A HOUSE PRICE-AT-RISK MODEL TO MONITOR THE DOWNSIDE RISK FOR THE SPANISH HOUSING MARKET

2022

BANCO DE ESPAÑA
Eurosistema

Documentos de Trabajo
N.º 2244

Gergely Ganics and María Rodríguez-Moreno

A HOUSE PRICE-AT-RISK MODEL TO MONITOR THE DOWNSIDE RISK FOR THE SPANISH HOUSING MARKET

A HOUSE PRICE-AT-RISK MODEL TO MONITOR THE DOWNSIDE RISK FOR THE SPANISH HOUSING MARKET

Gergely Ganics (*)

BANCO DE ESPAÑA

María Rodríguez-Moreno (**)

BANCO DE ESPAÑA

(*) Address: Alcalá, 48, 28014 Madrid, Spain. E-mail: gergely.ganics@bde.es.
(**) Address: Alcalá, 48, 28014 Madrid, Spain. E-mail: maria.rodriguezmoreno@bde.es.

https://doi.org/10.53479/29472

Documentos de Trabajo. N.º 2244

December 2022

ISSN: 1579-8666 (on line)

Abstract

We present a house price-at-risk (HaR) model that fits the historical developments in the Spanish housing market. By means of quantile regressions we show that a model including quarterly house price growth, a misalignment measure and a consumer confidence index is able to accurately forecast the developments in the Spanish housing market up to two years ahead. We also show how the HaR model can be used to monitor the downside risk.

Keywords: house price-at-risk, house prices, quantile regressions.

JEL classification: C31, E37, G01, R31.

Resumen

Este artículo presenta un modelo *at-risk* para el precio de la vivienda que se ajusta a los desarrollos históricos observados en el mercado residencial español. Por medio de regresiones cuantílicas, mostramos que un modelo que contiene la tasa de crecimiento trimestral del precio de la vivienda, una medida de sobrevaloración del precio de la vivienda y el índice de confianza del consumidor es capaz de predecir de forma precisa los desarrollos del mercado de la vivienda español hasta a dos años vista. Además, también exponemos algunos usos potenciales del modelo *at-risk* para el seguimiento de los riesgos a la baja del mercado inmobiliario.

Palabras clave: *house price-at-risk,* precio de la vivienda, regresiones cuantílicas.

Códigos JEL: C31, E37, G01, R31.

1. Introduction

House Price-at-Risk (HaR) measures aim to identify the accumulation of downside risk in the housing market. It consists of forecasting extreme realizations in the left tail of the conditional distribution of the house prices (commonly the 5th or 10th percentile) to identify in advance whether these extreme realizations correspond to large drops in the housing markets. In this paper, we develop a HaR measure adapted to the main features of the Spanish housing market.

The development of these tools is key for policy makers due to the tight relationship between house price dynamics, the general macroeconomic environment and financial stability. Concretely, residential investment has accounted on average for almost 7% of GDP and 31% of gross fixed capital formation since 2000. Moreover, housing is also an important determinant of consumption via wealth effects and as loan collateral. Indeed, it has been well documented that recessions are deeper and last longer when house prices fall more and more quickly (Claessens, Kose, and Terrones 2012). In addition, more than two-thirds of the nearly 50 systemic banking crises in recent decades were preceded by boom-bust patterns in house prices.

Recently, partly inspired by the Growth-at-Risk framework of Adrian et al. (2019), different surveillance institutions have developed their own HaR measures to monitor the accumulation of downside risk. The International Monetary Fund (IMF, 2019) developed their HaR model for a sample of 22 major advanced economies and 10 emerging market economies where the set of conditioning variables include a financial condition index, real GDP growth, credit growth and an overvaluation measure. At the European level, the European Central Bank (ECB, 2021) has developed a model that includes as explanatory variables the following: the lag of real house price growth, overvaluation (the average of the deviation of house price-to-income ratio from its long-term average and an econometric model), a systemic risk indicator, a consumer confidence indicator, a financial market conditions indicator capturing stock price growth and volatility, a government bond spread, the slope of yield curve, a euro area non-financial corporate bond spread, and the interaction of overvaluation and a financial conditions index.

In this paper we propose a model to monitor the Spanish residential real estate market, paying special attention to downside risk. In doing so, we identify a set of potential explanatory variables based on the literature on vulnerabilities. However, contrary to related papers' HaR models (e.g., IMF, 2019 or ECB, 2021), which study real house prices, we focus on the developments of the Spanish housing market in nominal terms. The reason is because nominal developments are particularly binding from a macroprudential angle. Concretely, the evolution of the nominal prices is especially important, since on the bank balance sheets, collateral values are computed in nominal rather than in real terms. In a similar vein, households make buy/sell housing decisions based on the nominal movements of the market.

For the construction of a HaR model, we use quantile regressions to capture the sensitivity of different points of the density function to changes in the explanatory variables. We next employ the output of the quantile regressions to fit the forecasted probability density function. Finally, we study the out-of-sample (OOS) performance of the different models by means of a Dynamic Quantile test (DQT) and focus on their performance at the four-quarter-ahead horizon, which is a potentially relevant target from a policy perspective.

Our results show that a model of HaR estimated using as explanatory variables the quarterly growth of the house price index, a measure of the house price misalignment, and the consumer confidence index, is able to accurately forecast the developments of the Spanish housing market. In addition, we document the historical performance of this model and potential uses of the model to monitor the downside risk.

The rest of this paper is organized as follows. Section 2 describes the model estimation. Section 3 and 4 details the explanatory variables and the data. Section 5 explains the model selection criteria. Section 6 shows the performance of the selected model and Section 7 concludes.

2. Model Estimation

HaR models are estimated in three steps. First, we estimate the sensitivity of the house price index (HPI) at different points of the distributions through quantile regressions. Second, we forecast the HPI at different horizons and quantiles. Finally, we estimate the probability density function (PDF) at different horizons which enables us to measure the downside risk by monitoring the 5th or 10th percentiles of the distribution. Note that the final step is motivated by the specific interest in the left tail of the distribution, where it would be difficult to fit a quantile regression model due to the small sample size. In what follows, we describe each step in turn.

The models are estimated in recursive fashion, where the first estimation window spans the period between 1987Q1 and 2002Q1, and the last estimation sample ranges from 1987Q1 to 2021Q4.

Quantile Regressions

Koenker and Bassett (1978) developed the concept of quantile regression, which identifies how changes in a set of conditioning variables affect the shape of the distribution of a dependent variable at specific quantiles.

The quantile regression model is defined as

$$\boldsymbol{Q}_{y_{t+h}}(\tau|\boldsymbol{X}_t) = \boldsymbol{X}'_t\beta_\tau \ , \tag{1}$$

where the left-hand side corresponds to the conditional quantile, τ denotes the specific quantile, y_{t+h} is the HPI *h* quarters after the forecast origin *t*, while $\boldsymbol{X}_t$ is a vector of predictors, and β_τ is the vector of coefficients specific to the quantile. All models contain an intercept and the first lag of the HPI, and the additional predictors are all the two-element combinations of the 10 variables described in Section 3, leading to 45 models in total. In line with previous studies, we focused on the 10th, 25th, 50th, 75th and 90th percentiles ($\tau = 0.10, 0.25, 0.50, 0.75, 0.90$) and let the forecast horizon range from 1 to 8 quarters ahead ($h = 1, 2, 3, 4, 5, 6, 7, 8$). At each combination of quantiles and horizons, the coefficient vector can be estimated consistently by minimizing the quantile-weighted absolute value of errors:

$$\widehat{\boldsymbol{\beta}}_{\tau,h} \ = \ \underset{\beta_\tau}{argmin} \sum_{t=1}^{T} \tau \cdot \mathbf{1}_{(y_{t+h} \geq \boldsymbol{X}'_t\beta)} |y_{t+h} - \boldsymbol{X}'_t\beta_\tau| + (1-\tau) \cdot \mathbf{1}_{(y_{t+h} < \boldsymbol{X}'_t\beta)} |y_{t+h} - \boldsymbol{X}'_t\beta_\tau| \ , \tag{2}$$

where $\mathbf{1}$ is an indicator function signaling whether the estimated errors are positive or negative. The last observation in each recursive window corresponds to T, which ranges from 2002Q1 to 2021Q4, but for simplicity we omit this index when referring to the parameter estimates.

Forecasting HPI

Next, using the beta sensitivities estimated in equation (2), we predict conditional quantiles as

$$\widehat{\boldsymbol{Q}}_{y_{T+h}}(\tau|\boldsymbol{X_T}) \ = \ \boldsymbol{X}'_T\widehat{\boldsymbol{\beta}}_{\tau,h} \ . \tag{3}$$

Predictive densities

Finally, we estimated the full predictive density for the different horizons by fitting Jones and Faddy's (2003) skew *t*-distribution to the conditional quantiles estimated in equation (3) to smooth the quantile function and estimate a probability density function. Relative to the commonly used symmetric Student's *t*-distribution, this skew *t*-distribution has two parameters *a* and *b*, which regulate the skewness, and allow for heavy tails.

We fitted the skew t-distribution by minimizing the squared distance between our estimated quantile function $\widehat{\boldsymbol{Q}}_{y_{T+h}}(\tau|\boldsymbol{X}_T)$ in equation (3) and the quantile function of the skew t-distribution $F^{-1}(\tau;\mu,\sigma,a,b)$, where μ and σ are the location and scale parameters:

$$\{\hat{\mu},\hat{\sigma},\hat{a},\hat{b}\} = \underset{\mu,\sigma,a,b}{\text{argmin}} \sum_{\tau} \left(\widehat{\boldsymbol{Q}}_{y_{T+h}}(\tau|\boldsymbol{X}_T) - F^{-1}(\tau;\mu,\sigma,a,b)\right)^2 , \tag{4}$$

where $\mu \in \mathbb{R}$ and $\sigma, a, b > 0$. As a robustness check, we also fitted Azzalini and Capitanio's (2003) skew t-distribution and obtained very similar results.

COVID-19 Crisis

To mitigate the impact of the unprecedented economic downturn caused by the recent COVID-19 pandemic, at forecast origins between 2020Q1 and 2020Q3 we imposed the Banco de España's internal House Price Index prediction on the fitted skew t-distribution as its mode. This adjustment is in line with the procedure that the IMF followed to produce its Growth-at-Risk measure during the pandemic.

3. Explanatory Variables

There exists an extensive theoretical and empirical literature on the determinants of house price valuations, which link the evolution of the housing market to a wide set of factors such as market characteristics, marcrofinancial conditions, economic growth or household income.[1] For the particular case of the Spanish housing market, Martínez Pagés and Maza (2003) show that income and nominal interest rates are pivotal explanatory factors, and Gimeno and Martínez-Carrascal (2010) document that disequilibrium in aggregate credit has an impact on house prices. Recently, Álvarez and García-Posada (2021) stress the importance of modelling housing prices at regional level, estimating a model based on the per capita real income, unemployment rate and demographic density.

Most of the research interest have focused on the central tendency of the house price movements. Nevertheless, in recent years, researchers have started to analyse the factors that help understanding large housing price declines. In this new framework, factors which are directly or indirectly related to the accumulation of vulnerabilities in the housing sector play a key role. Concretely, these models employ factors related to the price misalignment in the housing market, financial factors, household and macroeconomic conditions as well as structural factors to understand future developments in the left tail of the house price distribution. To construct a downside risk model for the Spanish housing market, we consider the following set of potential explanatory variables, which are summarized in Table 1.

[Insert Table 1 here]

House Price Misalignment

House price misalignment is proxied through a property *overvaluation* measure relative to fundamentals. This measure is key in the analysis of the vulnerabilities in the residential real

[1] See Gen (2018) or IMF (2019).

estate (RRE) market. When house prices are on the rise, overvaluation might exacerbate banks' adverse selection problem which may lead to externalities in the downturn and have implications for both financial stability and the real economy (see ESRB, 2019). In addition, "exuberant" price dynamics and misalignments could signal the formation of price bubbles early on, which could also lead to financial instability and deep recessions (Barell et al., 2010). Overvaluation *(Overval)* is computed through an Error Correction Model (ECM) which compares the observed price and the long-term equilibrium relationship between household disposable income, mortgage interest rates and fiscal effects.[2,3]

Financial factors

Housing finance is considered the "fuel" of the global financial crisis (Cerutti et al., 2017), which caused the largest drop in the housing market witnessed in the last decades. The reason is because, before the crisis, booming mortgage markets were supported by rising house prices and economic activity. When the bubble burst, the spiral inverted. Falling house prices led to household debt overhang and several overleveraged financial institutions found themselves in distress. To address the potential role of financial factors, we consider the evolution of bank credit and the developments of interest rates.

The relationship between "exuberant" lending patterns and real estate bubbles and its negative consequences on the housing prices has been widely documented. For example, Cerutti et al. (2017) show that house-price booms accompanied by a boom in credit are more likely to lead to large adjustments in house prices and recessions. Similarly, Crowe et al. (2013) show that busts tend to be more costly when booms are financed through credit and leveraged institutions are directly involved. This is because the balance sheets of borrowers (and lenders) deteriorate sharply when asset prices fall. We proxy the lending pattern through changes in the credit to GDP ratio (*CreditToGDP*).

Developments in the interest rates are directly interlinked with developments in the credit market, since declining interest rates also fuel housing demand (Geng, 2018). We proxy this factor using the nominal households lending rate (*LendingRate*).

Finally, we account for financial stress, since high levels of financial stress are associated with a more pronounced economic downturn (Duprey et al., 2017). To that aim, we consider the

---

[2] This variable is used in the Financial Stability Report to monitor the vulnerability in the Spanish residential real estate market. See, for instance: https://www.bde.es/f/webbde/INF/MenuHorizontal/Publicaciones/Boletines%20y%20revistas/InformedeEstabilidadFinanciera/fsr_spring2019.pdf. The model imposes a one-to-one long-run relationship between the logarithm of the nominal house price index and the logarithm of the HICP (Harmonised Index of Consumer Prices).

[3] Alternative measures of house price misalignment have been discarded after analyzing their information content using the pseudo-R2 proposed by Koenker and Machado (1999).

Country-Level Index of Financial Stress (*CLIFS*) for Spain, which is a composite indicator provided by the ECB that captures the distress in the bond, stock and foreign exchange markets.[4]

Macroeconomic and household conditions

To understand how house price downturns arise, the previous literature developed a comprehensive macroeconomic framework. In these models, housing crises are a vicious cycle of GDP and house price declines. When household debt levels are high, further borrowing by households in response to income declines makes the collateral constraint bind. Fire sales of homes follow, leading to a decline in house prices and further tightening of the collateral constraint. As a result, aggregate demand and household incomes drop and another round of deteriorating conditions ensues (Deghi et al., 2011). To address this link, we use the changes in GDP (*GDP*).

Household conditions also play a key role in shaping house price trends since the better their economic position, the more they can spend to purchase a house or service a mortgage, pushing up house prices. These conditions are captured through the disposable income (*DI*), the unemployment rate (*Unemp*) and the consumer confidence index (*CCI*).[5]

In addition, the previous literature on house price at risk models mainly focuses on the real house price growth. However, from a macroprudential perspective, the evolution of the nominal prices is particularly important, since on the bank balance sheets, collateral values are computed in nominal rather than in real terms. In a similar vein, households take buying/selling housing decisions based on the nominal movements of the market. Thus, nominal developments are particularly binding from a macroprudential angle. To address for the potential impact of pure price pressures, we include the change in the Harmonised Index of Consumer Prices (*HICP*).

Structural factors

It has been widely documented that demographic developments can raise housing demand, thereby increasing price levels (see Girouard et al., 2006). In particular, increases in population shares of cohorts of individuals in their thirties potentially boost housing demand by increasing

---

[4] See, for example:
https://sdw.ecb.europa.eu/browseExplanation.do?node=9693347#:~:text=CLIFS%20%2D%20Country%2DLevel%20Index%20of%20Financial%20Stress%20(CLIFS)&text=The%20CLIFS%20includes%20six%2C%20mainly,markets%20and%20foreign%20exchange%20markets.

[5] To account for household indebtedness and credit constraints, we experimented with including the ratio of household credit to disposable income as a predictor, but found this variable to have little predictive power. In particular, in the dynamic quantile test, models featuring this ratio led to two non-rejections across quantiles at most.

the share of the population of household formation age. This variable might be particularly important in Spain given the great immigration flows registered in Spain. To address for this factor, we employ the changes in working-age population growth (*Popu*).

4. Data

The House Price Index (HPI) measures the evolution of sale prices of free-priced housing, both new and second-hand, free from seasonal movements.[6] The variable of interest is the quarterly annualized average growth (y_{t+h}) over different horizons which range from 1 to 8 quarters, defined as follows:

$$y_{t+h} = \log\left(\frac{HPI_{t+h}}{HPI_t}\right) / \left(\frac{h}{4}\right); h = 1, \ldots, 8. \tag{5}$$

Figure 1 depicts the relative frequency of (annualized) one- and two-year growth rates of the HPI from 1987Q1 to 2021Q4. Although the distributions look similar, the one-year growth rate historically presents larger drops. Indeed, Table 2 contains the descriptive statistics of the annualized HPI quarterly average growth over one- and two-years and the explanatory variables described in Section 3.[7] Historically, half of quarters grew at rates higher than 5%, which corresponds to the median of both distributions. Looking at the tails of the historical distribution, we observe that large increases are more likely than large drops. Indeed, the left tail of the distribution reveals that a 9.5 percentage decline corresponds to the 5th percentile of the distribution of the 1-year growth rate, which means that such a decline is expected on average, one quarter every 20 years.

[Insert Figure 1 here]

[Insert Table 2 here]

Figure 2 shows the bivariate association between one-year-ahead house price growth (y_{t+h}) and current developments in the ten considered explanatory variables, described in Table 1, for different parts of the distribution of house price growth. To that aim, we estimate equation (2) for the 10th, 50th and 90th percentiles using the whole sample period. The results suggest that, in line with previous literature, variables related to fundamental house price valuations and vulnerabilities might be informative about downside risks in the Spanish housing market. Concretely, we find that higher overvaluations in the housing market, unemployment rates, or financial stress have a negative impact on the future developments of the housing market, moving the whole density function left. On the contrary, higher credit, lending rates, GDP

[6] HPI is seasonally adjusted to abstract from calendar movements.

[7] For variables which are estimated on a recursive basis, Table 2 contains the descriptive statistics for the last available vintage.

growth, disposable income, consumer confidence or population growth have a positive impact on the one-year ahead house prices. Note that the results on credit are not against the previous literature but they highlight the slow build-up of the downside risk through credit, since we need longer horizons to observe a negative relation between credit and the 10th percentile of the distribution.

[Insert Figure 2 here]

5. Model selection

The model selection is based on the formal evaluation of the out-of-sample performance of each model we estimated in Section 2. We evaluate 45 different models, which are the result of the combination of the 10 predictor variables in pairs of 2. All models also include the lag of the HPI quarterly growth. The forecast target dates range from 2002Q1+*h* to 2021Q4 for the *h*-quarter-ahead forecasts, leaving 80-*h* out-of-sample periods for forecast evaluation.

The formal evaluation of the models is conducted by means of a dynamic quantile test (DQT) as proposed by Engle and Manganelli (2004). The DQT is a joint test of the independence of violations and correct coverage. It employs a regression-based model of the violation-related variable "hit", defined as $\mathrm{Hit}_{T+h} \equiv 1\left(y_{T+h} \leq \widehat{\boldsymbol{Q}}_{y_{T+h}}(\tau|\boldsymbol{X}_T)\right) - \tau$, which will, on average, be zero if conditional coverage is correct (i.e., if on average the proportion of realizations below a specific quantile prediction $\widehat{\boldsymbol{Q}}_{y_{T+h}}(\tau|\boldsymbol{X}_T)$ is equal to the quantile τ. A regression-type test is then employed to examine whether the "hits" are related to lagged "hits", lagged forecasts, or other relevant regressors (in our case, a constant), over time. Let Z_T denote the vector of regressors known at time T, forming the matrix Z. Then the DQ test statistic is given by

$$DQ_\tau = \frac{\hat{\gamma}'(Z'Z)\hat{\gamma}}{\tau(1-\tau)}, \qquad (6)$$

where $\hat{\gamma}$ is the ordinary least squares coefficient estimate in the regression of Hit_{T+h} on Z_T. Under the null hypothesis of correctly calibrated quantile forecasts, none of the explanatory variables is significant, and the test statistic asymptotically follows a chi-squared distribution whose degrees of freedom equals the dimension of Z_T. Due to the relatively small sample size, we included a constant, and the first two lags of the "hits" and the quantile forecasts themselves.

Given the policy-relevance of the one-year-ahead horizon, we focused on evaluating the performance of each of the models at *h=4*, considering each of the 10th, 25th, 50th, 75th and 90th percentiles. In the next step, we aggregated the results across quantiles by counting the number of cases when at the 1% significance level we could not reject the null hypothesis of correct calibration. The results of the DQT are summarized in Figure 3, where the models are ordered in decreasing order of rejections from left to right.

[Insert Figure 3 here]

As we can see, the model featuring the overvaluation measure and the consumer confidence index performs particularly well (labeled as "Overval, CCI"), as we could not reject the correct calibration of this model's quantile forecast at any of the quantiles. Furthermore, the overvaluation index seems to be the driving factor behind this performance, as the models including this variable tend to have the least number of rejections of correct calibration. This result highlight the importance of the house price misalignment measures to monitor the Spanish residential real estate market in general and the downside risk, in particular. Interestingly, the inflation rate does not stand out as a particularly good predictor, as models featuring the HICP do not tend to appear in the left hand side of Figure 3 (except the model which includes the overvaluation measure in addition to inflation). This could be explained by the fact that inflation was low and stable in the recent 10 years or so, and this low variation could presumably hinder the predictive power of inflation.

6. Predicting House Prices in the Spanish Market

This section shows the performance of the HaR model for Spain on a historical basis and its main characteristics. We also show how this tool would have reacted to the accumulation of downside risk during the period 2006 – 2008, and the most recent developments of this measure.

Historical Performance of the HaR Model

As documented in Section 2, the HaR model is estimated on a recursive basis since 2002Q1 to appropriately evaluate its out-of-sample performance. Figure 4 depicts the historical realization of the house price growth and the forecasted 10th, 50th and 90th percentiles. In the interest of comparability, we have synchronized the dates, so that, for every period t we report the change in the house price between t-h and t (*realization*) and the forecasted quantiles at time t-h. Panel A presents the results at the 4-quarter-ahead horizon (i.e., $h = 4$), and Panel B reports the outcomes at the 8-quarter-ahead horizon (i.e., $h = 8$).

[Insert Figure 4 here]

We observe that at the beginning of the sample period, which coincided with a period of rapid build-up of vulnerabilities, the predicted house price growth at 10th percentile shows a significant increase of the downside risk 4 and 8 quarters ahead. In addition, the largest drop observed in the Spanish housing market during the period 2010-2012 was captured by the 10th percentile of the model. However, during non-distress periods realizations commonly fall close to the median.

Sensitivity of the Model

We next discuss the sensitivity of the different percentiles of the house price growth distribution to changes in the variables of the model. To that aim, Figure 5 depicts the impact of the three factors of the HaR model previously selected for the 10th, 50th and 90th percentiles of the distribution of the house price growth. They correspond to the beta coefficients of equation (2) estimated from 1 to 8 quarters ahead using the full sample period: 1987Q1 – 2021Q4. For comparability reasons, explanatory variables are normalized using the in-sample mean and standard deviation. Results show that current overvaluation considerably pulls down the house price growth prediction at longer horizons. On the contrary, low consumer confidence has a sizable impact on the downside risk in the short run. Thus, these to variables enable us to monitor the building-up of vulnerabilities in the housing market while the quarterly growth of the housing market allows us to capture the most recent market dynamics.

[Insert Figure 5 here]

HaR model around the 2006 – 2008 period

As previously discussed, the HaR model enables us to monitor the downside risk of the housing market. To show the usefulness of this tool, Figure 6 depicts the predicted distribution function estimated using equation (4) (that is, after fitting the skew t-distribution) for 4 quarters ahead in 2006Q4, 2007Q4 and 2008Q4. Note that in this exercise models are estimated using quasi-real time variables, and thus, the forecasted distribution functions are not equal to the ones that we would have estimated in a real-time setting. Concretely, in this work we employ *revised macrofinancial* variables rather than real-time data that was available at that time, which might be less informative of the downside risk than later revisions of the data. Thus, we are aware that our density forecast might overestimate the information that the policymaker would have had at a certain period of time. In spite of this caveat, Figure 6 shows a clear deterioration of the future developments of the housing market.

[Insert Figure 6 here]

HaR model in 2021Q4

We finally show the most recent output of the HaR model, to document the exercises that can be carried out to monitor the developments of the housing market. In the interest of brevity, we just focus on to the 4-quarter-ahead horizon. Figure 7 depicts the forecasted density function, the value of the HaR model at the 10th percentile (HaRq10) and the unconditional 10th percentile of the historical distribution. We can see that HaRq10 is well above the unconditional 10th percentile, showing that the downside risk remains subdued. In addition, by decomposing HaRq10 into its components, we can see that the factors related to the vulnerabilities (i.e., *Overval* and *CCI*) have an almost negligible contribution, and the current HaRq10 is mainly driven by the quarterly growth of the house price index (*HPI*), which captures the most recent dynamics of the market, and includes the impact of the recent surge in inflation.

[Insert Figure 7 here]

7. Conclusion

In this paper we propose a model to monitor the developments of the Spanish housing market, paying special attention to the downside risk. For that aim, we use as a starting point the literature on the vulnerabilities to identify an initial set of variables. Then, we use quantile regressions to capture the sensitivity of different points of the probability density function to changes in the explanatory variables. The output of the quantile regressions helps us to fit a forecasted probability density function, which belongs to the skew *t* family. We then study the out-of-sample performance of the different models by means of a Dynamic Quantile Test (DQT) and focus on the performance 4 quarters ahead, which is the potential target from a policy perspective. By doing that, we select the model that contains as explanatory variables: i. the quarterly growth of the house price index; ii. a measure of the house price misalignment (Overvaluation); and iii. the consumer confidence index (CCI). We finally show the usefulness of this tool to monitor the developments of the housing market and, in particular, to identify the accumulation of vulnerabilities.

References

Adrian, T. A., N. Boyarchenko, and D. Giannone (2019). «Vulnerable growth», *American Economic Review,* 109 (4), pp. 1263-1289. https://doi.org/10.1257/aer.20161923

Álvarez, L., and M. García-Posada (2021). «Are house prices overvalued in Spain? A regional approach», *Economic Modelling,* 99, 105499. https://doi.org/10.1016/j.econmod.2021.105499

Barrell, R., E. P. Davis, D. Karim, and I. Liadze (2010). «Bank regulation, property prices and early warning systems for banking crises in OECD countries», *Journal of Banking & Finance,* 34 (9), pp. 2255-2264. https://doi.org/10.1016/j.jbankfin.2010.02.015

Borio, C., and M. Drehmann (2009). *Towards an operational framework for financial stability: 'fuzzy' measurement and its consequences,* BIS WP No. 284. https://doi.org/10.2139/ssrn.1458294

Cerutti, E., J. Dagher, and G. Dell'Ariccia (2017). «Housing finance and real-estate booms: A cross-country perspective», *Journal of Housing Economics,* 38, pp. 1-13. https://doi.org/10.1016/j.jhe.2017.02.001

Claessens, S., A. Kose, and M. E. Terrones (2012). «How Do Business and Financial Cycles Interact?», *Journal of International Economics,* 87, pp. 178-190. https://doi.org/10.1016/j.jinteco.2011.11.008

Crowe, C., G. Dell'Ariccia, D. Igan, and P. Rabanal (2013). «How to deal with real estate booms: Lessons from country experiences», *Journal of Financial Stability,* 9 (3), pp. 300-319. https://doi.org/10.1016/j.jfs.2013.05.003

Deghi, A., M. Katagiri, S. Shahid, N. Valckx, and J. Vandenbussche (2020). *Predicting Downside Risks to House Prices and Macro-Financial Stability,* IMF WP No. 11. https://doi.org/10.5089/9781513525839.001

Duprey, T., B. Klaus, and T. Peltonen (2017). «Dating systemic financial stress episodes in the EU countries», *Journal of Financial Stability,* 32, pp. 30-56. https://doi.org/10.1016/j.jfs.2017.07.004

ECB (2021). *Financial Stability Review,* November.

ESRB (2019). «Vulnerabilities in the residential real estate sectors of the EEA countries», September.

Gen (2018). *Fundamental Drivers of House Prices in Advanced Economies,* IMF WP No. 164. https://doi.org/10.5089/9781484367629.001

Gimeno, R., and C. Martínez-Carrascal (2010). «The relationship between house prices and house purchase loans: The Spanish case», *Journal of Banking & Finance,* 34 (8), pp. 1849-1855. https://doi.org/10.1016/j.jbankfin.2009.12.011

Girouard, N., M. Kennedy, P. van den Noord, and C. André (2006). *Recent House Price Developments: The Role of Fundamentals,* OECD Economics Department WP No. 475.

IMF (2019). *Global Financial Stability Report,* April.

Jones, M. C., and M. J. Faddy (2003). «A skew extension of the t-distribution, with applications», *Journal of the Royal Statistical Society: Series B (Statistical Methodology),* 65, pp. 159-174. https://doi.org/10.1111/1467-9868.00378

Koenker, R., and J. A. F. Machado (1999). «Goodness of Fit and Related Inference Processes for Quantile Regression», *Journal of the American Statistical Association,* 94, pp. 1296-1310. https://doi.org/10.1080/01621459.1999.10473882

Martínez Pagés, J., and L. A. Maza (2003). *Analysis of House Prices in Spain,* Banco de España WP No. 0307.

Figures and Tables

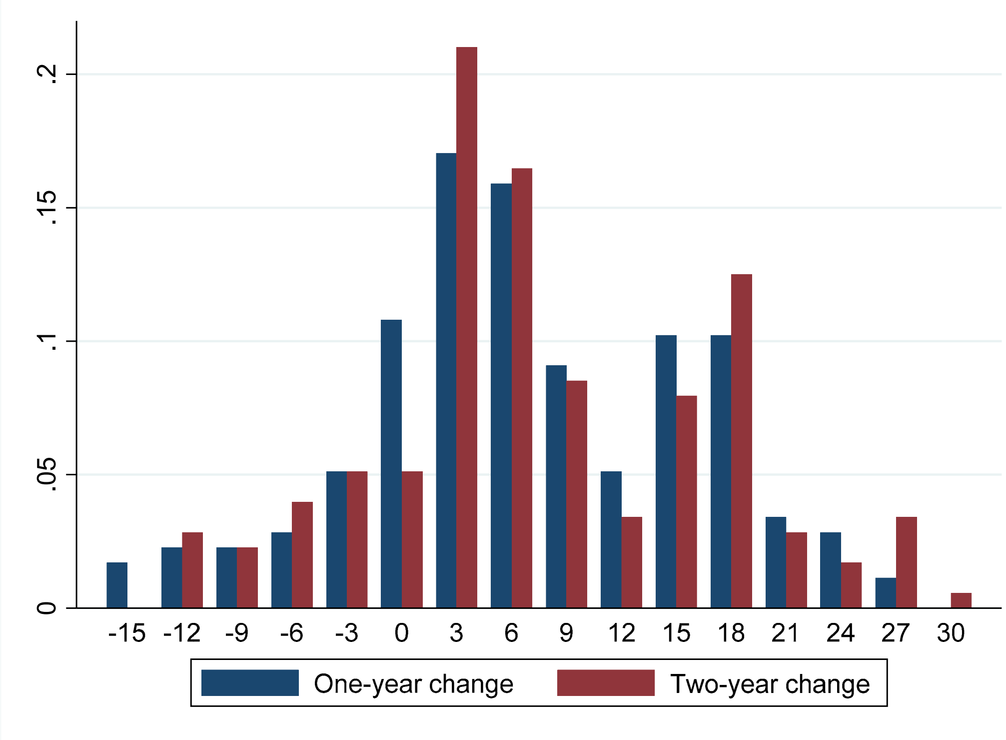

Figure 1: Frequency Distribution of House Price Growth

This figure depicts the relative frequency of one-year and two-year quarterly house price changes (annualized, in percentage points) over the period 1987Q1 to 2021Q4.

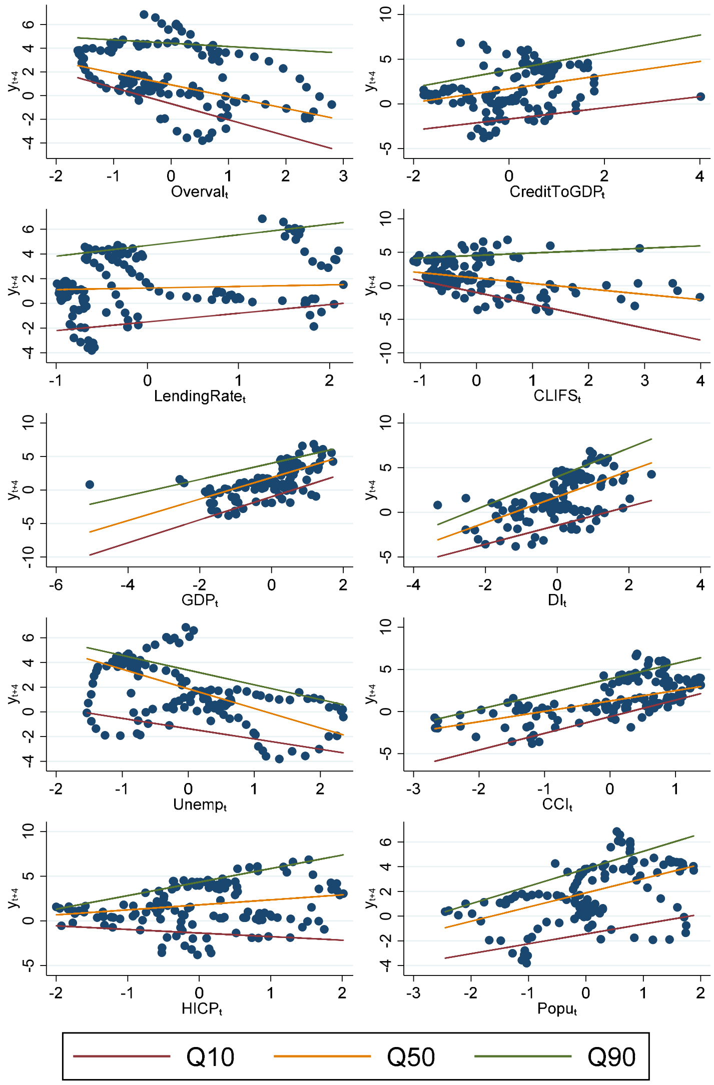

Figure 2: Potential Determinants of the HPI Growth Rate

This figure depicts the association between one-year ahead house price growth (y_{t+4}) and current developments in the ten considered variables: Overvaluation (Overval); Credit to GDP (CreditToGDP); Lending Rate (LendingRate); Country-Level Index of Financial Stress (CLIFS); GDP growth (GDP); Disposable Income growth (DI); Unemployment (Unemp); Consumer Confidence Index (CCI); Harmonized Consumer Price Index growth (HICP); and Population (Popu). For comparability, dependent and explanatory variables are standardized using their sample mean and standard deviation. The sample spans 1987Q1 to 2021Q4. Lines show the estimated relationship between these variables and house prices growth rate at the 10th (red line), 50th (yellow line) and 90th (green line) percentiles.

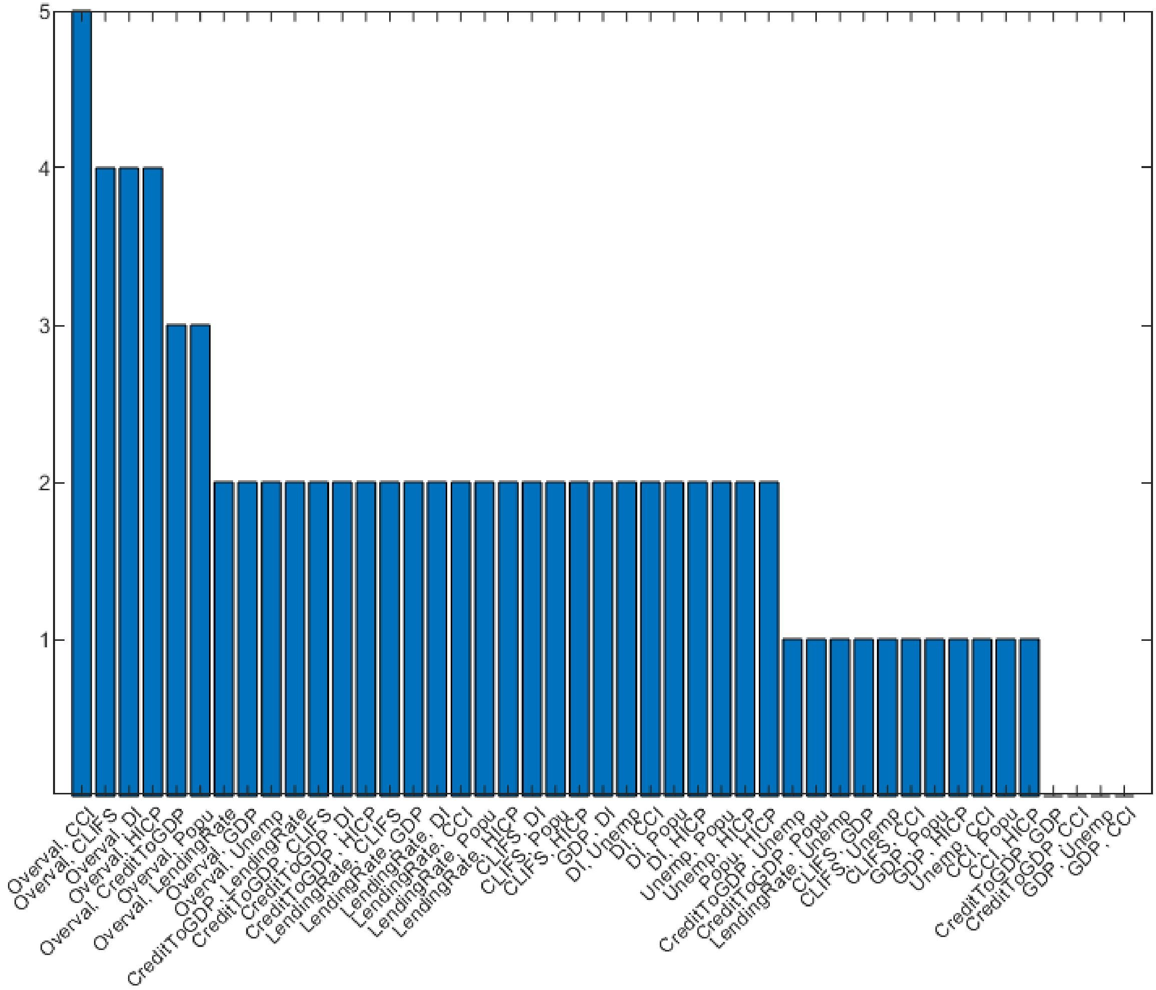

Figure 3: Summary of the Dynamic Quantile Test

This figure shows the number of percentiles (out of five in total: the 10th, 25th, 50th, 75th and 90th) at which we cannot reject the correct calibration of the quantile forecasts of each model (explanatory variables in addition to lagged HPI growth shown on the horizontal axis) at the 1% significance level. Better performance corresponds to higher values.

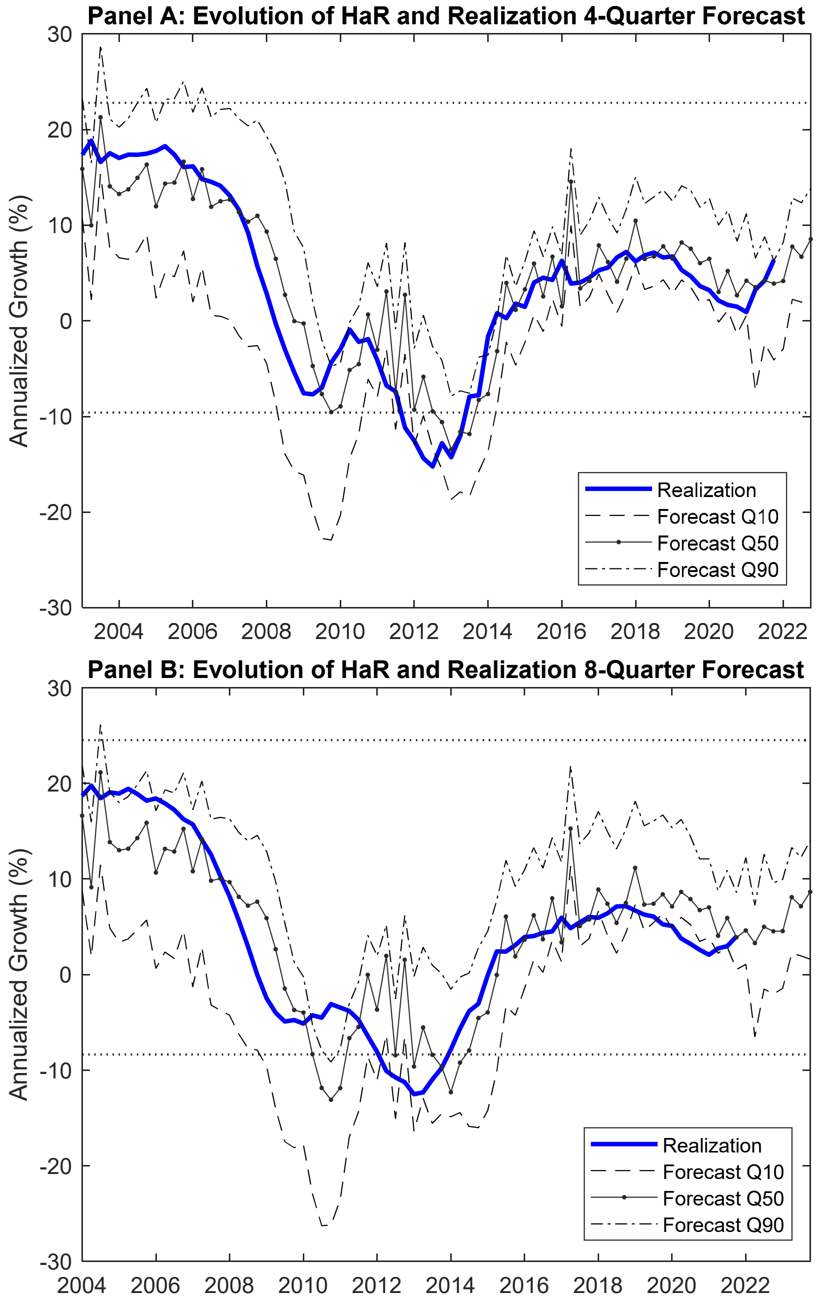

Figure 4: Historical realization of HaR Model

This figure depicts the historical realization of the house price growth and the forecasted 10, 50 and 90th percentiles of the HaR model estimated on a recursive basis since 2002. Dates are synchronized, so that, for every period t "Realization" reports the change in the house price between t-h and t and "Forecast" reports the forecasted quantile at time t-h. Panels A and B report the predictions at the 4-quarter-ahead (i.e., h=4) and 8-quarter-ahead (i.e., h=8) horizons, respectively. The dotted horizontal lines refer to the unconditional 5th and 95th quantiles of the historical distribution.

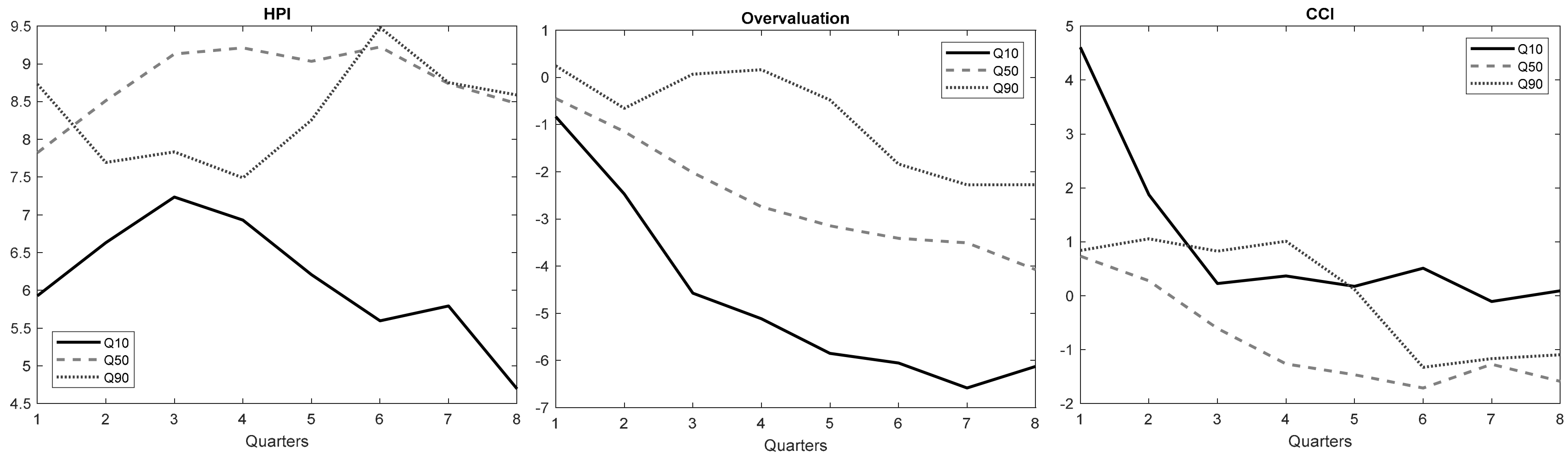

Figure 5: Impact of Three Factors on House Price Growth

This figure depicts the impact of the three selected factors of the HaR model for Spain on the 10th, 50th and 90th percentiles of the distribution of the house price growth from 1 to 8 quarters ahead (marked on the horizontal axis) for the full sample period: 1987Q1 – 2021Q4. HPI refers to the quarterly growth of the house price index, while Overvaluation and CCI refers to the deviation from the long-term equilibrium price and the consumer confidence index, respectively (see Table 1). Explanatory variables are normalized using the sample mean and standard deviation.

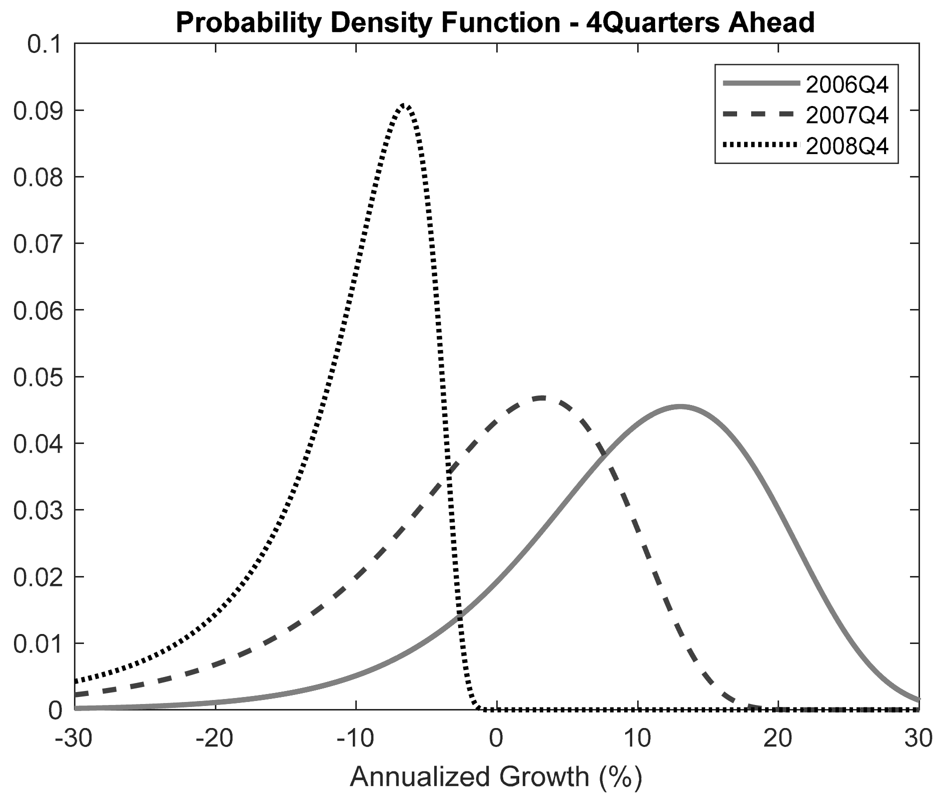

Figure 6: Probability Density Function

This figure depicts the probability density function estimated using equation (4) in 2006Q4, 2007Q4 and 200Q8 for 4 quarters ahead. We restrict the sample to available information at each period of time.

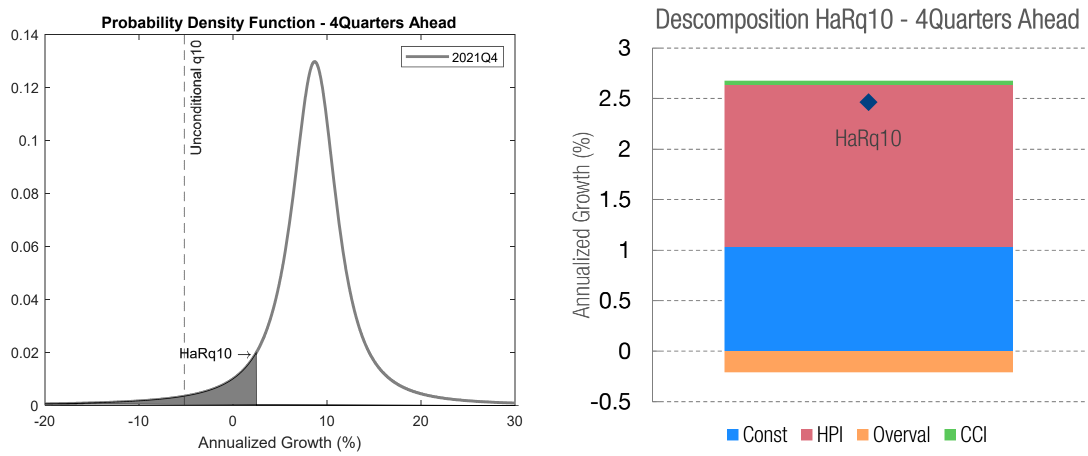

Figure 7: House Price at Risk Model in 2021Q4

This figure depicts the outcome of the HaR model in 2021Q4 for 4 quarters ahead. In the left panel we show the forecasted density function, the predicted 10th percentile (HaRq10) and the unconditional 10th percentile of the historical distribution (dashed vertical line). In the right panel we show the decomposition of the HaR model at 10th percentile into four components: i. constant (Const); ii. quarterly growth of the house price index (HPI); iii. Overvaluation (Overval); and iv. consumer confidence index (CCI). The diamond refers to the HaR model's prediction of the 10th percentile of the HPI.

Table 1: Summary of explanatory variables

Category	Variable	Description	Source
House Price Misalignment	Overvaluation (*Overval*)	A measure computed through an Error Correction Model (ECM) which compares the observed price and the long-term equilibrium relationship between household disposable income, mortgage interest rates and fiscal effects. Long-term prices are computed on a recursive basis since 2002.	Authors' calculation
Financial Factors	Credit to GDP (*CreditToGDP*)	Year-on-year changes in the real bank credit to real GDP ratio.	INE
	Lending Rate (*LendingRate*)	Mortgage lending rate.	BdE
	Country-Level Index of Financial Stress (*CLIFS*)	Stress index based on Duprey et al. (2017) which identifies periods of high financial stress in the bond, equity and exchange rate markets.	ECB
Macroeconomic and Household Conditions	Gross Domestic Product (*GDP*)	Year-on-year growth rate in the GDP.	INE
	Disposable Income (*DI*)	Year-on-year growth changes in the disposable income.	INE
	Unemployment (*Unemp*)	Unemployment rate.	INE
	Consumer Confidence Index (*CCI*)	Consumer Confidence Index.	OECD
	Harmonised Index of Consumer Prices (*HICPI*)	Year-on-year growth changes in the HICP.	INE
Structural Factors	Population (*Popu*)	Year-on-year growth rate of working-age population.	INE

Notes: INE stands for Instituto Nacional de Estadística (the Spanish National Statistics Institute), BdE refers to the Banco de España (the Bank of Spain), while ECB and OECD correspond to the European Central Bank and the Organisation for Economic Cooperation and Development, respectively.

Table 2: Descriptive Statistics

	Units	# Obs.	Mean	Median	SD	P5	P95
Annualized HPI Quarterly Growth							
y_{t+4}	%	140	6.73	5.30	9.72	-9.55	22.82
y_{t+8}	%	140	7.57	5.50	10.07	-8.93	25.18
House Price Misalignment							
Overval	%	140	-0.19	-3.91	20.36	-30.88	46.42
Financial Factors							
CreditToGDP	p.p.	140	1.11	1.11	3.51	-4.60	6.73
LendingRate	%	140	6.59	4.71	4.83	1.96	15.81
CLIFS	-	140	0.12	0.10	0.09	0.04	0.33
Macroeconomic and Household Conditions							
GDP	%	140	5.22	6.57	5.11	-3.43	12.23
DI	%	140	4.94	5.48	4.50	-2.99	11.60
Unemp	%	140	15.21	14.59	4.71	8.63	24.93
CCI	-	140	99.97	100.81	3.08	93.79	103.68
HICP	%	140	2.96	2.94	2.05	-0.62	6.47
Structural Factors							
Popu	%	140	0.66	0.66	0.82	-0.75	2.02

BANCO DE ESPAÑA PUBLICATIONS

WORKING PAPERS

2130 MATÍAS LAMAS and DAVID MARTÍNEZ-MIERA: Sectorial holdings and stock prices: the household-bank nexus.

2131 ALBERT BANAL-ESTAÑOL, ENRIQUE BENITO, DMITRY KHAMETSHIN and JIANXING WEI: Asset encumbrance and bank risk: theory and first evidence from public disclosures in Europe.

2132 ISABEL ARGIMÓN and MARÍA RODRÍGUEZ-MORENO: Business complexity and geographic expansion in banking.

2133 LUIS GUIROLA: Does political polarization affect economic expectations?: Evidence from three decades of cabinet shifts in Europe.

2134 CHRISTIANE BAUMEISTER, DANILO LEIVA-LEÓN and ERIC SIMS: Tracking weekly state-level economic conditions.

2135 SERGI BASCO, DAVID LÓPEZ-RODRÍGUEZ and ENRIQUE MORAL-BENITO: House prices and misallocation: The impact of the collateral channel on productivity.

2136 MANUEL ARELLANO, STÉPHANE BONHOMME, MICOLE DE VERA, LAURA HOSPIDO and SIQI WEI: Income risk inequality: Evidence from Spanish administrative records.

2137 ANGELA ABBATE and DOMINIK THALER: Optimal monetary policy with the risk-taking channel.

2138 MARTA BAŃBURA, DANILO LEIVA-LEÓN and JAN-OLIVER MENZ: Do inflation expectations improve model-based inflation forecasts?

2139 MÁXIMO CAMACHO, MARÍA DOLORES GADEA and ANA GÓMEZ LOSCOS: An automatic algorithm to date the reference cycle of the Spanish economy.

2140 EDUARDO GUTIÉRREZ, AITOR LACUESTA and CÉSAR MARTÍN MACHUCA: Brexit: Trade diversion due to trade policy uncertainty.

2141 JULIO A. CREGO and JULIO GÁLVEZ: Cyclical dependence in market neutral hedge funds.

2142 HERVÉ LE BIHAN, MAGALI MARX and JULIEN MATHERON: Inflation tolerance ranges in the new keynesian model.

2143 DIEGO COMIN, JAVIER QUINTANA, TOM SCHMITZ and ANTONELLA TRIGARI: Measuring TFP: the role of profits, adjustment costs, and capacity utilization.

2144 ROBERTO PASCUAL: Do analysts forecast differently in periods of uncertainty? An empirical analysis of target prices for Spanish banks.

2145 BEATRIZ GONZÁLEZ, GALO NUÑO, DOMINIK THALER and SILVIA ABRIZIO: Firm heterogeneity, capital misallocation and optimal monetary policy.

2201 RYAN BANERJEE and JOSÉ-MARÍA SERENA: Dampening the financial accelerator? Direct lenders and monetary policy.

2202 JUAN S. MORA-SANGUINETTI and ISABEL SOLER: La regulación sectorial en España. Resultados cuantitativos.

2203 JORGE E. GALÁN, MATÍAS LAMAS and RAQUEL VEGAS: Roots and recourse mortgages: handing back the keys.

2204 MONICA MARTINEZ-BRAVO and CARLOS SANZ: Inequality and psychological well-being in times of COVID-19: evidence from Spain.

2205 CORINNA GHIRELLI, DANILO LEIVA-LEÓN and ALBERTO URTASUN: Housing prices in Spain: convergence or decoupling?

2206 MARÍA BRU MUÑOZ: Financial exclusion and sovereign default: The role of official lenders.

2207 RICARDO GIMENO and CLARA I. GONZÁLEZ: The role of a green factor in stock prices. When Fama & French go green.

2208 CARLOS MONTES-GALDÓN and EVA ORTEGA: Skewed SVARs: tracking the structural sources of macroeconomic tail risks.

2209 RODOLFO G. CAMPOS, ILIANA REGGIO and JACOPO TIMINI: Thick borders in Franco's Spain: the costs of a closed economy.

2210 MARCO CELENTANI, MIGUEL GARCÍA-POSADA and FERNANDO GÓMEZ POMAR: Fresh start policies and small business activity: evidence from a natural experiment.

2211 JOSE GARCIA-LOUZAO, LAURA HOSPIDO and ALESSANDRO RUGGIERI: Dual returns to experience.

2212 ADRIÁN CARRO and PATRICIA STUPARIU: Uncertainty, non-linear contagion and the credit quality channel: an application to the Spanish interbank market.

2113 MARIO IZQUIERDO, ENRIQUE MORAL-BENITO, ELVIRA PRADES and JAVIER QUINTANA: The propagation of worldwide sector-specific shocks.

2214 HENRIQUE S. BASSO: Asset holdings, information aggregation in secondary markets and credit cycles.

2215 JOSÉ MANUEL CARBÓ and SERGIO GORJÓN: Application of machine learning models and interpretability techniques to identify the determinants of the price of bitcoin.

2216 LUIS GUIROLA and MARÍA SÁNCHEZ-DOMÍNGUEZ: Childcare constraints on immigrant integration.

2217 ADRIÁN CARRO, MARC HINTERSCHWEIGER, ARZU ULUC and J. DOYNE FARMER: Heterogeneous effects and spillovers of macroprudential policy in an agent-based model of the UK housing market.

2218 STÉPHANE DUPRAZ, HERVÉ LE BIHAN and JULIEN MATHERON: Make-up strategies with finite planning horizons but forward-looking asset prices.

2219 LAURA ÁLVAREZ, MIGUEL GARCÍA-POSADA and SERGIO MAYORDOMO: Distressed firms, zombie firms and zombie lending: a taxonomy.

2220 BLANCA JIMÉNEZ-GARCÍA and JULIO RODRÍGUEZ: A quantification of the evolution of bilateral trade flows once bilateral RTAs are implemented.

2221 SALOMÓN GARCÍA: Mortgage securitization and information frictions in general equilibrium.

2222 ANDRÉS ALONSO and JOSÉ MANUEL CARBÓ: Accuracy of explanations of machine learning models for credit decisions.

2223 JAMES COSTAIN, GALO NUÑO and CARLOS THOMAS: The term structure of interest rates in a heterogeneous monetary union.

2224 ANTOINE BERTHEAU, EDOARDO MARIA ACABBI, CRISTINA BARCELÓ, ANDREAS GULYAS, STEFANO LOMBARDI and RAFFAELE SAGGIO: The Unequal Consequences of Job Loss across Countries.

2225 ERWAN GAUTIER, CRISTINA CONFLITTI, RIEMER P. FABER, BRIAN FABO, LUDMILA FADEJEVA, VALENTIN JOUVANCEAU, JAN-OLIVER MENZ, TERESA MESSNER, PAVLOS PETROULAS, PAU ROLDAN-BLANCO, FABIO RUMLER, SERGIO SANTORO, ELISABETH WIELAND and HÉLÈNE ZIMMER. New facts on consumer price rigidity in the euro area.

2226 MARIO BAJO and EMILIO RODRÍGUEZ: Integrating the carbon footprint into the construction of corporate bond portfolios.

2227 FEDERICO CARRIL-CACCIA, JORDI PANIAGUA and MARTA SUÁREZ-VARELA: Forced migration and food crises.

2228 CARLOS MORENO PÉREZ and MARCO MINOZZO: Natural Language Processing and Financial Markets: Semi-supervised Modelling of Coronavirus and Economic News.

2229 CARLOS MORENO PÉREZ and MARCO MINOZZO: Monetary Policy Uncertainty in Mexico: An Unsupervised Approach.

2230 ADRIAN CARRO: Could Spain be less different? Exploring the effects of macroprudential policy on the house price cycle.

2231 DANIEL SANTABÁRBARA and MARTA SUÁREZ-VARELA: Carbon pricing and inflation volatility.

2232 MARINA DIAKONOVA, LUIS MOLINA, HANNES MUELLER, JAVIER J. PÉREZ and CRISTOPHER RAUH: The information content of conflict, social unrest and policy uncertainty measures for macroeconomic forecasting.

2233 JULIAN DI GIOVANNI, MANUEL GARCÍA-SANTANA, PRIIT JEENAS, ENRIQUE MORAL-BENITO and JOSEP PIJOAN-MAS: Government Procurement and Access to Credit: Firm Dynamics and Aggregate Implications.

2234 PETER PAZ: Bank capitalization heterogeneity and monetary policy.

2235 ERIK ANDRES-ESCAYOLA, CORINNA GHIRELLI, LUIS MOLINA, JAVIER J. PÉREZ and ELENA VIDAL: Using newspapers for textual indicators: which and how many?

2236 MARÍA ALEJANDRA AMADO: Macroprudential FX regulations: sacrificing small firms for stability?

2237 LUIS GUIROLA and GONZALO RIVERO: Polarization contaminates the link with partisan and independent institutions: evidence from 138 cabinet shifts.

2238 MIGUEL DURO, GERMÁN LÓPEZ-ESPINOSA, SERGIO MAYORDOMO, GAIZKA ORMAZABAL and MARÍA RODRÍGUEZ-MORENO: Enforcing mandatory reporting on private firms: the role of banks.

2239 LUIS J. ÁLVAREZ and FLORENS ODENDAHL: Data outliers and Bayesian VARs in the Euro Area.

2240 CARLOS MORENO PÉREZ and MARCO MINOZZO: "Making text talk": The minutes of the Central Bank of Brazil and the real economy.

2241 JULIO GÁLVEZ and GONZALO PAZ-PARDO: Richer earnings dynamics, consumption and portfolio choice over the life cycle.

2242 MARINA DIAKONOVA, CORINNA GHIRELLI, LUIS MOLINA and JAVIER J. PÉREZ: The economic impact of conflict-related and policy uncertainty shocks: the case of Russia.

2243 CARMEN BROTO, LUIS FERNÁNDEZ LAFUERZA and MARIYA MELNYCHUK: Do buffer requirements for European systemically important banks make them less systemic?

2244 GERGELY GANICS and MARÍA RODRÍGUEZ-MORENO: A house price-at-risk model to monitor the downside risk for the Spanish housing market.