RISK AND VULNERABILITY INDICATORS FOR THE SPANISH HOUSING MARKET

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Abstract

The residential real estate market has a significant weight in the Spanish economy and its performance is closely linked to that of the financial cycle. In addition, as evidenced by the real estate crisis that began in Spain in 2008, the risks generated in this sector have important implications for financial stability. The development of a framework for the early identification of risks in this market is therefore key. This article presents two complementary tools to meet this objective. The first is a heat map that provides a visual interpretation of risk levels in this market for a wide selection of individual indicators. The second is a synthetic indicator that summarizes the information provided by the individual indicators. This index complements the information of the heat map, since it measures both the intensity of the risks in each period and their composition. Both the heat map and the synthetic indicator suggest that, in recent months, the vulnerabilities that had been accumulating in the housing market since 2021 have somewhat reverted.

Keywords: housing market, early warning indicators, heat map, synthetic index.

JEL classification: R30, R31, G21, G51, C43.

Resumen

El mercado inmobiliario residencial tiene un peso importante en la economía española y su evolución está muy ligada a la del ciclo financiero. Además, tal y como evidenció la crisis inmobiliaria iniciada en España en 2008, los riesgos generados en este sector tienen importantes implicaciones para la estabilidad financiera. Por ello, es clave el desarrollo de un marco para la identificación temprana de los riesgos en este mercado. En este artículo se presentan dos herramientas complementarias que permiten cumplir con este objetivo. La primera es un mapa de riesgos que proporciona una interpretación visual de los niveles de riesgo en este mercado para una amplia selección de indicadores individuales. La segunda es un indicador sintético que resume la información de los indicadores individuales. Este índice permite complementar la información del mapa de riesgos, ya que mide tanto la intensidad de los riesgos en cada período como su composición. Tanto el mapa de riesgos como el indicador sintético sugieren que, durante los últimos meses, se estaría produciendo una cierta reversión de algunas de las vulnerabilidades que se estaban acumulando en el mercado de la vivienda desde 2021.

Palabras clave: mercado de la vivienda, indicadores de alerta temprana, mapa de riesgos, índice sintético.

Códigos JEL: R30, R31, G21, G51, C43.

Contents

1 Introduction

The housing market is very important to the economy of any country. Residential real estate accounts for a high proportion of households' asset holdings (around 59% on average in euro area countries and 70% in the case of Spain),[1] and housing loans are the most common form of their debt, accounting for approximately 73% of household debt in Spain.[2] Housing loan portfolios also often make up a large part of banks' balance sheets, meaning that, aside from being relevant as business generators, they are also a significant source of collateral for lenders. Furthermore, housing construction tends to be an important component of the economy, as a source of job creation, investment and economic growth (European Systemic Risk Board (ESRB), 2019a).

The residential real estate market exhibits boom-bust cycles that are typically synchronised with the business cycle, although they generally tend to be somewhat longer and larger (Rünstler and Vlekke, 2018). During upswings, price dynamics and risk-taking by lenders and borrowers sometimes enter a vicious circle (Jordà, Schularick and Taylor, 2015). Thus, during the expansionary phase of the real estate cycle there are incentives for greater leverage and excessive risk-taking for households, construction firms and credit institutions, as they stand to benefit the most from such market developments. However, during the cycle's contractionary phase, these agents' behaviour has adverse implications not only for themselves, but for society as a whole, as it affects financial stability and the real economy. In other words, they cause negative externalities for the whole economy, and their incentives are therefore misaligned with those of the rest of society. This lack of internalisation of the agents' behaviour, coupled with the importance of the housing market to the economy, can have very significant macroeconomic effects. When house prices rise, banks have greater difficulty in discerning between good and bad borrowers, so they cannot properly assess the latter's creditworthiness, owing to the market failure known as "asymmetric information". Borrowers usually know their risk profile much better than lenders. However, in a period of rising house prices (typically associated with economic growth), the information gap between them may widen, as for example the bank may perceive the borrower as having greater job stability (and therefore income stability) than is actually the case. This is further exacerbated during bullish phases of the housing market cycle by banking competition for new customers and property overvaluation. Moreover, as shown by the academic literature (Dell'Ariccia, 2012), credit standards tend to ease during the real estate cycle's expansionary phase.

Over the last 50 years, the Spanish residential real estate sector has experienced several crises (namely in the mid-1970s, early 1980s, early 1990s and during the 2008 crisis),

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1 Figures at end-2022. In the case of the euro area, these data are available in Chapter 3.2 of the *Statistics Bulletin* of the European Central Bank, while for Spain they can be found in Chapter 16.6 of the *Statistical Bulletin* of the Banco de España.

2 As of December 2022. Calculated as the ratio of loans for house purchase and renovation taken out by households and non-profit institutions serving households (NPISHs) to the total liabilities of these sectors in the form of loans (from monetary financial institutions, general government and the rest of the world). The numerator of this ratio is available in Chapter 3.21 of the *Statistical Bulletin* of the Banco de España, while the denominator can be found in the *Financial Accounts of the Spanish Economy* published by the Banco de España.

when house prices fell in nominal and real terms (García-Montalvo, 2007). The crisis that began in 2008 was particularly deep and long-lasting, and affected both the financial system and the economy as a whole. The large build-up of imbalances in the real estate sector in the run-up to this crisis contributed decisively to its depth (Banco de España, 2017, or Santos, 2017).

Responsibility for helping prevent the build-up of risks, to preserve financial stability in different segments and sectors of the financial system, lies with the European Central Bank (ECB), the ESRB and the national authorities which, in the case of Spain, are the Banco de España and the Spanish macroprudential authority (AMCESFI).[3] Given the housing market's relevance as a potential source of risk, fulfilling this task calls for analysing the vulnerabilities related to the residential real estate sector.

In view of the significance of the real estate sector, because of both its weight in the economy and its potential impact on financial system stability, having available warning indicators linked to housing market developments is crucial. First, an appropriate set of indicators enables potential vulnerabilities and risks in this sector to be correctly monitored. In addition, such risk identification metrics serve to guide decision-making on activating, deactivating and calibrating the macroprudential tools for mitigating potential systemic vulnerabilities in this market.[4] One of the tools envisaged in Spanish legislation is the countercyclical capital buffer (CCyB), which is determined by developments in the financial cycle as a whole. Real estate market developments have a significant bearing on CCyB decisions, given that mortgage loans account for a large share of the portfolio of Spanish credit institutions. Moreover, other macroprudential measures have recently been developed to address potential vulnerabilities specific to the real estate sector, such as limits on credit standards (borrower-based measures, or BBMs[5]). These tools make it possible to address risks concentrated in specific sectors, such as the real estate sector, more effectively than aggregate macroprudential tools.

This paper presents a methodology developed by the Banco de España for monitoring and evaluating risks in the Spanish housing market. This methodology consists of two tools: a heat map and a synthetic indicator. The heat map is a data visualisation technique that colour-codes the magnitude of the risks. The variations in colour, as well as possible changes in the shade, allow the indicators to be read over time. Thus, drawing on a selection of key housing market indicators, a heat map is established in which the

3 AMCESFI is a collegiate body attached to the Ministry of Economic Affairs and Digital Transformation, dedicated to identifying, preventing and mitigating the build-up of systemic risk and ensuring a sustainable contribution by the financial system to economic growth. AMCESFI's powers include adopting opinions and issuing warnings and recommendations on macroprudential analysis and policy, i.e. its competences are advisory and non-binding in nature, and it plays an inter-institutional coordination role. For more details, see Royal Decree 102/2019 of 1 March 2019 creating the Spanish macroprudential authority, establishing its legal regime and implementing certain aspects relating to macroprudential tools.

4 See Recommendation of the ESRB of 4 April 2013 on intermediate objectives and instruments of macro-prudential policy (ESRB/2013/1).

5 See Circular 5/2021 of 22 December 2021 which implements three new macroprudential tools available to the Banco de España, including limits on credit standards.

observed values of each indicator are evaluated against certain critical thresholds, obtained from their historical statistical distribution. Each value therefore corresponds to a colour on the heat map (green, yellow, orange and red) indicating the different warning or risk levels (no warning, minor, moderate and high, respectively). Meanwhile, the synthetic risk indicator is constructed by aggregating all the information obtained from the individual indicators, and detects whether and to what extent the degree of vulnerability increases or decreases over time.

The paper is structured as follows. The section following this introduction describes the selection of warning indicators for the housing market, the methodology used to transform them into a heat map and the interpretation of the results from 2000 onwards. Section 3 presents a synthetic risk indicator for the housing market, describes its underlying methodology and shows developments therein since the early 2000s. Lastly, section 4 sums up the main conclusions drawn.

2 Heat map

2.1 Methodology

The heat map is constructed drawing on a selection of 26 indicators containing the information considered most relevant on various aspects characterising the Spanish residential real estate market. These indicators cover aspects ranging from real activity (such as the number of house purchases) and financing (the amount of housing loans granted and the terms and conditions of those loans) to price developments (how much transaction and rental prices change) and household financial position (level of indebtedness and saving rate).

The indicators selected have been classified into the following five categories: 1) real activity and demographic factors, 2) credit developments, 3) credit standards for new loans, 4) household financial position, and 5) house valuation. Table 1 lists the variables used according to this classification.

The indicators considered only provide information at national aggregate level, i.e. they do not take into account more granular developments that could potentially be relevant for identifying risks. For example, at a given point in time, the average debt of Spanish households may be at prudent levels, but this could be compatible with the existence of a growing subset of over-indebted households. Similarly, while the house valuation indicators may suggest there is no overvaluation at the national level, this may not be the case in certain areas,[6] as the housing market is highly heterogeneous and location is a key price determinant. In the future, the heat map could be enriched by incorporating more granular indicators to identify such developments. Similarly, the heat map allows for the inclusion of new variables that could be considered in the future to capture relevant aspects of the real estate market situation.

The heat map is constructed by drawing on changes in the original indicators selected and calculating some transformations (such as ratios between different variables, rates of change, and differences between the levels of two variables). Some of the variables used, such as some house valuation indicators, are derived from the results of econometric modelling. Thus, the original 26 variables yield a final set of 52 indicators, following the various transformations and manipulations of the original data. By way of example, based on the original time series of monthly house purchases, we calculate the cumulative 12-month figure (so as to reduce the volatility of the variable) and conduct three transformations: the annual rate of change, the three-year average annual rate of change and the share of house purchases to total households. Table A.1 of the Annex shows the complete list of the 26 base variables used, together with their definitions, the transformations carried out in each time series and how they are constructed, their source, frequency and the date from when they are available.

The heat map is created by associating a colour to each indicator value according to the warning level. Four colours are used: green, yellow, orange and red. Green indicates

6 See Álvarez and García-Posada (2019) for a modelling of long-term equilibrium house prices in Spain by province.

Table 1
CLASSIFICATION OF HOUSING MARKET INDICATORS BY CATEGORY

Category	Indicators
Real activity and demographic factors	Housing approvals House purchases Construction workers registered with Social Security Difference between housing starts and change in households
Credit developments	Stock of loans for construction and real estate activities Stock of housing loans New housing loans Non-performing loans for house purchase
Credit standards for new loans	Loan-to-value (LTV) ratio Loan-to-price (LTP) ratio Overvaluation ratio (LTP/LTV) Maturity period Proportion of mortgages with certain maturity and LTP characteristics Interest rates
Household financial position	Financial and total wealth Indebtedness Debt burden Saving rate
House valuation	Real transaction prices Valuation models: i) deviation of housing prices from their long-term equilibrium level, ii) deviation of housing prices from the Hodrick-Prescott trend, iii) deviation of the price-to-gross disposable income (GDI) ratio from its historical average and iv) the residual of the regression of housing prices on the GDI Affordability Gross housing rental yield Housing rental prices

SOURCE: Devised by authors.

the absence of any warnings, yellow indicates a minor warning, orange a moderate warning, and red a high warning. The warning level thresholds are calculated drawing on the historical percentiles of each indicator's distribution.[7] As shown in Table 2, in the case of right-tail indicators (the majority of the heat map variables), for which an increase in value denotes a higher risk, green is assigned when the value is below the 50th percentile of the historical statistical distribution, yellow when it is between the 50th and 69th percentiles, orange when it is between the 70th and 84th percentiles, and red when it is above this last threshold. In the case of the left-tail indicators, for which a lower value represents a higher risk,[8] the colours are assigned symmetrically with the indicators mentioned above. Finally, as regards the four indicators for the house valuation models,[9] which are also right-tail, a different procedure is

7 In the years leading up to the 2008 global financial crisis, risk-taking was clearly excessive and inclusion of this period could influence the tolerance level of the indicators. Therefore, an alternative exercise has been carried out, excluding the period 2003-2007, to assess the impact on the warning signals. The results show that, broadly speaking, there would be no significant changes, with only a few indicators yielding somewhat stronger warning signals in 2002 and in previous years.

8 Specifically, the indicators related to interest rates (the median spread over the benchmark market interest rate and the interquartile range of this spread), households' wealth (net financial and net total), the saving rate (gross and gross not earmarked for debt service) and gross rental yield.

9 Specifically, this criterion applies to the following indicators: deviation of housing prices from their long-term equilibrium level and deviation of housing prices from the Hodrick-Prescott trend, deviation of the price-to-gross disposable income (GDI) ratio from its historical average, and the residual of the regression of housing prices on GDI.

Table 2
HEAT MAP COLOUR CODES

Right-tail indicators

Increasing values → Greater vulnerability

Warning level	NO WARNING	MINOR	MODERATE	HIGH
Percentile	Below 50	Between 50 and 69	Between 70 and 84	85 or above

Left-tail indicators

Increasing values → Lesser vulnerability

Warning level	HIGH	MODERATE	MINOR	NO WARNING
Percentile	Below 15	Between 15 and 29	Between 30 and 49	50 or above

Indicators for house valuation models

Increasing values → Greater overvaluation

Warning level	NO WARNING	MINOR	MODERATE	HIGH
Threshold and percentile	0 or negative	Below 40	Between 40 and 69	70 or above
		Percentiles calculated using only positive values		

SOURCE: Devised by authors.

applied. Green is allocated when the value is zero or negative, as in such cases there are no signs of overvaluation. A positive value indicates there are signs of overvaluation and thus triggers a warning, whose colour is assigned based on the historical percentiles of the distribution, calculated on the basis of observations with positive values. Specifically, yellow is assigned when the value is below the 40th percentile of the distribution, orange when it is between the 40th and 69th percentiles, and red when it is above this last threshold. This procedure therefore generates the same relative size of the observations located in the warning zone (colour other than green) as in the two foregoing cases (right-tail and left-tail indicators).

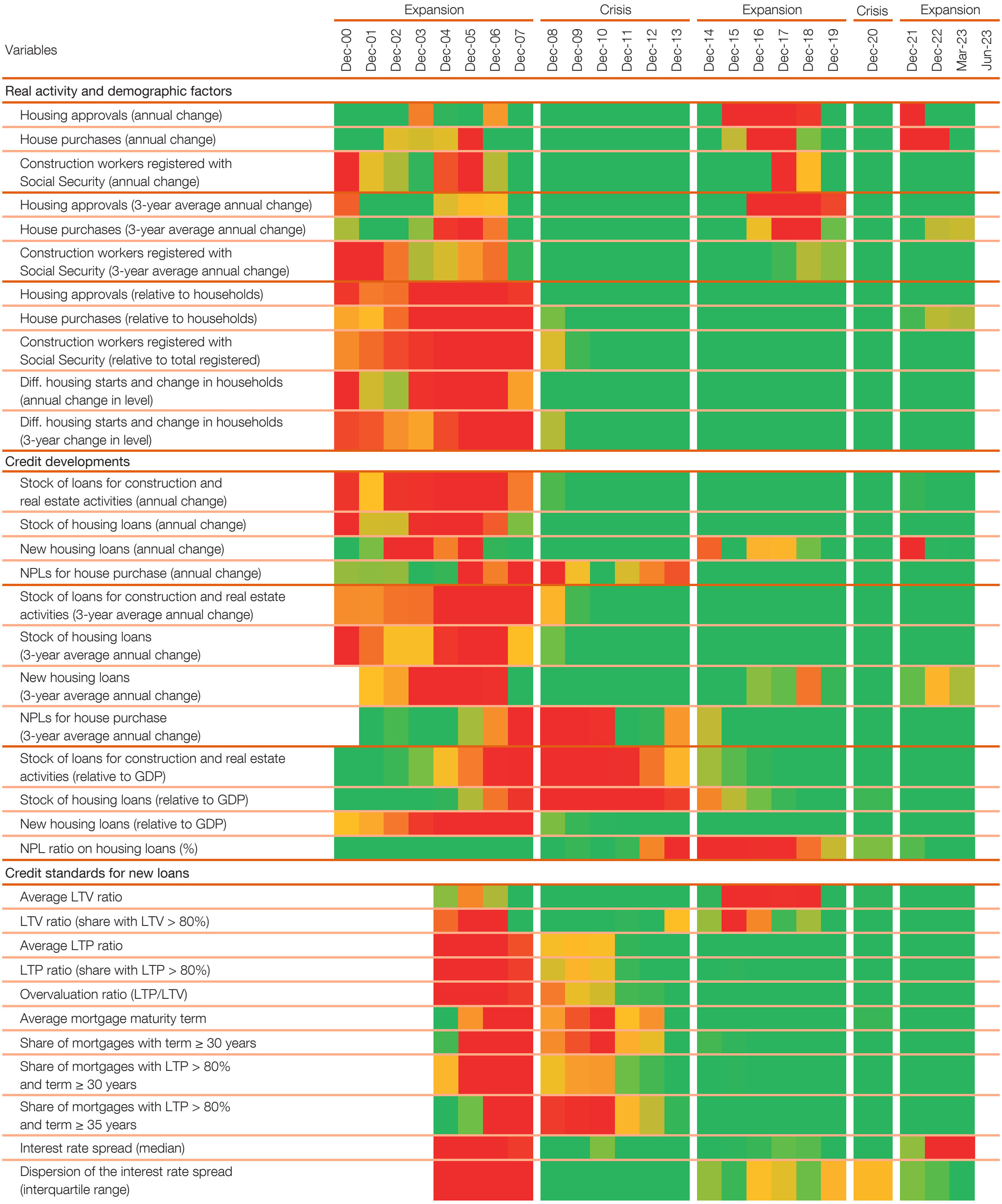
2.2 Results

The heat map results at each year-end between 2000 and 2022, and with a quarterly frequency thereafter, are presented in Table 3.[10] This enables a historical perspective on the changes in risks in the Spanish housing market in the 21st century to date.

10 The indicators for the credit standards for new loans category are only presented from 2004, as prior data are not available.

Table 3

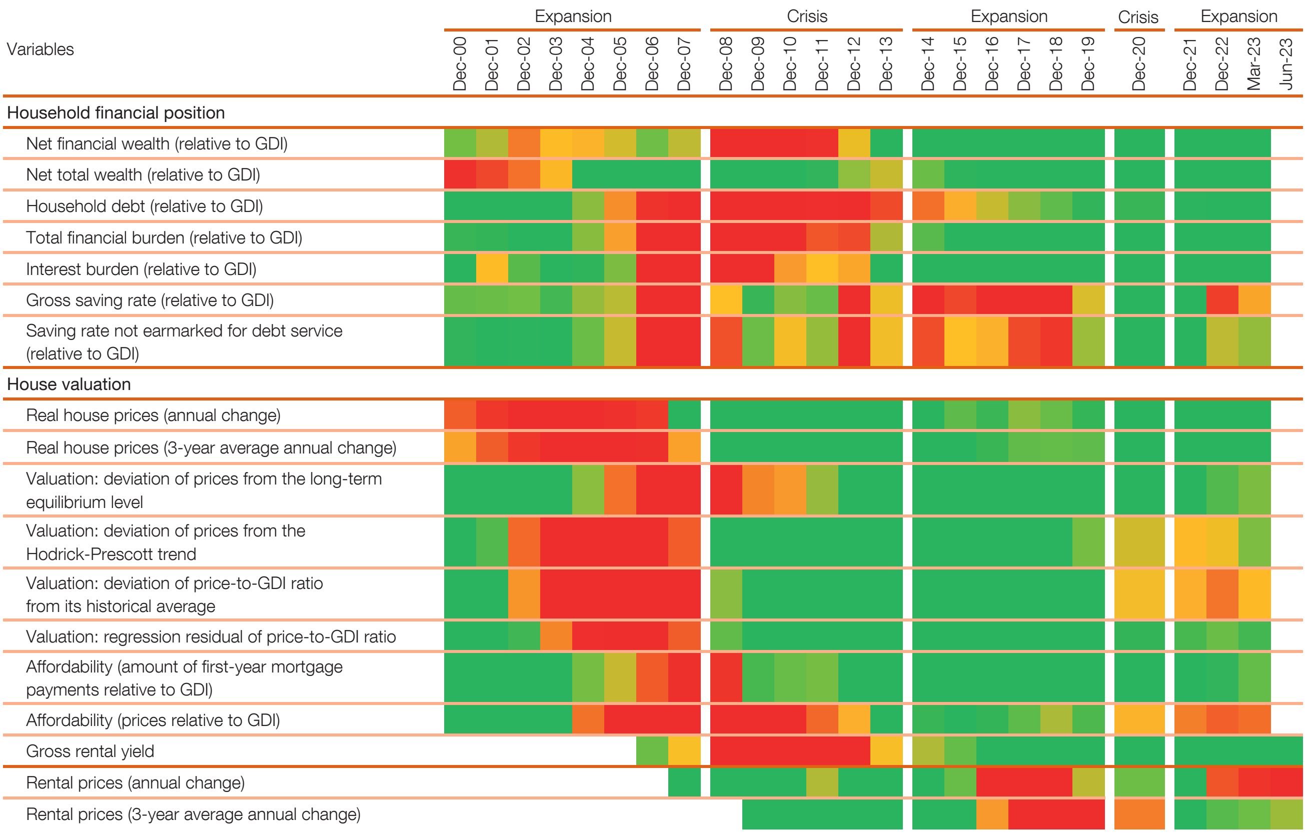
HEAT MAP OF THE SPANISH HOUSING MARKET SINCE 2000



SOURCE: Devised by authors. Latest observation: 2023 Q2.
NOTE: Green: no warning; yellow: minor warning; orange: moderate warning; red: high warning.

Table 3

HEAT MAP OF THE SPANISH HOUSING MARKET SINCE 2000 (cont'd)



SOURCE: Devised by authors. Latest observation: 2023 Q2.
NOTE: Green: no warning; yellow: minor warning; orange: moderate warning; red: high warning.

As can be seen in Table 3, during the early 2000s and until the 2008 global financial crisis, most indicators issued increasing warning signals, in many cases reaching peak levels (red) several years before the crisis began. For instance, this period saw very marked growth in activity (both housing supply and demand) and in bank financing, loose credit standards for new loans, a deterioration in households' financial position and signs of house price overvaluation.

As Table 3 shows, the warning signals are triggered earlier or later depending on the nature of the indicator. For example, high annual rates of change in an indicator, if they persist, translate into high three-year average annual rates of change, as observed in the activity and credit development indicators during the boom prior to the global financial crisis. In the case of house valuation, the first warning signal was observed in the form of strong transaction price growth, which, as it continued over time, led to signs of overvaluation. For other variables, such as non-performing loans (NPLs) for house purchase, the warning signal was very late and, indeed, there were no signals until 2005 (in the case of year-on-year growth in such loans) and 2012 (in the case of the NPL ratio).

During the 2008-2013 economic recession, the imbalances in the real estate market were progressively corrected, as reflected in the gradual disappearance of the warnings. The pace at which these warnings disappeared varied depending on the indicator used. Although they disappeared comparatively very quickly for the activity and price growth indicators, they were slower to fade in the case of those such as household indebtedness, the growth in NPLs and the NPL ratio, the debt burden and the credit-to-GDP ratio (both for construction and real estate activities, and for house purchase). This was attributable to the very nature of some of these variables and the particularities of this economic crisis.

In the period of economic growth that began in 2014 and continued until the outbreak of the COVID-19 pandemic in early 2020, both real estate activity and prices saw a recovery. Some indicators measuring growth in activity and new lending showed warning signals during this time, reflecting the strong growth in activity from very low levels after the long crisis. By contrast, activity and credit indicators in terms of percentages (ratios of housing approvals and house purchases to households, and ratios of new loans and the stock of new loans to GDP) did not issue warning signals, which qualifies and detracts from the signal drawn from the foregoing variables. Meanwhile, the warning for the NPL ratio on housing loans remained at high, albeit declining, levels owing to the long period of time taken to clean up banks' balance sheets. The credit standards for new housing loans indicators produced hardly any warning signals during this period, with only the average loan-to-value (LTV) ratio showing somewhat more persistent and stronger warning signals, while the share of mortgages with an LTV ratio above 80% (a measure of prudence in bank lending) issued more moderate and isolated warnings. In the case of house valuation indicators, the warning regarding rental price growth stands out. Turning to the household financial position, there were persistent warning signals for the saving rate (which remained at historically low values), and decreasing warnings in the case of the debt-to-income ratio, showing how slowly this imbalance was corrected.

The COVID-19 pandemic broke out when the housing market cycle in Spain was mature and there were no clear signs of imbalances. Real estate activity fell sharply in the early months of the pandemic, affected by the mobility restrictions introduced by the authorities. The warnings for household saving detected in previous years disappeared in 2020, as the health crisis led to a strong rebound in the saving rate, thanks to forced saving on account of the restrictions.[11] The warning for rental prices also disappeared, as such prices moderated.

Housing demand and lending volumes saw a strong boost from 2021 onwards, owing to the large savings accumulated by households, the new household needs arising from the increase in remote working, the historically low interest rates on new loans and the rebound effect of activity (which had come to a standstill during the worst of the pandemic). Thus, new housing loans grew strongly in 2021 and 2022 H1, triggering some warning

11 For an analysis of Spanish household savings during the pandemic, see Alves and Martínez-Carrascal (2023).

signals in the indicators that capture credit growth. The annual rates of change in some activity indicators also showed some warning signals, but these are partly explained by base effects and only proved more persistent in the case of house purchases. House purchases and lending started to slow down towards end-2022, largely on account of monetary policy tightening, which resulted in a sharp rise in financing costs. This led to the disappearance of warnings linked to real estate and mortgage market activity.

Transaction prices accelerated from 2021 onwards, triggering moderate warning signals from some valuation indicators. Since 2022 H2, the fall in housing demand, linked mainly to higher interest rates, has contributed to a sharp deceleration in prices, which has helped ease some warning signals. However, the interest rate hike has gradually raised the warning from valuation indicators that take into account the cost of financing.

The fact that higher interest rates are passed through more slowly to new housing loan rates than to market rates (a difference that appears to be even more pronounced in this cycle than in past rate hike episodes)[12] has led the spreads on mortgage rates to narrow, prompting warning signals from this indicator in the recent period.

Meanwhile, rental prices began to accelerate from mid-2022, and the warning signals have increased and become stronger so far in 2023. Finally, the elimination of all pandemic restrictions (which has been conducive to consumption), coupled with high inflation rates and below-inflation income growth, has led the gross saving rate to fall below its historical average since 2022 H2. In recent months, however, this loss of purchasing power appears to have slowed down, which, together with sluggish consumption, is helping improve households' ability to save.

12 For an analysis of the pass-through of market interest rates to bank interest rates, see Mayordomo and Roibás (2023).

3 Synthetic risk indicator

The heat map presented in the previous section depicts the current housing market situation and its evolution over time drawing on a broad set of indicators. However, while these indicators provide a comprehensive and detailed picture of the housing market situation, it may at times be difficult to interpret them together, as there are a high number of individual indicators in the heat map, which may not necessarily move in the same direction. A disaggregated analysis can therefore give mixed signals. For example, when the housing market began to recover in 2014, the activity indicators picked up significantly, triggering some warning signals, which would suggest a situation of greater vulnerability. Conversely, other indicators, such as household indebtedness, declined, which would suggest a reduction in risk.

To address the above-mentioned difficulties, a synthetic index has been developed that condenses into a single indicator the level of housing market vulnerability. This aggregate indicator is constructed from a subset of the individual heat map indicators,[13] and is partly inspired by similar exercises by other authorities to condense housing market information (ESRB, 2019b).

3.1 Methodology

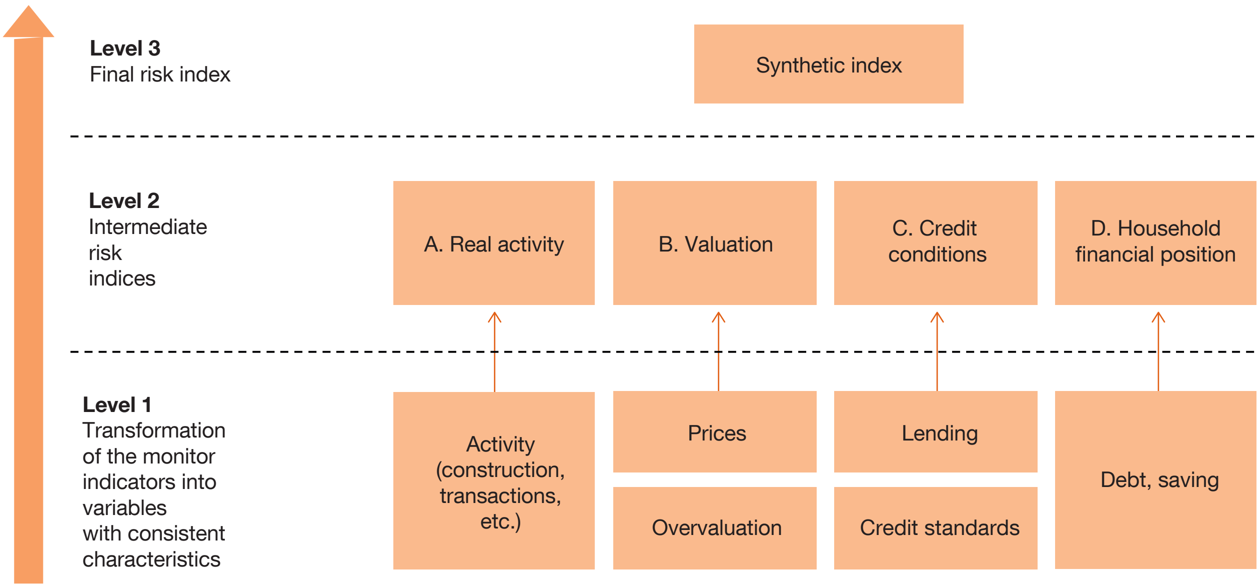
The synthetic index is constructed on the basis of a representative set of individual warning indicators (20 in total) covering the four most important market categories: 1) real activity; 2) house valuation; 3) credit conditions; and 4) household financial position.

Figure 1 summarises the methodology followed to construct the synthetic index, which consists of three stages. In the first stage, given their very different statistical distributions, the heat map indicators need to be transformed, to standardise them following a procedure described below. This first stage yields new variables with the same scale and distribution (level 1). In the second stage, all the individual variables standardised for each of the four categories defined above are aggregated, producing four intermediate indices. To do so, we calculate linear combinations of these indicators with optimal weights for each of the four categories by conducting a principal component analysis (level 2). These weights are optimal because they summarise the redundant information in the individual indicators by drawing on a statistical procedure. Finally, in stage three, we calculate the synthetic index for the housing market using a simple average of the intermediate indices (level 3).[14]

13 With some exceptions, indicators are taken at levels rather than at rates of change, as the latter are more volatile and provide less information about the severity of imbalances throughout the cycle. Among the activity indicators (see Table 3), we consider those that are presented as a percentage of total households, in addition to the difference between housing starts and changes in households (annual change in this indicator). Among the changes in lending indicators, those presented as a percentage of GDP are taken. For credit standards, a probability model based on Galán and Lamas (2023) is considered, which takes into account several indicators, most of which are included in the heat map. Moreover, all household financial position indicators, except for those measuring wealth, are taken. Lastly, real house price developments (annual change), all indicators under the “House valuation” heading in Table 3 and all indicators measuring affordability are taken into account.

14 There are other proposals for summarising the severity of housing market vulnerabilities. For example, ESRB (2019b) proposes weighting the indicators used to monitor risks in this market by their crisis-predictive power.

Figure 1
METHODOLOGY FOR PREPARING THE HOUSING MARKET SYNTHETIC INDEX



SOURCE: Devised by authors.

3.1.1 Transformation of the indicators

As mentioned above, the original heat map variables are transformed before being aggregated into the four intermediate indices. A very common technique for data harmonisation is to standardise the data, i.e. to calculate the Z-scores. To do this, the average of the indicator in the sample is subtracted from each observation and this difference is divided by the standard deviation. This normalisation yields homogeneous variables distributed as a normal variable with a zero mean and unit variance. However, this type of normalisation-based standardisation has some drawbacks. For example, some of the heat map indicators do not have normal distributions and, therefore, the results of this transformation could be highly sensitive to outliers (many observations in the tails of the distribution), which may in turn lower the information value of some normalised variables. In addition, a normalised index may be unstable if further outliers are added in the future, as these materially affect the calculation of the mean and standard deviations of the distributions.

To address these drawbacks, we decided to transform the indicators using their empirical cumulative distribution function (ECDF), in line with the literature on financial stress indicators (Holló, Kremer and Lo Duca, 2012). The calculation of the ECDF is relatively immediate. First, the observed values of the indicators x_t with sample size T are ordered so that for each original time series of indicator $x_t = (x_1, x_2, \ldots, x_T)$, a new time series is obtained with its values ordered $x_{[t]} = (x_{[1]}, x_{[2]}, \ldots, x_{[T]})$. In this transformed series, $x_{[1]}$ represents the indicator's lowest value and $x_{[T]}$ its highest value. To obtain the transformed indicator z_t, the numerical ranking is then assigned to each x_t (r) value and this result is divided by sample size T:

$$z_t = \frac{r}{T} \text{ for } x_{[r]} \leq x_t < x_{[r+1]},\ r = 1, 2, ..., T \tag{1}$$

where r indicates the position assigned to each value of the variable.[15] The new variables range from 1/T to 1, which represent the minimum and maximum values, respectively, of the original indicator's distribution. In other words, a value near zero would indicate that this figure is close to the variable's minimum value, while a value close to one indicates that it is close to the maximum value. To construct the housing market synthetic index and intermediate indices, the transformed individual variables, z_t, were calculated so that higher values indicate higher risk and lower values indicate lower risk.[16] In addition, to achieve a more stable synthetic index, from 2013 Q4 onwards all transformations were computed recursively, and the transformed indicators are recalculated whenever new observations are included, whereas before that date, the same sample is always considered for calculating the transformed indicators (z_t).

To illustrate this transformation, Chart 1 shows one of the house price imbalance indicators (the one that uses the Hodrick-Prescott filter) in its original form and after the ECDF-based transformation. The transformed indicator has a very similar pattern to the original indicator: both peak just before the financial crisis, while the trough occurs in 2013. In this case, higher (lower) values would be consistent with a high (low) degree of house price overvaluation, associated with a higher (lower) level of vulnerability.

By construction, the distance between two consecutive observations in the transformed indicators is always the same (1/T), so statistics such as the mean or the variance are comparable between these indicators. In addition, with this methodology it is easier to distinguish inflection points in the property cycle. This is because changes in the transformed variables are more pronounced at the central points of the distribution (start of upswings/slowdowns) than at the tails (peaks/troughs of the cycle).[17] However, the distance between consecutive observations of z_t being constant may result in some loss of information in the analysis of outliers. Therefore, z_t indicators should not be used to compare the severity of imbalances between the peaks in two upturns, or the extent of the downturns. For example, the original indicator in Chart 1 shows that the trough reached during the financial crisis is much lower than in the first part of the 1990s. However, disregarding the difference in scale, the disparity between the two troughs is much less evident in the transformed indicator. On the positive side, this property means the transformation is not sensitive to the presence of outliers.

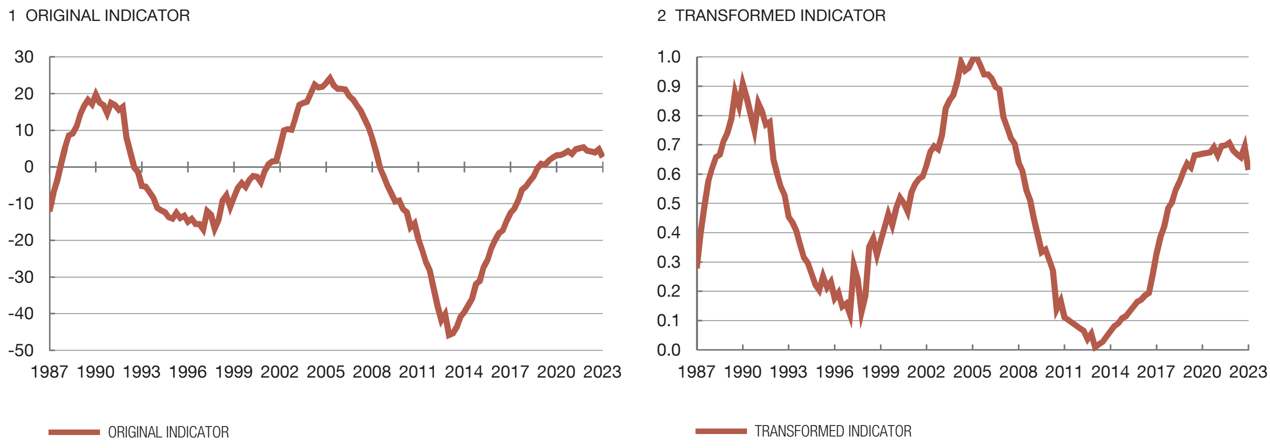
15 Repeated values are assigned the average of their position in the variable's order.

16 It should be noted that, in the case of certain indicators that signal risks when very low values are reached (left-tail indicators), a prior operation is necessary to ensure correct interpretation. An example of this is the gross saving rate indicator, where low values point to a deterioration in household financial position and, therefore, to greater risk. To modify this indicator, Y = 100% - X is calculated, where X is saving (as a percentage). This transformation means that higher values for Y signal greater risk.

17 In addition, real estate indicators typically exhibit some inertia, i.e. increases in the value are usually followed by further increases, and vice versa (Agnello and Schuknecht, 2011).

Chart 1

HOUSE PRICE IMBALANCES INDICATOR BASED ON THE HODRICK-PRESCOTT FILTER



SOURCE: Banco de España calculations. Latest observation: 2023 Q1.
NOTE: The original indicator is the house price imbalances indicator based on the Hodrick-Prescott filter.

Most indicators are close to one in the run-up to the 2008 financial crisis, signalling a high level of risk (see Chart 2). After this crisis broke, these values tend to decline gradually, suggesting that risks decrease once they have materialised and the imbalances start to be corrected.

3.1.2 Construction of the intermediate indices for each risk category

Once the individual indicators have been transformed, they are aggregated into intermediate indices for each of the four defined categories (real activity, house valuation, credit conditions and household financial position). These intermediate indices have the same statistical properties as the z_t indicators defined above.

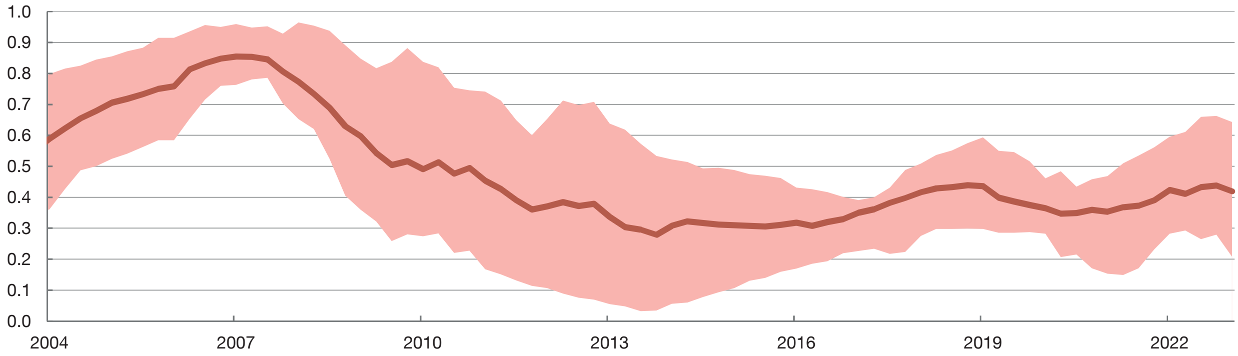
The main method used to aggregate the transformed individual indicators is based on a principal component (PC) analysis. This technique makes it possible to find linear combinations of the z_t indices with which to obtain one or a few PCs that explain most of the variability in these indicators, and whose information does not overlap.[18]

This PC-based statistical approach to aggregating individual indicators is particularly useful in those cases, as with most heat map indicators, where no objective economic criteria are available to determine the contribution of the individual indicators to risk severity. For example, it is difficult to discern which house price overvaluation indicator is most important for capturing real estate risks, as, among other factors, the equilibrium house price is not observable.

18 See Broto and Lamas (2016) for an exercise where a similar aggregation is proposed for a set of liquidity indicators in the United States.

Chart 2
DESCRIPTIVE STATISTICS OF THE TRANSFORMED INDICATORS

1 AVERAGE VALUE OF THE TRANSFORMED INDICATORS AND INTERQUARTILE RANGE



SOURCE: Banco de España calculations. Latest observation: 2023 Q1.
NOTE: The shaded area denotes the interquartile range of the transformed indicators, while the line shows their average value in each period.

One advantage of the PC-based method is that it strips out redundant information from highly correlated variables. This would be the case, for example, of the activity indicators, where certain metrics, such as numbers registered with Social Security in the construction sector and housing approvals, probably capture the same information.

This methodology is applied to all cases, except for credit standards (LTV ratio, LTP ratio, etc.), which fall under the credit conditions category, for which there is a model that approximates the probability of default based on credit standards.[19] The probability of default is subsequently transformed into a z_t indicator using its ECDF. The intermediate index of the credit conditions category is calculated as the simple average between this indicator and the indicator summarising the growth of financing in the housing market, obtained via the PC method.

The PC-based methodology used to aggregate the individual indicators is described below. First, for each risk category the PCs are obtained as follows:

$$PC_1 = \sum \left(a_{[t,1]} \times z_t\right),$$

$$PC_2 = \sum \left(a_{[t,2]} \times z_t\right),$$

$$\ldots$$

$$PC_N = \sum \left(a_{[t,N]} \times z_t\right), \quad (2)$$

19 A logit model. For a description of this model, see Galán and Lamas (2023).

where a indicates the weights corresponding to the transformed indicators z_t in each PC, and N the number of indicators z_t in each category.[20]

Given the strong correlation between the indicators within each category, one or two PCs are enough to explain most of the variability in the individual indicators (in particular, more than 80% of the variance). When in one category a single PC contains enough information on the indicators (i.e. when this PC explains more than 80% of the variance), the weights are obtained directly from that PC (by construction, the sum of the squares of a is equal to one, so the weights are calculated immediately). By contrast, when more than one PC needs to be considered to ensure that the explained variance exceeds 80%, the intermediate index is obtained by weighting each PC by its contribution to the variance of the original indicators in each category.[21, 22]

3.2 Results

The final synthetic index is calculated as the simple average of the four intermediate indices. Chart 3.1 depicts changes in the index from 2004 to 2023 Q1, as well as the contribution of each intermediate index. Meanwhile, Chart 3.2 shows the annual change in this index and breaks it down into each of the intermediate categories.[23]

Chart 3.1 illustrates how in the boom years prior to the global financial crisis, which started in late 2008, there was a significant increase in risks in the Spanish housing market. Chart 3.2 shows that all the intermediate categories, whose indices steadily increased, particularly in the case of household financial position and credit conditions, contributed to this increase, reaching the highest values of the time series during this period. All the indicators slowed down shortly before the real estate crisis broke, although the household financial position indicators did so somewhat later. Two phases can be distinguished in the crisis. In the first phase, which ran up to 2010 Q1, the adjustment in the activity indicators is the leading factor, accounting for more than half of the fall in the overall index during that period. The remainder of the decline is due to tightening credit conditions, in addition to the diminishing severity of the risks in the valuation and household financial position (deleveraging and higher levels of saving) categories. In the second phase of the crisis, which ran, with some ups and downs, to late 2013, credit conditions play a more important role in the decline of the index.

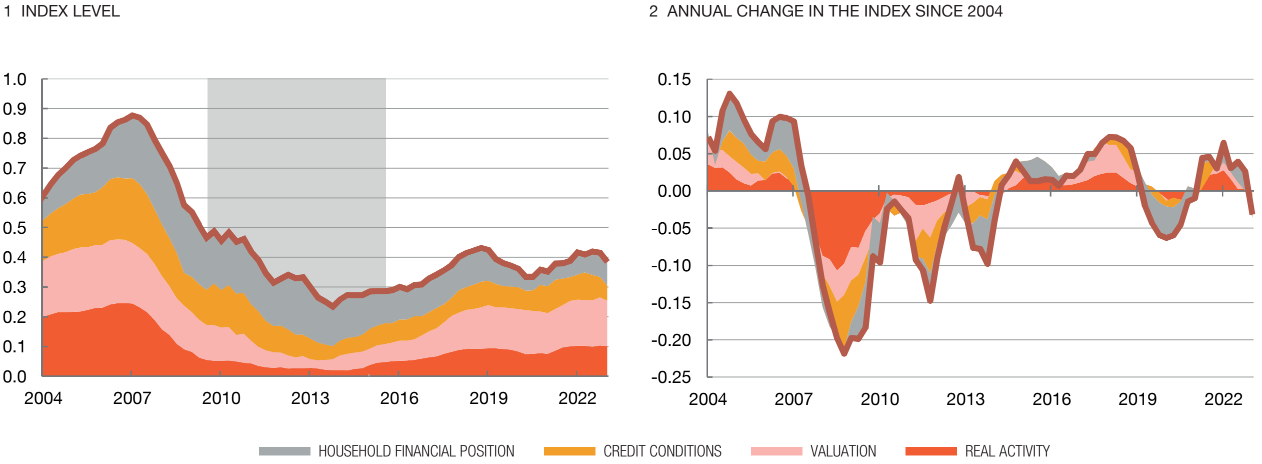
20 The weights a satisfy several conditions: 1) they are orthogonal; 2) the PCs are ordered so that the first PC explains the highest proportion of the Z_t indicator variance, while the last indicator explains the lowest percentage of the variance; and 3) $a_{t1}{}^2 + a_{t2}{}^2 + ... + a_{tN}{}^2 = 1$, where t = 1, 2, ..., N.

21 There are five N indicators in the activity indicator category, six for credit conditions, seven for valuation and five for household financial position.

22 We used the methodology proposed in OECD (2008) to summarise information from several PCs. First, for each individual indicator we selected the highest squared weight (a^2) from among the PCs (e.g. with two PCs, there will be two a^2 per indicator, and we chose the one with the highest value). Secondly, the weight of each a^2 is multiplied by the proportion of the variance in the original indicators explained by the PCs. By construction, this procedure ensures that the indicator weights in each category add up to one.

23 The year-on-year change is calculated as $I_t - I_{t-4}$, where I denotes the final housing market indicator and $_t$ indicates the quarter.

Chart 3
SYNTHETIC INDEX OF SPANISH HOUSING MARKET VULNERABILITIES



SOURCE: Banco de España calculations. Latest observation: 2023 Q1.
NOTE: The grey shaded area shows the period of the real estate crisis (2009 Q1-2013 Q4), which coincides with that identified by Lo Duca et al. (2017).

Between early 2014 and mid-2019 the index followed an upward path, which indicates an upturn in the real estate market. This trend was mainly driven by changes in the activity and valuation indicators, reflecting the recovery in demand and prices. By contrast, unlike during the pre-global financial crisis boom years, no significant increase in risks was detected in the other categories (credit conditions and household financial position) during this period. As a result, despite having risen, in mid-2019 the index stood at levels well below those observed in the years leading up to the global financial crisis.

During 2019 H2, the index followed a downward path that indicated that the real estate market was in a mature phase of the expansionary cycle, which was reflected in weaker activity and a slowdown in prices. The outbreak of the COVID-19 crisis in early 2020 initially intensified these trends. However, as the mobility restrictions were eased, the real estate market regained momentum in terms of prices and transactions. All this resulted in an increase in the synthetic indicator that was driven by the activity, credit conditions and, to a lesser extent, valuation indicators. The index has started to decline since 2022 Q4, reflecting the real estate market's loss of steam resulting from monetary policy tightening.

In short, the synthetic index seems to adequately capture both the severity and composition of the real estate market risks at each point in time. Therefore, this index is a very useful tool to complement the analysis derived from the individual warning signals described in the first part of this paper.

4 Conclusions

The housing market plays a pivotal role in maintaining financial stability. Indeed, over the last 50 years it has undergone several crises, some of them with negative financial stability implications, such as the crisis that broke in 2008. Various authorities, such as the ECB, the ESRB and AMCESFI, stress the need for an appropriate analytical framework to assess developments in this market and, where appropriate, guide the activation of macroprudential measures, i.e. actions that mitigate the risks stemming from this market.

This paper presents a methodology to develop a heat map of the housing market in Spain. The heat map is a tool that uses colour-coding to depict risk severity and is based on a broad set of indicators that measure different dimensions of risk. Thus, it includes indicators of buyer and seller activity, supply and price developments, and metrics that report on possible price imbalances, in addition to indicators that measure lending and the credit quality of the loans granted by institutions. The colour codes denote the level of risk calculated drawing on the historical distribution of each of the indicators considered.

The heat map information is then condensed into a synthetic indicator, which consists of a single metric obtained from a statistical procedure where potentially redundant information is stripped out from the individual indicators. The aggregate synthetic indicator is suitable for assessing whether vulnerabilities increase or decrease over time according to the historical information available. Its design also allows changes in the property cycle to be detected during early phases of risk build-up, which is precisely when it is most advisable to activate macroprudential tools. However, this paper does not examine the crisis-predictive power of the aggregate synthetic indicator.

Changes in the individual indicators and the synthetic measure efficiently summarise the course of the property cycle in Spain. Specifically, both show a significant build-up of vulnerabilities prior to the financial crisis, which then materialised after it broke. From late 2013, the indicators showed some moderate warning signals, mainly linked to the recovery in activity and prices. During the pandemic the real estate cycle slowed somewhat, but once the worst phase was over, the cycle regained momentum. More recently, and amid the current monetary policy tightening, the property cycle is slowing once again, with the build-up of housing market vulnerabilities easing.

References

Agnello, Luca, and Ludger Schuknecht. (2011). "Booms and busts in housing markets: Determinants and implications". *Journal of Housing Economics,* 20(3), pp. 171-190. https://doi.org/10.1016/j.jhe.2011.04.001

Álvarez, Laura, and Miguel García-Posada. (2019). "Modelling regional housing prices in Spain". Documentos de Trabajo, 1941, Banco de España. https://www.bde.es/f/webbde/SES/Secciones/Publicaciones/PublicacionesSeriadas/DocumentosTrabajo/19/Fich/dt1941e.pdf

Alves, Pana, and Carmen Martínez-Carrascal. (2023). "The accrual and use of the excess savings built up by Spanish households since the onset of the pandemic". *Economic Bulletin - Banco de España,* 2023/Q2, 08. https://doi.org/10.53479/30229

Banco de España. (2017). *Report on the financial and banking crisis in Spain,* 2008-2014. https://repositorio.bde.es/bitstream/123456789/15112/1/InformeCrisis_Completo_web_en.pdf

Broto, Carmen, and Matías Lamas. (2016). "Measuring market liquidity in US fixed income markets: A new synthetic indicator". *The Spanish Review of Financial Economics,* 14(1), pp. 15-22. http://dx.doi.org/10.1016/j.srfe.2016.01.001

Dell'Ariccia, Giovanni. (2012). "Property Prices and Bank Risk-taking". In Heath, Alexandra, Frank Packer and Callan Windsor (eds.), *Property Markets and Financial Stability.* Reserve Bank of Australia. https://www.rba.gov.au/publications/confs/2012/pdf/dellariccia.pdf

ESRB. (2013). "Recommendation of the European Systemic Risk Board of 4 April 2013 on intermediate objectives and instruments of macro-prudential policy". *Official Journal of the European Union,* 15 June. https://www.esrb.europa.eu/pub/pdf/recommendations/2013/ESRB_2013_1.en.pdf

ESRB. (2019a). *Vulnerabilities in the residential real estate sectors of the EEA countries.* https://www.esrb.europa.eu/pub/pdf/reports/esrb.report190923_vulnerabilities_eea_countries~a4864b42bf.en.pdf

ESRB. (2019b). *Methodologies for the assessment of real estate vulnerabilities and macroprudential policies: residential real estate.* https://www.esrb.europa.eu/pub/pdf/reports/esrb.report190923_methodologies_assessment_vulnerabilities_macroprudential_policies~7826295681.en.pdf

Galán, Jorge E., and Matías Lamas. (2023). "Beyond the LTV ratio: lending standards, regulatory arbitrage and mortgage default". *Journal of Money, Credit and Banking,* February. https://doi.org/10.1111/jmcb.13041

García-Montalvo, José. (2007). "Algunas consideraciones sobre el problema de la vivienda en España". *Papeles de Economía Española,* 113, pp. 138-155. https://www.funcas.es/wp-content/uploads/Migracion/Articulos/FUNCAS_PEE/113art11.pdf

Holló, Dániel, Manfred Kremer and Marco Lo Duca. (2012). "CISS - A Composite Indicator of Systemic Stress in the Financial System". Working Paper Series, 1426, ECB. https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1426.pdf

Jordà, Òscar, Moritz Schularick and Alan M. Taylor. (2015). "Leveraged bubbles". *Journal of Monetary Economics,* 76, pp. S1-S20. https://doi.org/10.1016/j.jmoneco.2015.08.005

Lo Duca, Marco, Anne Koban, Marisa Basten, Elias Bengtsson, Benjamin Klaus, Piotr Kusmierczyk, Jan Hannes Lang, Carsten Detken and Tuomas Peltonen. (2017). "A New Database for Financial Crises in European Countries: ECB/ESRB EU Crises Database". Occasional Paper Series, 194, ECB. https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op194.en.pdf

Mencía, Javier, and Jesús Saurina. (2016). "Macroprudential policy: objectives, instruments and indicators". Documentos Ocasionales, 1601, Banco de España. https://repositorio.bde.es/bitstream/123456789/6354/1/do1601e.pdf

Mayordomo, Sergio, and Irene Roibás. (2023). "The pass-through of market interest rates to bank interest rates". Documentos Ocasionales, 2312, Banco de España. https://doi.org/10.53479/34572

Organisation for Economic Co-operation and Development (OECD). (2008). *Handbook on Constructing Composite Indicators.* https://www.oecd.org/sdd/42495745.pdf

Rünstler, Gerhard, and Marente Vlekke. (2018). "Business, housing and credit cycles". *Journal of Applied Econometrics,* 33(2), pp. 212-226. https://doi.org/10.1002/jae.2604

Santos, Tano. (2017). "El Diluvio: The Spanish Banking Crisis, 2008-2012". Columbia Business School and NBER, 13 July. https://ypfsresourcelibrary.blob.core.windows.net/fcic/YPFS/Santos_The_Spanish_Banking_Crisis_2017.pdf

Annex

Table A.1
DESCRIPTION OF THE INDICATORS FOR THE RESIDENTIAL REAL ESTATE MARKET IN SPAIN

Indicator	Source	Frequency	Start date	Transformation/ units	Observations
REAL ACTIVITY AND DEMOGRAPHIC FACTORS					
Housing approvals	Ministry of Transport, Mobility and Urban Agenda	Monthly Monthly Quarterly	Oct-93 Oct-95 Dec-92	Annual change (%) 3-year average annual change (%) Level (% of households)	Shows the number of residential building approvals granted in a month. The original time series comes from the official associations of architects and is one of the main indicators that anticipate the future course of residential investment. The predictive power of this indicator is conditioned by the lag between a project's approval and its completion, and by the pace at which the works are carried out, meaning that its timing needs to be estimated. In the specific case of residential building approvals, the time frame usually considered is 3 months from issuance of the permit to the construction start date, and 18 months thereafter for construction. Construction work gathers pace during the first 12 months after the works begin, and subsequently begins to decrease. Given the lag between the start and completion of a housing unit, the volume of construction in progress in the following quarters is largely determined by observed approval data. The rates of change and the ratio to households are calculated by accumulating the dataset over 12 months, i.e. they are calculated after the data have been accumulated. This is done to reduce volatility and obtain a clearer signal.
House purchases	Registrars Association and INE	Monthly Monthly Quarterly	Dec-96 Dec-98 Dec-95	Annual change (%) 3-year average annual change (%) Level (% of households)	This indicator captures the number of house purchases recorded in the Land Registers. Despite showing some lag vis-à-vis the statistics provided by the Notarial Statistical Information Centre (CIEN), it was selected owing to its lesser volatility and the greater historical data available. The rates of change and the ratio to households are calculated by accumulating the dataset over 12 months, i.e. they are calculated after the data have been accumulated. This is done to reduce volatility and obtain a clearer signal.
Construction workers registered with Social Security	Ministry of Inclusion, Social Security and Migration	Monthly	Jan-96 Jan-98 Jan-95	Annual change (%) 3-year average annual change (%) Level (% of total number registered)	Average number of people registered with Social Security in the construction sector in each month. The ratio is calculated relative to the total average number registered with Social Security each month.
Difference between housing starts and the change in the number of households	Ministry of Transport, Mobility and Urban Agenda and INE	Quarterly	Mar-89 Mar-91	Annual change in the level (thousands) 3-year average annual change in the level (thousands)	The number of housing starts is initially obtained from the construction statistics published by the High Council of the Associations of Architects. These statistics are based on an indirect estimation. Drawing on housing approval data, the monthly data on housing starts are obtained by applying an adjustment factor to residential buildings approved three months earlier, as construction does not actually begin on all projected and approved housing. As a result, the estimated open-market housing units started in month t [VLI_(t)] is equal to factor α multiplied by the open-market housing included in the construction projects approved by the official associations of architects in month t-3 [PEV_(t-3)]. In other words, VLI_(t) = α*PEV_(t-3). Factor α has varied based on the data obtained from other complementary statistical sources, but it stands around 0.9. The figures for the number of households are taken from the Spanish Labour Force Survey published every quarter by the INE. This indicator can be interpreted as a proxy of possible housing demand pressures. These time series are calculated as the number of housing starts in a period less the change in the number of households during the same period.

SOURCE: Devised by authors.

Table A.1

DESCRIPTION OF THE INDICATORS FOR THE RESIDENTIAL REAL ESTATE MARKET IN SPAIN (cont'd)

Indicator	Source	Frequency	Start date	Transformation/ units	Observations
				CREDIT DEVELOPMENTS	
Stock of loans for construction and real estate activities	Banco de España	Quarterly	Dec-93 Dec-95 Dec-92	Annual change (%) 3-year average annual change (%) Level (% of GDP)	Stock of loans secured by real estate collateral granted by deposit institutions and specialised lending institutions (SLIs) for the construction (NACE Rev. 2: F) and real estate activities (NACE Rev. 2: L) sectors. The original time series is available in Chapter 4.18 of the *Statistical Bulletin* of the Banco de España.
Stock of housing loans	Banco de España	Monthly Monthly Quarterly	Dec-93 Dec-95 Dec-92	Annual change (%) 3-year average annual change (%) Level (% of GDP)	Stock of loans for house purchase and renovation. Includes loans on the balance sheet of deposit institutions and SLIs, loans that have been derecognised and transferred to securitisation special purpose vehicles and to Sareb (an asset management company) and other transfers. The original time series is available in Chapter 3.21 of the *Statistical Bulletin* of the Banco de España. Data prior to December 1994 come from Chapter 4.13 of the *Statistical Bulletin* of the Banco de España, and have a quarterly frequency; as a result the data for each quarter-end are repeated in the previous two months. Rates of change are calculated as the actual flow of the period relative to the stock of credit at the beginning of the period. For more details, see Alves, Pana, Fabián Arrizabalaga, Javier Delgado and Irene Roibás. (2019). “Box 1. Statistical information for the analysis of outstanding balances of financing and credit”. *Economic Bulletin – Banco de España,* 3/2019, Analytical Articles, p. 12. For data prior to December 1994, the rates of change are calculated as the stock of loans in the period relative to the stock of loans in the previous reference period.
New housing loans	Banco de España	Monthly Monthly Quarterly	Dec-99 Dec-01 Dec-98	Annual change (%) 3-year average annual change (%) Level (% of GDP)	The principal amount of secured loans, with real or personal guarantee, for residential investment, including purchases, construction, renovation and alterations; see the definition in Circular 4/2004 of 22 December 2004 to credit institutions on public and confidential financial reporting rules and formats. The original time series is available in Chapter 19.12 of the *Statistical Bulletin* of the Banco de España, although from December 2014 the data used do not include renegotiated transactions (i.e. loans granted and not cancelled that are renegotiated in the month, entailing the active involvement of the household in the modification of the contract terms). Data prior to January 2003 have a quarterly frequency, and the data for each quarter-end are therefore repeated in the following two months. The rates of change and the ratio to GDP are calculated by accumulating the dataset over 12 months. i.e. they are calculated after the data have been accumulated. This is done to reduce volatility and obtain a clearer signal.
Non-performing loans for housing purchase	Banco de España	Quarterly	Dec-99 Dec-01 Dec-88	Annual change (%) 3-year average annual change (%) NPL ratio (%)	The amount of non-performing loans (NPLs) to households for house purchase and renovation. Only on-balance sheet loans are included. The original time series is available in Chapter 4.13 of the *Statistical Bulletin* of the Banco de España. The ratio is calculated as the ratio of NPLs to households for house purchase and renovation to total loans to households for house purchase and renovation. This time series is also available in Table 1.5 of the Banco de España's *Summary Indicators,* particularly for data prior to December 1998.

SOURCE: Devised by authors.

Table A.1

DESCRIPTION OF THE INDICATORS FOR THE RESIDENTIAL REAL ESTATE MARKET IN SPAIN (cont'd)

Indicator	Source	Frequency	Start date	Transformation/ units	Observations
CREDIT STANDARDS FOR NEW LOANS					
Loan-to-value (LTV) ratio	Registrars Association	Quarterly	Mar-04	Average LTV (%) Share with LTV > 80% (%)	The new loan-to-value (LTV) ratio is calculated as the ratio of the loan principal to the appraisal value recorded for the mortgage with the Registrars Association. Only includes information for mortgages where the counterparty is a natural person and with housing as collateral. To calculate the average LTV ratio, it has been weighted by the capital of each mortgage granted in the quarter. To calculate the share of mortgages with LTV ratio > 80%, the capital of all mortgages granted in the quarter with LTV ratio > 80% is added together and divided by the total amount of new mortgage financing in the quarter.
Loan-to-price (LTP) ratio	Registrars Association	Quarterly	Mar-04	Average LTP (%) Share with LTP > 80% (%)	The new loan-to-price (LTP) ratio is calculated as the ratio of the loan principal to the declared price of the purchase transaction recorded with the Registrars Association. Only includes information for mortgages where the counterparty is a natural person and with housing as collateral. To calculate the average LTP ratio, it has been weighted by the capital of each mortgage loan granted in the quarter. To calculate the share of mortgages with LTP ratio > 80%, the capital of all mortgage loans granted in the quarter with LTP ratio > 80% is added together and divided by the total amount of new mortgage financing in the quarter.
Overvaluation ratio (LTP/LTV)	Registrars Association	Quarterly	Mar-04	LTP/LTV ratio (%)	Ratio of the two foregoing indicators (LTP/LTV). This indicator reflects the ratio between the house appraisal and the declared purchase price, and is therefore a measure of the overvaluation/undervaluation of appraisals.
Maturity period	Registrars Association	Quarterly	Mar-04	Average (years)	Only includes information for mortgages where the counterparty is a natural person and with housing as collateral. To calculate the average maturity period, it is weighted by the capital of each mortgage granted in the quarter.
Share of mortgages with certain maturity and LTP characteristics	Registrars Association	Quarterly	Mar-04	Term ≥ 30 years (%) LTP > 80% and term ≥ 30 years (%) LTP > 80% and term ≥ 35 years (%)	Only includes information for mortgages where the counterparty is a natural person and with housing as collateral. To calculate the share of mortgages that have maturity periods of 30 years or more/maturity periods of 30 years or more and LTP ratio higher than 80%/maturity periods of 35 years or more and LTP ratio higher than 80%, the capital of all mortgages with these characteristics granted in the quarter is added together and divided by the total amount of new mortgage financing in the quarter.
Interest rates	Registrars Association	Quarterly	Mar-04	Median spread (bp) Interquartile range of the spread (bp)	Only includes information for mortgages where the counterparty is a natural person and with housing as collateral. For each mortgage, the difference is obtained between the mortgage interest rate compiled by the Registrars Association and the risk-free rate based on the euro IRS curve. The indicators refer to the median value and the value of the interquartile range of this variable (result of subtracting the value of the first quartile from that of the third).

SOURCE: Devised by authors.

Table A.1

DESCRIPTION OF THE INDICATORS FOR THE RESIDENTIAL REAL ESTATE MARKET IN SPAIN (cont'd)

Indicator	Source	Frequency	Start date	Transformation/ units	Observations
HOUSEHOLD FINANCIAL POSITION					
Financial and total wealth	Banco de España	Quarterly	Mar-96 Mar-96	Net financial (% of GDI) Net total (% of GDI)	Net financial wealth is calculated as total financial assets less total liabilities. Includes households and non-profit institutions serving households (NPISHs). Net total wealth is equal to net financial wealth plus housing wealth. The latter is estimated on the basis of the estimated evolution of the housing stock and the average house price per m^2, drawing on various sources. Thus, for the historical statistics part, the average appraised value published by the Ministry of Public Works from 1987 to 2004 Q4 is used. From 2007 onwards, the rates of change in the INE's Housing Price Index (HPI) are applied. For the period 2005-2006, the corresponding rates from Tinsa's General Housing Price Index (IMIE) are used. For the final calculation of housing wealth, the linked and seasonally adjusted house price time series is used. For more details on the calculation of housing wealth, see the "Methodological note to Table 1.5" in the Banco de España's *Summary Indicators*. Both time series are available in Table 1.5 of the Banco de España's *Summary Indicators* .
Indebtedness	Banco de España	Quarterly	Mar-87	% of GDI	Of the total liabilities of households and NPISHs, only those that comprising loans raised from financial institutions, general government and the rest of the world are used. Trade credits and advances, as well as other accounts payable, are therefore excluded. These data are available in the *Financial Accounts of the Spanish Economy* published by the Banco de España.
Debt burden	Banco de España	Quarterly	Mar-96 Mar-96	Total (% of GDI) Interest burden (% of GDI)	The total debt burden is estimated considering the outstanding stock of household credit in the various credit segments and at different residual maturities. The loan principal and interest payments are obtained using the interest rates on the amounts outstanding at the different maturities, and assuming an average repayment period according to the credit segment and the residual maturity. Therefore, the total debt burden is the sum of both burdens (principal and interest). The ratio to GDI is calculated by accumulating the debt burden over four quarters relative to the GDI for four quarters so as to reduce volatility, particularly in the denominator. The interest burden ratio is calculated, as mentioned above, taking into account the interest payments on the loans.
Saving rate	Banco de España and INE	Quarterly	Dec-80 Sep-94	Gross (% of GDI) Not earmarked for debt service (% of GDI)	The gross saving rate is calculated by taking the gross savings of households and NPISHs, accumulating the time series over four quarters and dividing it by the GDI of the same sectors, also accumulated over four quarters. Both time series are available in the INE's *Quarterly Non-Financial Accounts for the Institutional Sectors* . The gross saving rate not earmarked for debt service is calculated in the same way as the gross saving rate, but the debt burden for capital repayments is subtracted from gross saving in the numerator.

SOURCE: Devised by authors.

Table A.1

DESCRIPTION OF THE INDICATORS FOR THE RESIDENTIAL REAL ESTATE MARKET IN SPAIN (cont'd)

Indicator	Source	Frequency	Start date	Transformation/ units	Observations
					HOUSE VALUATION
Real transaction prices	INE	Quarterly	Mar-81 Mar-83	Annual change (%) 3-year average annual change (%)	The original source of this indicator is the Notaries' Register containing the official prices of all purchases in Spain, which correspond to the value in the housing deed. Includes the prices of new and second-hand open-market housing, and therefore excludes government-subsidised housing. Housing is considered new when it is the first transfer in the sale deeds. These prices are deflated by the Consumer Price Index (CPI) published by the INE, to obtain the variable in real terms.
Valuation model: deviation of prices from the long-term equilibrium level	Banco de España	Quarterly	Mar-80	Percentage points (pp)	Obtained from an error correction model that estimates house prices based on households' disposable income, mortgage rates and certain fiscal effects. Overvaluation is defined as the difference between the observed house price and its long-term equilibrium level.
Valuation model: deviation of prices from the Hodrick-Prescott trend	Banco de España	Quarterly	Mar-70	Percentage points (pp)	Calculated as the percentage point difference between observed real prices and their long-term trend calculated by applying a one-sided Hodrick-Prescott statistical filter with a smoothing parameter equal to 400,000.
Valuation model: deviation of the price-to-gross disposable income (GDI) ratio from its historical average	Banco de España	Quarterly	Mar-70	Percentage points (pp)	Calculated as the percentage point difference between the observed ratio and its long-term trend calculated by applying a one-sided Hodrick-Prescott statistical filter with a smoothing parameter equal to 400,000.
Valuation model: regression residual of the price-to-GDI ratio	Banco de España	Quarterly	Mar-70	Percentage points (pp)	Ordinary least squares (OLS) model that estimates house prices based on long-term trends in household disposable income and mortgage rates calculated using Hodrick-Prescott statistical filters.
Affordability	Banco de España	Quarterly	Mar-87 Mar-87	First-year mortgage payments relative to GDI (%) Price relative to GDI (years)	Instalments payable in the first year after the purchase of typical housing, financed by a standard loan of 80% of the house value, as a percentage of the median household's annual disposable income. The calculation of the instalment assumes a French amortisation system, in which the interest rate applied is the quarterly average rate on new loans to households for house purchase and the average maturity of new mortgages is a 12-quarter moving average of that published by the Registrars Association. The median household's gross income is calculated drawing on the results of the successive rounds of the Spanish Survey of Household Finances (EFF, by its Spanish acronym), interpolating and extrapolating them based on the evolution of average gross household income obtained from the National Accounts and the number of households in the Spanish Labour Force Survey (EPA, by its Spanish acronym). Both time series are available in Table 1.5 of the Banco de España's *Summary Indicators.* The ratio of house prices to GDI is calculated by taking the average price of open-market housing with an average surface area divided by the estimated gross income of the median household. For more information on average house prices, see the observations on total wealth. For the average surface area of typical housing from 2004 to 2020, the *annual* information provided by the Registrars Association on the average size in m^2 of housing purchased in recorded transactions is used. From 2020 Q3 onwards, the *quarterly* information provided by the Registrars Association on the average size in m^2 of housing purchased in recorded transactions is used. To obtain the entire time series, it is linked by means of a linear interpolation from 93.75 m^2 (previous estimated surface area of typical housing in Spain from the former Ministry of Public Works) and, from 2004 onwards, the figure for each quarter is a moving average for the last three years.

SOURCE: Devised by authors.

Table A.1

DESCRIPTION OF THE INDICATORS FOR THE RESIDENTIAL REAL ESTATE MARKET IN SPAIN (cont'd)

Indicator	Source	Frequency	Start date	Transformation/ units	Observations
					HOUSE VALUATION
Gross housing rental yield	Idealista	Monthly	Dec-06	%	The gross housing rental yield is calculated as the 12-month average of housing rental prices in Spain per m^2, multiplied by 12 and divided by the 12-month average price of housing for sale in Spain. Both time series are available on Idealista.
Housing rental prices	Idealista	Monthly	Jan-07 Jan-09	Annual change (%) 3-year average annual change (%)	The rates of change are calculated by taking the housing rental prices in Spain per m^2 from Idealista.

SOURCE: Devised by authors.

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