credit growth observed in 2015. Prior to the GFC, the upper tail to median distance and the upper to lower tail distance, taken together, point to the upper tail dynamics as the main contributor to the uncertainty regarding future credit growth. The expected longrise, comprising more information concerning the upper tail, confirms the previous findings from CaR. The probability measures, associated with high and/or fast credit growth, exhibit high levels before the GFC and sharp falls during the recession periods related to the GFC and the European Sovereign Debt Crisis (ESDC) (2008Q1-2009Q2 and 2010Q3-2013Q1), signalling credit contractions. The expected values associated to the probability measures further strengthen the results, exhibiting an upward trajectory before the GFC. All the tail risk measures point to an increase in risk between 2013 and 2018. We argue that this result depends on the structural change in credit growth dynamics that occurred in the early 2000s: the magnitude of the risk is lower when we exclude data before 1999 from our analysis. In 2020, there is a decline in tail risk driven by a deterioration of the confidence indicator. Such deterioration is the result of the effects of the COVID-19 pandemic.

Regarding HHs' credit growth, a rise in financial vulnerabilities and consumers' confidence has opposite effects on the upper percentiles of the conditional distribution, both at the short term and at the medium to long term. In terms of tail risk assessment, the estimated CaR provides information about increases occurring before the GFC and the ESDC. It anticipates the two falls observed during the recession periods and the recovery trajectory after 2014. The results from complementary measures add useful information. Before 2009, the results from the upper tail to median distance and the upper to lower tail distance signal higher uncertainty surrounding above-median (central scenario) realizations of credit growth than below-median realizations, as the mass of the conditional distribution concentrates on the left side while the upper tail becomes "heavier".

When the entire upper tail behavior is taken into account by computing the expected longrise, CaR findings are confirmed. Regarding the probability measures related to increases in future credit growth, as for the NFCs, the highest values are observed before the recession periods and after 2014, indicating the contraction and recovery in credit growth. The expected values associated to the probability measures further reinforce the results, signalling build-ups of risk before the GFC and the ESDC. As for NFCs, the early 2000s structural change in credit growth dynamics influences the magnitude of the increase in tail risk estimated between 2013 and 2018. The results for 2020 stress the predominant role of the confidence indicator: a decline in risk is observed, coinciding with reduced HHs' economic expectations due to the COVID-19 pandemic.

The paper is organized as follows. Section 2 presents the methodological approach, the empirical models to be estimated and an overview of the data used. Section 3 presents the results from model estimation and discusses the use of the CaR measure and other complementary tail risk measures for macroprudential surveillance and section 4 concludes.

2. Methodology and Data

2.1. Methodology

Quantile regressions proposed by Koenker and Bassett (1978) and local projections as introduced by Jordà (2005) are combined to assess the potential heterogeneous link between explanatory variables and the percentiles of the distribution of a variable of interest at different projection horizons. The use of quantile regressions allows to estimate the whole distribution of the variable of interest while local projections enable the estimation of the same distribution for different projection horizons, without the need to extrapolate it from a given model. Thus, we assume from the start that the relationship between the predictors and the variable of interest may vary across the percentiles of the distribution and over time. We follow a two-steps approach as it is commonly used in the literature (e.g., Adrian *et al.* 2019). In the first step, we fit a quantile regression to a variable of interest, as follows:

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

where Y^q_{t+h} is the dependent variable or variable of interest projected h quarters ahead at the q^{th} 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 ($\alpha^{q,h}$ and $\beta^{q,h}$) are estimated through an optimization problem, in which the weighted sum of the absolute value of the residuals is minimized. Koenker and Bassett (1978) show that the resulting non-parametric estimators for the unknown parameters are consistent.[3] Equation (1) is, then, estimated for the percentiles (q) between 1% and 99% in steps of 1 and for a projection horizon (h) that ranges between 1 and 12 quarters ahead. As a result, we estimate, in total, 99 times 12 quantile regression models of the type presented in equation (1).

We estimate the quantile regressions using two distinct information sets based on data at quarterly frequency (data are described below in more detail). The first information set uses all the available information to retrieve estimates for the unknown parameters of the model. We label this exercise as in-sample exercise. The second information set follows an iterative procedure to define the estimation sample. We first estimate the quantile regressions using data from 1991Q1 to 2005Q1 for all percentiles and prediction horizons considered.[4] Then, iteratively we estimate the quantile regressions adding each time to the estimation sample one more quarter of information. This procedure is ran until the end of the sample, 2020Q2. The objective is to mimic the information available to policymakers in each moment. We label this exercise as pseudo real-time exercise. We rely on final data vintages, meaning that we abstract from periodic revisions to which data is often subject to, therefore this analysis does not constitute a true real time exercise. Our focus will be on assessing the performance of the risk measures that result from this latter exercise since it allows their evaluation in a similar environment to which they are designed to be used, for macroprudential purposes. However, the comparison of the results between exercises can also provide insights regarding on how fast the model "learns" from past events.

As in Adrian *et al.* (2019) and others thereafter, the second step entails fitting a distribution to the quantile regression estimates from equation (1). The goal is to obtain a smoothed version of the conditional distribution of the variable of interest and obtain a probability density function. While Adrian *et al.* (2019) fit a parametric distribution, the skewed *t*-distribution, we map the quantile regression estimates into a kernel distribution in order to capture potential multimodality in the conditional distribution of the variable of interest and to obtain a distribution closer to the estimated quantiles. The case for multimodality in the joint distribution of economic and financial conditions was recently introduced by Adrian *et al.* (2021). A gaussian kernel with optimized bandwidth as proposed by Bowman and Azzalini (1997) was used to smooth the quantile regression estimates. Also differently from the related literature, we fit each percentile of the probability density function to its quantile regression estimate counterpart to increase the accuracy of the resulting distribution.

3. For a comprehensive discussion on the properties of the quantile regression estimators see Koenker (2005).

4. This estimation sample is also known as the training sample. Since the available time span for the data is not as long as desired, we decided to end the training sample in 2005Q1 in order to strike a balance between the minimum number of observations that guarantees the properties of the estimator and covers the period before the GFC.

Provided with model estimates (step 1) and with the fitted conditional distributions (step 2), several measures to detect future periods of excessive credit growth (upside tail risk) are put forward. This set of informative measures of upside risks encompasses specific percentiles, the expected longrise measure which measures the expected severity of upside tail risks and measures that provide the likelihood of observing positive and excessive credit growth. All metrics are described in detail in section 3.

2.2. Model specifications and data

We apply the above framework to study the relationship between the prevailing financial environment and future bank credit growth (variable of interest). The goal is to derive risk metrics that allow detecting, in advance, periods of rapid credit growth (upside risks). Several factors can motivate credit booms; among them are an easing of credit standards and financial liberalization.[5] Periods of loose financial conditions usually precede credit booms given that there are less constraints to access credit. The loosening in credit standards might be a response to an expansionary monetary policy stance (Afanasyeva and Güntner 2014). Competition across banks can also explain a substantial variation in credit standards as screening intensity falls during expansions, along with the increase in credit supply, facilitating lending to riskier borrowers (Ruckes 2004; Dick and Lehnert 2010). Another side effect of loosening credit standards is the deterioration of bank portfolios along with lower and more volatile profits.

As the drivers of credit granted to NFCs differ from those of the credit granted to HHs, we conducted separate analyses for the two credit segments.[6] Credit granted to the NFCs' sector has usually different volumes and smaller maturities when compared with loans granted to HHs – especially in the case of mortgages. Loans granted to NFCs have smaller maturities because they are usually in the form of revolving credit, although these maturities have increased in the last decade, even before the introduction of public loans' guarantees in the context of the COVID-19 pandemic. Moreover, a large part of the credit granted to HHs is in the form of mortgages, a segment that requires collateral and can present different interest rate spreads.[7] Therefore, the impact of financial variables may change depending

5. van der Veer and Hoeberichts (2016) shows that the level of credit standards has an impact on credit cycles. Arena *et al.* (2015) shows that financial liberalization can contribute to the increase in credit aggregates as 22% of credit booms are preceded by above-median increases in the financial liberalization index.

6. Mortgage and consumer lending have different characteristics and may have different drivers. Nonetheless, the total HHs credit growth series we use does not diverge much from the series for mortgage credit growth, as consumer lending - even if shows a different growth rate path - represents a small share of total HHs' credit in Portugal.

7. At the end of 2019, 19.1% of the credit to NFCs was granted with no guarantees (collateral and/or other types, such as personal guarantees), against the 0.5% for mortgage and 9.6% for the total HH credit (which includes mortgage, consumption and other purposes credit). Concerning the

on the credit segment considered. This observation is also in line with the changes in the regulation of capital-based macroprudential instruments occurred in the early 2000s, namely in terms of the scope of application of the systemic risk buffer. This buffer can now be used to tackle cyclical systemic risk that is not covered by the countercyclical capital buffer and as such may be applied as a sectoral buffer to containing excessive credit growth in a particular sector. Moreover, the regulation requires the definition of different risk weights for different types of credit. In this context, it may be useful for policymakers to gauge credit market developments at the sector level.[8] Notwithstanding, this information may also be useful to inform the discussions on the countercyclical capital buffer.

Against this background, the two proposed baseline quantile regression models have, respectively, as dependent variable the annual rate of change of loans granted by banks to NFCs (NFC) and HHs (HH). This variable is published monthly by the Banco de Portugal and is included in a set of information that is regularly published on monetary financial institutions' balance sheet.[9] The set of regressors considered in the quantile regression models is based on the evidence that periods of rapid credit growth are often the result of strong economic performance coupled with overly optimism in the financial system (Bordalo *et al.* 2016; Fahlenbrach *et al.* 2018; Baron and Xiong 2017).

Both baseline models include as explanatory variables the systemic risk indicator (SRI) and a confidence indicator. The SRI is a composite indicator proposed by Lang *et al.* (2019), which contains information regarding domestic credit, residential real estate market, asset prices and external imbalances. This is one of the best performing early warning indicators of systemic financial crises as documented in Lang *et al.* (2019). This composite indicator results from an extensive evaluation exercise comprising a large set of univariate early warning indicators. It can be seen as a measure that track vulnerability in the financial system. The inclusion of the SRI in the model, which accounts for the 2-year real total credit growth, allows for a more parsimonious model where the lagged dependent variable can be excluded from the regressors, while mitigating endogeneity problems[10].

interest rates, the difference between the interest rate applied to NFC credit below 1 million euros and the interest rate applied to NFC credit above 1 million euros is around 1.5 p.p. on average for the period from January 2003 to December 2019. For the HH segment, the difference between the interest rate applied to credit for consumption and other purposes and the interest rate applied to mortgage credit is significantly larger, being around 5.7 p.p. on average over the same period.

8. For the application of the systemic risk buffer, discriminating credit by sectors of activity would also be relevant. However, this particular specification is not considered in this analysis.

9. This variable gauges the developments in financial transactions associated with changes in stock positions, where financial transactions are computed by subtracting from the stock position the exchange rate effect, the price effect, reclassifications and other adjustments. For a precise definition, see https://bpstat.bportugal.pt/conteudos/metainformacao/390.

10. For the SRI, we are able to account for the impact of data revisions as we have available a stream of data vintages.

The confidence indicator allows to incorporate agents' expectations in the model, given that the way economic agents perceive future economic activity may influence their decisions to apply for bank loans. For the NFCs sector, we consider the industrial confidence indicator (ICI).[11] The ICI is a composite indicator that reflects entrepreneurs confidence regarding present and future condition of their businesses in terms of, among others, production, employment, orders and capacity utilisation. We expect this variable to have a positive effect on credit growth since improved economic expectations should increase the willingness of firms to finance their investment plans with new loans. The proposed baseline model for the NFCs sector is as follows:

$$\hat{Q}_{NFC_{t+h}}\left(q|ICI_t, SRI_t\right) = \hat{\alpha}^{q,h} + \hat{\beta}^{q,h}_{ICI} ICI_t + \hat{\beta}^{q,h}_{SRI} SRI_t \tag{2}$$

The baseline model for credit granted to HHs includes instead the consumer confidence indicator (CCI). The CCI provides insights about future developments of HHs' consumption and saving based upon answers regarding their expected financial situation, their sentiment about the general economic outlook, unemployment and capability of savings.[12] As for the case of NFCs, we expect this variable to positively affect credit growth: improved expectations about future economic conditions incentivize HHs to apply for new loans. Thus, the proposed baseline model is as follows:

$$\hat{Q}_{HH_{t+h}}\left(q|CCI_t, SRI_t\right) = \hat{\alpha}^{q,h} + \hat{\beta}^{q,h}_{CCI} CCI_t + \hat{\beta}^{q,h}_{SRI} SRI_t \tag{3}$$

A financial stress indicator, CLIFS (Duprey *et al.* 2017), was also considered for both regressions. CLIFS is an index that aims at identifying, in a timely fashion, stress in equity, bond and foreign exchange markets. This indicator provides contemporaneous information about financial stress and it can be considered as a measure of financial conditions. Nevertheless, this variable was not statistically significant across most percentiles and projection horizons of interest. From a demand side perspective, in what concerns NFC, this result can be related to the characteristics of NFCs business in Portugal, mostly small and medium enterprises without access to capital markets. As a result, raising financing through financial markets does not constitute a substitute to bank credit and, as such, stress in equity and bond markets does not seem to influence funding' decisions of firms in Portugal. The case of HHs is slightly different, as developments in financial markets might influence HHs' wealth and their expectations for economic activity, despite the limited participation of Portuguese households in equity markets. However,

11. Substituting the industrial confidence indicator with a service sector confidence indicator does not improve the model. Moreover, the service sector confidence indicator time series is only available from 1997Q2 onwards.

12. Angelico (2018) finds empirical evidence that survey data on households expectations have strong predictive power for the dynamics of household debt. In the same line, Kłopocka (2017), using data for Poland, concludes that consumer confidence indexes have strong predictive power for future household' credit growth.

the confidence indicator is also able to reflect these effects. Thus, it could be the case that the confidence indicator "absorbs" the contribution of CLIFS to the model. Considering the supply side, stress in the equity, bond and foreign exchange markets can impact banks' financing costs and therefore their decisions of credit supply. Nonetheless, after the GFC, banks in Portugal rely much less on capital markets' funding, lowering the impact of financial stress on banks credit supply.[13,14] However, the need to comply with Minimum Requirement for own funds and Eligible Liabilities (MREL) requirements might increase banks' funding costs.

We estimate the models specified above in equations (2) and (3) using quarterly data for Portugal between 1991Q1 and 2020Q2. Table 1 summarizes the data used in the estimation of the quantile regression models, the sample available and their sources.

Variable	**Category**	**Sample**	**Source**
NFC Credit (NFC)	Dependent	1980 Q4 – 2020 Q2	BdP
HH Credit (HH)	Dependent	1980 Q4 – 2020 Q2	BdP
Systemic risk indicator (SRI)	Vulnerability	1991 Q1 – 2020 Q2	BdP
Industrial confidence indicator (ICI)	Confidence	1987 Q1 – 2020 Q2	EC
Consumer confidence indicator (CCI)	Confidence	1986 Q2 – 2020 Q2	EC

Note: NFC, HH, ICI and CCI are converted from monthly to quarterly frequency by taking the value of the last month of each quarter. EC stands for European Commission.

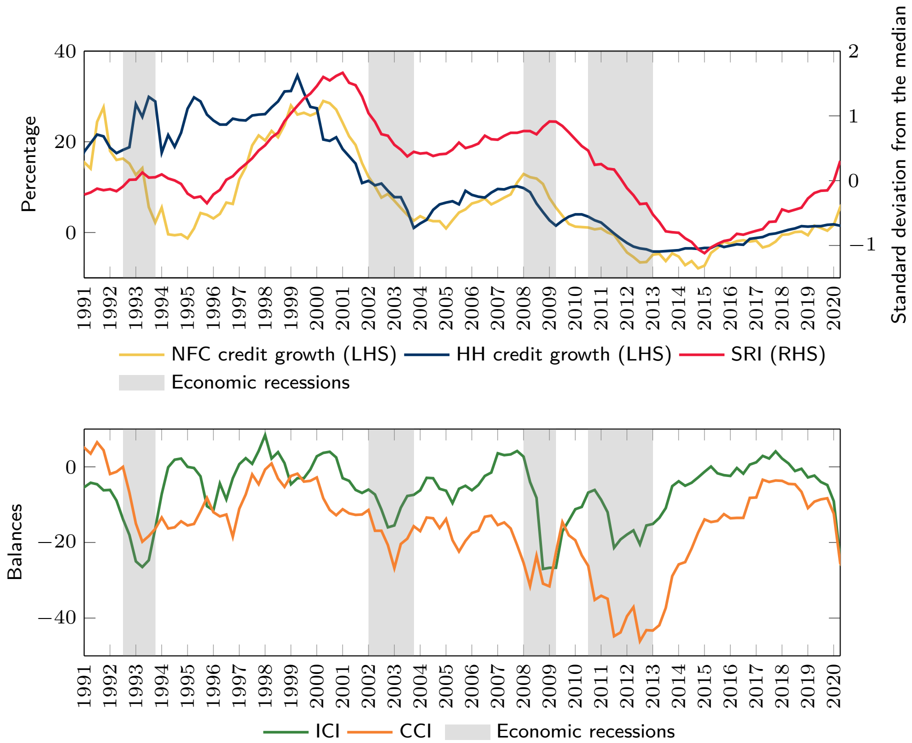
Table 1. Data overview

Figure 1 shows the behavior of our variables over the estimation sample. Even though credit to NFC is more volatile than credit to HH, both time series share a similar behavior over time. The credit variables exhibit a significant change in volatility and magnitude in the early 2000s, getting smoother and closer to 0 as we approach the end of the sample period. In the second half of the 1990s, the convergence to a low level of interest rate (due to the reduction in inflation expectations) and the improvement in economic expectations promoted the fast growth of credit. Afterwards, the increase in interest rates, the slowdown of economic activity and the large level of indebtedness led to a decline of credit growth. After 2012, with the lasting negative effects of the GFC, the ESDC and the prolonged ECB stimulus packages, credit growth has remained low, even attaining negative values during some periods. SRI co-moves with our dependent variables, and we can observe how sharp credit growth drops follow its

13. This argument does not exclude the possibility to use CLIFS to assess other sources of risks (see De Lorenzo Buratta *et al.* (2022)).

14. We tested several alternative variables, both demand- and supply-related (spreads, deposits, interest rates, capital ratios, etc.) but none of them seem to improve the models we present here. Credit standards could potentially be a valid candidate variable for our purposes, but the time series is only available from 2003Q1.

peaks in 2001 and 2009. The confidence indicators show similar dynamics over time, with the consumer indicator stably providing more pessimistic sentiment regarding the economic situation between 1994 and 2020. Nevertheless, the series show differences in the evolution of economic sentiment before crises, as their dynamics diverge in 2007 and 2010. Recessions coincide with deep decreases of both sentiment indicators.



Note: Dates for the economic recessions as defined in Rua (2017). For ICI and CCI, balances are constructed as the difference between the percentages of respondents giving positive and negative replies to selected questions.

Figure 1: Time series of variables

3. Results

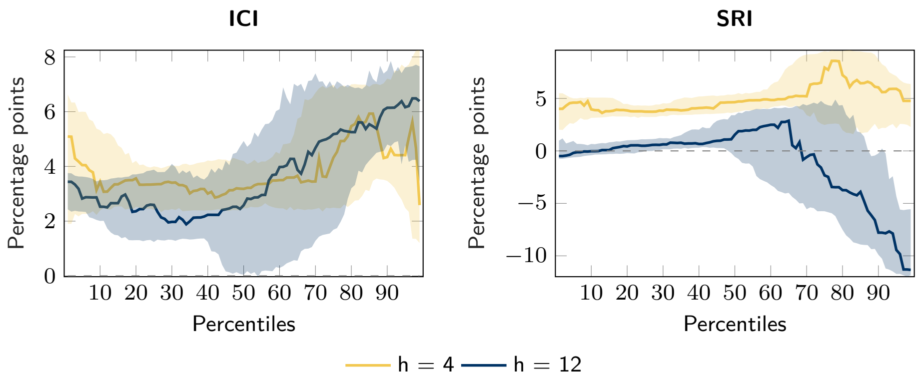
The discussion of the results starts with the analysis of the estimated marginal effects of the regressors on the conditional distribution of future credit growth (computed following the in-sample exercise) and then moves to the analysis of the proposed measures of upside tail risk (computed following both the in-sample and the pseudo real-time exercises).

3.1. Estimated marginal effects

This subsection presents the results associated with step 1 of the approach previously described. In what follows, we focus the discussion on results from the in-sample exercise for the sake of brevity. The use of quantile regressions jointly with local projections allows analysing the results according to two dimensions: (i) analyse the estimated effects on future credit growth across percentiles for a given projection horizon; and (ii) analyse the estimated effects on future credit growth across projection horizons for a given percentile. The estimated effects are conditional on a one standard deviation increase of each regressor holding constant all other regressors in the model. Firstly, we present the results for NFCs and then for HHs.

Non-financial corporations

Figure 2 displays the estimated marginal effects of the confidence indicator and of the SRI across percentiles for two projection horizons, $h = 4$ equivalent to one year ahead (short term) and $h = 12$ equivalent to three years ahead (medium to long term). The results suggest that both the ICI and the SRI have different effects across the percentiles of the conditional distribution of future credit growth. This observation justifies the use of quantile regression models to gauge the link between macro-financial conditions and future events of high credit growth.



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 2: Estimated marginal effects on NFCs credit growth quantiles for projection horizons equal to one $(h = 4)$ and three years $(h = 12)$.

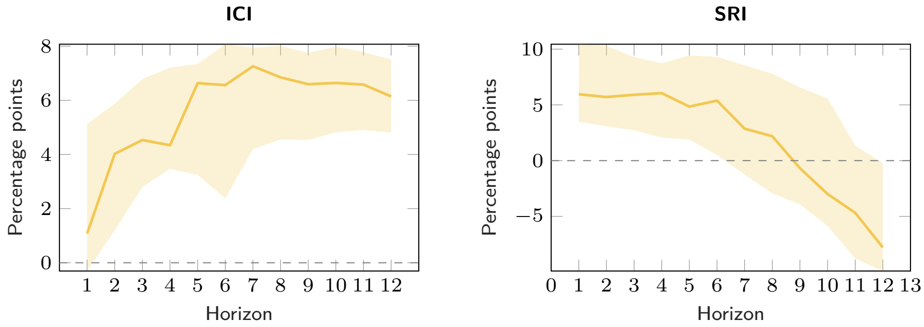
In the short term, improvements in firms' confidence about economic conditions, approximated by an increase in ICI, have a positive and statistically significant marginal effect at all the percentiles, i.e., shifts the whole conditional distribution of future credit growth to the right. However, the impact is more pronounced on the upper tail because the marginal effect is of a larger magnitude at the higher percentiles than the effect on the median or lower percentiles. Consequently, the conditional distribution of one-year ahead credit growth will be characterized by asymmetric tails, with the right tail being slightly "heavier" than the left tail. This result suggests that changes over time in the distribution shape of the dependent variable can provide relevant information regarding future credit growth realizations. We explicitly address this analysis in section 3.2.2. In terms of magnitude, the impact of a one standard deviation unit increase in ICI on the higher percentiles is between 4 and 6 percentage points. An increase in cyclical systemic risk, approximated by an increase in SRI, has an impact on the conditional distribution of one-year ahead credit growth similar to that of an increase in ICI. Accordingly, following an increase in cyclical systemic risk and all else equal, the one-year ahead conditional credit growth distribution will shift to the right and will be characterized by a "heavier" right tail. Also, the SRI has positive and statistically significant estimated marginal effects at all percentiles. These results support the idea that a favorable outlook for economic activity or an increase in cyclical systemic risk are associated with an increasing likelihood of observing extreme realizations of credit growth and increasing uncertainty regarding the credit growth projections. While linking economic sentiment and credit growth is more straightforward, it is less intuitive to understand how cyclical systemic risk can lead to a high short-term increase in credit growth. The reason could rely on the fact that before systemic risk peaks – which often precede crises in our sample – banks continue to lend regularly, specifically to more profitable NFCs with a high return on assets.[15] The unsustainability of the credit build-up will be then responsible for the subsequent drop in financial intermediation.

In the medium to long terms, an increase in ICI has an impact on the conditional distribution of three-years ahead credit growth similar to the one observed for the one-year ahead. The marginal effects are positive and heterogeneous across the different percentiles, being more pronounced at the upper tail. Regarding the SRI, the results change significantly compared to the short term. Nonetheless, there is still evidence of heterogeneity in the impact of cyclical systemic risk on the percentiles of the conditional distribution of future credit growth. The estimated marginal effect of SRI is close to zero or slightly positive for the percentiles below the 70^{th} percentile and in most cases is not statistically significant. As we move towards higher percentiles of the conditional distribution, the estimated marginal effect of the SRI steadily decreases turning negative, though not statistically significant for most percentiles as before. Accordingly, an increase in cyclical systemic risk and all else equal implies a conditional distribution for the three-year ahead credit growth that will be characterized by a higher concentration around lower values of credit growth and a "lighter" right tail. In

15. Lopes *et al.* (2021) show this result for Portuguese NFCs before the ESDC.

terms of magnitude, the impact of a one standard deviation unit increase in SRI on the higher percentiles ranges between -7 and -10 percentage points.

Figure 3 shows the estimated marginal effect of each regressor on the 90^{th} percentile of the conditional distribution of credit growth over different projection horizons.[16] The choice to focus on the 90^{th} percentile is grounded in the fact that this percentile is analysed below as one of the proposed measures of upside tail risks.



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 on the 90^{th} percentile of the conditional distribution of NFCs credit growth at different projection horizons.

The estimated marginal effect on the upper tail of an increase in ICI is positive and statistically significant at the one to twelve quarters horizon. The impact seems to be economically large. A one standard deviation increase in this indicator leads to an increase in the 90^{th} percentile of the conditional distribution of about 4 percentage points one-year ahead and around 6 percentage points three-years ahead, reflecting the long-lasting impact of higher economic expectations.[17] These results are evidence on how improvements in firms' confidence are associated to increases in tail risk in credit growth. The estimated marginal effect on the upper tail of an increase in SRI is positive and statistically significant at the 1 to 6 quarters horizon. This impact amounts to around 6 percentage points. After that point, the estimated marginal effect steadily decreases as the projection horizon increases, turning negative at $h = 9$. However, it is only statistically significant at the twelve quarters horizon, in which an impact of -7.8 percentage points is estimated. This

16. This exercise is defined in the reference literature as "term structure" (see Adrian *et al.* 2018; Galán 2020). It can be interpreted as the impulse-response function of credit growth given a unit increase of the considered explanatory variable, *ceteris paribus*.

17. Mendicino and Punzi (2013) findings show that shocks in industrial confidence indicator and in the economic sentiment indicator account for a significant share of the variance in industrial production, inflation and unemployment rate. A positive shock on the indicators also has a positive and long-lasting effect on economic activity.

means that an increase in cyclical systemic risk has heterogeneous effects on the tail risk in credit growth across horizons, contributing positively at short-term horizons and negatively at medium to long-term horizons. This evidence describes the risk path to credit growth that follows a rise in financial vulnerability: an increase in the probability of observing extreme (positive) realizations in one year (risk build-up phase) and a sharp decrease in a three years horizon (risk materialization phase).[18]

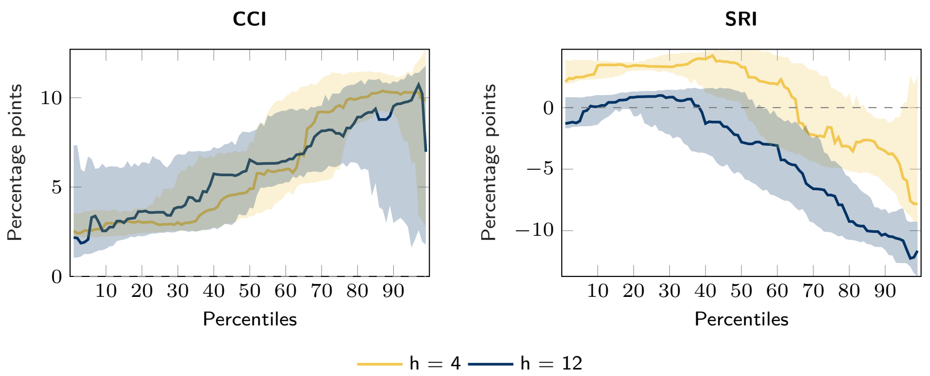
Households

Figure 4 displays the estimated marginal effects of the confidence indicator and of the systemic risk indicator across percentiles for projection horizons $h = 4$ and $h = 12$. The estimates suggest that changes in the CCI or in the SRI have asymmetric effects over the different percentiles of the credit growth conditional distribution. A one standard deviation increase in consumers confidence about economic conditions has a positive and statistically significant effect on all the percentiles of the conditional distribution of credit growth one and three years ahead. However, the magnitude of these effects is larger at the upper percentiles, reflecting that a strong economic outlook entails higher upside tail risks in credit growth. Similar results were found for NFCs credit growth, even if the difference between the estimated impact on the 90^{th} percentile and the 50^{th} percentile is substantially higher for HHs: optimism regarding the economic situation seems to trigger higher upside tail risks than for firms. In the case of the SRI results are mixed. For the one year horizon, the impact of the SRI is positive, statistically significant and relatively stable as we move from the lower percentiles up to the median. After that percentile, the effects of the SRI start to decrease and become negative around the 70^{th} percentile but are, in most cases, not statistically significant. For the three years horizon, the trajectory of the impact of the SRI on the percentiles of the conditional distribution of credit growth is similar to the one estimated for the one year horizon. However, the negative impact is only statistically significant from the 60^{th} percentile onwards. This result flags risk materialization: when cyclical systemic risk increases, the above-median credit growth distribution becomes more concentrated, and extreme realizations are more unlikely to occur in three years. The magnitude of the effects on the upper percentiles is economically significant and similar to the one obtained for NFCs.

Figure 5 plots the estimated marginal effects of each regressor on the 90^{th} percentile of the conditional distribution of credit growth over different projection horizons.

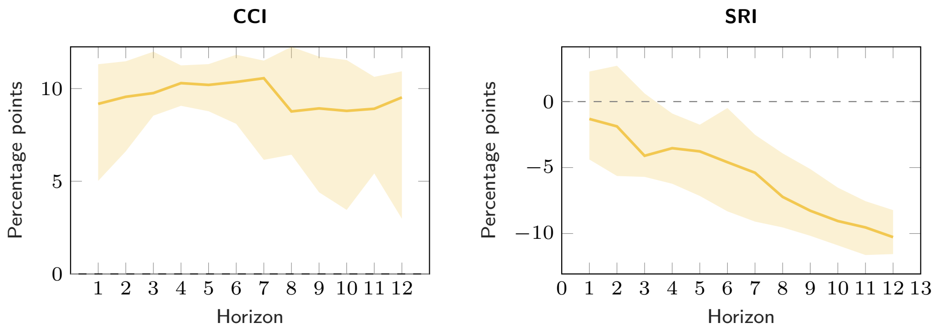
The estimated effect on the upper tail of an increase in consumers confidence is always positive, statistically significant and very stable over the full range of projection horizons considered. The impact is estimated to be between 9 and 10

18. Checking for the marginal contribution of each SRI sub-indicator, we found that the debt service ratio and the current account deficit-to-GDP ratio contribute most to these results.



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 on HHs credit growth quantiles for projection horizons equal to one ($h = 4$) and three years ($h = 12$).



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 5: Estimated marginal effects on the 90^{th} percentile of the conditional distribution of HHs credit growth at different projection horizons.

percentage points, which contrasts with the more moderate results obtained for the case of NFCs.[19] The estimated marginal impact of the SRI on the 90^{th} percentile is negative and statistically significant for all projection horizons of one year and thereafter. An increase today in cyclical systemic risk is linked to lower credit growth in the future – when risk will effectively materialize – and as such to lower upside

19. The estimated marginal effects for the confidence indicator are consistent with Barsky and Sims (2012) findings, where confidence innovations have a positive impact on consumption and income many periods in the future. Benhabib and Spiegel (2019) results also confirm the long-lasting impact that sentiment or consumer confidence shocks have on output and consumption.

risks in credit growth. This result is in line with the empirical evidence in which periods of financial stress or of financial crises, characterized by more limited credit growth and high risk aversion, are preceded by periods of high cyclical systemic risk. According to the model, the impact is estimated to be around 4.5 percentage points one year ahead and 10 percentage points three years ahead.

3.2. Measures of upside tail risks in credit growth

In this subsection, we discuss our proposed measures to detect upside tail risks in credit growth focusing on results for the 4 and 12 quarters ahead projection horizons.[20] These are the horizons relevant from a macroprudential policymaker point of view given that they provide sufficient time to take preemptive measures if deemed as necessary.[21] The measures related to the percentiles of the conditional distribution of credit growth are computed using directly the estimates from the quantile regressions obtained in step 1. The remaining measures are obtained from the smoothed conditional distributions fitted in step 2. The discussion of the measures considers both the in-sample and the pseudo real-time estimation exercises. However, our focus will be on the latter to assess their value for guiding macroprudential policy decisions. As discussed by Orphanides and van Norden (2002), in the context of output gaps, and by Edge and Meisenzahl (2011), in the context of credit-to-GDP gaps, booms are easily identified with the benefit of future observations while in real-time there is considerably uncertainty. The proposed measures for monitoring upside tail risks in credit growth are the following:

Credit-at-Risk (CaR)*:*

Refers to the 90^{th} percentile of the conditional distribution of future credit growth.

$$\hat{\mathcal{F}}_{Y_{t+h}|X_t}(CaR_{t+h}|X_t) = \mathcal{P}(Y_{t+h} \leq CaR_{t+h}|X_t) = 0.90 \tag{4}$$

where $\hat{\mathcal{F}}_{Y_{t+h}|X_t}(y|X_t)$ is the conditional cumulative distribution of future credit growth estimated in step 1. To distinguish between the CaR obtained under the

20. All the measures presented in De Lorenzo Buratta *et al.* (2022), to which we refer the reader for details, were tested. We only present the more meaningful measures in this section, but the other ones are available upon request.

21. Drehmann and Juselius (2014) argue that early warning indicators to be used for macroprudential policy purposes should give signals at least one year and a half before a crisis: banks should have one year to comply with increased capital requirements in order to avoid disruptive measures, but the timing should also take into account some possible implementation and data development lags. They also consider five years to be the "too early" upper limit for an early warning indicator – the timing for which the costs offset the benefits of the measure implementation. Aikman *et al.* (2019) state that the relevant horizons for macroprudential policy are 3 to 5 years, as the implementation of policy measures requires earlier warning due to implementation lags. Given that there is no clear agreement in the literature regarding the optimal horizons, we decided to choose 1 year as short term horizon and to be conservative on the "too early" limit, considering 3 years as medium to long term horizon.

in-sample exercise from that obtained under the pseudo real-time exercise, we label CaR as CaR^{in}_{t+h} and CaR^{pseudo}_{t+h}, respectively. This identification strategy is used in the remaining upside risk metrics.

Difference between percentiles of the distribution:
Refers to the difference between the 90^{th} percentile (CaR) and the 50^{th} percentile (median) and to the difference between the 90^{th} percentile and the 10^{th} percentile of the estimated conditional distribution of future credit growth (henceforth designated as upper tail to median distance and upper to lower tail distance, respectively). An increase in these metrics signals an increase in uncertainty regarding future credit growth, indicating a rise in the likelihood of tail realizations of credit growth that can be either in the left or right tail.

Expected longrise (ELR)*:*
Refers to a measure of the expected severity of an event that occurs in the right tail of the fitted conditional distribution of future credit growth. It is the average credit growth rate that would be observed conditional on the occurrence of a tail event targeted, in our case, to be the 90^{th} quantile. Thus, an increase in this measure signals rising upper tail risk.

$$ELR_{t+h} = \mathbb{E}_t[Y_{t+h|X_t}|Y_{t+h} \geq CaR_{t+h}] = \frac{1}{0.10}\int_{0.9}^{1} \hat{\mathcal{F}}^{-1}_{Y_{t+h}|X_t}(q|X_t)dq \quad (5)$$

where $\hat{\mathcal{F}}_{Y_{t+h}|X_t}(q)$ is the fitted conditional cumulative distribution.

Probabilities:
We compute:

(i) the probability of future credit growth above the mean $\mathbb{P}_{mean,t+h} = \mathcal{P}(Y_{t+h} > \Xi_t|X_t) = 1 - \hat{\mathcal{F}}_{Y_{t+h}|X_t}(\Xi_t|X_t)$, where Ξ_t is the three-year rolling-window mean of observed credit growth.

(ii) the probability of future credit growth one standard deviation above its present value $\mathbb{P}_{std,t+h} = \mathcal{P}(Y_{t+h} > \Theta_t|X_t) = 1 - \hat{\mathcal{F}}_{Y_{t+h}|X_t}(\Theta_t|X_t)$, where Θ_t is the observed credit growth plus one standard deviation of its historical quarterly increases.

Conditional expected values:
We compute the expected value of future credit growth given: (i) a future credit growth above the mean and (ii) a future credit growth one standard deviation above its present value.

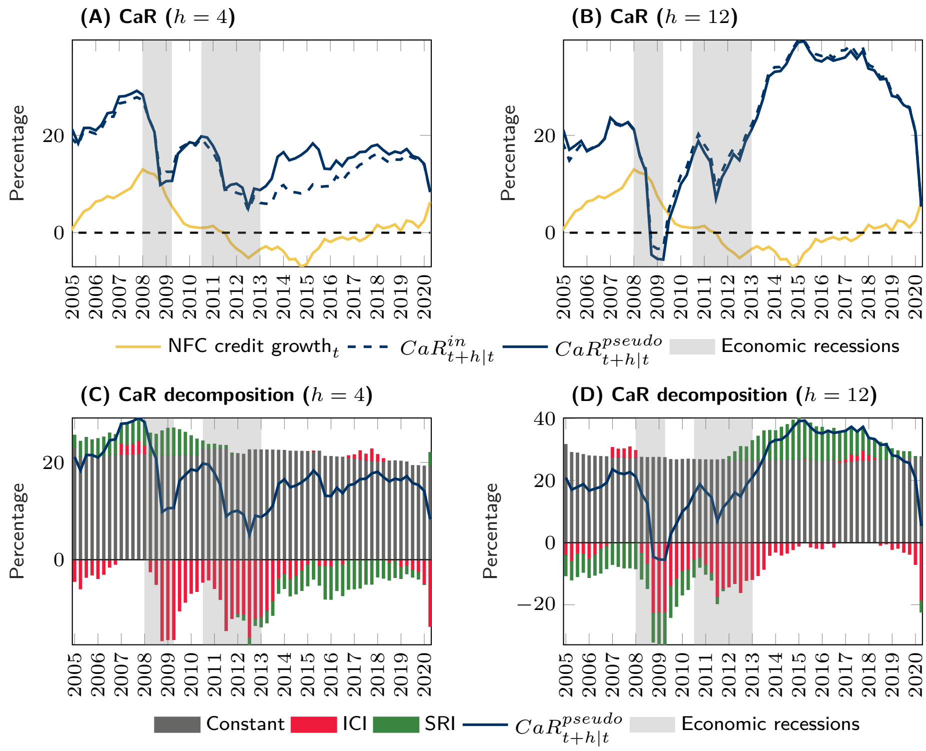
3.2.1. Credit-at-risk (CaR)

The CaR metric for NFC follows:

$$\widehat{NFC}^{90}_{t+h|t} = \hat{\alpha}^{90,h} + \hat{\beta}^{90,h}_{ICI} ICI_t + \hat{\beta}^{90,h}_{SRI} SRI_t \quad (6)$$

where $\widehat{NFC}^{90}_{t+h|t}$ identifies the estimated 90^{th} percentile of the conditional distribution of future NFC credit growth, projected for $t+h$ using information up to t. This measure is informative of the risk of extreme (positive) realizations of credit growth in the future, and inherently of the materialization of risks itself. The early warning properties of this measure make it potentially useful from a macroprudential policymaker perspective, given that the overgrowth of credit may lead to deep busts and negative spillovers to the real economy. For this reason, the focus is on the results obtained from the pseudo real-time approach although we also show the results obtained from the in-sample approach with the goal of comparing the results and assessing how the model performs once it uses all the information available.

Panels A and B of Figure 6 show the comparison between the NFC credit growth observed at time t with the CaR estimated following both in-sample and pseudo real-time approaches for $h=4$ and $h=12$. In both approaches, CaR at time t is computed using observed values of the explanatory variables at t (see equation 6). For example, $CaR_{t+4|t}$ at 2009Q4 is the projection made for 2010Q4 using information up to 2009Q4. In order words, it is the projection for 2010Q4 that a policymaker would make in 2009Q4.



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

Figure 6: Credit-at-risk and Credit-at-risk decomposition for NFC credit growth

In-sample and pseudo real-time exercises provide similar results for the two projection horizons. Then, even with a relatively small sample, we can argue that the model "learns" relatively well from past events. With this model we aim to predict upside tail risks associated to NFC credit growth and link these risks to both the GFC and the ESDC: a steep increase (from 0% in 2005 to 10% in 2008) followed by a sharp decrease of growth rate that brings it to persistently negative values between the end of 2011 and 2018. Ahead of the GFC, the CaR estimated for both $h = 4$ and $h = 12$ increases, signalling a rise in upside tail risks in credit growth that could have justified macroprudential policy action if it was available at the time. The measures start to diverge one year before the peak of the credit boom in 2008: CaR for $h = 4$ seems to perform better than CaR for $h = 12$ in predicting the imminent decrease in credit growth, showing a more steady and regular increase. From the policymaker's point of view, the sharp decline in CaR observed between 2008 and 2009 (at both horizons) signals the materialization of risk. CaR for $h = 4$ captures the mild increase in credit observed in 2011 and then anticipates the upward trend that will only start to materialise in 2015. CaR for $h = 12$ signals in 2009 a sharp drop in credit reaching negative regions, meaning that the most optimistic future expectations about the realizations of credit growth for 2012 are predicted to be below zero. This result is consistent with the observed credit growth series, which takes negative values from mid 2011 onwards. The CaR measure for $h = 12$ also captures the credit growth recovery starting in 2015, although the magnitude of such increase seems to be overestimated. We argue that the high levels and volatility of credit observed before the early 2000s are responsible for such an increase in risk: in the periods of negative and relatively stable credit growth values (2012-2018), the model points to a return to fluctuations comparable to the past. We confirmed this hypothesis considering a shorter dataset (1999-2020) and conclude that, although still present, the increase in risk after 2013 has a smaller magnitude than the one observed for the full sample.[22] The CaR measure for both horizons predicts a drop in credit growth at the end of the sample, signalling a decreasing likelihood to observe high NFC credit in the future. The sharp decline in confidence observed in 2020, due to the COVID-19 pandemic, makes the fall more pronounced.

Panels C and D of Figure 6 display the drivers of CaR estimates in the pseudo real-time exercise over our sample. For $h = 4$, the contribution of the constant is very high and very stable over time.[23] While SRI is the main driver of the increase in CaR before the GFC, ICI is mainly responsible for the sharp decreases in 2009 and mid 2011. After 2012, the SRI contribution is negative: the decrease in cyclical systemic risk in the aftermath of the GFC – materialization of risk –

22. The results are provided in the Appendix, Figure 12.

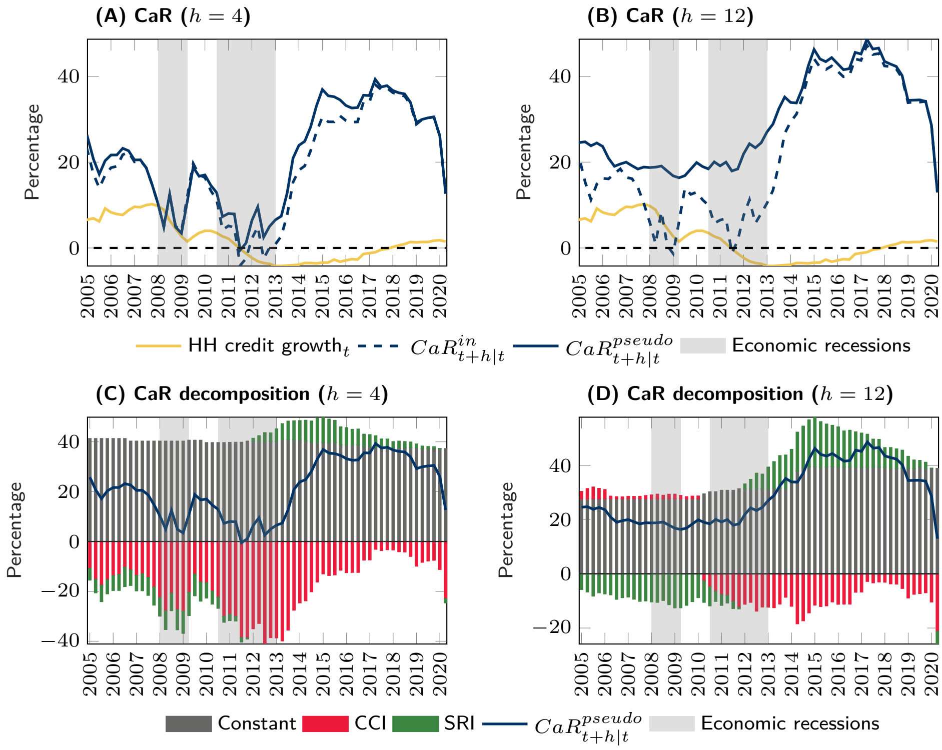
23. Given the stable contribution of the constant over time, we argue that its magnitude is not a source of concern in the analysis: it simply shifts the measure up to match the targeted (high) percentile. The use of relatively conservative models – including only two explanatory variables to account for the limited number of observations – can also explain the contribution of the constant.

decreases the upside tail risks of credit growth peaking in 2016, and then gradually starts losing power. At the end of the sample, the ICI drives the decline in CaR, signalling negative expectations about the future economic outlook. The decline is further exacerbated in 2020, as the expectations are influenced by the COVID-19 pandemic. For $h = 12$ we observe again a stable contribution of the constant over time. The contribution of ICI does not change with respect to the $h = 4$ exercise, while the contribution of SRI is reversed: it is negative before the GFC, then co-moves with the ICI, exacerbating the 2009 drop, displays a positive contribution from 2012 to 2020Q1, and finally contributes negatively in the last quarter of the sample. This result is in line with the marginal effect analysis presented in subsection 3.1, where we show that the positive effect of SRI on extreme (positive) credit growth realizations wears off as we increase the projection horizon, signalling the risk materialization that follows the build-ups.

The CaR metric for HHs follows:

$$\widehat{HH}^{90}_{t+h|t} = \hat{\alpha}^{90,h} + \hat{\beta}^{90,h}_{CCI}CCI_t + \hat{\beta}^{90,h}_{SRI}SRI_t \tag{7}$$

where $\widehat{HH}^{90}_{t+h|t}$ identifies the estimated 90^{th} percentile of the conditional distribution of future HH credit growth, projected for $t + h$ using information up to t. Panels A and B of Figure 7 show the HH credit growth observed over our sample period jointly with the CaR estimates for the in-sample and pseudo real-time exercises for $h = 4$ and $h = 12$, respectively. The in-sample and pseudo real-time CaR estimates are very similar for $h = 4$ and tail risks to credit growth have significantly fluctuated over the sample period. In the quarters previous to the GFC, CaR was increasing. The policymaker could have at the time interpreted this dynamic as a sign of an imminent boom-bust credit event and reflected upon the need to implement preemptive measures, upon availability. However, it must be observed that one year may not be enough to fully implement macroprudential policy measures to mitigate the impact of a financial crisis and its spillover effects on economic activity. The CaR metric for $h = 4$ also signalled increasing tail risks in mid 2009. Despite the substantial differences between the ESDC and the GFC, the model is able to anticipate the build-up in risk that precedes the ESDC. For $h = 12$, the pseudo real-time estimates are very different from the in-sample estimates, at least until 2014. This implies that for the period 2005-2013 the pseudo-real time early warning properties of the CaR regarding increases in upside tail risk in credit growth were very limited. In fact, the indicator remains stable throughout this period. After the two crises, the CaR starts to increase signalling the accumulation of upside tail risks for HH credit growth, which seem to recede or at least stabilise after the introduction of limits on LTV and DSTI ratios and maturity for credit to HHs. Even if the model does not explicitly account for such policy measures, SRI might be indirectly capturing their effect. As for NFC credit, considering a shorter estimation sample also reduces the magnitude of the increase in risk detected after



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

Figure 7: Credit-at-risk and Credit-at-risk decomposition for HH credit growth

2013[24], while the deep decline at the end of the sample is driven by the marginal contribution of the confidence indicator.

Panels C and D of Figure 7 display the drivers of CaR estimates in the pseudo real-time exercise over our sample. As for NFC credit, the contribution of the constant for tail risks to credit growth is positive, very high and stable over time for $h = 4$ and $h = 12$. Prior to the GFC and apart from the contribution of the constant, the upside tail risk to credit growth was mostly driven by a negative contribution of the consumer confidence indicator and to a lesser extent by the systemic risk indicator. In the aftermath of the ESDC, tail risks to credit growth rapidly increase partially due to the positive contribution of the SRI and to a less negative contribution of consumer expectations. This result is not at odds with the observed recovery in HH credit growth, which remained at extremely low rates. The contribution of CCI reduces as we move from a one-year to a three-years projection horizon, reflecting the greater relevance of this indicator at

24. The results are provided in the Appendix, Figure 12

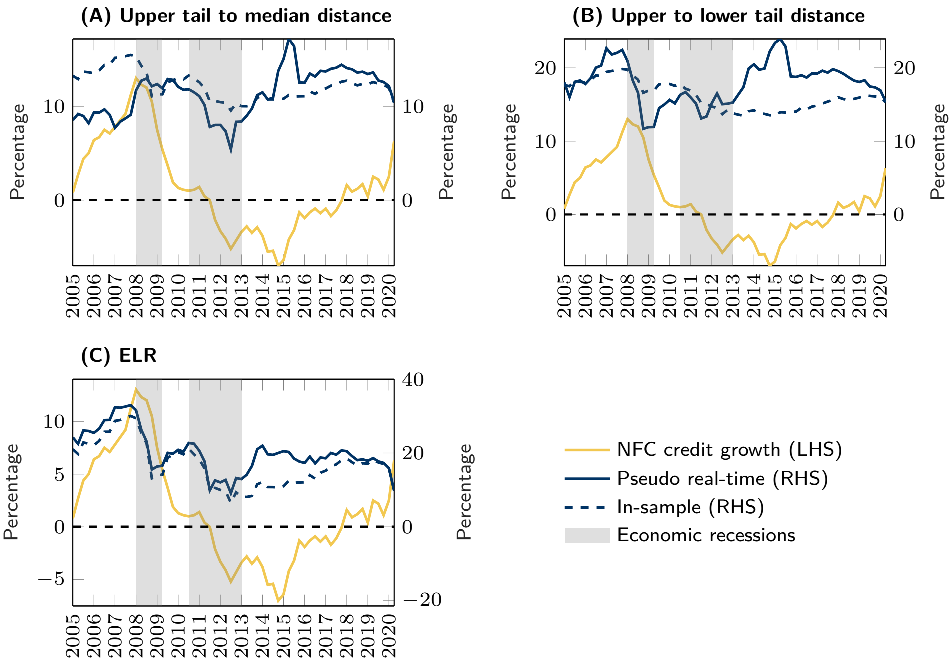
shorter projection horizons as argued above. The opposite happens for SRI, with its contribution slightly increasing when we consider a longer projection horizon.

3.2.2. Complementary risk measures

Non-financial corporations

Figure 8 presents the results for three of the complementary risk measures introduced above, considering both in-sample and pseudo real-time exercises for $h = 4$. In particular, it shows the two distances between percentiles and the expected longrise.[25] The goal of the upper tail to median and upper to lower tail distances is to signal changes in the distance between relevant points of the distribution of future credit growth. An increase in these distances indicates not only an increase in the uncertainty surrounding future credit growth but also an increase in the likelihood of extreme realizations of credit growth. Under the pseudo real-time approach, the upper tail to median distance (panel A) increases between 2007 and 2009, meaning that the extreme (high) prediction scenarios regarding credit growth for $h = 4$ are increasing more than the most likely ones. As the increase occurs near to the onset of the GFC, this information is not very useful from a policymaker perspective since the measure is predicting the build-up of risks in an horizon that precludes the possibility of implementing macroprudential policies. After the ESDC, the upper tail to median distance exhibits an increase which signals higher uncertainty surrounding the recovery of credit growth. The upper to lower tail distance (panel B) is a smoother version of the CaR measure. Although the measure adds little information compared to CaR, this result identifies the upper tail dynamics as the main responsible of the uncertainty regarding future credit growth. The similarity between these measures and CaR suggests that the median and the lower tail are more stable across time than the upper tail. Given this evidence, these measures can complement CaR by identifying the sources of uncertainty and confirming whether it is the 90^{th} percentile that drives changes in the distances between points in the distribution. The upper to lower tail distance seems to perform better than the upper tail to median distance: the measure peaks in 2007Q1, meaning that is predicting the highest uncertainty surrounding the credit growth to happen in 2008Q1, which is consistent with the fall observed in the data during the GFC. This measure also properly anticipates the slight increase, the subsequent collapse and the timid recovery happening between 2010 and 2013. The two distance measures show a sharp increase after 2013 and a decrease starting in 2018, but becoming prominent only in 2020. As already flagged when discussing CaR measures, the increase is driven by the substantial change in credit development occurring in the early 2000s: the high levels and volatility of

25. The results for $h = 12$ are provided in the Appendix for both NFCs and HHs (Figures 13 to 16). Nonetheless, the results obtained for the longer horizon do not add useful information for the discussion on the results analysis.



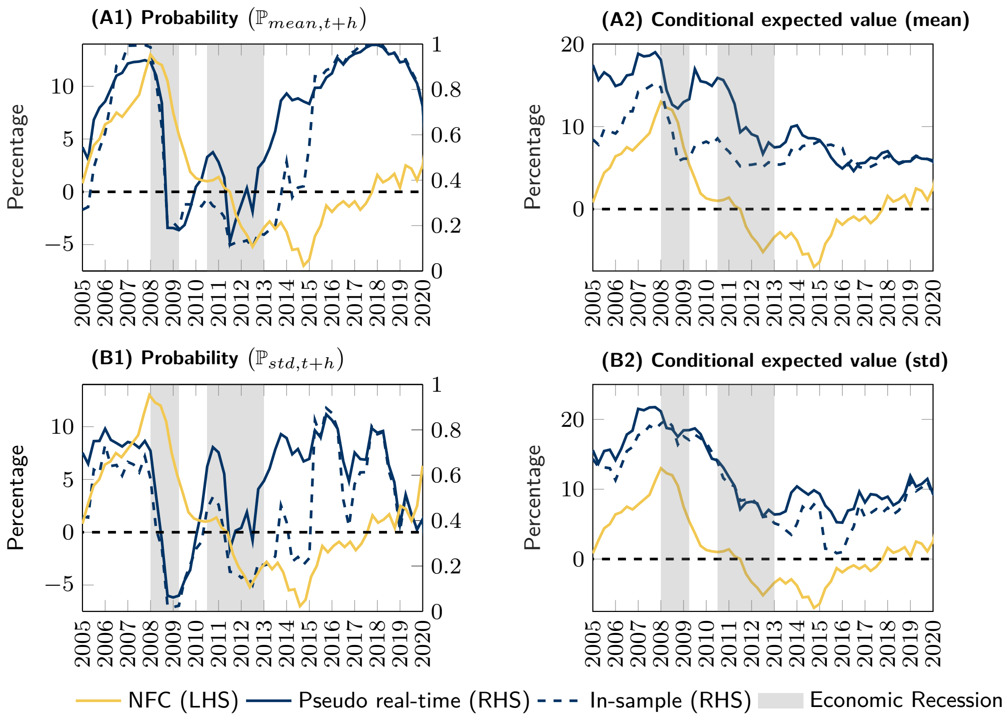
Note: Dates for the economic recessions as defined by Rua (2017).

Figure 8: Difference between percentiles of the distribution and expected longrise for $h = 4$

credit growth before the early 2000s induce the model to predict in 2013 a return to values comparable to the past. The subsequent decrease is due to the negative marginal contribution of the confidence indicator. In particular, the pessimistic economic expectations of 2020 in response to the COVID-19 pandemic outbreak are responsible for the deep decline at the end of the sample. Overall, the changes in distances are far less responsive in the in-sample exercise than in the pseudo real-time exercise: both measures are in fact almost flat across time. Given these results we may conclude that the in-sample approach mainly captures the distribution's shifts, being less responsive to changes in the right tail's "weight" with respect to the other points of the distribution.

The expected longrise (panel C of Figure 8) is the average credit growth rate that would be observed conditional on the occurrence of a tail event, that in our case is chosen to be the 90^{th} percentile. This measure complements the CaR metric in the sense that is comprises information about all the extreme possible outcomes of credit growth weighted by their respective probability instead of relying solely on the value of the 90^{th} percentile. Even if the dynamics is quite similar to the one obtained for the CaR, it allows to identify more clearly the falls in upside tail risk and a similar and consistent upward trend before the two credit contractions, which makes this measure a potentially useful tool for policymakers. The measure shows the same characteristics as the previous ones at the end of the sample, with the marginal contribution of the confidence indicator driving the effect. The results are almost indifferent to changes in the sampling approach.

Figure 9 displays the different probabilities measures and the respective conditional expected values for $h = 4$ and for the in-sample and pseudo real-time exercises. In panel A1 of Figure 9, we compute the probability of observing a credit growth rate for NFCs above its historic three-year mean. It is noteworthy that the results for this probability are highly conditional on the last observations of the credit growth and the information that it provides can be seen as a recovery (deterioration) of credit growth perspectives whenever the probability approaches one (zero). Before 2008, the probability rapidly increases from near 50% to around 90%, before it sharply drops to lower values in 2009. At the end of the sample, the probability approaches 1: due to the peculiar change in levels and volatility of credit that we highlighted above, the measure points to a fast recovery of credit growth. The associated conditional expected value and CaR share the same dynamics, but the former seems to show a overall steeper downward trend. This measure seems to behave better than CaR after 2014: it shows contained and stable values that are more consistent with the observed credit growth series. The series is flatter when computed for the in-sample exercise (panel A2 of Figure 9).



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

Figure 9: Probabilities and associated conditional expected values for $h = 4$

To stress the importance of acceleration/deceleration in credit growth at detecting credit booms and busts, we compute the probability of observing future credit growth one standard deviation above its present value. We take as an example the exercise for the $h = 4$ horizon to illustrate our approach. In such a case, the value for 2008Q1 reflects the probability of observing in 2009Q1 credit growth above its 2008Q1 value plus its standard deviation computed with information until the previous year (2008Q1). In panel B1 of Figure 9, we note how the probability stays relatively high and stable until the GFC, signalling the strong acceleration in credit growth observed between 2005 and 2008. After 2009, it identifies a possible acceleration and recovery of the credit growth that does not materialize and vanishes after 2011, in the middle of the ESDC. After 2014 the increase of the probability is compatible with the recovery environment, although the model is again overreacting, probably due to the change in the evolution of credit that occurred in the early 2000s. From 2019 on, it starts falling, in a magnitude similar to the one observed during the ESDC, indicating a possible deceleration is the near future. This fall is sharpened in 2020 by the effect of the economic confidence indicator, which encompasses information regarding the negative perspective on the economic effects of the COVID-19 pandemic. The probability measures computed for the in-sample and the pseudo real-time exercises diverge once again between 2012 and 2017. The associated conditional expected value (panel B2 of Figure 9) does not improve the results we observe from CaR, even if we obtain a smoother indicator especially between 2009 and 2011. The differences between the in-sample and the pseudo real-time exercises are almost insignificant.

Overall, in-sample and pseudo real-time exercises share the same behavior. Nonetheless, the fall in the probabilities during the crises is more persistent in the in-sample exercise, and the estimated recovery is postponed to 2015. These differences have no material impact on the conclusion concerning the conditional expected values.

Households

Figures 10 and 11 show the results for the complementary risk measures over time, considering both in-sample and pseudo real-time exercises for the HHs case.

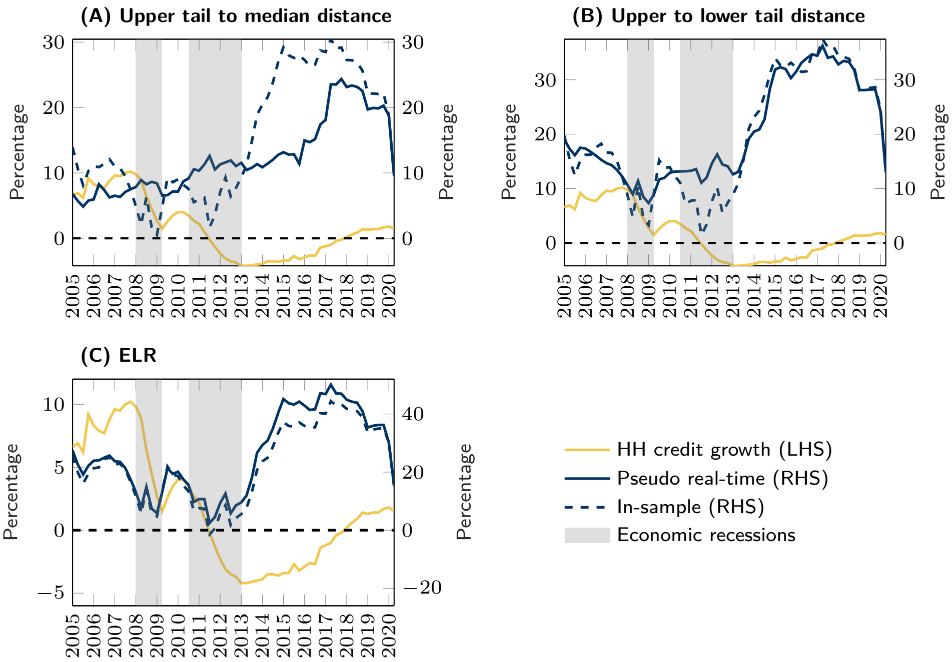
The upper tail to median distance, considering the pseudo real-time exercise, adds little useful information with respect to CaR: the measure barely matches credit growth fluctuations and shows a upward trend across the whole sample, signalling that the upper tail is constantly moving away from the median (Panel A). The measure strongly diverges from its in-sample version, especially from 2013 to 2019. The upper to lower tail distance displays a downward trend since 2006, providing an overly pessimistic forecast of the materialization of risk (Panel B). Such trend persists until 2009, thus predicting a concentration of the credit growth distribution over this time span. Along with the results for the upper tail to median distance, we may conclude that during this period the distribution becomes more biased to the left with an increase in the likelihood of the lower realizations of credit growth.[26] Considering the credit growth observed before 2009, one may argue that these results expose the risks of unsustainable credit growth, as we observe higher uncertainty around above-median future realizations of credit growth compared to the uncertainty around below-median ones. From the beginning of the GFC to the end of the ESDC, the measure is a smoother version of CaR, but a clear anticipation of the second credit growth peak in 2010 is missing. After 2014, the measure is again very similar to CaR and does not provide any useful additional information. The upper to lower tail distance in the pseudo real-time exercise diverges from its in-sample version until the end of the ESDC but almost matches it from 2013 on (Panel B).

The expected longrise dynamics provides some anticipation about future credit growth behavior until the onset of the ESDC, and can usefully complement the CaR measure, but after 2010 this measure adds little information regarding future credit growth. This result is not affected by changes in the sampling approach.

The sharp increase observed after the crises for the measures described so far are caused again by the magnitude of the oscillations prior to the early 2000s. These results are influenced by the fact that the model expects credit growth to go back to its past dynamics. The drop observed at the end of the sample is sharpened by the negative expectations for 2020 related to the COVID-19 pandemic which are captured by the confidence indicator.

The probability of credit growth exceeding the three-year mean has a behavior similar to the CaR, providing a good anticipation of the boom-bust cycles happening between 2005 and 2013 (panel A1 of Figure 11). Namely, starting from a high probability that gets closer to 1 in 2007Q1 it falls in the following quarters reaching a very low probability (near but different from zero) in 2008Q1, when the observed credit growth was still 8.9%, signalling one-year in advance the trough of the credit growth. Later on, in 2009Q1, the probability reaches zero despite one year later the credit growth reaches his peak. This is mainly due to the high credit growth observed between 2006Q1 and 2009Q1 (whose mean is used for the probability computation) and the low economic expectations during the crisis. During the ESDC a similar behavior is observed, with the probability falling during the economic recession period (reaching the lowest probability in 2011Q3) anticipating the trough despite it only happens one year and a half later. From policymakers' point of view, the results – indicating a sharp fall in the probability of observing credit growth above the three-year mean – would have signaled the increasing likelihood of credit build-up materialization for the following year. Nevertheless, one year in advance can be short to fully implement preemptive measures to preserve financial stability and mitigate the contagious effects between the financial system and the real economy. The in-sample and pseudo real-time approaches share similar evolution over time. The associated conditional expected

26. If the median to upper tail increases and the lower to upper tail does not, the distribution is more concentrated around the lowest realizations: one half of the probability is concentrated in a smaller interval at the left-hand side of the distribution.

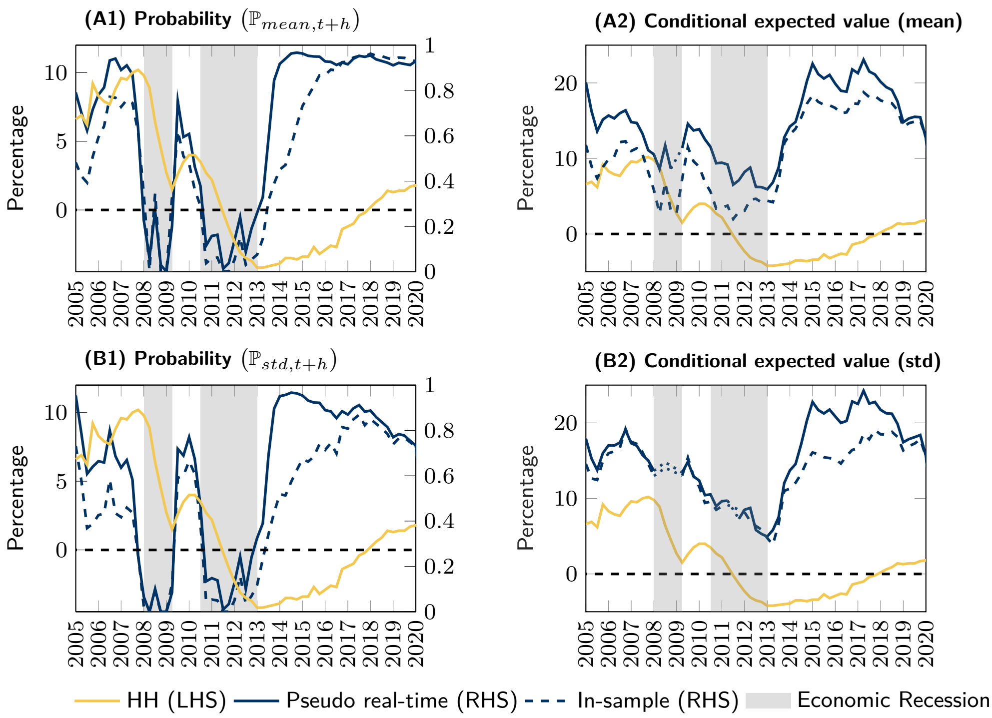


Note: Dates for the economic recessions as defined by Rua (2017).

Figure 10: Difference between percentiles of the distribution and expected longrise for $h = 4$

value shows smoother oscillations with respect to CaR (panel A2 of Figure 11). Considering the in-sample or the pseudo real-time exercise does not substantially change the results.

The probability of credit growth exceeding the relative standard deviation of credit growth exhibits a close behavior to the one observed for the probability in panel A1, with strong reductions in the beginning of the economic recession periods. This result indicates a tendency of a deceleration with some delay. The same is true for the periods with stronger acceleration. Overall, it does not accurately predict the acceleration/deceleration behavior of credit growth, although it sheds some lights before the GFC with the downward trend in the probability and a strong fall in 2008Q1. After 2008, the evolution of the measure over time is not different from those described above (panel B1 of Figure 11), and the same applies to the associated conditional expected value (panel B2 of Figure 11). All the probability measures and relative conditional expected values show a sharp increase in 2013 and a decrease at the end of the sample. As we discussed above, these results are deeply influenced by the change in credit development that happened after the early 2000s and by the effects of the COVID-19 pandemic on the economic outlook. Nonetheless, the most recent developments in the probability of of future credit growth one standard deviation above its present value (panel B1) might reveal the slowdown in credit growth recovery and indicate its stabilization around



Note: Dates for the economic recessions as defined by Rua (2017). The dotted lines refer to when the probability reaches zero and the associated expected value cannot be calculated.

Figure 11: Probabilities and associated conditional expected values for $h = 4$

more contained values. The stabilization of credit growth is also followed by a convergence of the conditional expected value (panel B2) to lower values, entailing lower tail risks. As for the difference between in-sample and pseudo real-time exercise is concerned, we observe the series mainly diverging after 2013, in line with the previously analysed measures.

4. Conclusions

In this paper, we aim to quantify the effect of financial and economic indicators on non-financial corporations and households' credit growth for Portugal following the *Growth-at-risk* methodology. In particular, we refer to the right tail of the future credit growth distribution: credit build-ups can undermine financial stability, as they are often followed by deep falls that have deleterious spillovers on economic activity. A set of measures of the upside tail risk in credit growth are put forward with the aim of providing policymakers with information to better anticipate credit build-ups: CaR, distances between percentiles of the credit growth distribution, expected longrise, probability to observe future credit growth above its mean, probability to observe future credit growth one standard deviation above its present value and associated conditional expected values.

Rising financial vulnerabilities and industrial sector confidence regarding present and future overall business conditions increase the upper tail risk of non-financial corporations' credit growth in the short term. At the medium to long term, they have opposite effects on future credit growth tail risk and an increase in one standard deviation nearly cancel each other. The confidence indicator has a positive contribution for the upper tail risk. The estimated CaR measure signals the credit growth rise before the GFC, detects the increase in credit growth observed in 2011 and then signals the upward trend in credit growth that will only occur in 2015. Before the GFC, the joint analysis of the measures concerning the distances between percentiles of the distribution allows us to identify the upper tail evolution as responsible for the uncertainty about future credit growth. The expected longrise, adding extra details about the upper tail behavior, gives us information consistent with the CaR measure. The probability measures show high values before the GFC and signal credit busts with swift decreases during recessions. The upward trajectory before the GFC of the expected values associated to the probability measures confirms the results observed for the other measures. The 2013-2018 results suffer from the structural change in credit growth dynamics that occurred in the early 2000s. The predominant role of the confidence indicator is responsible for the decline in tail risk at the end of the sample, especially in 2020 when the COVID-19 pandemic has downgraded economic expectations.

As for the households, an increase in financial vulnerabilities and in consumers' confidence have opposite effects on the upper tail risk of credit growth, both at the short term and medium to long term. The estimated CaR detects increases in upper tail risks before the GFC and the ESDC, signals the two sharp credit growth drops observed during recessions and the recovery trend of credit growth after 2014. Before 2009, the results from the measures concerning the distances between percentiles of the distribution signal higher uncertainty regarding above-median (central scenario) realizations of credit growth, when compared to the one regarding below-median realizations. This result is due to the fact that the mass of the conditional distribution is concentrated on the left side while the upper tail becomes "heavier". The expected longrise, taking into account the entire upper tail behavior, confirms the results we observed for CaR. The probability measures are coherent with non-financial corporations' results, showing high levels before the recessions. The expected values associated to the probability measures strengthen the results of the previous measures signalling build-ups of tail risk before the GFC and the ESDC. As for non-financial corporations, the results for households between 2013 and 2018 are influenced by the structural change in the evolution of credit growth occurred in the early 2000s. The marginal contribution of the confidence indicator - which points to a deterioration in the economic outlook, especially in 2020, following the COVID-19 pandemic - leads the results at the end of the sample.

References

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone (2019). "Vulnerable Growth." *American Economic Review*, 109(4), 1263–1289.

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone (2021). "Multimodality In Macrofinancial Dynamics." *International Economic Review*, 62(2), 861–886.

Adrian, Tobias, Federico Grinberg, Nellie Liang, and Sheherya Malik (2018). "The Term Structure of Growth-at-Risk." IMF Working Papers 18/180, International Monetary Fund.

Afanasyeva, Elena and Jochen Güntner (2014). "Lending Standards, Credit Booms and Monetary Policy." Economics working papers 2014-11, Department of Economics, Johannes Kepler University Linz, Austria.

Aikman, David, Jonathan Bridges, Sinem Hacioglu Hoke, Cian ONeill, and Akash Raja (2019). "Credit, capital and crises: a GDP-at-Risk approach." Bank of England working papers 824, Bank of England.

Aikman, David, Andrew G. Haldane, and Benjamin D. Nelson (2015). "Curbing the Credit Cycle." *Economic Journal*, 125(585), 1072–1109.

Alessi, Lucia and Carsten Detken (2018). "Identifying excessive credit growth and leverage." *Journal of Financial Stability*, 35(C), 215–225.

Alter, Adrian and Elizabeth Mahoney (2020). "Household Debt and House Prices-at-risk: A Tale of Two Countries." IMF Working Papers 2020/042, International Monetary Fund.

Angelico, Cristina (2018). "Household Expectations and the Credit Cycle." In *Paper presented at the CEPR European Conference on Household Finance 2018*.

Arena, Marco, Kerstin Gerling, Serpil Bouza, Lamin Njie, and Era Dabla-Norris (2015). "Credit Booms and Macroeconomic Dynamics: Stylized Facts and Lessons for Low-Income Countries." IMF Working Papers 2015/011, International Monetary Fund.

Baron, Matthew and Wei Xiong (2017). "Credit Expansion and Neglected Crash Risk." *The Quarterly Journal of Economics*, 132(2), 713–764.

Barsky, Robert B. and Eric R. Sims (2012). "Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence." *American Economic Review*, 102(4), 1343–1377.

Benhabib, Jess and Mark M Spiegel (2019). "Sentiments and Economic Activity: Evidence from US States." *Economic Journal*, 129(618), 715–733.

Boissay, Frédéric, Fabrice Collard, and Frank Smets (2016). "Booms and Banking Crises." *Journal of Political Economy*, 124(2), 489–538.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer (2016). "Diagnostic Expectations and Credit Cycles." NBER Working Papers 22266, National Bureau of Economic Research, Inc.

Bowman, A.W. and A. Azzalini (1997). *Applied Smoothing Techniques for Data Analysis: The Kernel Approach with S-Plus Illustrations*. Oxford Statistical Science Series, OUP Oxford.

Chuliá, Helena, Ignacio Garrón, and Jorge M. Uribe (2021). "Vulnerable Funding in the Global Economy." IREA Working Papers 202106, University of Barcelona, Research Institute of Applied Economics.

Davino, C., M. Furno, and D. Vistocco (2013). *Quantile Regression: Theory and Applications*. Wiley Series in Probability and Statistics, Wiley.

De Lorenzo Buratta, Ivan, Marina Feliciano, and Duarte Maia (2022). "How Bad Can Financial Crises Be? A GDP Tail Risk Assessment for Portugal ." Working Paper Series 04, Banco de Portugal.

Deghi, Andrea, Mitsuru Katagiri, Mr. Sohaib Shahid, and Nico Valckx (2020). "Predicting Downside Risks to House Prices and Macro-Financial Stability." IMF Working Papers 2020/011, International Monetary Fund.

Dick, Astrid A. and Andreas Lehnert (2010). "Personal Bankruptcy and Credit Market Competition." *Journal of Finance*, 65(2), 655–686.

Drehmann, Mathias and John Juselius (2014). "Evaluating early warning indicators of banking crises: Satisfying policy requirements." *International Journal of Forecasting*, 30(3), 759–780.

Duprey, Thibaut, Benjamin Klaus, and Tuomas Peltonen (2017). "Dating systemic financial stress episodes in the EU countries." *Journal of Financial Stability*, 32(C), 30–56.

Edge, Rochelle and Ralf Meisenzahl (2011). "The Unreliability of Credit-to-GDP Ratio Gaps in Real Time: Implications for Countercyclical Capital Buffers." *International Journal of Central Banking*, 7(4), 261–298.

Fahlenbrach, Rüdiger, Robert Prilmeier, and René Stulz (2018). "Why Does Fast Loan Growth Predict Poor Performance for Banks?" *Review of Financial Studies*, 31(3), 1014–1063.

Galán, Jorge E. (2020). "The benefits are at the tail: uncovering the impact of macroprudential policy on growth-at-risk." Working Papers 2007, Banco de España.

Hodula, Martin, Simona Malovana, and Jan Frait (2019). "Too Much of a Good Thing? Households' Macroeconomic Conditions and Credit Dynamics." Working Papers 2019/11, Czech National Bank.

Jordà, Òscar (2005). "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review*, 95(1), 161–182.

Jordà, Òscar, Moritz Schularick, and Alan Taylor (2011). "Financial Crises, Credit Booms, and External Imbalances: 140 Years of Lessons." *IMF Economic Review*, 59(2), 340–378.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor (2013). "When Credit Bites Back." *Journal of Money, Credit and Banking*, 45(s2), 3–28.

Kłopocka, Aneta Maria (2017). "Does Consumer Confidence Forecast Household Saving and Borrowing Behavior? Evidence for Poland." *Social Indicators Research: An International and Interdisciplinary Journal for Quality-of-Life Measurement*, 133(2), 693–717.

Koenker, Roger (2005). *Quantile Regression*. Cambridge University Press.

Koenker, Roger W and Jr Bassett, Gilbert (1978). "Regression Quantiles." *Econometrica*, 46(1), 33–50.

Korobilis, Dimitris (2017). "Quantile regression forecasts of inflation under model uncertainty." *International Journal of Forecasting*, 33(1), 11–20.

Korobilis, Dimitris, Bettina Landau, Alberto Musso, and Anthoulla Phella (2021). "The time-varying evolution of inflation risks." Working Paper Series 2600, European Central Bank.

Lang, Jan Hannes and Marco Forletta (2020). "Cyclical systemic risk and downside risks to bank profitability." Working Paper Series 2405, European Central Bank.

Lang, Jan Hannes, Cosimo Izzo, Stephan Fahr, and Josef 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.

Lopes, Andresa, Vítor Oliveira, Ângelo Ramos, and Fátima Silva (2021). "Has the Crisis Introduced a New Paradigm in Banks' Credit Allocation? The Nonfinancial Corporations' Perspective." *Financial Markets, Institutions & Instrument*, 30(2), 31–62.

López-Salido, J. David and Francesca Loria (2020). "Inflation at Risk." Finance and Economics Discussion Series 2020-013, Board of Governors of the Federal Reserve System (U.S.).

Mendicino, Caterina and Maria Tereza Punzi (2013). "Confidence and economic activity: the case of Portugal." *Economic Bulletin and Financial Stability Report Articles and Banco de Portugal Economic Studies*.

Orphanides, Athanasios and Simon van Norden (2002). "The Unreliability of Output-Gap Estimates in Real Time." *The Review of Economics and Statistics*, 84(4), 569–583.

Reinhart, Carmen M. and Kenneth S. Rogoff (2009). "The Aftermath of Financial Crises." *American Economic Review*, 99(2), 466–72.

Rua, António (2017). "Dating the Portuguese business cycle." *Economic Bulletin and Financial Stability Report Articles and Banco de Portugal Economic Studies*.

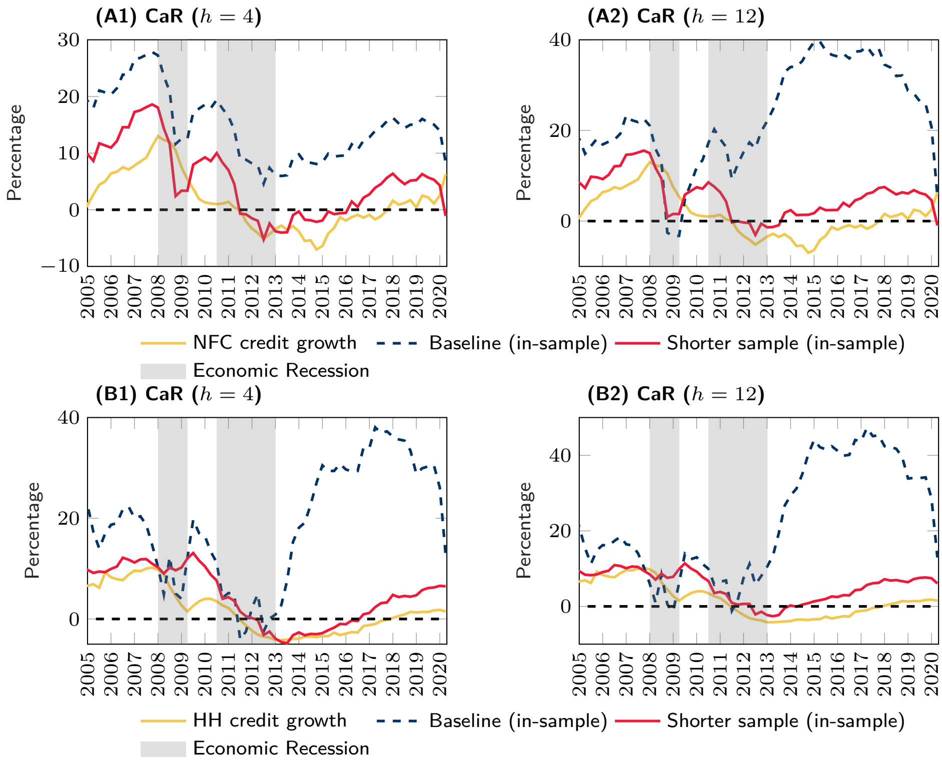
Ruckes, Martin (2004). "Bank Competition and Credit Standards." *Review of Financial Studies*, 17(4), 1073–1102.

Schularick, Moritz and Alan M. Taylor (2012). "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008." *American Economic Review*, 102(2), 1029–1061.

van der Veer, Koen and Marco Hoeberichts (2016). "The level effect of bank lending standards on business lending." *Journal of Banking & Finance*, 66(C), 79–88.

Appendix

Alternative sample length (1999Q1 to 2020Q2)

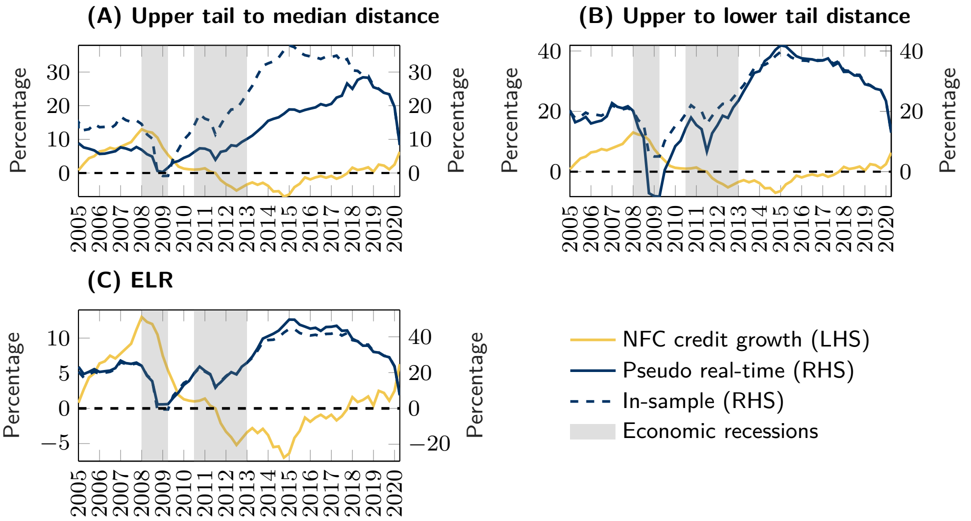


Note: Dates for the economic recessions as defined by Rua (2017).

Figure 12: Credit-at-risk for the full sample (Baseline) and a shorter sample starting in the first quarter of 1999 (Shorter sample)

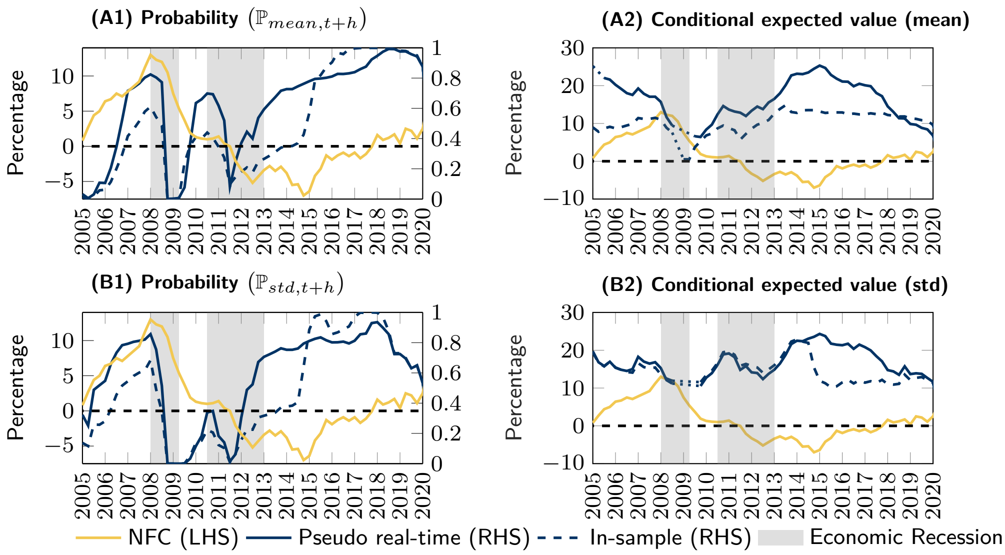
Complementary measures: results for $h = 12$

Non-financial corporations



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

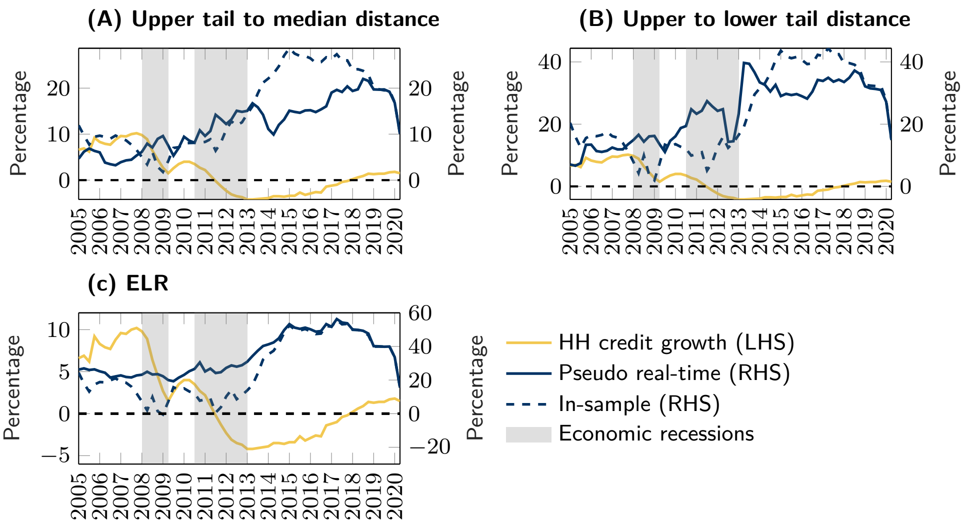
Figure 13: Difference between percentiles of the distribution and expected longrise for $h = 12$



Note: Dates for the economic recessions as defined by Rua (2017). The dotted lines refer to when the probability reaches zero and the associated expected value cannot be calculated.

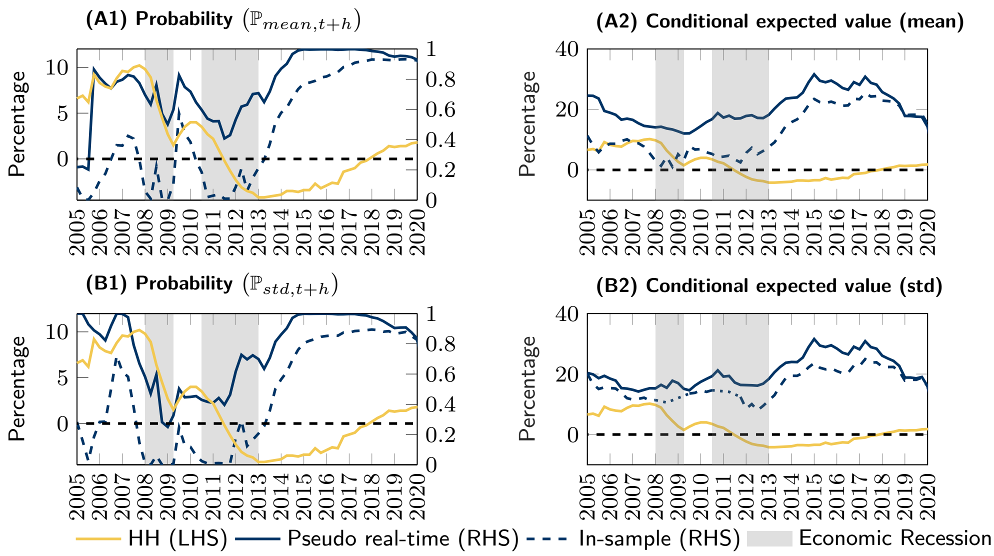
Figure 14: Probabilities and associated conditional expected values for $h = 12$

Households



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

Figure 15: Difference between percentiles of the distribution and expected longrise for $h = 12$



Note: Dates for the economic recessions as defined by Rua (2017). The dotted lines refer to when the probability reaches zero and the associated expected value cannot be calculated.

Figure 16: Probabilities and associated conditional expected values for $h = 12$

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