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The predictive power of house price imbalance indicators

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Rationale

The Banco de España regularly uses indicators that measure imbalances arising in the residential real estate sector to inform its quarterly decisions on the countercyclical capital buffer. This article analyses these indicators' power to predict systemic crises.

Takeaways

- The residential real estate sector is particularly important for financial stability, as evidenced by the housing crisis in Spain that began in 2008. It is, therefore, essential to have early warning indicators for effective risk identification.
- In the recent period, on data to 2023 Q3, house price imbalance indicators suggest that house prices remain moderate and around their equilibrium value.
- After describing recent developments in these indicators, their predictive power is assessed using the AUROC metric.

Keywords

Residential real estate sector, early warning indicators, predictive power, AUROC.

JEL classification

C52, R30, C18, E32, E58.

Author:

Esther Cáceres
Financial Stability and Macroprudential
Policy Department. Banco de España

Introduction

The real estate sector is highly significant in the Spanish economy because of its importance for employment and investment (although real estate investment has fallen since the global financial crisis) and because of its potential impact on financial stability. This became clear during the real estate crisis that started in 2008 in Spain, which was itself part of the larger aforementioned global financial crisis. Mortgage lending is the main source of household debt, with an average maturity at origination of 26 years; on data to September 2023, it accounts for 40.1% of all bank lending to other resident sectors in Spain. Moreover, bank lending to the construction and real estate development sectors accounts for 17.8% of lending to the resident private sector. In addition, house price imbalances exacerbate housing affordability problems, which generate social challenges and macroeconomic inefficiencies.[1] Accordingly, it is important to monitor the sector and be equipped to prevent the build-up of risk.

One of the responsibilities of the Banco de España is to ensure financial stability, using macroprudential policy to help prevent risks building up in the different segments of the financial system, including those linked to the residential real estate sector. This policy is intended to rein in imbalances that would affect the wider financial system (thereby becoming systemic) and to bolster banks' solvency to protect them should such imbalances materialise (Mencía and Saurina, 2016). To that end, the Banco de España has a range of tools at its disposal to prevent systemic risk materialising, be it over the financial cycle or across the financial system (structurally).[2] Specifically, the countercyclical capital buffer (CCyB) is one of the macroprudential tools available in Spanish legislation to address these risks, which develop over the course of the financial cycle and can impair economic growth and citizens' welfare. The Banco de España has additional macroprudential tools, such as limits and conditions on loan origination, which are activated more in response to borrower-level analysis than to developments in the financial cycle.[3]

The CCyB is built up when cyclical systemic risk is at a standard or high level and released when such risk materialises or dissipates. A battery of indicators is used to determine the cyclical systemic risk level. The benchmark indicator that informs CCyB decision-making is the credit-to-GDP gap, which measures the deviation, on any given date, of the ratio of total credit to the private non-financial sector to GDP. Periods of strong credit growth push the credit-to-GDP gap above its long-run trend, meaning that positive and rising values in this indicator are a sign of imbalance.[4] However, the credit-to-GDP gap's capacity for risk identification is somewhat

1 See, for example, Directorate General Economics, Statistics and Research (2020).

2 See the definition of systemic risk in European Central Bank (2009).

3 The additional macroprudential tools based on national regulations include the sectoral component of the CCyB, sectoral concentration limits and limits and conditions on loan origination, all of which address risks concentrated in the real estate sector (Broto, Cáceres and Melnychuk, 2022, and Banco de España Circular 05/2021 of 22 December 2021).

4 Various papers tie excessive credit growth to subsequent financial crises. See, for example, Schularick and Taylor (2012).

limited,[5] so the Banco de España uses additional indicators to decide whether to activate the CCyB, as envisaged in the regulations (see the briefing note on the new framework for setting the CCyB). The recommendation of the European Systemic Risk Board (ESRB) on CCyB decisions envisages, for instance, measures of house price overvaluation.[6] These additional variables include indicators such as the output gap, credit intensity, the debt service ratio and indicators of possible imbalances in the real estate sector. In the case of the latter, an aggregate measure based on four individual indicators of house price imbalances is analysed as part of the monitoring framework for setting the CCyB. In addition, the two-year change in house prices is considered. This is a simpler indicator that is also used in the Banco de España to detect signs of house price imbalances.[7]

This article focuses on these five indicators of house price imbalances as, despite their relevance, no formal analysis focusing specifically on their power to predict the materialisation of cyclical systemic risks has yet been carried out. Such an analysis is key to assessing their effectiveness in providing early warning signs of real estate crises and warning of the sector's vulnerabilities. Specifically, this article will describe how these individual indicators have evolved and will propose a study of the power to predict systemic crises of each of the three indicators based on the Hodrick-Prescott (HP) filter.[8] This will be done by analysing the area under the receiver operating characteristics (AUROC) curve under different assumptions about the smoothing parameter, the value of which is used to account for the duration of real estate cycles. The article then compares the power of the five variables to predict systemic crises.

Indicators of price imbalances in the residential real estate sector

Four indicators[9] that identify house price imbalances are first analysed as part of the monitoring framework for setting the CCyB. The difference between them is the methodology used to estimate the equilibrium price levels, that is, either purely statistical procedures (the first two) or econometric models (the second two):

— The real house price gap measures the deviation of house prices from their long-run trend.

$$\text{House price gap} = \ln(\text{real house prices}) - \\ - \text{HP trend}(\ln(\text{real house prices}), \lambda)$$

— The house price-to-disposable household income gap measures the deviation of the house price-to-disposable income ratio from its long-run trend.

5 The credit-to-GDP gap is particularly useful in expansionary phases of the credit cycle. However, under certain circumstances it has limitations, such as during the period following the COVID-19 pandemic, which caused GDP to fall sharply, resulting in a drastic change in the cyclical position of the Spanish economy.

6 For further information, see Recommendation ESRB/2014/1.

7 See Chart 3.3 of the Financial Stability Report. Spring 2023.

8 For more details, see Hodrick and Prescott (1981 and 1997).

9 All the indicators are recursive, which means that they consider only past values in their estimates.

$$\text{Ratio gap} = \ln\left(\frac{\text{real house prices}}{\text{real disposable income per capita}}\right) -$$
$$- \text{HP trend}\left(\ln\left(\frac{\text{real house prices}}{\text{real disposable income per capita}}\right), \lambda\right)$$

— The ordinary least squares (OLS) model provides an indicator that is the residual of a model estimating house prices on the basis of long-term trends in household disposable income and mortgage rates calculated using HP filters. The parameters of the model are obtained using the OLS method.

$$\varepsilon_t = \ln(\text{real house prices}) - \alpha - \beta_1 \times \text{HP trend}(\text{real gross disposable income}, \lambda) -$$
$$- \beta_2 \times \text{HP trend}(\text{real rates}, \lambda)$$

— An error correction model (ECM) for house prices is estimated based on household disposable income, mortgage rates and tax effects.[10] It includes short-term effects (the relationship between the rates of change of the variables) and long-term effects (the relationship between the levels of the variables). The measure of price imbalance and the residuals of the long-term relationship are cointegrated variables.

Three of the four indicators use the HP filter, as does the credit-to-GDP gap. This is a statistical filter that separates series into a trend and a cyclical component.[11] For these three indicators, a one-sided HP filter[12] is assumed, adjusted with a smoothing parameter (usually represented by lambda, λ) of 400,000.[13] The duration of the cyclical component depends on the smoothing parameter chosen: the larger the parameter, the longer the duration of the cycle. For example, a smoothing parameter of 400,000 corresponds to a cycle of around 30 years (Drehmann, Borio, Gambacorta, Jiménez and Trucharte, 2010). The purpose of the exercise is not only to analyse which of the four indicators is best able to predict systemic crises, but also to check whether the smoothing parameter of 400,000 is indeed the most suitable for the three real estate sector imbalance indicators calculated using the HP filter.[14]

Chart 1 tracks this index since 1978. It also depicts the two-year change in house prices. Overall it shows that the indicators generally rise in advance of risk materialising, after which they drop sharply. As a result, and as on previous occasions, the real estate sector was highly significant in the most recent systemic banking crisis. Indeed, all the indicators were pointing to overvaluation

10 The model is based on the one presented in Martínez Pagés and Maza (2003).

11 For more details, see Hodrick and Prescott (1981 and 1997).

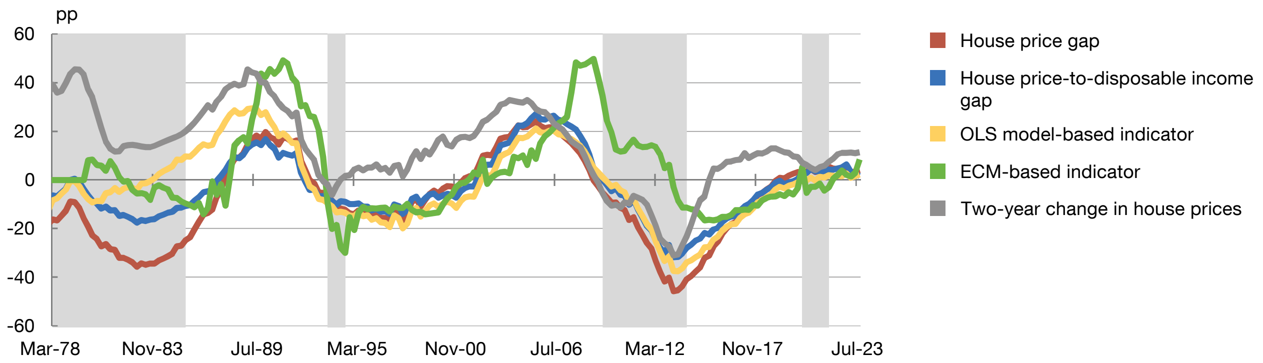
12 In its two-sided version, both past and future values are taken into account for the estimates, which necessitates the use of forecasts, while the one-sided filter employs only past values, meaning that the estimates it provides in real time are not affected by new data being collected.

13 The credit-to-GDP gap is calculated in accordance with the guidance of the Basel Committee on Banking Supervision (2010), using a smoothing parameter of 400,000. However, this standard gap is not appropriate for countries such as Spain where the credit cycle is shorter. The Banco de España also calculates an adjusted gap using a smoothing parameter of 25,000 (Galán, 2019).

14 Assuming that the duration of the real estate cycle is 30 years may not be appropriate, given some evidence that its duration is closer to that of the credit cycle, which is around 17 years (Bedayo, Estrada and Saurina, 2018). Studying this paper is instructive when investigating this issue.

Chart 1
Indicators of imbalances in the real estate sector (a)

1.a Change in the indicators of imbalances in the real estate sector



SOURCES: Banco de España and INE.

a The indicators based on the HP filter (house price gap, house price-to-disposable income gap and the OLS model-based indicator) are calculated using a lambda parameter of 400,000. The vertical grey bands show four crisis periods in Spain since 1978: the economic crisis of the 1980s (1978 Q1 to 1985 Q3), the economic crisis of the 1990s (1993 Q3 to 1994 Q3), the most recent systemic banking crisis (2009 Q1 to 2013 Q4) and the crisis caused by COVID-19 (2020 Q1 to 2021 Q4). Data to September 2023.

in the quarters prior to the crisis and even the ECM reached its all-time high. Following the outbreak of the crisis, the systemic event materialised and all five indicators plunged, with house prices falling far below their equilibrium values.

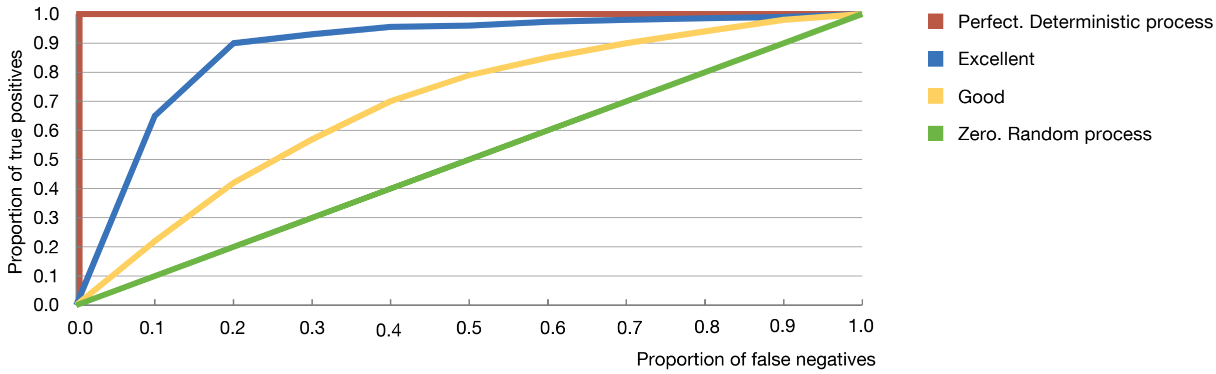
These indicators have risen gradually since early 2013. They have now resumed levels close to equilibrium (around 0), and have shown signs that house prices are above equilibrium. Monetary policy tightening by the European Central Bank (ECB), which began in July 2022, has not been immediately passed through to these indicators, as house prices have continued to increase relative to other variables, such as interest rates or real disposable income. Indeed, all the indicators rose in 2023, although on data to September 2023 those based on the HP filter stand below their end-2022 levels. This suggests that, although there are no warning signals, cyclical systemic risks may well be at an intermediate level, meaning that close attention should be paid to the real estate sector.

Methodology

To assess the ability to anticipate systemic crises and thus identify the best indicators of housing sector imbalances, we measure the predictive power of the indicators using an AUROC metric which measures the relationship between hits and errors in the alarm signals of a binary indicator. More specifically, the methodology assesses the predictive power of each indicator by calculating the proportion of false alerts or unidentified crises (false positives or false negatives) to the proportion of correct alerts or no alerts in crisis-free periods (true positives or true negatives). An AUROC equal to 1 suggests that the prediction is accurate. This methodology is commonly used to assess the suitability of the early warning indicators, such as the credit-to-GDP gap, that are used to guide decisions on the CCyB (Galán, 2019, and Castro, Estrada and Martínez, 2016).

Chart 2
Illustration of possible receiver operating characteristics (ROC) curves (a)

2.a Predictive power according to the ROC curve



SOURCE: Own calculations.

a If an indicator predicts systemic crises perfectly, its AUROC value would be equal to 1 and the process would be deterministic. An AUROC value of 0.5 would indicate that the predictive information is zero and the process would be entirely random. As a result, the aim is to achieve AUROC values over 0.5 and close to 1.

To assess the predictive power of housing sector imbalance indicators using the AUROC metric, univariate logit regressions are estimated, with the indicators as explanatory variables and a binary dependent variable that takes the value of 1 in the event of a systemic crisis and of 0 otherwise. The analysis considers a range of 1 to 16 quarters prior to the materialisation of the crisis[15] and a data sample that runs from March 1970 to September 2019.[16] This period includes three systemic events identified in the ECB/ESRB database (Duca et al., 2017) and also used in Galán (2019): the economic crisis of 1978 Q1 to 1985 Q3, the economic crisis of 1993 Q3 to 1994 Q3, and the global financial crisis of 2009 Q1 to 2013 Q4.[17] The sample is used to assess the predictive power of the three indicators based on the HP filter, according to the smoothing parameter used. However, when analysing the predictive power of these indicators along with that of the ECM-based indicator and the two-year change in house prices, a sample that runs from March 1980 to March 2019, containing two systemic events, is used.[18]

Results

Chart 3 shows the results, since the 1970s, of the analysis of the predictive performance of the indicators based on the HP filter according to the smoothing parameter used. In general, it can

15 From a macroprudential standpoint, we are interested in indicators that anticipate crises over the longer term, given that macroprudential measures are subject to legal requirements that entail a long-term view and, moreover, their effects on the economy are not immediate.

16 Given the forward-looking nature of the AUROC, the most recent 16 quarters (2019 Q4 to 2023 Q3) are excluded from the analysis.

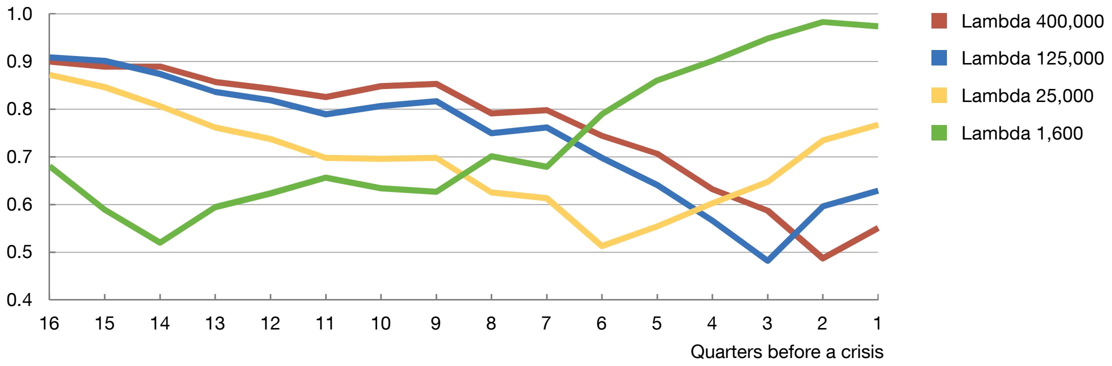
17 The crisis triggered by the COVID-19 pandemic may also be considered systemic, but we do not include it as such in this analysis because its origin was exogenous to the financial system.

18 For the ECM, data availability starts in 1980.

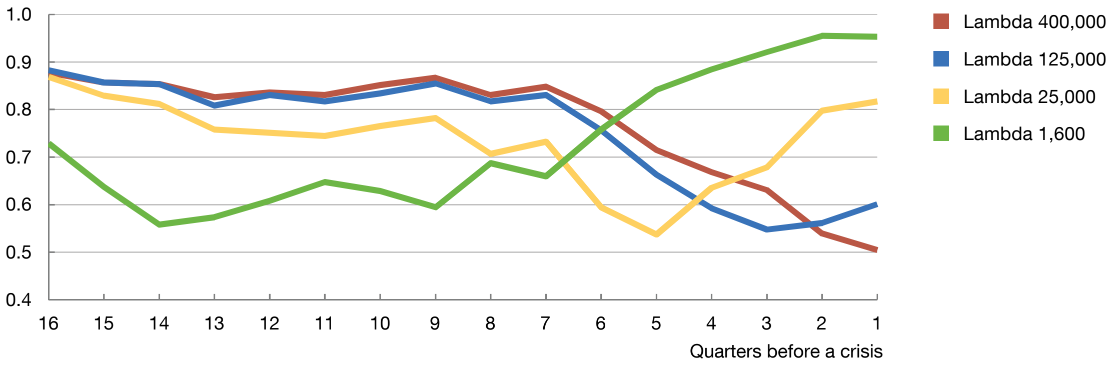
Chart 3

Predictive power of indicators based on the HP filter. Sample with three systemic events (a)

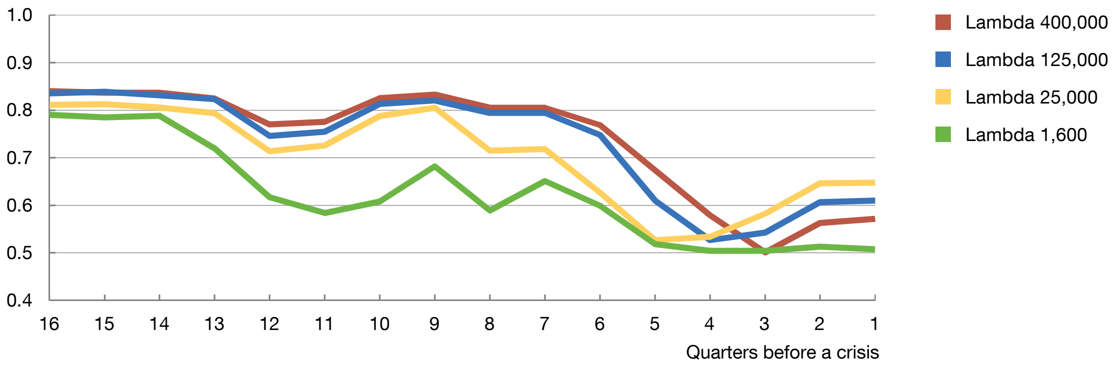
3.a House price gap



3.b House price-to-disposable income gap



3.c OLS model



SOURCES: Banco de España, INE and own calculations.

a The predictive power is assessed using the AUROC metric. The sample contains three systemic events: 1978 Q1 to 1985 Q3, 1993 Q3 to 1994 Q3 and 2009 Q1 to 2013 Q4.

be concluded that, from 7 to 16 quarters forward, the indicators obtained with a higher smoothing parameter have a higher AUROC value. The differences are small between smoothing parameter values of 400,000 and 125,000, and for some indicators (OLS) with a parameter up to 25,000, although in this case there are larger prediction differences. The biggest difference in results is seen when the lambda parameter takes a value of 1,600.

This result supports the use of a relatively high smoothing parameter, higher than the appropriate parameter for calculating the credit-to-GDP gap, equal to 25,000 (Galán, 2019). A higher parameter means that more historical data from the series are used to estimate the trend, and the adjustment to the new data is therefore slower than when using lower parameters. This is one of the possible causes of the difference between the credit series and the house price series: in the wake of the 2008 crisis, both credit and house prices fell, but while house prices recovered their pre-crisis trend, credit failed to do so. For this reason, higher smoothing parameters are less suitable for decomposing the credit series, as the structural change in trend it underwent after the 2008 crisis would appear much further down the line if a high parameter was used.

Although indicators calculated with lower smoothing parameters have a better predictive performance for shorter horizons, from a macroprudential standpoint this is less relevant. Macroprudential measures are subject to legal requirements that entail a long-term view. Moreover, their effects on the economy are not immediate.[19]

Chart 4 includes in the comparison the analysis of the predictive power of the ECM-based indicator and of the two-year change in house prices, in this case using data available since the 1980s. The ECM has the best predictive power one year forward and, overall, its predictive performance is acceptable over the entire macroprudential policy-relevant horizon. In addition, this metric does not rely on the HP filter and is, therefore, free from some of its limitations.[20] The indicator based on the two-year change in house prices has lower predictive capacity than the others over the macroprudential policy-relevant horizon, although over shorter horizons its predictive power converges with that of the ECM.[21] It is also important to note that the predictive power of this simple indicator moves closer to that of the others as the crisis recedes over the horizon (16 quarters).

Moreover, the properties of an indicator requiring a Hamilton filter[22] rather than the HP filter could also be analysed in the future, given the latter's limitations with end-of-sample data. Lastly, a Markov switching model[23] could be considered for house prices, which would make it possible to determine the timing of crises endogenously.

19 Activating macroprudential measures typically requires several quarters, and it can take 8 quarters for their effects to pass through to the real economy (Galán, 2020). Accordingly, the appropriate time frame may be between 8 and 12 quarters.

20 Hamilton (2018).

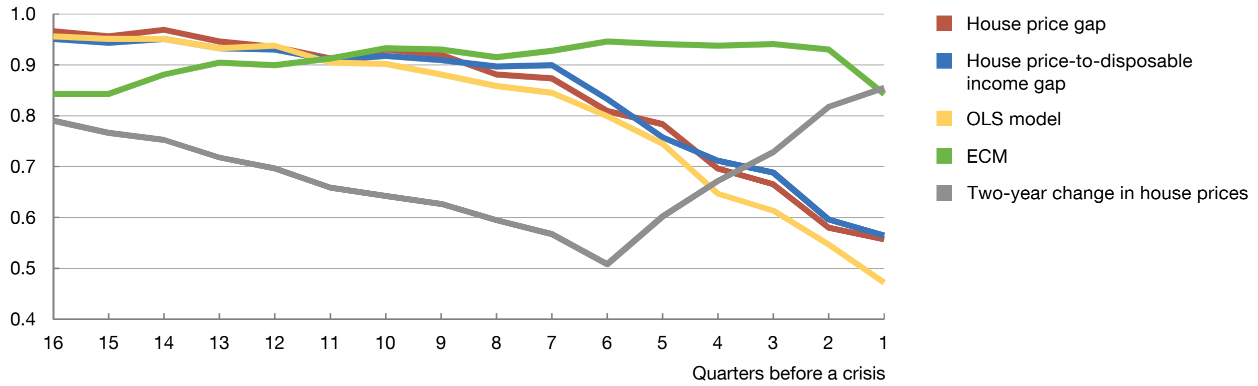
21 Other systemic risk indices incorporate indicators of this kind, such as the three-year change in the house price-to-disposable income ratio in the risk index presented in Lang, Izzo, Fahr and Ruzicka (2019).

22 According to the Hamilton filter, the cyclical component of a series is the error term of a regression that is performed recursively in each period using the past information available (Hamilton, 2018).

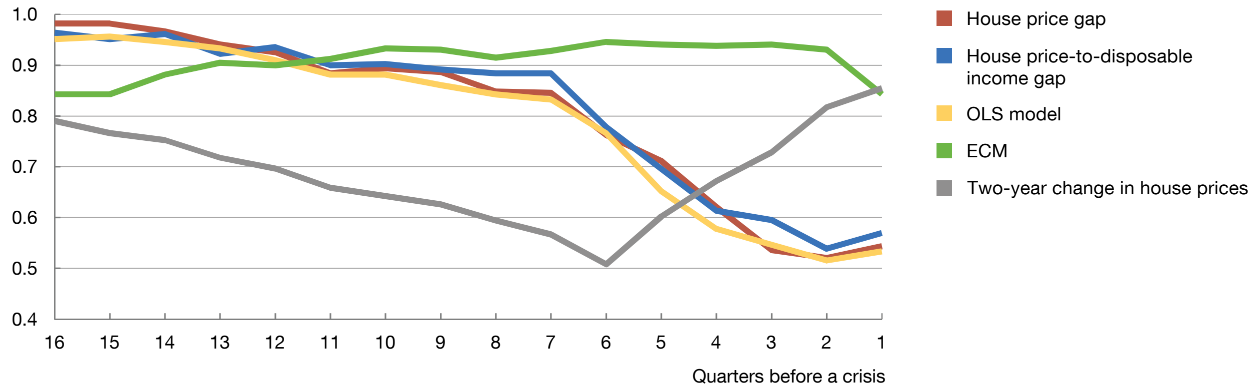
23 The Markov switching model makes it possible to characterise data non-linearities without imposing crisis dates (see Hamilton, 1989).

Chart 4
Predictive power of indicators of real estate sector imbalances. Sample with two systemic events (a)

4.a Lambda 400,000



4.b Lambda 125,000



SOURCES: Banco de España, INE and own calculations.

a The predictive power is assessed using the AUROC metric. Data for the ECM are only available from 1980, meaning that the sample cannot include the crisis in the late 1970s and, therefore, covers just two systemic events: 1993 Q3 to 1994 Q3 and 2009 Q1 to 2013 Q4. The indicators based on the HP filter (house price gap, house price-to-disposable income gap and the OLS model) are calculated using the lambda factor specified in the title of each panel.

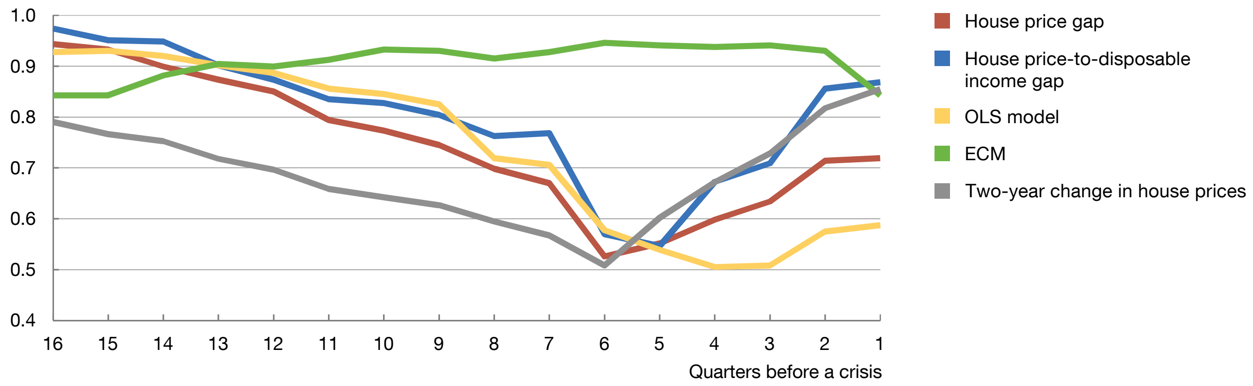
Conclusions

This article analyses the predictive capacity of the four indicators currently used to identify the level of cyclical systemic risk in the residential real estate sector, which helps to guide CCyB decisions. It also analyses the predictive power of the complementary data on the two-year change in house prices. Given the importance of the housing sector, an analysis of the ability of these indicators to anticipate future crises is essential. The level of these indicators on the latest date available within the sample analysed suggests that cyclical systemic risk in the sector is not high, but nor is it low. Indeed, the HP filter-based indicators point to some overvaluation since the post-pandemic quarters, and both the ECM-based indicator and the two-year change in house prices are on an upward trajectory.

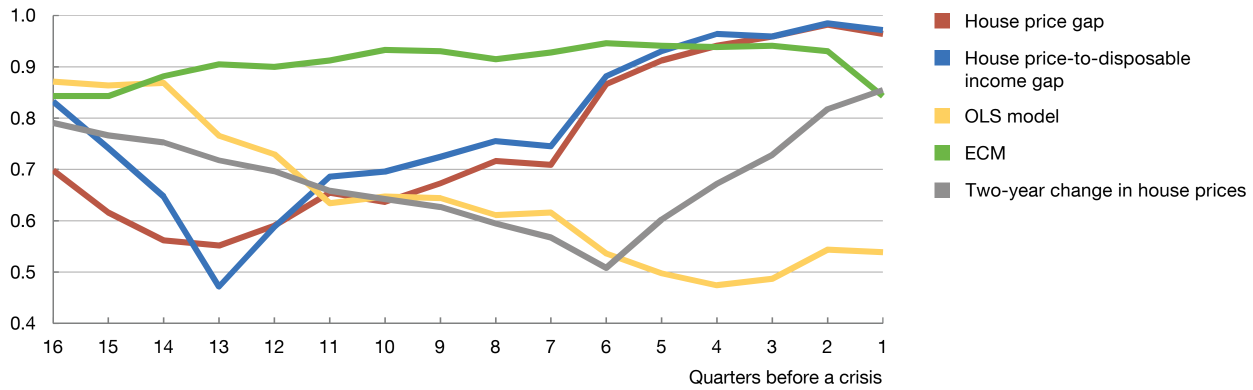
Chart 4

Predictive power of indicators of real estate sector imbalances. Sample with two systemic events (a) (cont'd)

4.c Lambda 25,000



4.d Lambda 1,600



SOURCES: Banco de España, INE and own calculations.

a The predictive power is assessed using the AUROC metric. Data for the ECM are only available from 1980, meaning that the sample cannot include the crisis in the late 1970s and, therefore, covers just two systemic events: 1993 Q3 to 1994 Q3 and 2009 Q1 to 2013 Q4. The indicators based on the HP filter (house price gap, house price-to-disposable income gap and the OLS model) are calculated using the lambda factor specified in the title of each panel.

The results obtained show that the ECM-based indicator – the only one that does not use the HP filter – is the one that is best able to predict the build-up of risks in the housing sector. The predictive power of all the other indicators is best when the higher smoothing parameter (400,000) is used, especially over 7 to 16 quarters, with similar results for a smoothing parameter of 125,000. At horizons close to 16 quarters, a simple indicator such as the two-year change in house prices is also useful as an early warning signal.

The analysis of the capacity to predict systemic crises shows that the ECM-based indicator that does not use the HP filter has the best predictive performance. This finding demonstrates the potential for using models based on economic variables, rather than on statistical procedures such as the HP filter, to assess house price imbalances.

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