HOW DO CENTRAL BANKS IDENTIFY RISKS? A SURVEY OF INDICATORS

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Banco de España Strategic Plan 2024:
Risk identification for the financial and macroeconomic stability

HOW DO CENTRAL BANKS IDENTIFY RISKS? A SURVEY OF INDICATORS

Banco de España Strategic Plan 2024: Risk identification for the financial and macroeconomic stability (*)

BANCO DE ESPAÑA

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Abstract

For central banks, it is crucial to develop and maintain risk identification frameworks that allow them to detect in good time and address potential threats to financial stability with the most appropriate policy tools. This paper reviews the main indicators developed for this purpose by the Banco de España and by other central banks and prudential authorities. In this way, this stocktaking exercise contributes to improving the transparency and effective communication of the financial stability-related tasks carried out at the Banco de España. Some of the indicators are used in regular Banco de España surveillance activities, whereas others pertain to specific research activities. We classify our set of measures into two broad categories depending on the risk monitored: standard or systemic risks. Given the multidimensional nature of systemic risk, its identification goes beyond the sum of the standard risks explored in this paper (namely credit, macroeconomic, market, and liquidity and bank risks). This survey also classifies indicators by the type of institutional segment that triggers risks; namely, sovereigns, households, non-financial corporations, banks, non-bank financial sector, residential real estate and the financial markets. This work shows how the measures developed and regularly used at the Banco de España allow potential vulnerabilities to be comprehensively monitored. Nevertheless, maintaining an adequate risk-identification framework requires continuous adaptation to new theoretical developments and econometric tools, and, more importantly, to emerging challenges. In this respect, there is a current drive to develop new indicators to assess potential risks arising from climate change and those linked to the risk of system-wide cyber incidents. It is expected that the monitoring needs related to these risks will increase in the future.

Keywords: risk identification, systemic risk, systemic risk indicators, standard risk indicators, financial stability.

JEL classification: E58, C43, G10, G21, G32, G50.

Resumen

Para los bancos centrales son cruciales el desarrollo y el mantenimiento de un marco de identificación de riesgos que permita la detección temprana de posibles amenazas para la estabilidad financiera y que facilite la aplicación de las políticas más adecuadas. Este documento resume los principales indicadores desarrollados para la identificación de riesgos tanto por parte del Banco de España como por otros bancos centrales y autoridades prudenciales. Así, esta recopilación de indicadores contribuye a mejorar la transparencia y la comunicación del Banco de España en su objetivo de potenciar la estabilidad del sistema financiero. El Banco de España utiliza algunos de estos indicadores en sus tareas regulares de identificación y seguimiento de riesgos, mientras que otros proceden de trabajos de investigación concretos. Este conjunto de medidas puede clasificarse en dos amplias categorías, en función del tipo de riesgo monitorizado: estándar o sistémico. Dada la naturaleza multidimensional del riesgo sistémico, su identificación va más allá de la propia suma de los riesgos estándar presentados en este documento (concretamente, riesgos de crédito, macroeconómico, de mercado, de liquidez y bancario). Este estudio también clasifica los indicadores en función del tipo de segmento institucional donde se originan los riesgos; concretamente, sector público, hogares, sociedades no financieras, bancos, sector financiero no bancario, mercado inmobiliario residencial y mercados financieros. Este trabajo muestra que los indicadores desarrollados y utilizados habitualmente por el Banco de España permiten una monitorización exhaustiva de las vulnerabilidades potenciales. En cualquier caso, el mantenimiento de un sistema de identificación de riesgos requiere una adaptación continua a los nuevos desarrollos teóricos y herramientas econométricas, así como a los nuevos desafíos. En este sentido, actualmente se están desarrollando nuevos indicadores para evaluar los riesgos derivados del cambio climático y los relacionados con los ciberriesgos. Se espera que las necesidades de seguimiento relacionadas con estos riesgos aumenten en el futuro.

Palabras clave: identificación de riesgos, riesgo sistémico, indicadores de riesgo sistémico, indicadores de riesgo estándar, estabilidad financiera.

Códigos JEL: E58, C43, G10, G21, G32, G50.

Contents

1 Introduction

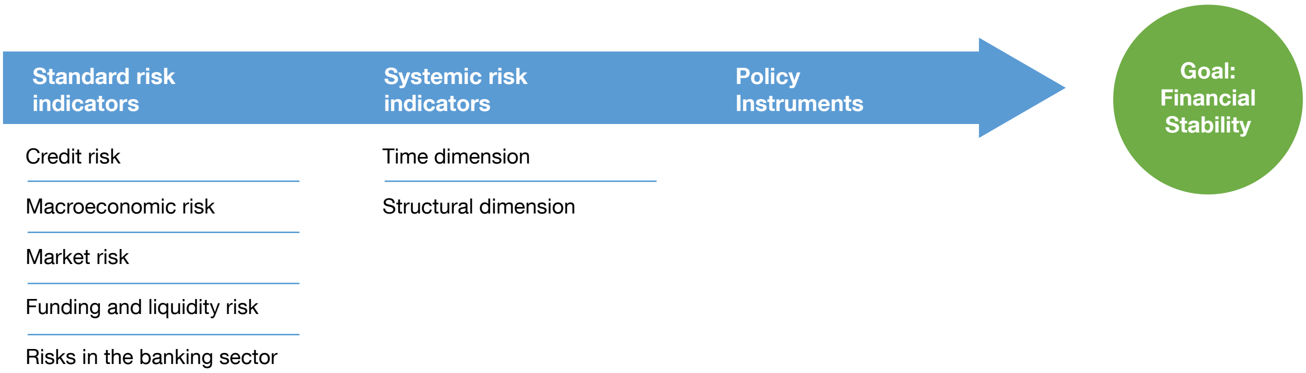
Central banks play a key role in ensuring economic and financial stability. While the monetary policy function of central banks has been discussed extensively in the literature, their financial stability role has gained attention more recently, especially in the aftermath of the Great Financial Crisis (GFC). Thus, over the last decade central banks and prudential authorities have acquired greater responsibilities to preserve financial stability through the adoption of macroprudential policy frameworks. The objective of this new role is to strengthen financial stability by mitigating the risks stemming from macro-financial imbalances and the destabilising interactions across financial institutions and markets (Restoy, 2020).[1] Thus, central banks currently approach risks to financial stability from two complementary perspectives with the potential to interact: either entity by entity, in the case of the traditional microprudential approach, or system-wide for this new macroprudential approximation. However, despite the significant progress in this area, a full analytical framework with well-defined and quantifiable indicators for its correct functioning has yet to be developed (Mencía and Saurina, 2016). In particular, there is still no widespread consensus on which risk indicators should be used. Among other factors, this limitation of current identification frameworks is a result of the diffuse nature of financial stability objectives, which hinders risk identification, and the fact that macroprudential policy is still in its infancy. Besides, assessment of the stability of the financial system as a whole is complex as it involves the continuous monitoring and analysis of a wide range of potential risks and vulnerabilities that may threaten it.

The development of an appropriate and transparent risk identification framework is crucial for at least two reasons. First, as shown in Figure 1, accurate risk identification is a prerequisite for achieving the final goal of financial stability. An adequate set of identification tools promotes an early and better-informed detection of potential threats and helps to address them by taking appropriate policy actions. Second, a proper communication of an adequate risk identification approach helps to increase the transparency of the financial stability function, which can itself contribute to reducing uncertainty (Oosterloo and de Haan, 2004) and to stakeholders adopting mitigating actions.

The aim of this paper is to provide an overview of the main indicators used by the Banco de España to identify risks and vulnerabilities. Some of these measures are part of the regular surveillance work carried out by the Banco de España, whereas other indicators are the result of specific research activities. This survey allows the risk identification toolkit used at the Banco de España to be compared with that of other institutions, identifying potential gaps that may merit further work. However, a huge variety of diverse and heterogeneous

1 In the case of Spain, Law 10/2014 on the regulation, supervision and solvency of credit institutions designates the Banco de España as the sectoral authority in charge of macroprudential policy to address systemic risks that pose a threat to the stability of the banking system. Besides, the Spanish Macroprudential Authority (AMCESFI) has the mandate to regularly monitor and analyse the sources of systemic risk. AMCESFI is headed by the Ministry of Economic Affairs and Digital Transformation with the participation of senior officials from this Ministry and from the Banco de España, the CNMV (Spanish National Securities Market Commission) and the DGSFP (Directorate General of Insurance and Pension Funds).

Figure 1
RISK IDENTIFICATION IS AT THE HEART OF THE FINANCIAL STABILITY FUNCTION OF CENTRAL BANKS



SOURCE: Devised by authors.

indicators have been designed for risk identification, which illustrates the complexity of this type of analysis. Besides, the number of identification tools is constantly increasing, as a result of the development of new econometric methodologies and the incorporation of the experience of new crises. In fact, in the aftermath of the GFC, considerable attention has been devoted to the measurement of systemic risks and, in parallel, the literature has proposed a plethora of alternative risk metrics (see Bisias et al., 2012 and Hattori et al., 2014 for some surveys).

This abundance of indicators in the literature prevents us from attempting a comprehensive overview. Therefore, this survey contains a non-exhaustive summary of the main indicators developed and used by the Banco de España, and by other selected institutions. The different measures have been chosen in light of their relevance or their novel approach. They range from purely data-driven indicators to some identification instruments that require more complex models.

As reported in Figure 1, indicators may be broadly classified into two groups depending on the nature of the risks they aim to capture: standard risks and systemic risk. First, we focus on five standard risk categories, namely: (1) credit risk, (2) macroeconomic risk, (3) market risk, (4) funding and liquidity risks, and (5) risks related to banks' profitability and solvency. Our approach to classifying these categories draws on standard taxonomies of risk identification indicators (broadly used by central banks and other relevant institutions) such as that followed in the ESRB risk dashboard.[2] Besides, we also examine different measures to analyse these standard risks across different segments (sovereigns, households, non-financial corporations, banks, non-bank financial sector, residential real estate (RRE) and financial markets). Second, we review systemic risk indicators, which are linked to threats

2 The ESRB risk dashboard is a non-exhaustive list of both quantitative and qualitative indicators to measure systemic risk https://www.esrb.europa.eu/pub/rd/html/index.en.html.

that may affect a significant part or the whole of the financial system and, ultimately, the real economy too. For these indicators, we use a standard classification that depends on whether they aim to capture the time dimension of systemic risks (i.e. the accumulation of risks over the credit cycle) or the structural cross-section dimension of systemic risk. Finally, we also analyse other sources of systemic risk which merit further study, namely climate change-related risks and some operational risks, such as cyber risks.[3] The Appendix briefly summarises all the indicators portrayed in this document.

This paper is organised as follows. In Section 2 we summarise the main indicators developed at the Banco de España and by other central banks and prudential authorities for the analysis of standard risk categories. Section 3 then reviews the main tools to address systemic risks. Finally, Section 4 concludes.

3 For example, operational risk is one of the areas for which this survey lacks a complete description of the attendant indicators and identification instruments, as it falls outside the scope of this survey.

2 Standard risks

Our approach to classify traditional risk categories is inspired by standard taxonomies commonly employed by central banks. Specifically, we focus on the indicators related to six different categories, namely: (1) credit risk, (2) macroeconomic risk, (3) market risk, (4) funding and liquidity risks, (5) banks' profitability and solvency and (6) structural risks. The huge variety of indicators across risk categories and segments advocates prioritising the indicators examined in this section, rather than an exhaustive listing. Therefore, indicators have been chosen for their widespread use or their importance in terms of early-warning properties to signal systemic financial crises.

2.1 Credit risk

Credit risk may be defined as the potential that the borrowing counterparty in a debt contract will fail to meet its obligations in accordance with agreed terms. In this section, we summarise the main indicators to identify this risk for two types of borrowers (households and non-financial corporations), and for the specific case of loans related to activities in the real estate market.

2.1.1 Households

Aggregate indicators of households' financial position, such as their aggregate debt-to-income ratios or their debt-to-wealth position, provide interpretable information about the financial situation of the population as a whole. However, those magnitudes alone cannot indicate whether a small set of households is heavily indebted or whether, alternatively, many households have a limited amount of debt. The aggregate consequences may differ across both scenarios, because financial fragility depends precisely on the resources available to indebted households to keep up with their payments.

Against this background, disaggregated information on household debts, payments and income together with socio-demographic data allow us to characterise which population groups are most vulnerable. The Spanish Survey of Household Finances (EFF) has been conducted by the Banco de España since 2002 every three years, and collects such information together with data on Spanish household assets and spending.

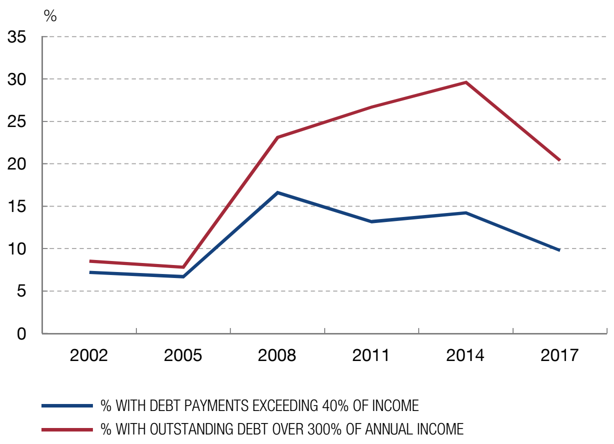
One initial use of this dataset is to calculate vulnerability measures among indebted households. That is to say, unlike debt-to-GDP ratios, disaggregated data on households allow calculation of the fraction of households that owe more than three times their gross income, or that devote more than 40% of their gross income to debt payments (see Banco de España, 2019a or HFCN, 2020). Chart 1.1 shows both measures from 2002 to 2017. Debt payments relative to income could be interpreted as a proxy for short-term financial commitments, while outstanding debt as a proportion of income approximates long-term financial commitments.

In addition, survey information about the complete balance sheet of households enables reconstruction of the total amount of resources available in the event of an interest

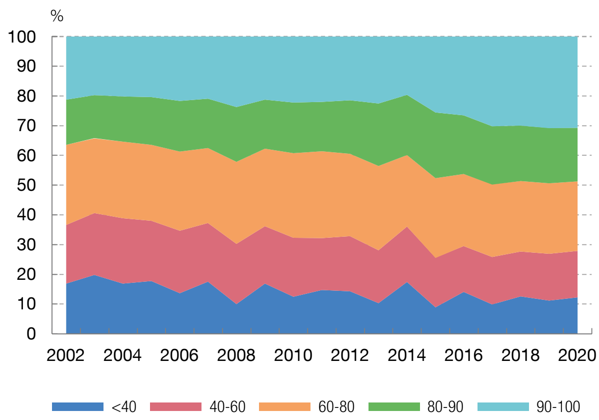
Chart 1
HOUSEHOLD CREDIT RISK

While the fraction of households that assign more than 40% of their gross income to debt payments proxies for short-term financial commitments, the proportion of households with outstanding debt more than threefold their gross annual income proxies for long-term financial commitments (left-hand panel). A larger share of accumulated debt in lower-income households indicates potentially greater financial vulnerabilities (right-hand panel).

1 FRACTION OF HOUSEHOLDS WITH LARGE FINANCIAL AND DEBT BURDEN (a)



2 AGGREGATE DEBT FOR RESIDENTIAL PURCHASE BY INCOME QUINTILE (b)



SOURCE: Banco de España.

a Population estimates.
b The distribution of the aggregate debt for residential purchase across income quintiles of the population is calculated on an annual basis. The distributions are based on Chow-Lin (1971) using EFF and Financial Accounts data over the period 2002 to 2017. The data points after 2017 are out-of-sample estimations based on Financial Accounts data. These are preliminary results of a work in progress at the Banco de España by Cobreros, García-Uribe & Villanueva (2021).

rate increase or a fall in income. Given the delays in the release of that information, stress tests are used to simulate the impact of macro developments and, at the same time, to detect vulnerable groups (see IMF, 2012; Bhutta et al., 2020; or Ampudia et al., 2016).

Again, given delays in the release of disaggregated information, distributional financial accounts have recently been constructed by combining data on macroeconomic developments with household balance sheets (see Batty et al., 2019 and Ahnert et al., 2020). Under this approach, the distribution of household indebtedness across population groups becomes a timelier indicator. Chart 1.2 presents preliminary estimates of a work in progress at the Banco de España on the annual distribution of total outstanding debt for residential purchase across income groups in Spain. A larger (smaller) share of cumulative debt in groups with lower income indicates potentially larger (smaller) financial vulnerabilities.

2.1.2 Non-financial corporations

Vulnerable non-financial corporations (NFC) could have a direct impact on economic growth and add pressures to the banking system. This central role explains why national and supranational surveillance authorities closely monitor developments in this sector, notably through the analysis of their financial position. Along these lines, there is a broad use of financial indicators such as the growth rates of loans to NFCs, the cost of borrowing for NFCs and the changes in credit standards for loans to NFCs, among others.[4] Besides, since the onset of the GFC, credit default swap (CDS) spreads have gained importance as a tool for approximating credit risk – not only for corporates, but also for banks and sovereigns – as this market becomes more liquid.[5]

Furthermore, the Banco de España also closely monitors the evolution of the most vulnerable firms on a granular basis. This is supported by the empirical evidence that links a higher share of these firms to lower investment and employment growth of the non-vulnerable firms and less productivity-enhancing capital reallocation (McGowan et al., 2017).[6] To that end, Menéndez and Mulino (2019) focus on the distribution of the interest coverage ratio (ICR), and pay special attention to the size and sector of activity – see Chart 2 –.[7] The ICR is the ratio of ordinary profit (i.e. gross operating profit plus financial revenue) to financial costs, and it serves as an indicator of the degree of the firm's financial pressure. In particular, when the ICR value remains below one over a prolonged period it is considered to be a sign of vulnerability, since it implies that the firm is not capable of paying the interest on its debt out of ordinary profit in a sustained manner. This approach also enables the Banco de España to simulate potential liquidity needs under severe stress situations such as that posed by the COVID-19 pandemic shock (Blanco et al., 2020).

The Banco de España also assesses the credit quality of the NFCs in the context of the implementation of monetary policy. In line with its statute, the Eurosystem provides liquidity to monetary policy counterparties only against the provision of collateral that meets adequate credit standards. The measurement of credit quality is based on ratings or probabilities of default from any of the following sources: external credit assessment institutions (ECAIs); in-house models developed by counterparties to calculate minimum capital requirements under the internal ratings-based (IRB) approach; and national central banks' in-house credit assessment systems (ICAS). To facilitate the provision of adequate collateral, the Banco de España has developed an ICAS (ICAS BdE) compliant with the Eurosystem Credit Assessment Framework (ECAF). The ICAS BdE performs credit assessments of public and private Spanish NFCs, with the aim of allowing the loans extended to them to be used as collateral by the counterparties themselves.[8] The rating

4 For more details on data-based risk indicators for NFCs see, for instance, the ESRB risk dashboard https://www.esrb.europa.eu/pub/rd/html/index.en.html.

5 A CDS is an OTC (over-the-counter) derivative that functions as an insurance contract, where a protection buyer pays a fixed amount (the CDS premium) to the seller until maturity or until the occurrence of the credit event (Duffie, 1999). For instance, for a corporate CDS, the credit event would be equivalent to the issuer firm defaulting on its payment commitments.

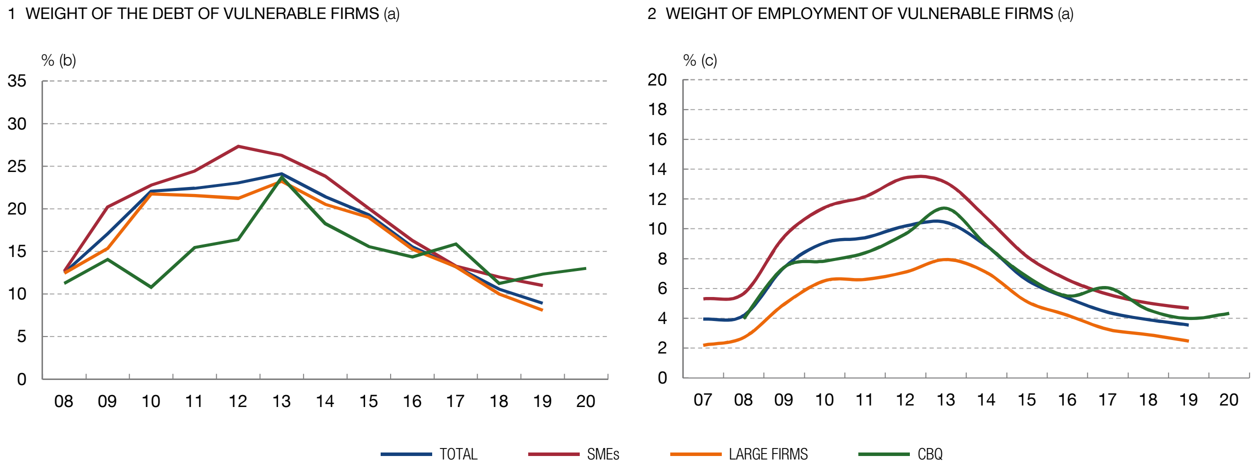
6 In addition, McGowan et al. (2017) also document that the market congestion generated by "zombie" firms can also create barriers to entry and constrain the post-entry growth of young firms. They link the rise of "zombie" firms to the decline in OECD potential output growth through two key channels: business investment and multi-factor productivity growth.

7 To that end, Menéndez and Mulino (2019) resort to the CBI (Integrated Central Balance Sheet Data Office Survey), obtained on the basis of merging the CBA (CBSO Annual Survey) and the CBB (information on company filings with the Spanish Mercantile Registries). The CBI contains information on the balance sheets and income statements of a most extensive sample of companies, which enables the ICR to be calculated for each of these companies in each year.

8 https://repositorio.bde.es/bitstream/123456789/13555/1/Banco_Espana_in_house_credit.pdf.

Chart 2
NON-FINANCIAL CORPORATIONS' CREDIT RISK

Non-financial corporations' credit risk is assessed by analysing the proportion of debt and employment associated with vulnerable firms. Vulnerable firms are defined as those having an Interest Coverage Ratio [(gross operating profit + financial revenue) / financial costs] of less than one for two consecutive years. Firms without any financial costs are not considered vulnerable.



SOURCE: Banco de España.

a Newly created companies and holding companies are excluded from the sample. The size of non-financial corporations is defined in line with European Commission Recommendation 2003/361/EC. CBQ stands for the Central Balance Sheet Data Office Quarterly Survey. The data source of all the indicators except the CBQ is the CBI (Integrated Central Balance Sheet Data Office Survey).
b Percentage of total debt of their group.
c Percentage of total employment of their group.

model is calculated in two stages. First, the statistical model, which provides an automatic rating based on the latest financial statements of the company, is obtained in the spirit of Papke and Wooldridge (1996). Second, the expert model allows the analyst to incorporate all those relevant aspects that the statistical model has not been able to capture in the final rating of the company. Currently, the ICAS BdE rates around one million companies via statistical and expert models.

2.1.3 Real estate markets

House prices have sometimes been used as an indicator of the financial cycle and, in fact, they usually fluctuate in tandem with credit, sometimes amplifying it. In particular, rapid increases in real estate prices impact on the availability of borrowers' collateral and may trigger excessive credit growth (Galati et al., 2016; Rünstler and Vlekke, 2018). For this reason, it is important to regularly monitor house prices and spot signs of overvaluation in the housing market in early phases of the cycle. Overvaluation (undervaluation) occurs when house prices are too high (too low) compared to a non-observable equilibrium level.

Micro and macro supervisors actively monitor house price developments (see, for instance, the analytical framework of ESRB, 2019). The monitoring framework of the Banco de España relies on two sets of methodologies to estimate the degree of overvaluation in the real estate market. The first approach is purely statistical and aims to identify large deviations in house price variables from long-term trends. Trends are obtained with a Hodrick-Prescott filter to separate cyclical from long-run components (Hodrick and Prescott, 1997). If prices are too high in relation to their trend, they could be overvalued.

The second approach to the analysis of imbalances is model-based. Given that the relationship between house prices and some fundamental variables describes patterns that can be fitted, models may help to understand the key drivers of changes in house prices. For instance, Martínez and Maza (2003) measure the degree of disequilibrium in the Spanish real estate market with a model where house prices are regressed, among other explanatory variables, on household disposable income per inhabitant or the mortgage rate on new loans. If the estimated prices stand below the observed prices, the market is said to be overvalued. The Banco de España also complements this analysis through equations that explain house prices by means of Hodrick-Prescott filtered trends in fundamental variables, such as disposable income or rental prices. In this case, departures from long-term trends would be consistent with a build-up of vulnerabilities (see Chart 3.1).

Regarding alternative model-based indicators to analyse overvaluation in the real estate markets, it is worth highlighting the "misalignment indicator" of the ECB (2016). It is based on a Bayesian model that explains real house prices using real disposable income per household, the real housing stock per capita and the mortgage rate as explanatory variables.[9] The residuals represent the misalignment or the degree of overvaluation of house prices. Alternatively, the misalignment may also be calculated comparing the return on investing in housing to yields in the rental market (or to the return on assets with similar risk). See ECB (2011) for a survey or Hiebert and Sydow (2011) for an application to euro area markets.

The Great Financial Crisis (GFC) showed that policymakers need to consider not only the most likely (baseline trend) future path of house prices, but also the distribution of all possible outcomes around that path, and pay special attention to the downside risk. In this connection, House Price-at-Risk (HaR) measures, which are based on quantile regressions, enable the whole distribution of future price growth rates to be fully characterized and the accumulation of downside risks in the housing market to be identified. Specifically, the HaR measure consists of forecasting extreme realisations in the left tail of the conditional distribution of real house prices (commonly the 5th percentile) to identify risks of large price falls. The development of these tools is based on the application of quantile regressions and it is key for policymakers owing to the close relationship between house price dynamics, macroeconomics and financial stability.

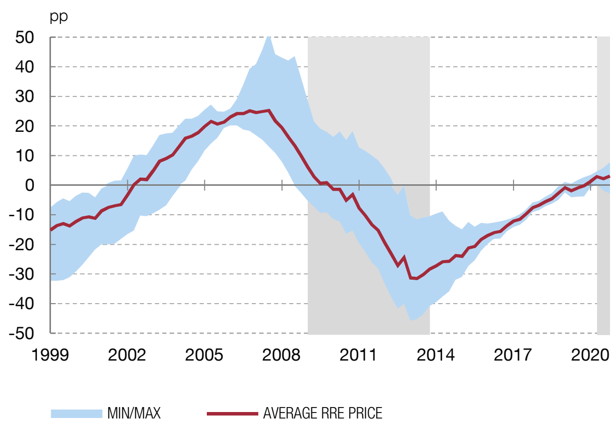
Different institutions increasingly calculate their own House Price-at-Risk (HaR) measures. For example, the IMF fits a HaR model for 22 major advanced economies and

9 The Bayesian techniques allow the distributions of model coefficients to be modified according to their estimated values in other papers.

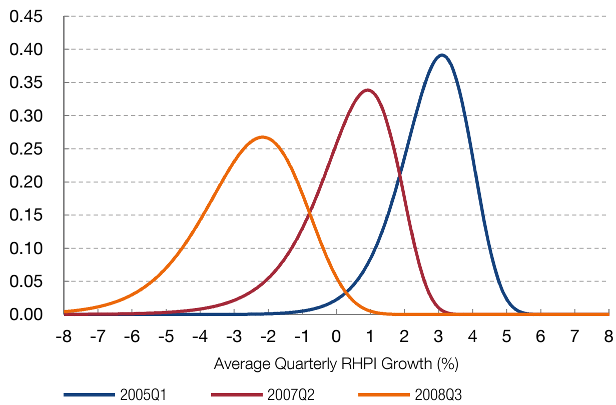
Chart 3
MONITORING HOUSE PRICE DISEQUILIBRIA IN REAL ESTATE MARKETS

To monitor house prices, the Banco de España relies on several methodologies to estimate the degree of overvaluation in the real estate market. Moreover, central banks increasingly make use of quantile regression models, such as the House Price at Risk (HaR) model. Specifically, the HaR measure consists of forecasting extreme realisations in the left tail of the conditional distribution of real house prices to identify risks of large falls in real house prices (RHPI) in very adverse scenarios.

1 RESIDENTIAL REAL ESTATE PRICES (a)



2 PROBABILITY DENSITY FUNCTION FOR THE EVOLUTION OF THE RHPI AT 1-YEAR HORIZON (b)



SOURCES: Banco de España, INE and own elaboration.

a Grey shaded areas represent systemic crisis periods. Ranges show minimum and maximum values of a set of indicators of RRE prices relative to their long-term trends. Some of these indicators are obtained using a statistical filter and others using econometric models.
b Forecast density functions in three periods: i) 2005 Q1; ii) 2007 Q2; and iii) 2008 Q3. See Galán and Rodríguez-Moreno (2020) for details.

10 EMEs, and the ECB estimates a HaR model for the euro area.[10] In both cases they document the usefulness of the HaR measure as an early-warning indicator that can be used for financial stability surveillance. The Banco de España is also developing a HaR model that captures the idiosyncratic developments of the Spanish real estate market (see Galán and Rodríguez, 2020). To demonstrate the usefulness of this tool, Chart 3.2 depicts the deterioration of the density function of real house price growth from 2005 to 2008 for the 1-year-ahead forecast horizon. The sizable shift of the full distribution to the left clearly signals an increase in downside risk, even in positive scenarios.

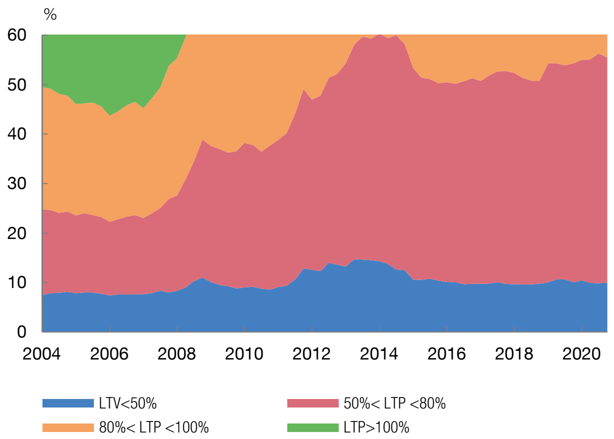
Additionally, the link between the deterioration in lending standards, or the quality of loans, and systemic crises is well-documented in the literature (see, for instance, Duca et al., 2010; Estrada and Saurina, 2016; Kelly et al., 2018). Certainly, there are multiple examples of lax credit standards translating into higher default rates in mortgages during downturns in the real estate market (Schelkle, 2018). In this respect, awareness has increased in recent years

10 The set of explanatory variables of the HaR model of the IMF includes a financial condition index, real GDP growth, credit growth and an overvaluation measure, while that of the ECB consists of the lag of house price growth, an overvaluation measure, systemic risk indicator, consumer confidence indicator, financial market conditions indicator, government bond spread, slope of yield curve, euro area non-financial corporate bond spread, and an interaction of overvaluation and a financial conditions index. See IMF (2019) and ECB (2020a) for details.

Chart 4
CREDIT RISK IN THE REAL ESTATE MARKET: LENDING STANDARDS

The share of loans with high leverage (LTP > 80%) diminished after the outbreak of the financial crisis, and it has remained broadly unchanged in recent years. A synthetic indicator or credit-at-risk, which is based on the probability of default of new mortgage loans, suggests that the credit quality of mortgagors has improved substantially in relation to the pre-crisis period.

1 LOAN-TO-PRICE RATIO OF NEW MORTGAGES (a)



2 CREDIT-AT-RISK IN THE MORTGAGE MARKET (b)

SOURCES: Banco de España and Colegio de Registradores (land registries).

a LTP data refer to a representative sample of mortgage loans.
b The index captures the risk of new mortgage lending, calculated on a quarterly basis. Higher values imply more risk. The index takes into account the riskiness of mortgages using a default probability model, in which lending standards are explanatory variables of default rates. The model is estimated over the period 2003-2017 following Galán and Lamas (2019), with some adjustments. The data points after 2017 are out-of-sample estimates.

on the need to closely monitor lending standards in the real estate market. For instance, the Recommendation of the European Systemic Risk Board ESRB/2016/14, on closing real estate data gaps, is an important initiative to construct a complete set of harmonised indicators to monitor vulnerabilities in this segment.[11] The ECB (2019) has also proposed a formal framework to define the intensity of vulnerabilities arising from overly easy lending standards. This framework relies on early-warning models that consider the distribution of indicators over time and across countries together with the subsequent likelihood of crises.[12]

In this connection, the Banco de España regularly evaluates lending standards on new credit for the residential mortgage market as this represents the largest segment of collateralised loans. To this end, the Banco de España regularly calculates indicators from its credit register and from administrative data (land registries). These measures could refer either to leverage, to the terms of mortgage contracts or the situation of the borrower. Among the former, the loan-to-price (LTP) measure developed by Bover et al. (2019), which

11 The Recommendation addresses supranational and national authorities in the European Union and asks for the implementation of a comprehensive dashboard of indicators, including indicators for the physical market, credit growth and, of course, lending standards. The monitoring framework of the Banco de España is fully aligned with the provisions of the ESRB Recommendation and with the other orientations of this institution.

12 Analogous approaches can be found in Bengtsson et al. (2020) and Ferrari et al. (2015). The IMF (2010) follows a similar methodology but integrates lending standards and other real estate indicators into a single vulnerability index.

is the ratio between the principal amount of the loan to the price of the house, represents a material driver of defaults (Galán and Lamas, 2019). Indeed, the share of loans with high LTP values (i.e. an LTP of over 80%) was particularly high in Spain before the financial crisis, which coincided with booming conditions in the housing market (Chart 4.1). Other indicators that explain default risk include the maturity and the spread of mortgages over a risk-free rate, and metrics that proxy borrowers' ability to pay, such as the ratio of the principal amount of the loan to the borrower's income, i.e. the loan-to-income ratio (LTI). In general, longer maturities, wider spreads and higher LTI are associated with higher risk.

While individual indicators (and their distributions) provide useful information on different aspects of credit, they sometimes do not move in tandem, and can even emit ambiguous signals. For instance, during upturns LTP ratios may remain unchanged while LTI may deteriorate. To address this issue, the Banco de España has developed a synthetic indicator, the so-called "credit-at-risk", which estimates the risk of new mortgage operations by means of a default probability model with lending standard indicators as explanatory variables (see Banco de España, 2019b, for details). Chart 4.2 exhibits the course of this indicator, which depicts the expected pattern of growing vulnerabilities in the run-up to the financial crisis and more contained risks in the most recent period.

2.2 Macroeconomic risk

2.2.1 International environment

Risks from the external environment refer to the potential consequences for the Spanish financial system of the negative economic, financial or political performance of those countries in which Spanish companies and banks have higher investment positions. In this section we highlight two of the indices that the Banco de España has developed to monitor these external risks in its regular assessment: a synthetic index of the vulnerability of the most relevant emerging economies (EMEs) for Spain, the so-called "Sherloc",[13] and an Economic Policy Uncertainty (EPU) index (see Chart 5).

First, the Sherloc index of vulnerability for EMEs by Alonso and Molina (2019) is a tool to detect the accumulation of risks in 25 large EMEs for three different types of crisis (sovereign, currency and banking crises). The index is calculated via a signalling approach and a logistic estimation that allows the predicted probability of being in a vulnerable state to be obtained for each type of crisis. In-sample and out-of-sample, this index outperforms the best single crisis indicators, such as the sovereign spread or the credit change in real terms. Besides, the use of a synthetic index for each type of crisis predicts vulnerable states better than the use of an aggregate index for all crises.

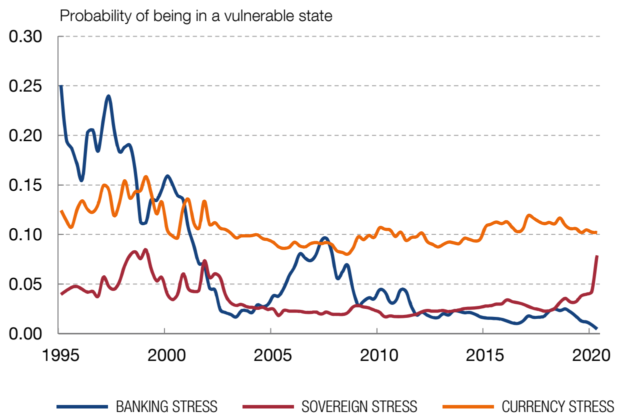
Along these same lines, policy uncertainty can also affect banks' and firms' performance in the most relevant EMEs for Spain, which have historically been prone to

13 "Sherloc" stands for Signalling Heightened Emerging Risks that Lead to the Occurrence of Crises. See Alonso and Molina (2019).

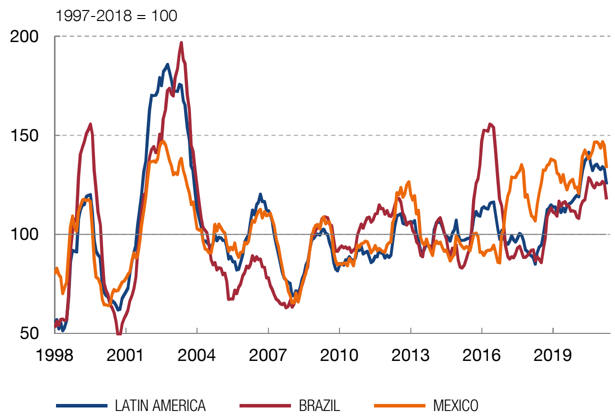
Chart 5
MACROECONOMIC RISK: INTERNATIONAL ENVIRONMENT

Among others, the Banco de España uses two indices to assess macroeconomic risks arising from the international environment: the SHERLOC and the Economic Policy Uncertainty (EPU indices). The former is a synthetic index of the probability of being in a vulnerable state against a currency, sovereign or banking crisis, whereas the latter reflects the frequency of articles in leading newspapers that contain "uncertainty" associated with "economic policy".

1 SHERLOC VULNERABILITY INDEX (a)



2 EPU INDEX (b)



SOURCE: Banco de España.

a Probability of being in a vulnerable state for currency, banking or sovereign crises, estimated from a signalling and a logit approach. Average of countries belonging to each region. For more information, see Alonso and Molina (2019).
b Articles containing words related to economic policy and uncertainty in the 7 main Spanish newspapers, with reference to each country. For more information, see Ghirelli, Gil, Pérez and Urtasun (2020).

suffer from abrupt policy changes. The Banco de España estimates an Economic Policy Uncertainty (EPU) index for Spain and the seven largest economies of Latin America (see Ghirelli et al., 2019 and Ghirelli et al., 2020). The procedure, which follows the seminal paper by Baker et al. (2016), consists of analysing the number of articles that contain simultaneously at least one keyword related to the categories of “uncertainty”, “economy” and “policy”.[14]

The above-mentioned indices employed to analyse the external environment are useful for monitoring country risk. In particular, country risk arises in transactions with holders resident in a given country due to circumstances other than standard commercial risk. Therefore, this risk is a broad concept that does not only include sovereign default risk but also that of private external debt derived from circumstances unrelated to the solvency or liquidity status of the private debtor, and usually related to transfer risk.[15] The assessment of country risk is usually based on both risk models and experts’ judgments. The best-known econometric approach is the Country Risk Assessment Model (CRAM)

14 These EPU indices can also be used to quantify the macroeconomic impact of political uncertainty by means of SVAR models. Thus, an unexpected shock in the EPU leads to negative responses in Spanish GDP, private consumption and investment (Ghirelli et al., 2019).

15 For further information, see Iranzo (2008).

used by the OECD to deliver its country risk classification.[16] Another approach is the development of internal credit ratings to assess the credit quality of investment counterparties. For instance, Bank of Canada has developed this method based on the scoring methodology by Muller and Bourque (2017).[17] Finally, sovereign ratings and market indicators, such as the sovereign and CDS spreads or the EMBI+, also provide useful information to detect risks in these third countries. These market-based indicators are supposed to be early indicators of sovereign risk, but they can also overreact due to short-term events.

2.2.2 Current account imbalances

External imbalances are a symptom of an unsustainable pattern of global growth (Blanchard and Milesi-Ferretti, 2009). These imbalances are traditionally characterised as divergences in the current accounts of surplus and deficit countries. This indicator is regularly monitored at the Banco de España, along with additional commonly used indicators, such as the net international investment position (NIIP), the net external debt and the net external position (either in portfolio, FDI or other investment). Recently, Alberola et al. (2020) have analysed the role played by the net foreign assets (NFA) position of creditor and debtor countries to characterise global imbalances from a stock perspective.[18]

Against this background, the development of early-warning indicators of external stress events is key to identifying potential turbulence in international markets and implementing suitable policies. More specifically, Martín (2017) constructs an early-warning system of external stress episodes for a set of euro area countries. His results show that the ratio of net and gross foreign liabilities to GDP and current account imbalances are significant stress predictors. This study finds that euro area peripheral countries‘ external indebtedness remains higher than the proposed risk threshold. However, this type of analysis entails some caveats. First, these early-warning indicators are based on historical crisis observations, so that triggers from future episodes may differ from past ones. Besides, the predictive power of out-of-sample forecasts significantly falls. Finally, data quality limitations could reduce its usefulness as policy tool.

2.2.3 Public sector vulnerabilities

Heightened and protracted public debt levels are associated with several risks, ranging from economic slowdowns to limited fiscal room for manoeuvre or greater vulnerability to changes in market investor sentiment. Against this backdrop, several frameworks have been proposed to help identify and quantify risks to fiscal sustainability. Some methodologies

16 This model is developed by the Belgian export credit agency (ONDD) and its details remain confidential.

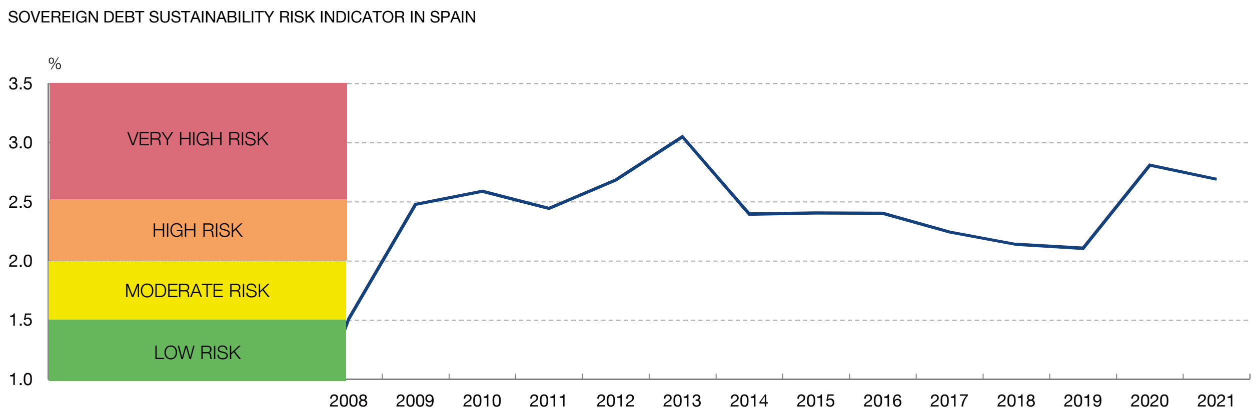
17 Muller and Bourque (2017) assign an internal rating to sovereigns based on the institutional framework of countries, their economic outlook, their external vulnerabilities, fiscal flexibility and monetary policy. These ratings are used by the Bank of Canada “to set eligibility requirements and credit limits as part of the Bank’s and government’s risk-management policy”.

18 Their results show that stock imbalances are self-correcting in debtor countries but self-feeding in creditor countries. This asymmetry is mostly explained by the differential behavior of the trade balance, which fails to adjust in the case of creditors.

Chart 6

MACROECONOMIC RISK: SOVEREIGN DEBT SUSTAINABILITY RISK INDICATOR IN SPAIN

The sovereign debt sustainability risk indicator draws together information from a large number of variables and simulations on the dynamics of public debt and its determinants. Its course highlights the impact of worsening macroeconomic conditions on the health of public finances, especially during the Great Recession.



SOURCE: Own elaboration based on Boubdalla et al. (2017).

have focused on the calculation of early-warning indicators, aimed at signalling the build-up of fiscal stress in advance and helping prevent crises by means of a timely counteraction of fiscal and macroeconomic policies (see Hernández de Cos et al., 2014).

More recently, the analysis of fiscal sustainability has evolved towards the use of debt sustainability analysis (DSA) frameworks. These tools are currently employed by most international organisations and financial institutions in their surveillance of fiscal imbalances.

The European Central Bank (ECB) also produces and maintains its own DSA framework (see Bouabdallah et al., 2017). This tool generates a score that measures risks to fiscal sustainability (ranging from low to very high), by combining three main building blocks: i) a deterministic analysis based on the debt-to-GDP path as a response to economic shocks, ii) stochastic simulations to provide uncertainty around the benchmark estimates, and iii) the use of a very broad set of fiscal indicators that provide information on potential liabilities and challenges to the sustainability of public finances in the short and medium run.

When applied to the case of Spain, the DSA documents the impact of macroeconomic conditions on the health of public finances, especially during the Great Recession (see Chart 6). Although the risks to public debt sustainability had gradually eased from their peak in 2013, these have risen in 2020, against the background of the fiscal effort enacted to combat the economic consequences of the COVID-19 pandemic.

Despite its usefulness in tracking risks to debt sustainability, it should be noted that the composition of this indicator relies on the precise measurement of variables, such as the output gap or potential GDP, which cannot be accurately assessed in real time. Therefore, its interpretation should take into account the uncertainty over the estimates.

2.2.4 Growth-at-risk

Historically, financial crises have been accompanied by large GDP losses (Claessens et al., 2012; Aikman et al., 2015). Against this background, Adrian et al. (2019a) identify the fact that tight financial conditions have large negative effects on the left tail of the GDP growth distribution. That is to say, deteriorating growth-at-risk (GaR), defined as the growth rate observed under an adverse scenario that occurs with certain probability (e.g. 5%). The concept of GaR is of great importance for financial stability given its link with the occurrence and severity of financial crises. In this context, Galán (2020) extends the use of quantile regressions of GDP growth to account for cyclical risk, financial stress and macroprudential policy. This model is a useful tool to assess the effects of macrofinancial risk on the GDP growth distribution and how macroprudential measures can mitigate them.

In particular, the GaR model implemented by the Banco de España distinguishes between the risks derived from the build-up of cyclical imbalances and those derived from the materialisation of financial stress events, while accounting for their interaction and their impact over time. The inclusion of macroprudential policy variables also allows the identification of the macroprudential policy stance and the assessment of the impact of their implementation. Here, Galán (2020) identifies positive and significant effects of macroprudential policy on GaR, which may offset the negative effects of the accumulation of systemic risk and financial shocks. In particular, the increased probability of future severe contractions (increase in the left-skewness of the GDP growth distribution) as a consequence of the accumulation of financial imbalances during expansionary periods can be mitigated by tightening macroprudential policy, which reduces the magnitude of the GDP losses observed under future adverse scenarios (see Chart 7).

2.2.5 Inflation

Price stability is a primary objective of the ECB, which conducts monetary policy to achieve the goal of low and stable inflation, while maintaining financial stability. Price stability implies that prices should not go up (inflation) significantly, and an ongoing period of falling prices (deflation) should also be avoided. The Banco de España closely monitors inflation and inflation expectations. To that end, the Banco de España employs a wide range of measures. For instance, inflation swaps provide information on market inflation expectations at different horizons (see Chart 8.1). In addition, the Banco de España also uses internal models to extract implicit probabilities of being in a situation of deflation at different horizons (see Chart 8.2).

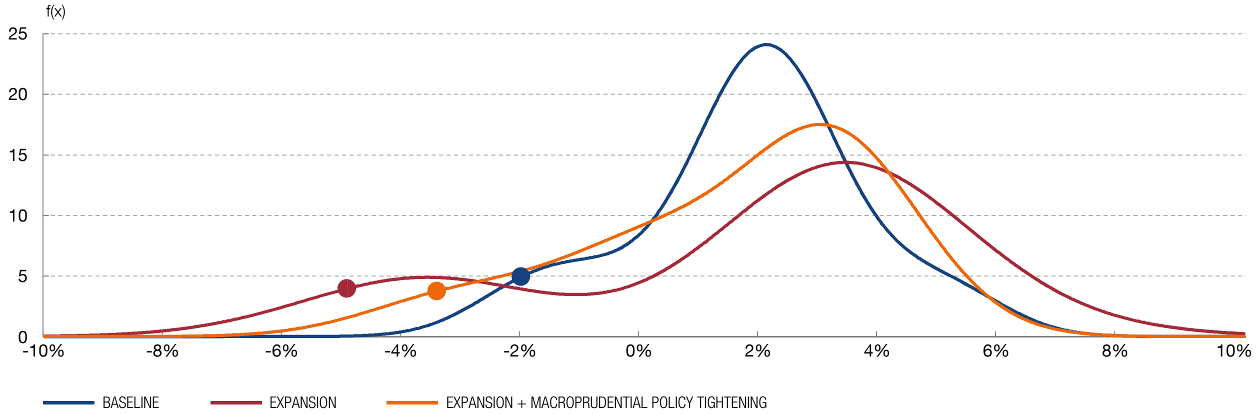
Commodity prices also provide useful information on inflation. Oil affects inflation through different channels: direct first-round effects on consumers (higher energy bills), indirect effects on producers (higher production costs) and second-round effects related

Chart 7

MACROECONOMIC RISK: GROWTH-AT-RISK (GaR)

The GDP growth distribution changes throughout the financial cycle (a). The build-up of cyclical risk during financial expansions increases the left skewness of the GDP growth distribution, which increases the downside risk of GDP growth. Macroprudential policy may offset the negative effects of risk by reducing the skewness of the distribution and then improving future growth-at-risk.

GDP ANNUAL GROWTH RATE



SOURCE: Galán (2020).

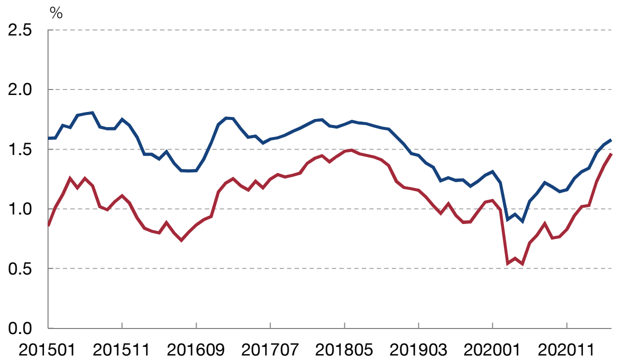
a Estimated 8-quarters-ahead GDP growth distributions obtained after mapping the fitted values of quantile regressions of GDP growth into a probability density function using a kernel-based method. The regressors include variables related to cyclical risk, financial stress, macroprudential policy, binary variables distinguishing between expansionary and crisis periods, and their interactions with macroprudential policy. The grey density represents average values under a normal-times situation, defined as periods not classified as expansions or crises; the red density represents the average values in an expansion of the financial cycle; and the blue density represents the GDP growth distribution after tightening one macroprudential measure departing from the expansion scenario. The circles denote the growth-at-risk (5th percentile) estimations. For more details, see Galán (2020).

Chart 8

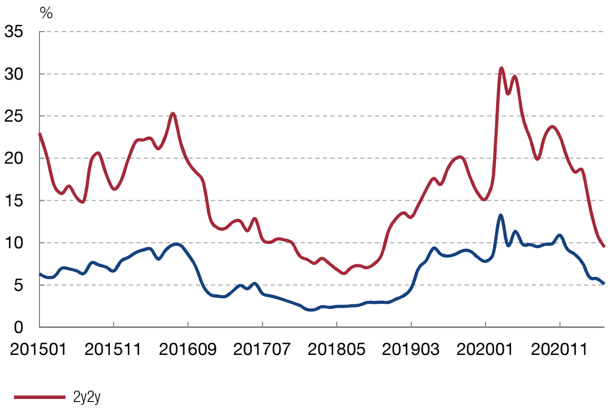
MACROECONOMIC RISK: INFLATION

The Banco de España closely monitors inflation and inflation expectations by means of different measures. For instance, inflation swaps provide information on market inflation expectations at different horizons, and internal models allow implicit probabilities of entering into a deflation period to be extracted.

1 INFLATION SWAPS (a) (b)



2 PROBABILITY OF DEFLATION (a) (c)



SOURCES: Refinitiv Datastream and own elaboration based on Bloomberg Data License.

a Monthly averages.
b Implicit forward calculated from Inflation-Linked Swaps.
c Calculated from forward rates 2y 2y and 5y 5y obtained with a joint estimation of the implicit density function of 1y through 10y inflation rates (see Gimeno and Ibañez, 2017) using euro area daily swaps and inflation options data.

to agents' expectations that affect consumption and investment plans.[19] In this context, correctly disentangling the drivers of oil price dynamics is fundamental for the calibration of the monetary policy response.[20] There are different approaches to assessing the relevance of supply and demand factors. For instance, the NY Federal Reserve identifies supply and demand shocks by looking at their impact on financial prices[21], while Kilian and Muphy (2014) propose a structural vector autoregressive (SVAR) model with sign restrictions to identify global demand, oil supply and precautionary demand shocks. Moreover, future oil prices are generally seen as a reflection of market expectations of future oil spot prices, and are therefore widely used for oil price projections. Finally, commodity prices are major drivers of capital flows to emerging market economies, especially for Latin American countries, thus amplifying or mitigating global financial cycles (Molina and Viani, 2019).

2.3 Market risk

According to the EBA, market risk can be defined as "the risk of losses in on and off-balance sheet positions arising from adverse movements in market prices".[22] There are numerous, widely used market risk indicators to address this risk, such as equity indices, exchange rates and interest rates. In this section, we focus on two families of measures. Namely, implied volatility measures and price-to-earnings ratios (PERs) (see Chart 9 for an illustration).

First, implied volatility indices are broadly used by central banks to interpret and forecast current and future stock price dynamics for different markets (i.e. equity, fixed income, exchange rates, commodity markets and ETFs markets).[23] These indices reflect the market expectations for the future volatility of the underlying asset. For the specific case of the VIX, which is derived from the S&P 500 options, there is evidence backing its capacity to proxy global risk aversion, lead market uncertainty and forecast volatility and returns,[24] and even economic activity.[25] Given the leading indicator capacity of implied volatility indices also at a regional level, most analysts, including central banks, use in their regular assessment not only the VIX but also other regional VIX-like indices, such as the VSTOXX, VDAX, VCAC, VIBEX, VSMI, and customised volatility indices of interest. The wide variety of volatility indices recently aroused interest among researchers to calculate a common

19 However, in recent years the pass-through of oil to inflation has weakened considerably, partly due to an increase in energy efficiency and the globalisation of the economy in which most of the value added by companies is in the form of differentiated products and services.

20 While demand-driven oil shocks move output and inflation in the same direction, negative oil shocks stemming from the supply side tend to lead to higher inflation and lower output, giving an ambiguous signal to the central bank.

21 See Groen et al. (2013), who use a partial least squares (PLS) model to build linear combinations of the financial market variables which have maximum explanatory content for oil-price changes, and then examine the estimated factors to determine whether they resemble a demand or supply shock.

22 https://www.eba.europa.eu/regulation-and-policy/market-risk.

23 Among the more broadly used volatility indices on commodities and exchange rates, it is worth highlighting the OVX (oil), EVZ (euro), and GVZ (gold). The literature supports the use of the CBOE crude OVX to forecast future oil spot volatility at long horizons, see Benedetto et al. (2020) and Chen et al. (2018), among others. Besides, several studies, such as Dimpfl et al. (2018), use the EVZ to study the volatility transmission between the equity, gold, oil and currency markets.

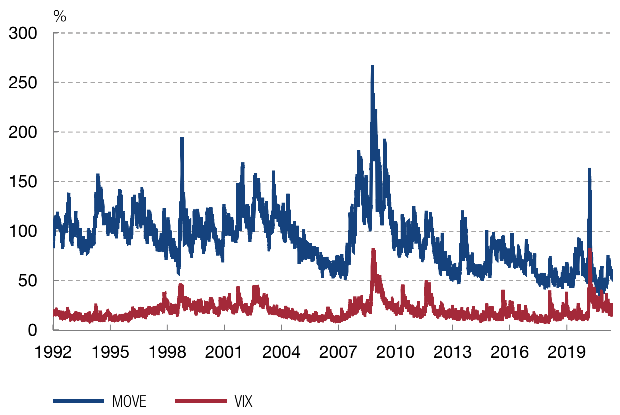
24 See Blair, Poon and Taylor (2001), Poon and Granger (2003), Becker, Clements, and McClelland (2009), Han and Park (2013), Pan et al. (2019), Wang et al. (2020), among many others.

25 Bekaert and Hoerova (2014), Tiwari et al. (2019), Cesa-Bianchi et al. (2020), and Bhattarai et al. (2020), among others.

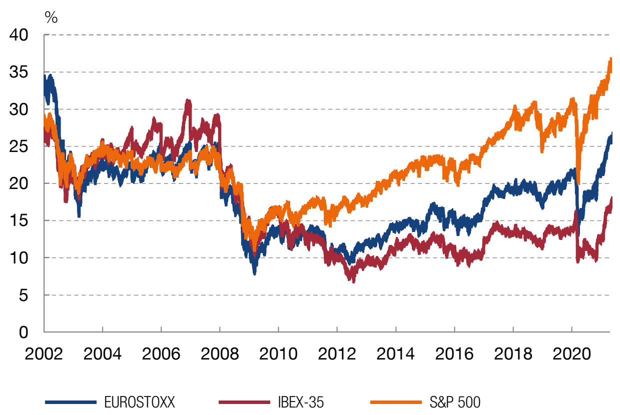
Chart 9
MARKET RISK INDICATORS

Market risk is associated with asset value losses as a consequence of adverse price movements. Indicators used to assess this risk include volatility indices, such as the MOVE (fixed-income) or the VIX (equity), and the price-to-earnings ratio (10-year moving average PER).

1 VOLATILITY INDICES



2 PRICE-TO-EARNINGS RATIO



SOURCES: CBOE and Bloomberg.

volatility factor to identify the main volatility drivers worldwide (see, for instance, Londono and Wilson, 2018). Recently, González-Pérez (2019) have made use of the information content of the idiosyncratic volatility component of these factor models to study spillovers across markets.[26]

The second set of indicators studies to what extent the price of an asset is misaligned with the value justified by its current and future economic fundamentals. Indeed, there is an increasing amount of research that analyses whether these indicators could anticipate potential market bubbles.[27] Such indicators include the price-to-earnings ratio (PER), and equity risk premium proxies. The PER ratio relates the risk of current or future market overvaluation to investors' future cash flow expectations. Their dynamics incorporate investors' beliefs about future cash-flows, economic activity and growth. One limitation of the PER is that current profit and dividend information is used to calculate it, so that this measure is influenced by cyclical patterns in these variables. For this reason, Campbell and Shiller (1998) proposed the CAPE (Cyclically-Adjusted Price to Earnings ratio), which smooths out the standard PER.[28] The excess CAPE yield (inverse CAPE minus the 10-year secured bond yield) is also useful for approaching stock market profit expectations, helping

26 News-based indicators also contribute to monitoring market risk. For instance, Baker et al. (2019) propose a daily newspaper-based Equity Market Volatility (EMV) index that tracks VIX and S&P500 movements as a result of changes in a variety of uncertainty sources.

27 See, among others, Gonçalves and Laonard (2021).

28 To calculate the CAPE the standard PER should be divided by the last ten years' average inflation-adjusted earnings to assess the long-term performance, under the assumption that economic cycles last from around six to seven years.

to portray the expected stock earnings per share above the risk-free rate (Shiller et al., 2020), and even for approaching likely bubbles. Finally, the implied equity risk premium could be defined as the excess expected return from the equity market over the bond market.[29]

2.4 Funding and liquidity risk

Funding liquidity is the ability to settle obligations when due. Consequently, funding liquidity risk is related to the possibility of failing to settle obligations with immediacy over a specific horizon (Drehmann and Nikolaou, 2009). The materialisation of funding liquidity risks was at the core of the onset of the great financial crisis (GFC), as many market intermediaries, including banks, relied excessively on short-term debt, and were unable to meet their financial obligations when market conditions worsened. This in turn prompted massive central bank liquidity injections and, over time, resulted in the introduction of new liquidity tools in the regulatory framework to increase the resilience of the financial system to liquidity shocks.[30]

A well-known indicator of liquidity stress is the Libor-OIS spread, which is the difference between the Libor, a representative interest rate in the interbank market, and a risk-free interest rate of the swap market (for a specified term). Different versions of this spread include the Euribor-OIS spread (depicted in Chart 10) and the TED spread. When the spread increases, banks charge a premium for lending money to their peers over the risk-free rate. This premium has been found to embed both credit risk and liquidity risk (see Akdi et al., 2020; McAndrews et al., 2008; Michaud and Upper, 2008; Sengupta and Tam, 2008; among others).

Another relevant indicator of liquidity tensions are the implicit borrowing costs in cross-currency swaps (CCS) contracts. A CCS is an agreement to borrow in one currency (e.g. dollars) from a counterparty, and lend in another (e.g. euro) to this same counterparty (by way of illustration, Chart 10 shows the EUR/USD CCS). During the life of the CCS the two parties also exchange interest payments in the two currencies. In theory, borrowing costs using a CCS should be similar to the cost of taking out loans in another currency in the cash market.[31] Distortions in CCS instruments have persisted since the onset of the GFC, including during quiet times, which suggests that structural factors are likely driving this outcome (see Borio et al., 2016 for a detailed discussion). This outcome calls into question the use of CCS rates to proxy for liquidity frictions.

Together with funding liquidity, or the ability to meet financial obligations, analysis of the easiness to trade securities, or market liquidity, is also relevant for central banks. For

29 For further analysis on this set of indicators, see Box 1.1 of the Banco de España Financial Stability Report, May 2018, entitled "Stock-market valuation metrics".

30 For instance, in 2015 the Basel Committee on Banking Supervision (BCBS) introduced the Liquidity Coverage Ratio (LCR), which requires banks to store liquid assets on their balance sheets to withstand periods of distress in funding markets (BCBS, 2013).

31 For instance, borrowing dollars directly in the cash market should be financially equivalent to 1) borrowing euro and 2) entering a CCS to obtain dollars, taking into account interest rate differentials in the two currencies. However and since the financial crisis, borrowing in dollars has become more costly in certain CCS contracts. See Baba et al. (2009) for further insights into the interpretation of the CCS.

Chart 10
LIQUIDITY RISK INDICATORS

The Banco de España analyses liquidity and funding risks through indicators based on prices. Interbank interest rate spreads, such as EURIBOR - OIS, indicate potential stress in funding liquidity and in fixed-income markets. Additionally, EUR/USD Cross Currency Basis Swap accounts for potential stress in the USD funding market (high absolute CCS values are linked to higher tensions).

1 EURIBOR 3M - OIS 3M

2 CCS EUR/USD 3M (a)

SOURCE: Bloomberg.

a Cross Currency Basis EUR/USD Swap.

instance, the IMF (2015) pointed to the presence of fragile liquidity conditions in a number of markets, including the U.S. Treasury market, after some short-lived episodes of illiquidity spikes such as the well-known flash event of October 2014. Thus, market illiquidity may pose new risks to financial stability. This is because the gradual build-up of liquidity buffers since the financial crisis, in part driven by regulatory initiatives such as the LCR, may be of little use if these assets cannot be converted into cash during bouts of market turbulence, when liquidity is most needed. Against this backdrop, there are some analytical approaches that analyse the resilience of market liquidity (for instance, Broto and Lamas, 2020), which may help authorities understand the complex nature of liquidity risks and strengthen their monitoring capacity.

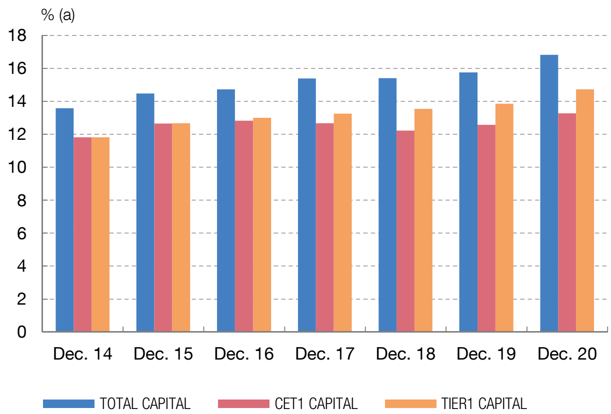
2.5 Banks: profitability and solvency

Regarding the banking sector, the Banco de España regularly analyses commonly used indicators to evaluate their profitability and solvency. The former metric reflects the ability of a financial institution to generate return, whereas the latter refers to the ability to meet its financial obligations. The main measures to evaluate bank profitability are financial ratios, such as the return on equity (ROE) and the return on assets (ROA), which measure profit earned in relation to the level of capital and assets, respectively. The ROA quantifies how well the total funds invested in the bank are used to generate income and, contrary to the ROE, it is not affected directly by leverage. Net interest income, which is the difference between interest received for assets and interest paid on liabilities, is also a complementary measure of profitability. As to the main indicators of banks' solvency, capital ratios – with

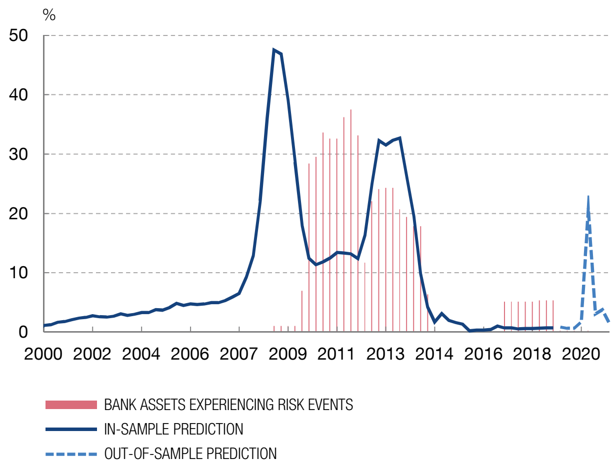
Chart 11
BANKS: PROFITABILITY AND SOLVENCY

Banks' solvency is analysed through capital-based ratios, whereas profitability is usually assessed through ratios, such as the return on equity (ROE) and the return on assets (ROA). The Banco de España further complements its regular analysis of banks with model-based indicators such as CREWS (CAMELS rating-based early-warning system), which measures the portion of bank assets that are expected to be in a situation of risk two-years ahead.

1 CAPITAL RATIOS



2 CREWS (b)



SOURCE: Banco de España. Own elaboration.

a Percentage of total risk-weighted assets.
b The indicator is the sum of the probabilities of risk events in a two-year horizon of each individual bank weighted by its total assets. The probability is estimated through a conditional logit model where the dependent variable is an indicator of a bank experiencing a risk event in the following two years, where a risk event is defined as either default, public intervention or recapitalisation of the bank, absorption by another institution or capital needs derived from stress-testing exercises. The explanatory variables are those derived from the CAMELS-based rating system, which include bank characteristics associated with capital, size, management, earnings and liquidity; and macrofinancial variables (GDP growth and change in interest rates). The sample includes 82 banking institutions with quarterly data from 2000 Q1 to 2021 Q1. The indicator is an aggregate measure, so it considers the overall default probability and not individual ones, which is why it seemed not to increase before the 2017-2018 crisis, caused by the bankruptcies of Evo Banco and Popular.

either total, Tier 1 or Core Equity Tier 1 (CET1) capital in the numerator relative to their risk-weighted assets – are the most frequently used measures (see left-hand panel of Chart 11). An adequate level of capital would preserve banks' capacity to absorb losses.[32]

Although these traditional indicators are regularly used, central banks also complement this regular analysis with model-based tools to ascertain banks' health. For instance, the Banco de España has developed a model to analyse the probability of occurrence of banking crises using bank-level data. This model complements the signals provided by the aggregate macrofinancial indicators. The model is a conditional logit that incorporates variables from the six categories defined in the international banking rating system known as CAMELS. CAMELS is the acronym for capital, assets, management, earnings, liquidity and sensitivity to the macroeconomic environment, so that the whole

32 Market-based measures, such as bank CDS spreads, are also alternative tools to analyse the health of the banking sector. In the case of bank CDS spreads, Hammoudeh et al. (2013) find that the banking sector plays a CDS price-leading role compared to the CDS spreads for financial services and insurance sectors in the US.

set of variables reflects an institution's risk. This type of model has shown a high predictive capacity of banking failures in the past (Thomson, 1991; Erdogan, 2008). In particular, the model implemented by the Banco de España estimates the probability of a bank entering into a situation of distress, defined as public interventions or capitalisations, absorptions, or the need to raise capital as signalled by stress testing exercises, over a two-year horizon. Results are aggregated, accounting for the size of the banks, into a CAMELS rating-based early-warning system (CREWS) indicator of risk of the banking sector (see right-hand panel of Chart 11). This indicator demonstrated a high predictive performance before the last financial crisis. Recently, as a consequence of the COVID-19 pandemic, the indicator has risen suddenly, but has subsequently decreased in line with the improved macrofinancial environment.

The Banco de España also analyses the health of financial entities by means of stress tests. Faced with the uncertainty posed by the current health crisis over the future performance of the economy, the analysis of Spanish banks by means of stress tests is especially important, given the forward-looking nature of these tools.[33]

33 The methodology used by the Banco de España's stress tests, known by the acronym FLESB (Forward-Looking Exercise on Spanish Banks), is applied to a 3-year horizon to measure Spanish banks' resilience in terms of solvency and liquidity. The Banco de España designed FLESB using a top-down approach, under which a set of models developed internally are applied to the information available from regulatory and supervisory reports. For further details, see the Financial Stability Report of the Banco de España (Autumn 2020).

3 Systemic risk

Following the work by the IMF, FSB and BIS for the G20 (2009), systemic risk can be defined as "a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy".

Systemic risk can be analysed either in its time dimension or in its cross-sectional dimension. First, the time dimension is related to the build-up of risks over time and the pro-cyclical accumulation of financial vulnerabilities. Identifying it is addressed with indicators with different degrees of complexity. Thus, they run from data-based tools, such as heatmaps or financial stress indices, to more sophisticated model-driven indicators, such as the conditional capital shortfall-based measures. Second, the structural (or cross-sectional) dimension of systemic risk focuses on how a specific shock to the financial system can propagate and become systemic. Both dimensions are critical, as financial stability cannot be guaranteed simply by assessing the health of individual institutions; continuous evaluation of the system as a whole is needed. The cross-sectional dimension is often analysed by means of the level of interconnectedness of the financial system, which is useful for disentangling contagion risks, or asset commonalities. Systemically important financial institutions are another relevant aspect of cross-sectional systemic risk. Finally, we will also analyse indicators that capture both systemic risk dimensions and other sources of systemic risk, such as climate change or cyber risks, whose analysis is less developed but whose importance has recently increased.

3.1 Systemic risk: time dimension

3.1.1 Heatmaps

Heatmaps are a useful visual tool to issue early warnings about potential systemic risks which merit in-depth analysis. This instrument consists of two-dimensional tables that draw together information on a wide range of indicators by means of a colour code linked to their current position on the percentile scale of their corresponding frequency distributions. Colour codes tend to range from red to green, the former being associated with higher risks and the latter with a normal range of values. For the sake of simplification, individual indicators are usually aggregated into categories, so that the final output represents the risk of each category.

Given their simplicity and straightforward interpretation, heatmaps are broadly used by central banks and other institutions to monitor risks. Among others, for instance, the IMF regularly monitors in its Global Financial Stability Report (GFSR) a broad set of indicators in a matrix by type of macrofinancial imbalance across types of lenders and borrowers (Adrian et al., 2019b). The BIS has also developed a framework for Global Risk Surveillance for both advanced and emerging economies. Despite this widespread use of heatmaps, they are simply a graphical representation of the data. Therefore, they should always be reinforced by expert judgement and complemented by more sophisticated models.

The Banco de España also relies on heatmaps to identify potential systemic risks. For example, Alonso and Molina (2021) develop a vulnerability dashboard that focuses on 27 emerging market economies (EMEs) whose situation may pose a threat to financial stability in Spain. This dashboard includes 34 indicators related to financial markets, macroeconomic fundamentals – including macro, fiscal, banking and external variables – and other institutional and political indicators dating from 1993. The main novelty of this heatmap is that risk levels associated with indicators are based not only on the historical frequency distribution, but also on the cross-sectional one. The cross-country perspective tends to signal the countries that may be more exposed to global turbulence, while the historical perspective focuses on crises arising from more idiosyncratic factors. Thus, the combination of both dimensions enriches the vulnerability analysis.

Furthermore, the Banco de España regularly updates a heatmap that issues alerts on systemic risks from the Spanish banking system (Mencía and Saurina, 2016). This tool summarises information dating back to 1971 for more than 100 indicators that are regularly revised and extended when deemed appropriate.[34] For the sake of simplicity, indicators are aggregated into six broad groups.[35] The highest level of aggregation includes: 1) credit growth and leverage, 2) transformation of maturity and market illiquidity, 3) concentration, 4) incentives and moral hazard, 5) macroeconomic imbalances, and 6) actual conditions in the economy and in the banking sector. While the first four categories correspond to the ESRB's intermediate objectives,[36] the last group does not include early-warning indicators, but rather variables that assess the position of the economy, which is key to adjusting the macroprudential policy stance.

3.1.2 Financial stress indices

A financial stress index (FSI) is a real-time measure of systemic risk that summarises high-frequency financial data, usually daily or weekly, from different segments to proxy the current state of uncertainty of a specific financial system in a single number. FSIs could be interpreted as an ex-post measure of systemic risk, i.e. they are useful for analysing risks once a systemic event has already materialised. In other words, an FSI is not a leading indicator of recessions, as it summarises the volatility and turbulence of financial variables.

While there are many methodological proposals to calculate FSIs,[37] the approach proposed by Holló et al. (2012) in their composite indicator of systemic stress (CISS) is broadly used among central banks. This method is based on two steps. Thus, once the raw

34 There are two types of indicators: some indicators are one-tailed, so that higher vulnerability is signalled by an increase, whereas other indicators are two-tailed, since either an increase or a decrease signal higher risk. The non-performing loans ratio is an example of a one-tailed indicator, whereas the rate of change of credit is an example of a two-tailed indicator.

35 The aggregation is done linearly, taking into account both early-warning capacity and correlation. A higher weight is assigned to indicators with greater predictive power while higher correlated indicators are assigned a lower weight so as not to double-count the same source of risk.

36 See recommendation of the ESRB of 4 April 2013 on intermediate objectives and instruments of macroprudential policy (ESRB/2013/1).

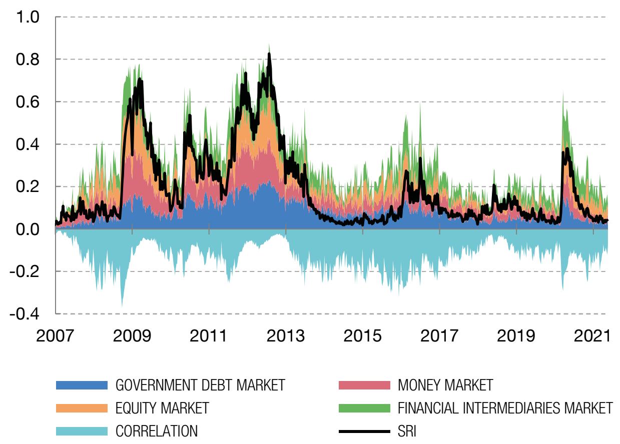
37 See, for instance, Cardarelli et al. (2011) or Balakrishnan et al. (2009).

Chart 12

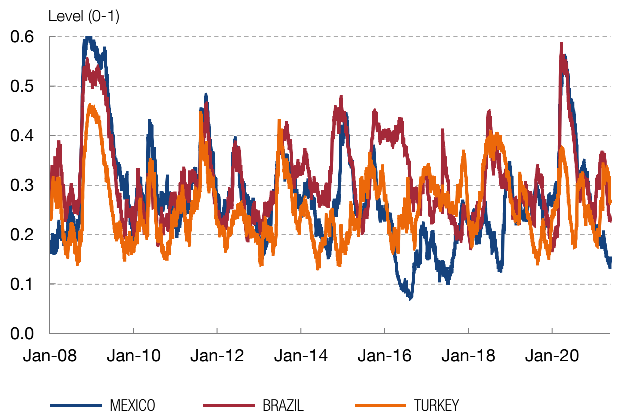
TIME DIMENSION OF SYSTEMIC RISK: FINANCIAL STRESS INDICES

Financial stress indices (FSIs) are useful for analysing risks once a systemic event has already materialised. For instance, at the onset of the pandemic, the Systemic Risk Indicator (SRI) for the Spanish financial system rebounded. Subsequently, this indicator gradually declined and currently shows levels close to those prior to the pandemic. Similarly, the FSIs have reached new highs since the Global Financial Crisis in many of the markets relevant for the Spanish Banking system.

1 SPAIN: SYSTEMIC RISK INDICATOR (a)



2 FINANCIAL STRESS INDEX (b)



SOURCE: Banco de España.

a The indicator measures the current status and the frictions in the financial markets that can potentially impact the real economy. It gathers information on the main segments of the financial system (government debt, equity, financial intermediaries and money markets) and provides a single value that reflects financial instability.

b The index captures the stress of each financial market using 3 standardised variables for 6 segments (equity, public and corporate debt, money markets, banks, exchange rates and commodities), giving more weight to those situations in which stress predominates in several markets at the same time.

financial market individual indicators are transformed by means of order statistics to make them homogeneous, these new indicators are aggregated taking into account the cross-correlations between individual variables. Thus, FSIs set greater store by situations in which stress predominates in several market segments at the same time.

Currently, the Banco de España regularly calculates FSIs following the aforementioned method by Holló et al. (2012) for two purposes. First, the systemic risk indicator (SRI) for the Spanish financial system is regularly updated.[38] This indicator draws together information on the money market, government debt, equity and financial intermediaries segments.[39] Besides, FSIs are also calculated for the usual assessment of the financial markets of all countries material to the Spanish banking sector (namely Brazil, Chile, Colombia, Mexico, Turkey, the US and the UK)[40] except Peru, and also for Russia

38 For a detailed explanation of this indicator, see Box 1.1 of the May 2013 Financial Stability Report of the Banco de España.

39 See Cambón and Estévez (2016) for an alternative proposal of FSI for the Spanish financial system. This indicator is regularly updated by the CNMV (National Securities Market Commission).

40 For the annual update of the list of material third countries by the Banco de España, see https://www.bde.es/bde/en/areas/estabilidad/herramientas-macroprudenciales/colchon-de-capital-anticiclico/fijacion_del_po_abd79f06544b261.html.

(see Andrés et al., forthcoming). For each country, the FSI summarises the information of six market segments (equity, public and private debt, banks, money markets, exchange rate markets and commodity prices) with three individual indicators for each segment. Chart 12 illustrates the recent evolution of the SRI and the FSIs for Brazil and Mexico. These indices are bounded between zero (no financial stress) and one (maximum level of financial stress). At the onset of the pandemic in 2020, all FSIs rebounded and gradually declined afterwards.

3.1.3 Credit-to-GDP gap

The credit-to-GDP gap calculated following the recommendations of the Basel Committee on Banking Supervision (BCBS) is the reference indicator to set the Countercyclical Capital Buffer (CCyB) rate. The methodology is based on the estimation of the long-run trend component of the credit-to-GDP ratio using a Hodrick-Prescott filter, where deviations from the estimated trend represent the gap. Although this indicator had proven to have good early-warning properties of systemic crises before the last global financial crisis (Drehmann et al., 2010; Detken et al., 2014), the high persistence of its trend component produces large biases after rapid changes either in credit or GDP. To resolve these limitations, the Banco de España has adjusted the indicator, significantly reducing the memory of the trend component by adapting it to the empirical evidence on the duration of financial cycles in Spain. This adjustment, proposed by Galán (2019), lessens the biases before and after crises and significantly improves the systemic event predictive performance. The adjusted credit-to-GDP gap is regularly updated and is the main indicator to support the quarterly decisions on the CCyB (see Chart 13). This indicator recorded highly negative values following the global financial crisis, holding on a rising path thereafter consistently below 2 pp, a level usually considered as showing signs of imbalances. After the outbreak of the pandemic, and more specifically since June 2020, this indicator has remained above the alert threshold. However, this is due to the stimulus policies and the sharp impact of the shock triggered by COVID-19 on GDP rather than to new endogenous imbalances of the financial system which could be handled by the activation of the CCyB.

To compensate for the limitations of the credit-to-GDP gap in the current juncture and substantiate its analysis of the cyclical risk position, the Banco de España also takes into account other complementary macro-financial indicators. More specifically, the output gap has gained relevance when it comes to supporting CCyB decisions. As Chart 13 shows, the output gap remains at strongly negative levels, which suggests an unprecedented impact of the pandemic on economic activity.

3.1.4 Conditional capital shortfall-based measures of systemic risk

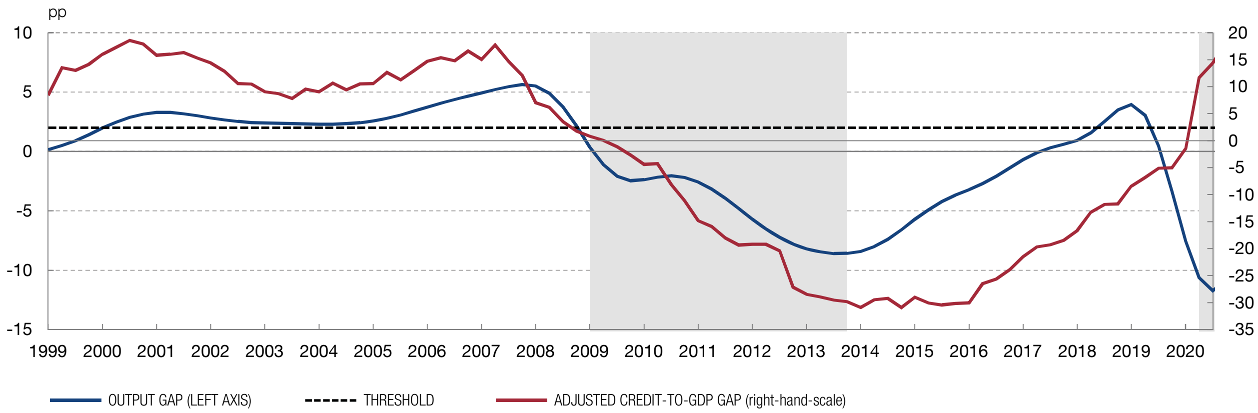
Since the Great Financial Crisis (GFC), the literature on market-based metrics to gauge systemic risk has significantly increased (for more information on this topic see Bisias et al. (2012) or Sylvain et al. (2016)). One of the most salient groups of indicators in this area requires the calculation of the expected capital shortfall of individual institutions, i.e. the capital that a financial institution would need under stressed conditions. The rationale is that undercapitalised institutions will no longer supply credit for ordinary business, and thus, this lack of lending would generate a negative externality for the overall financial system and the real economy.

Chart 13

SYSTEMIC RISK (TIME DIMENSION): ADJUSTED CREDIT-TO-GDP GAP (a) AND OUTPUT GAP (b) (c)

The credit-to-GDP gap is the main reference indicator for the activation of the countercyclical capital buffer. However, the great inertia of the trend induced by the method recommended by the BCBS generates sizable biases. The version used by the Banco de España is adjusted to the characteristics of the financial cycle in Spain. The indicator signals the imbalances before the last financial crisis and the recovery phase in recent years. Recently, the significant GDP losses derived from the COVID-19 pandemic have seen the indicator increase suddenly and exceed the CCyB activation threshold. Therefore, these recent developmentss should not be interpreted as a systemic risk warning and other indicators, such as the output gap, must be used to support the analysis.

ADJUSTED CREDIT-TO-GDP GAP AND OUTPUT GAP



SOURCE: Banco de España.
NOTE: Data refer to the end of 2020 Q4.

a The adjusted credit-to-GDP gap is calculated as the difference, in percentage points, between the observed ratio and the long-term trend calculated using a one-sided Hodrick-Prescott filter with a smoothing parameter equal to 25.000. This value is more in line with the financial cycles historically observed in Spain. For more details on the calculation of the adjusted credit-to-GDP gap, see Galán (2019).
b The output gap measures the difference between the actual and potential level of GDP. For further information, see Cuadrado et al. (2016).
c The shaded areas show the last period of systemic banking crisis (2009 Q1-2013 Q4) and the coronavirus pandemic (2020). The horizontal dashed line represents the CCyB activation threshold equal to 2 pp.

Along these lines, Adrian and Brunnermeier (2016) propose a conditional Value-at-Risk (CoVaR) measure, which captures the change in the Value-at-Risk of the financial system conditional upon an institution being under stress, relative to the Value-at-Risk conditional upon that institution being at its median state. In other words, CoVaR measures the contribution of a financial institution to systemic risk. Similarly, but based on a different methodology, Acharya et al. (2010) suggest a Marginal Expected Shortfall (MES) measure that estimates the expected drop in the stock returns conditional upon a poor performance of the overall system. Finally, Brownlees and Engle (2017) introduce the SRISK indicator, defined as the expected capital shortfall of a financial entity conditional upon a prolonged market decline. In addition and based on this last indicator, Engle and Ruan (2019) propose a measure of the probability of a crisis. All these measures may be calculated only for listed companies.

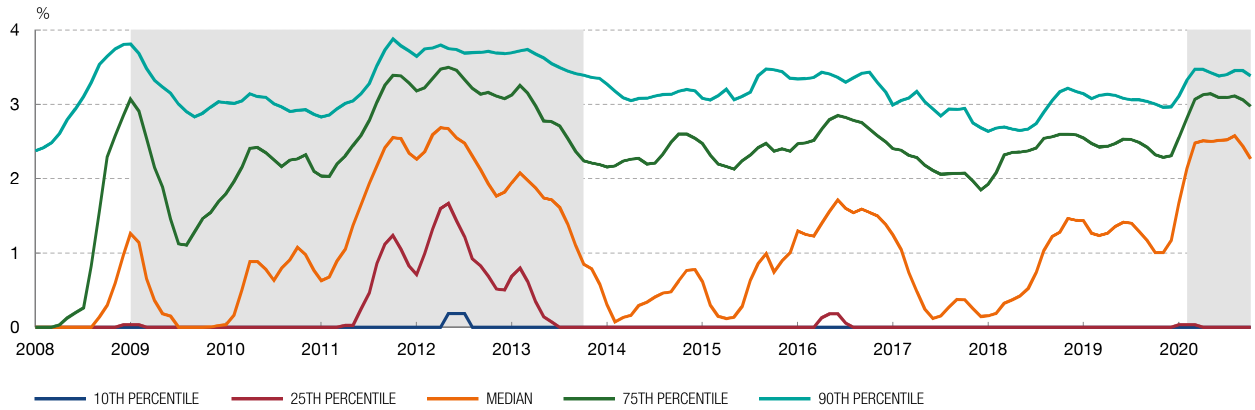
In line with other central banks, the Banco de España also monitors listed financial institutions according to these metrics. For instance, Chart 14 depicts the distribution of the SRISK indicator for banks in the Eurozone as a percentage of the total assets of each bank.

Chart 14

SYSTEMIC RISK (TIME DIMENSION): CONDITIONAL CAPITAL SHORTFALL-BASED MEASURES

The SRISK indicator approximates the expected capital shortfall of a bank after a substantial drop in equity markets. This figure represents the distribution of the SRISK indicator as a percentage of the total assets of each bank for listed companies in the eurozone. This indicator increased for most banks in March 2020 with the onset of the COVID-19 crisis, and subsequently declined along with the financial markets recovery.

SRISK INDICATOR DISTRIBUTION (a)



SOURCE: Datastream, SNL, INE and Banco de España.

a The SRISK indicator is expressed as a percentage of the total assets of each entity. Parameter assumptions are 4.5% for the capital requirement, 10% for the market drop and 22 business days for the period in which the potential market drop takes place [see Brownlees and Engle (2017) for further details]. Given data unavailability, the index as of December 2020 is calculated for most banks with asset and liability values as of 2020 Q3. Percentile series have been smoothed using a 3-month moving average.

This indicator increased for most banks in March 2020 with the onset of the COVID-19 crisis, and subsequently declined along with the financial markets recovery.

3.2 Systemic risk: structural dimension

3.2.1 Structural risks

Structural risks are related to long-term risks of a non-cyclical nature and to risks stemming from structural features of the financial system or the wider economy. In this respect, the Systemic Risk Buffer (SRB) is a fairly flexible macroprudential instrument that aims to address such risks and it is part of the agenda on regulatory changes (CRR II/CRD V). Although the CRD IV is not quite precise regarding the indicators for the activation or the release of the SRB, the ESRB (2017) proposed three broad categories of structural risk indicators. (1) The first category comprises indicators that reflect structural characteristics of the financial sector, as a large domestic banking sector can give rise to systemic risk. The main indicators in this category are related to the size and concentration of the domestic banking sector, foreign ownership and other structural risks such as the levels of NPLs. (2) The second set of indicators adresses the propagation and amplification of shocks within the financial system. The amplification channels are related to structural characteristics such as the exposure to concentration, asset and banking business model characteristics, and interconnectedness and intra-financial linkages, including the importance of non-bank financials. Regarding non-banks, although they offer broader-based funding to the economy, they may also become a source of systemic risk if they become involved in activities typically performed by banks, but without being subject to banking regulatory and supervisory standards. Therefore, international and national authorities use risk metrics to monitor these activities (such as credit intermediation, maturity or liquidity transformation and the creation of leverage) performed by non-banks. (3) The third group of indicators is related to structural risks to the banking sector stemming from the real economy. As the GFC demonstrated, shocks originating from the real economy can lead to significant losses for the financial sector, and reduce the banking credit available, which in turn would have an additional negative impact on the real economy. Such risks could be triggered by specific vulnerable economic sectors or, in the case of small open economies, by a crisis in a different country.

The regular monitoring of structural risks enables the early detection of vulnerabilities that may lead to a crisis. This is an area to be developed in the future in parallel with that of regulation. Various international organisations such as the Financial Stability Board (FSB)[41] and the ESRB have worked in this area. For instance, the ESRB quarterly dashboard of systemic risks includes structural indicators, among others.[42] Other national authorities have further developed their analysis of structural indicators. For instance, the Suomen Pankki regularly updates a set of structural indicators that compares Finnish variables with the EU in a dashboard,[43] and the Norges Bank has recently proposed a set of indicators to assess the Norwegian SRB.[44]

3.2.2 Interconnectedness among banks based on network analysis

As mentioned, systemic risk depends, among other factors, on the network of financial exposures among financial institutions, such as banks.[45] This kind of analysis is important since, in a strongly connected network of institutions, even a small shock can become systemic. Shock propagation in interbank markets can occur through multiple channels and market segments. Network models provide a flexible approach for assessing potential system-wide losses due to interconnectedness among banks. Nevertheless, this type of analysis requires granular data on financial networks that is often lacking, being one of the main challenges of this approach.

Although there is no consensus on the methodology to address this issue, research in this field is growing rapidly. Inspired by the seminal paper by Eisenberg and Noe (2001), a number of initial contributions focused on the assessment of the likelihood and the extent of default cascades via repayment failures. More recently, a number of other contagion channels

41 https://www.fsb.org/work-of-the-fsb/vulnerabilities-assessment/.

42 https://www.esrb.europa.eu/pub/rd/html/index.en.html.

43 https://www.suomenpankki.fi/en/Statistics/chart-gallery/pankkisektorin-rakennemittarit/rakennemittarien-yhteenveto/rakennemittarien-suomen-havaintojen-vertailu-muiden-eu-maiden-mediaaniin-ja-suomen-havaintojen-keskiarvoon/.

44 https://norges-bank.brage.unit.no/norges-bank-xmlui/handle/11250/2653109.

45 See Aymanns et al. (2018), Glasserman and Young (2016) and Caccioli et al. (2018) for some recent surveys on network analysis.

has been considered, such as short-term liquidity withdrawal (Hałaj, 2020), overlapping portfolios and fire sales (Cifuentes et al., 2005), or credit quality deterioration (Battiston et al., 2012, and Bardoscia et al., 2015).[46] Importantly, most of these channels allow for the contagion of financial distress even before the materialisation of a default.

Among recent works with relevant policy implications, Roncoroni et al. (2019) study possible contagion channels for banks in the Euro Area through direct or indirect exposures, and Caceres-Santos et al. (2020) look at systemic risk and interconnectedness in the Bolivian banking system. Other empirical exercises use similar methods to model contagion in the interbank market. For instance, Fink et al. (2016) propose a method which analyses shock transmission via changes in the PD of borrowers due to changes in their capital ratio. Besides, Aldasoro et al. (2020) analyse outcomes based on a fixed matrix of interbank exposures to total exposures and consider shocks to stem from changes in the value of total assets. All in all, this strand of the literature highlights the multiple applications of network-based analyses within central banks' risk monitoring activities.

3.2.3 Interconnectedness across financial sectors: direct and indirect interconnectedness

Interconnectedness between financial institutions – banks and other financial agents – is an inherent characteristic of developed financial systems that allows for risk-sharing between agents and facilitates the provision of and access to finance. However, at times of crisis/stress, it may also contribute to the propagation of shocks across the financial system. The Banco de España regularly updates its assessment of the links within the Spanish financial system (and between its institutions and foreign entities) in its Financial Stability Report (see Alonso and Stupariu, 2019). This analysis tends to focus on Spanish banks' interconnections and distinguishes between direct and indirect interconnectedness.

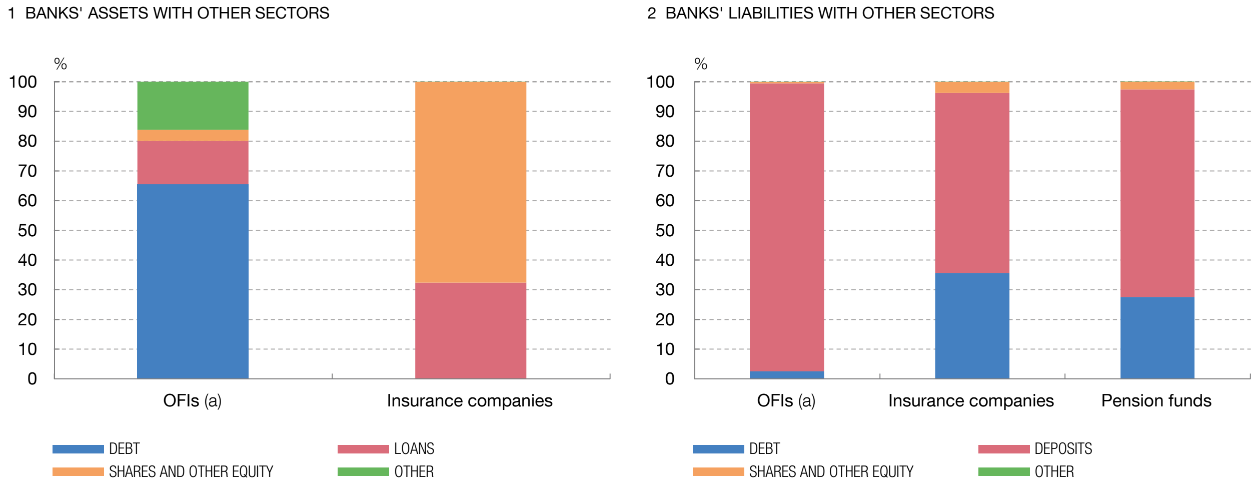
First, direct interconnectedness arises from counterparty relationships and exposures, whether on the asset or the liability side (examples would be direct borrowing/lending or investment exposures between two counterparties). Thus, these connections materialise where two entities are direct counterparties through debt instruments, shares or other contractual relationships. In general, analysis of these interlinkages focuses on cross-holdings: loans and issuances by one financial institution and held by another belonging to the same or a different financial sector. The most common indicator of direct interconnectedness is based on the volume of exposures that entities in each sector hold with others. To understand the significance of this volume, the ratios of the exposures or liabilities of the analysed sector to other sectors over the amount of total assets of that sector are monitored. These indicators are also used for cross-border exposures (exposures to the Rest of the World). Chart 15 illustrates direct interlinkages between sectors by means of the share of Spanish banks' financial assets corresponding to their exposures (assets and liabilities) to other sectors. This type of indicator is also used by institutions such as the FSB,

46 The DebtRank algorithm by Battiston et al. (2012) and Bardoscia et al. (2015) is a broadly extended approach to model the transmission of shocks by means of the credit quality channel.

Chart 15

SYSTEMIC RISK (CROSS-SECTIONAL DIMENSION): INTERCONNECTEDNESS BETWEEN FINANCIAL SECTORS

Banks' direct interconnectedness with other sectors accounts for a relatively small share (in no case more than 5% of banks' financial assets). This interconnectedness measure has remained relatively steady over time.



SOURCE: Financial Accounts of the Spanish Economy - Banco de España.
NOTE: All data refer to the end of 2020 Q4.

a The OFI (Other Financial Institutions) category comprises several sectors in the Financial Accounts: Other Financial Intermediaries, specialised lending institutions and investment funds (money market and non-money market funds).

the ESRB and the ECB to quantify direct exposures in their regular monitoring exercises of the financial system.[47]

Second, indirect interconnectedness occurs, for example, when financial institutions hold common exposures to certain sectors, markets or instruments. One of the risks stemming from these interlinkages is related to fire sales in one sector potentially leading to declines in asset prices that could affect the balance sheets of other institutions. Other types of links can also be considered when analysing indirect interconnectedness such as participation in collateral chains, affiliation to the same corporate groups, or exposure to reputational risk owing to financial support provided to subsidiaries or similar entities other than contractual relationships (step-in risk).

There are two types of indicators that are commonly used to quantify indirect interconnectedness.[48] The first consists of the assessment of the portfolio overlap, i.e. the common securities held by any pair of sectors in their portfolios. Indicators show the volume of holdings that a sector has in its securities portfolio that are also held by

47 See, for instance, Grillet-Aubert et al. (2016), ECB (2020b) or FSB and ESRB annual reports such as FSB (2020a) and ESRB (2020b).

48 See ECB (2018) and Banco de España (2021) for two examples of indirect interconnectedness analysis of these indicators.

other sectors (the analysis is granular and reflects the overlap on a security-by-security basis, or on an issuer basis). These figures can also be presented as percentages of the total sector portfolios. The second indicator is the portfolio correlation coefficient of the holdings of each sector pair on each date. This measure quantifies the extent of similarity of the distribution of the securities in the portfolios. This measure does not depend on portfolio size and, therefore, is not affected by the differences in total volume of each sector's holdings.

3.3 Other sources of systemic risk

3.3.1 Climate change

Climate Change (CC) is part of the environmental component of the environmental, social and governance (ESG) factors relevant for the assessment of the sustainability of economic and financial activities. CC risks include physical risks and transition risks. Whereas physical risks stem from the CC process itself,[49] transition risks arise from the actions taken by the economic agents to adapt and mitigate the effects of CC. Such mitigating actions, which are based on different global warming scenarios, include the adoption by public authorities of measures such as carbon taxes, the implementation of stricter CO2 (and equivalent) emissions targets, and other factors such as changes in consumer behavior or the implementation of technological improvements that could affect energy production and efficiency. Importantly, although most CC risks materialise in some of the risks analysed previously (credit, market, operational, etc.), they are a source of (emerging) financial risk to the economy for their potential effect on financial stability and its systemic implications (ECB and ESRB, 2020). Therefore, ensuring that the financial system is resilient to these risks falls within the mandate of central banks and supervisors (NGFS, 2019).

Climate-related risks can be classified in the traditional standard risk categories. Although credit risk has attracted the biggest analytical effort, market, liquidity, operational and even reputational risk might also become material. However, the measurement of CC-related financial risks entails serious limitations (BIS, 2021). The main drawback is the lack of comparable and reliable climate-related data to quantify the potential impact of physical and transition risks. Although there are several initiatives to improve available information,[50] the lack of harmonised definitions, metrics, disclosures and granular information (firm-level data rather than industry averages), and the fact that historical data might not provide an accurate estimation of forward-looking risks along with no previous experience of structural breaks of this nature, make the analysis highly challenging. Besides, in the realm of physical risks, additional complexity arises from the need to integrate output from global climate models with detailed regional/spatial information regarding the location of economic activities and

49 Physical risks are linked to the possibility of material losses in the value of assets of economic agents or value-chain disruptions as a result of, for example, a significant rise in the sea level, drought, floods or the increase in the severity of meteorological phenomena.

50 For instance, the FSB is currently working on data availability (FSB, 2020b). In parallel, the "bridging the data gaps" NGFS workstream also deals with the identification of the data items that are currently lacking.

the nature of production processes to achieve informative estimates as to the potential impact of this risk.[51]

This lack of proper data hinders the development of appropriate indicators to analyse how climate risks feed into the financial risks faced by economic agents, including banks. Also, reliable data scarcity limits research on the measurement of climate financial risks. For instance, Delgado (2019) is one of the few papers that attempts to quantify energy transition risks in Spain despite these data limitations. This work concludes that the banking system's exposures to risks affected by the energy transition make up around 25% of the portfolio of loans for productive activities. In this context, many supervisory and/or prudential authorities are opting to use stress tests and scenario analysis.[52] For instance, the Banco de España has developed macroeconomic scenarios to assess the consequences of CC (see Aguilar et al., 2021).[53]

The development of an adequate framework to improve data quality and the analysis of climate-related risks also requires a broader perspective. There are gaps related to climate risks in areas that cover regulatory, supervisory and disclosure elements. Regarding regulatory and supervisory matters, the Basel Committee on Banking Supervision (BCBS) task force on climate-related financial risks (TFCR)[54] will, in addition to laying down a set of principles or guidelines on effective supervisory practices for assessing climate-related financial risks, explore whether any policy measures under the regulatory framework should be taken. At the EU level, prudential regulation (CRR and CRD) mandates[55] the European Banking Authority (EBA) to assess the potential inclusion of ESG risks in the supervisory review and evaluation process (Pillar 2) and to evaluate whether a dedicated prudential treatment of exposures related to assets or activities associated substantially with environmental and social objectives would be justified (Pillar 1). Partly due to the close deadlines for the completion of some of the EBA's work and to acknowledge EBA's Action Plan on Sustainable Finance, several European supervisors, the Banco de España included (Banco de España, 2020), have already issued supervisory expectations (see, for instance, ECB, 2020c). The purpose of these supervisory expectations is to encourage entities to start taking into account CC risks and to be more prepared for possible future regulatory requirements in this area.

Finally, climate-related disclosure requirements could decisively contribute to the correct pricing of climate-related risks by financial markets. To date, disclosure is still at

51 In addition to the lack of data, relevant scientific knowledge is needed to properly make use of historical data and forward-looking projections when carrying out a financial risk assessment (see, for instance, Fiedler at al., 2021; IPCC, 2012). Besides, the quantification of CC risks also suffers from additional problems as traditional models may not accurately describe relevant phenomena at a more granular level.

52 See Regelink (2017), Banque de France and ACPR (2017), Bank of England (2018), Danmarks Nationalbank (2020) and Van Tendeloo (2020) for further examples of works by central banks that quantify the impact of CC risks. Also, ECB Banking Supervision will carry out a separate supervisory climate stress test of individual banks in 2022.

53 Vermeulen (2018), ECB and ESRB (2020c) and Banque de France and ACPR (2021) are examples of further stress test exercises.

54 The BCBS will undertake further work in three broad areas: regulatory, supervisory and disclosure-related elements for the banking system. For more details, see Pablo Hernández de Cos's remarks – Panel "What are the policies currently considered by central banks, regulators and supervisors – and their challenges – to address climate change?" (2021).

55 See article 98.8 CRD for Pillar 2 mandate and article 501 quarter CRR for Pillar 1.

an early stage and faces several limitations. Indeed, targets are not always supported by the relevant metrics, making it difficult to assess the performance of the institution against them. In this respect, there are several ongoing initiatives. For instance, the Network of Central Banks and Supervisors for Greening the Financial System (NGFS), a global initiative among central banks, has encouraged all non-financial corporations that issue debt or equity, along with financial sector institutions, to disclose in line with the recommendations of the Task Force on Climate-related Financial Disclosures (TCFD).[56] While compliance with TCFD recommendations is gaining traction, it is still very heterogeneous between institutions (Moreno and Caminero, 2020).[57] Also, the BIS Innovation Hub (BISIH) has a working group dedicated to looking into how interaction with technologies such as artificial intelligence, the internet of things (IOT) and blockchain can help green finance, given the importance of measurement and disclosure for new sustainability-linked products to emerge and for carbon trading markets to scale up.

At the European level, there are several initiatives under way. Among others, (1) since 2018 the Directive 2014/95/EU, also called the Non-Financial Reporting Directive (NFRD), which modified the Accounting Directive 2013/34/EU, has obliged certain business groups and large companies to include a non-financial statement as part of their annual public reporting obligations.[58] (2) Significantly, in April 2021, the European Commission adopted a proposal for a Corporate Sustainability Reporting Directive (CSRD), which would amend the existing reporting requirements under the NFRD, making them more consistent with other pieces of the EU legal framework, including the Sustainable Finance Disclosure Regulation (SFDR)[59] and the Taxonomy Regulation.[60] (3) In addition, in March 2021, International Financial Reporting Standards (IFRS) Foundation Trustees announced the formation of a new Sustainability Standards Board that will contribute to accelerating convergence in sustainability reporting standards at a global level.[61] (4) Finally, the EBA has recently published a consultation paper on draft implementing technical standards (ITS) on Pillar 3 disclosures on Environmental, Social and Governance (ESG) risks (EBA, 2021). Among other requirements, the draft ITS put forward comparable quantitative disclosures on climate-change related transition and physical risks. The EBA has also integrated proportionality

56 See NGFS (2019) for further information.

57 Moreno and Caminero (2020) use text-mining techniques to estimate a compliance index for twelve significant Spanish financial institutions with TCFD recommendations.

58 The objective of the NFRD is to facilitate the identification of risks to improve sustainability and increase the confidence of investors, consumers and society. This Directive is expected to be revised and its revision could be an opportunity to increase the coverage, comparability and consistency of the climate risk-related data.

59 The proposal for a CSRD is aimed at extending the scope of application to all large companies and all companies listed on regulated markets, requiring assurance of reported information, introducing a requirement to report according to mandatory EU sustainability reporting standards and requiring companies to digitally ‘tag’ the reported information, to make it machine-readable and able to feed into the European Single Access Point (ESAP) envisaged in the capital markets union action plan.

60 The EU taxonomy is a classification system to list environmentally sustainable economic activities and sets out four overarching conditions that any economic activity has to meet to qualify as environmentally sustainable. For further information, see Regulation (EU) 2020/852 of the European Parliament and of the Council of 18 June 2020 on the establishment of a framework to facilitate sustainable investment.

61 This initiative will contribute to the efforts of already-established initiatives including the Global Reporting Initiative (GRI), the International Integrated Reporting Council (IIRC), the Sustainability Accounting Standards Board (SASB), the Climate Disclosure Standards Board (CDSB) and the CDP (formerly the Carbon Disclosure Project).

measures that should facilitate institutions' disclosures, including transitional periods where disclosures in terms of estimates and proxies are allowed. Finally, the EBA has also recommended to the European Commission[62] the use of the green asset ratio (GRA), which is aimed at identifying and disclosing the institutions' assets financing activities that are environmentally sustainable according to the EU taxonomy, such as those consistent with the European Green Deal and the Paris agreement goals.

3.3.2 Operational risks

The meaning of such risks is not straightforward but, according to BCBS (2011), operational risk could be defined as the "risk of losses resulting from inadequate or failed internal processes, people and systems, or external events".

Among operational risks it is worth highlighting cyber-risks. Over the last decades the global financial system has become more digitalised and interconnected and, consequently, it increasingly relies critically on robust information and communications technology (ICT) infrastructures. Against this background, many stakeholders see cyber and IT-related risks in the form of cyber-incidents as a prominent threat to the financial system. Indeed, cyber-attacks on financial institutions and financial market infrastructures are becoming more frequent and sophisticated. The risk that an isolated cyber-attack could have consequences for the entire financial system is known as systemic cyber-risk.[63] In this respect, in 2020 the European Systemic Cyber Group (ESCG), which reports to the ESRB, developed a conceptual model for systemic cyber-risk to assess how it may become a source of systemic risk to the financial system through operational, confidence and financial contagion channels (see ESRB, 2020a, and Ros, 2020 for details).

In most jurisdictions, cyber-risk management practices are quite mature and are used to address cyber-risk and supervise cyber-resilience. Those approaches have focused on reported incidents, surveys, penetration tests and on-site inspections. Regrettably, to date there are no quantitative metrics or risk indicators to identify cyber-risks. This makes it very difficult for financial institutions and supervisors to quantify cyber-risks so as to engage in cyber-resilience.

Despite this lack of a quantitative metric, there are several initiatives that attempt to address this problem. For instance, the EBA guidelines on ICT risk assessment (EBA, 2017) are intended to promote common procedures and methodologies among competent authorities for the assessment of the ICT risk under the supervisory review and evaluation process (SREP). In light of these guidelines, the ECB, together with the national competent authorities, developed the IT Risk Questionnaire as part of a dedicated SREP IT risk

62 See EBA (2021) Advice to the Commission on disclosures under article 8 taxonomy regulation (EBA/Op/2021/03).

63 More specifically, the World Economic Forum (WEF) defined systemic cyber-risk as "the risk that a cyber event (attack(s) or other adverse event(s)) at an individual component of a critical infrastructure ecosystem will cause significant delay, denial, breakdown, disruption or loss, such that services are impacted not only in the originating component but consequences also cascade into related (logically and/or geographically) ecosystem components, resulting in significant adverse effects to public health or safety, economic security or national security." See WEF (2016).

assessment methodology for significantly important financial institutions in the Euro Area. This tool allows supervisors to collect information on the IT-risk level and on the IT-risk control maturity of significant institutions at individual level. The IT Risk Questionnaire is structured according to the five IT risk categories defined by the EBA: IT security risk, IT availability and continuity risk, IT change risk, IT outsourcing risk and IT data integrity risk, and contains some backward-looking indicators without predictive capacity that inform on the broad adequacy of an institution´s cyber-resilience levels for its business needs and risk appetite. However, no single indicator can be considered as a sufficient metric to identify ITC risks, and no standard set of indicators has been identified so far to provide a meaningful benchmark either. ECB Banking Supervision provides feedback to the industry with the publication of the annual report on the outcome of SREP IT Risk Questionnaire.[64] The report provides aggregated observations based on the horizontal analysis of the significant supervised institutions' self-assessments on ICT risk, which are useful for the public and can point to developments in the management of IT risk aspects of the ECB-supervised significant credit institutions.

Moreover, in recent years, there has been a clear tendency of institutions to outsource ICT services to external providers. Some services are concentrated in a small number of providers. Although their concentration is nothing new, the provision of services has changed, as there is a clear trend towards the movement to the cloud. Against this backdrop, the materialisation of a risk in a supplier that provides relevant services for a significant part of the financial sector could also have a systemic impact. To mitigate this risk, the European Commission has set provisions for a third-party oversight framework in the legislative proposal Digital Operational and Resilience Act.[65] According to the proposal, the ESAs will designate which ICT third-party service providers are critical for the European financial sector.

Finally, the entry of big tech companies in the provision at scale of banking services could entail a major structural overhaul of the banking sector. The systemic scope of the behavioural reactions unleashed by such a transformation would have a broad-based impact on financial intermediation and the efficacy of a wide range of policies (most prominently, monetary and macro-prudential policies). The monitoring and policy reaction to this still-incipient development is based on a set of ad-hoc qualitative signals, which inform about a deepening of the structural change at stake. Significant examples of these signals are the scope of products distributed in big tech platforms, and the funding models employed and use of non-bank originated APIs. The provision of crypto-instruments to make payments and/or store value (like stablecoins) by big tech companies further enhances the potential for systemic risks and leads to the monitoring of informative indicators such as outstanding balance and turnover.

64 See the Annual report on the outcome of the 2020 SREP IT Risk Questionnaire - Feedback to the industry at https://www.bankingsupervision.europa.eu/banking/srep/2021/html/ssm.srep202107_outcomesrepitriskquestionnaire.en.html.

65 See legislative Proposal for a regulation of the European Parliament and of the Council on digital operational resilience for the financial sector at https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52020PC0595.

4 Conclusions

Based on the experience of the Banco de España, this survey presents a broad overview of the identification tools employed by central banks to identify standard and systemic risks. This paper shows that the indicators developed and used at the Banco de España allow a comprehensive monitoring of potential risks across categories and segments. Besides, this survey confirms that the instruments used at the Banco de España are in line with those employed by other central banks and supervisory authorities.

Nevertheless, the maintenance of an adequate risk identification framework is not without its challenges and more work will be needed. For instance, the development of risk indicators to address climate change, both for the category of physical and transition risks, and those linked to the risk of system-wide cyber-incidents will merit further attention in the future. This latter aspect is a widespread problem across institutions that has not yet been addressed due to the lack of data to perform a proper analysis. Moreover, there is also room for improvement in the risk identification of some areas, such as structural risks. New regulation would allow for the adoption of new macroprudential tools in the future that would require further risk identification analysis. Finally, this paper does not analyse either which measures have the best properties as leading indicators of crises. The question is still an open issue for the whole set of indicators, although the predictive capacity of many of them has been broadly demonstrated.

References

Acharya, V., L. Pedersen, T. Philippon, and M. Richardson (2010). *Measuring systemic risk,* Technical Report, Department of Finance, New York University.

Adrian, T., D. He, N. Liang, and F. Natalucci (2019b). "A monitoring framework for global financial stability", Staff Discussion Notes, No. 19/06, International Monetary Fund, pp. 1-31.

Adrian, T., N. Boyarchenko, and D. Giannone (2019a). "Vulnerable Growth", *American Economic Review,* 109(4), pp. 1263-1289.

Adrian, T., and M. K. Brunnermeier (2016). "CoVaR", *American Economic Review,* 106(7), pp. 1705-1741.

Aguilar, P., B. González, and S. Hurtado (2021). "Construyendo escenarios macroeconómicos para las pruebas de estrés de cambio climático", *Financial Stability Review,* Banco de España, forthcoming.

Ahnert, H., I. K. Kavonius, J. Honkkila, and P. Sola (2020). *Understanding household wealth: linking macro and micro data to produce distributional financial accounts,* Statistics Paper Series 37, European Central Bank.

Aikman, D., A. G. Haldane, and B. D. Nelson (2015). "Curbing the Credit Cycle", *The Economic Journal,* 125, pp. 1072-1109.

Alberola, E., Á. Estrada and F. Viani (2020). "Global imbalances from a stock perspective: The asymmetry between creditors and debtors", *Journal of International Money and Finance,* 107, 102206.

Aldasoro, I., A.-C. Hüser, and C. Kok (2020). *Contagion Accounting,* BIS Working Paper.

Alonso, I., and L. Molina (2019). *The Sherloc: an EWS-based index of vulnerability for emerging economies,* Banco de España Working Papers 1946.

Alonso, I., and L. Molina (2021). *A GPS navigator to monitor risks in emerging economies: the vulnerability dashboard,* Banco de España Occasional Papers 2111.

Alonso, J., and P. Stupariu (2019). "Financial system interconnectedness", *Financial Stability Review,* Banco de España, Autumn.

Ampudia, M., H. van Vlokhoven, and D. Żochowski (2016). "Financial fragility of euro area households", *Journal of Financial Stability,* 27, pp. 250-262.

Andrés, E., J. C. Berganza, A. Buesa, and L. Molina (2021). *Estimates and uses of financial indices as analytical tools in International Economics,* Banco de España Occasional Papers (forthcoming).

Aymanns, C., J. D. Farmer, A. M. Kleinnijenhuis, and T. Wetzer (2018). "Models of financial stability and their application in stress tests", in *Handbook of Computational Economics* (Vol. 4, pp. 329-391), Elsevier.

Baker, S. R., N. Bloom, and S. J. Davis (2016). "Measuring Economic Policy Uncertainty", *The Quarterly Journal of Economics,* Vol. 131, Issue 4, November, pp. 1593-1636.

Balakrishnan, R., S. Danninger, S. Elekdag, and I. Tytell (2011). *The Transmission of Financial Stress from Advanced to Emerging Economies,* IMF WP 09/133.

Banco de España (2019a). "Survey of household finances (EFF) 2017: methods, results and changes in 2014", Analytical Articles, *Economic Bulletin*, 4/2019.

Banco de España (2019b). "Credit standards and mortgage default risk", *Financial Stability Report* (Autumn), Box 1.3.

Banco de España (2020). "Banco de España supervisory expectations relating to the risks posed by climate change and environmental degradation", Recommendations and general notifications, October.

Banco de España (2021). *Financial Stability Report,* Spring.

Bank of England (2018). "Transition in thinking: The impact of climate change on the UK banking sector", Bank of England - Prudential Regulation Authority, September.

Bank for International Settlements (BIS) (2021). "Climate-related financial risks – measurement methodologies", Basel Committee on Banking Supervision.

Banque de France and Autorité de Contrôle Prudentiel et de Résolution (ACPR) (2017). *Evaluating climate change risks in the banking sector,* Report required under Article 173 V of the Energy Transition and Green Growth Act No. 2015-992 of 17 Aug 2015.

Banque de France and Autorité de Contrôle Prudentiel et de Résolution (ACPR) (2021). *A first assessment of financial risks stemming from climate change: The main results of the 2020 climate pilot exercise,* Analyses et synthèses, No. 122-2021.

Bardoscia, M., S. Battiston, F. Caccioli, and G. Caldarelli (2015). "DebtRank: A Microscopic Foundation for Shock Propagation", *PLOS ONE,* 10(7), e0134888, https://doi.org/10.1371/journal.pone.0134888.

Basel Committee on Banking Supervision (BCBS) (2011). "Principles for the sound management of operational risk", June, https://www.bis.org/publ/bcbs195.pdf.

Battiston, S., M. Puliga, R. Kaushik, P. Tasca, and G. Caldarelli (2012). "DebtRank: Too Central to Fail? Financial Networks, the FED and Systemic Risk", *Sci Rep,* 2, p. 541, https://doi.org/10.1038/srep00541.

Batty, M., J. Bricker, J. Briggs, E. Holmquist, S. McIntosh, K. Moore, E. Nielsen, S. Reber, M. Shatto, K. Sommer, T. Sweeney, and A. Volz (2019). "Introducing the Distributional Financial Accounts of the United States", Finance and Economics Discussion, Series 2019-017, Washington, Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2019.017.

Benedetto, F., L. Mastroeni, G. Quaresima, and P. Viellucci (2020). "Does OVX affect WTI and Brent oil spot variance? Evidence from an entropy analysis", *Energy Economics,* 89, 104815.

Bengtsson, E., M. Grothe, and E. Lepers (2020). "Home, safe home: Cross-country monitoring framework for vulnerabilities in the residential real estate sector", *Journal of Banking & Finance,* Vol. 112, 105268.

Bhutta, N., J. Bricker, L. J. Dettling, J. Kelliher, and S. Laufer (2020). "Stress testing household debt", *Journal of Credit Risk,* 16(3).

Bisias, D., M. Flood, A. W. Lo, and S. Valavanis (2012). *A Survey of Systemic Risk Analytics,* Working Paper Series, No. 12-01, Office of Financial Research, US Department of the Treasury.

Blanchard, O., and G. M. Milesi-Ferretti (2009). "Global imbalances: in midstream?", IMF Staff Position Note.

Blanco, R., Á. Menéndez and M. Mulino (2020). *Las necesidades de liquidez y la solvencia de las empresas no financieras españolas tras la perturbación del Covid-19,* Documentos Ocasionales, No. 2020, Banco de España.

Bouabdallah, O., C. Checherita-Westphal, T. Warmedinger, R. de Stefani, F. Drudi, R. Setzer, and A. Westphal (2017). *Debt sustainability analysis for euro area sovereigns: a methodological framework,* Occasional Paper Series No. 185, April, European Central Bank (ECB), Frankfurt am Main.

Bover, O., M. Torrado, and E. Villanueva (2019). "The loan to value ratio for housing in Spain over the period 2004-2016", *Economic Bulletin,* 1/2019, Banco de España.

Brownlees, C., and R. Engle (2017). "SRISK: A Conditional Capital Shortfall Measure of Systemic Risk", *The Review of Financial Studies,* Vol. 30(1), pp. 48-79.

Caccioli, F., P. Barucca, and T. Kobayashi (2018). "Network models of financial systemic risk: a review", *Journal of Computational Social Science,* 1(1), pp. 81-114.

Cáceres-Santos, J., A. Rodríguez-Martínez, F. Caccioli, and S. Martínez-Jaramillo (2020). "Systemic risk and other interdependencies among banks in Bolivia", *Latin American Journal of Central Banking.*

Cambón and Estévez (2016). "A Spanish Financial Market Stress Index (FMSI)", *The Spanish Review of Financial Economics.*

Cardarelli, R., S. Elekdag, and S. Lall (2011). "Financial stress and economic contractions", *Journal of Financial Stability,* Vol. 7, Issue 2, pp. 78-97.

Chen, H., L. Liu, and X. Li (2018) "The predictive content of CBOE crude oil volatility index", *Physica A: Statistical Mechanics and its Applications,* 492, pp. 837-850.

Cifuentes, R., G. Ferrucci, and H. S. Shin (2005). "Liquidity risk and contagion", *Journal of the European Economic Association,* 3(2-3), pp. 556-566.

Claessens, S., M. A. Kose, and M. Terrones (2012). "How do business and financial cycles interact?", *Journal of International Economics,* 87, pp. 178-190.

Cuadrado, P., and E. Moral-Benito (2016). *Potential growth of the Spanish economy,* Occasional Paper 1603, Banco de España.

Danmarks Nationalbank (2020). *A gradual green transition supports financial stability,* November.

Delgado, M. (2019). "Energy transition and financial stability. Implications for the Spanish deposit-taking institutions", *Financial Stability Review,* Autumn, Banco de España.

Detken, C., O. Weeken, L. Alessi, D. Bonfim, M. Bouchina, C. Castro, S. Frontczak, G. Giordana, J. Giese, N. Jahn, J. Kakes, B. Klaus, J. H. Lang, N. Puzanova, and P. Welz (2014). *Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options,* ESRB Occasional Paper Series No. 5, June.

Dimpfl, T., and F. J. Peter (2018). "Analyzing volatility transmission using group transfer entropy", *Energy Economics,* 75, pp. 368-376.

Drehmann, M., C. Borio, L. Gambacorta, G. Jiménez, and C. Trucharte (2010). *Countercyclical capital buffers: exploring options,* BIS Working Papers No. 317, Bank for International Settlements.

Duca, J. V., J. Muellbauer, and A. Murphy (2010). "Housing markets and the financial crisis of 2007-2009: Lessons for the future", *Journal of Financial Stability,* 6, pp. 203-217.

Duffie, D. (1999). "Credit swap valuation", *Financial Analysts Journal,* 55, pp. 73-87.

Engle, R., and T. Ruan (2019). "Measuring the probability of a financial crisis", *Proceedings of the National Academy of Sciences,* 116(37), pp. 18341-18346.

Erdogan, B. E. (2008). "Bankruptcy prediction of Turkish commercial banks using financial ratios", *Applied Mathematical Sciences,* 2(60), pp. 2973-2982.

Estrada, Á., and J. Saurina (2016). "Spanish boom-bust and macroprudential policy", *Financial Stability Review,* 30, Banco de España, pp. 35-61.

European Banking Authority (EBA) (2017). *Guidelines on ICT Risk Assessment under the Supervisory Review and Evaluation Process (SREP),* Final Report EBA/GL/2017/05.

European Banking Authority (EBA) (2021). *Consultation Paper on draft implementing standards on prudential disclosures on ESG risks in accordance with Article 449a CRR,* EBA/CP/2021/06.

European Central Bank (ECB) (2011). "Tools for detecting a possible misalignment of residential property prices from fundamentals", *Financial Stability Review*, Box 3 (June).

European Central Bank (ECB) and European Systemic Risk Board (ESRB) (2020). *Positively green: Measuring climate change risks to financial stability,* June.

European Central Bank (ECB) (2016). "Monitoring euro area residential real estate markets from a macroprudential perspective", *Financial Stability Review*, Box 2 (November).

European Central Bank (ECB) (2018). *Financial Stability Review,* November.

European Central Bank (ECB) (2019). "Macroprudential risk and policy framework for residential real estate markets", *Macroprudential Bulletin*, No. 7 (March).

European Central Bank (ECB) (2020a). *Annual report on the outcome of the SREP IT Risk Questionnaire – Feedback to the industry,* July.

European Central Bank (ECB) (2020b). *Financial Stability Review,* May.

European Central Bank (ECB) (2020c). *Guide on climate-related and environmental risks. Supervisory expectations relating to risk management and disclosure,* November.

European Systemic Risk Board (ESRB) (2017). *The ESRB handbook on operationalizing macroprudential policy in the banking sector.*

European Systemic Risk Board (ESRB) (2019). *Methodologies for the assessment of real estate vulnerabilities and macroprudential policies: residential real estate,* European Systemic Risk Board reports.

European Systemic Risk Board (ESRB) (2020a). *Systemic cyber risk,* Report 200219.

European Systemic Risk Board (ESRB) (2020b). *EU Non-bank Financial Intermediation Risk Monitor 2020,* October.

European Systemic Risk Board (ESRB) (2020c). *Positively green: Measuring climate change risks to financial stability.*

Ferrari, S., M. Pirovano, and W. Cornacchia (2015). *Identifying early warning indicators for real estate-related banking crises,* Occasional Paper Series of the European Systemic Risk Board, No. 8.

Fiedler, T., A. J. Pitman, K. Mackenzie, N. Wood, C. Jakob, and S. E. Perkins-Kirkpatrick (2021). "Business risk and the emergence of climate analytics", *Nature Climate Change,* Vol. 11, pp. 87-94.

Financial Stability Board (FSB) (2020a). *Global Monitoring Report on Non-Bank Financial Intermediation 2020,* December.

Financial Stability Board (FSB) (2020b). *The implications of climate change for financial stability,* November.

Fink, K., U. Krüger, B. Meller, and L.-H. Wong (2016). "The credit quality channel: Modelling contagion in the interbank market", *Journal of Financial Stability.*

Galán, J. E. (2019). *Measuring Credit-to-GDP Gaps. The Hodrick-Prescott Filter Revisited,* Occasional Papers No. 1906, Banco de España.

Galán, J. E. (2020). "The benefits are at the tail: uncovering the impact of macroprudential policy on growth-at-risk", *Journal of Financial Stability,* forthcoming.

Galán, J., and M. Lamas (2019). *Beyond the LTV ratio: new macroprudential lessons from Spain,* Working Paper series of Banco de España, No. 1931.

Galán, J. E., and M. Rodríguez (2020). "At-risk measures and financial stability", *Financial Stability Report,* Autumn, Banco de España, pp. 71-96.

Galati, G., I. Hindrayanto, S. J. Koopman, and M. Vlekke (2016). "Measuring financial cycles in a model-based analysis: Empirical evidence for the United States and the euro area", *Economic Letters,* 145, pp. 83-87.

Ghirelli, C., M. Gil, J. Pérez, and A. Urtasun (2019). *A new economic policy uncertainty index for Spain,* Banco de España Working Paper 1906.

Ghirelli, C., J. Pérez, and A. Urtasun (2020). *Economic Policy Uncertainty in Latin America: Measurement using Spanish Newspapers and Economic Spillovers,* Banco de España Working Paper 2024.

Ghosh, S. R. (2016). *Monitoring Macro-Financial Vulnerability: A Primer,* MFM Discussion Paper, No. 14, World Bank, Washington, DC.

Gimeno, R., and A. Ibáñez (2017). *The Eurozone (expected) inflation: an option's eyes view,* Working paper 1722, Banco de España.

Glasserman, P., and H. P. Young (2016). "Contagion in financial networks", *Journal of Economic Literature,* 54(3), pp. 779-831.

Grillet-Aubert, L., J.-B. Haquin, C. Jackson, N. Killeen, and C. Weistroffer (2016). *Assessing shadow banking – non-bank financial intermediation in Europe,* Occasional paper, European Systemic Risk Board (ESRB), July.

Groen, J., K. McNeil, and M. Middeldorp (2013). *A New Approach for Identifying Demand and Supply Shocks in the Oil Market.*

Hałaj, G. (2020). "Resilience of Canadian banks to funding liquidity shocks", *Latin American Journal of Central Banking,* 1(1-4), 100002.

Hammoudeh, S., M. Nandha, and Y. Yuan (2013) "Dynamics of CDS spread indexes of US financial sectors", *Applied Economics,* 45 (Issue 2), pp. 213-223.

Hattori, A., K. Kikuchi, F. Niwa, and Y. Uchida (2014). *A Survey of Systemic Risk Measures: Methodology and Application to the Japanese Market,* IMES Discussion Paper Series 14-E-03. Institute for Monetary and Economic Studies, Bank of Japan.

Hernández de Cos, P., E. Moral-Benito, G. B. Koester, and N. Christiane (2014). *Signalling Fiscal Stress in the Euro Area: A Country-Specific Early Warning System,* Banco de España Working Paper 1418.

Hiebert, P., and M. Sydow (2011). "What drives returns to euro area housing? Evidence from a dynamic dividend-discount model", *Journal of Urban Economics,* Vol. 70, Issues 2–3, pp. 88-98.

Hodrick, R., and E. Prescott (1997). "Postwar U.S. Business Cycles: An Empirical Investigation", *Journal of Money, Credit and Banking,* Vol. 29, No. 1.

Holló, D., M. Kremer, and M. Lo Duca (2012). *CISS – A Composite Indicator of Systemic Stress in the Financial System,* ECB Working Paper Series No. 1426, March.

Household Finance and Consumption Network (HFCN) (2020). "The Household Finance and Consumption Survey: Results from the 2017 wave", ECB Statistics Series No. 36.

Intergovernmental Panel on Climate Change (IPCC) (2012). *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation,* Eds. Field, C. B., et al., Cambridge University Press.

International Monetary Fund (IMF) (2010). *The IMF-FSB Early Warning Exercise. Design and Methodological Toolkit.*

International Monetary Fund (IMF) (2012). *Spain: Financial System Stability Assessment,* Monetary and Capital Markets Department.

International Monetary Fund (IMF), Bank for International Settlements (BIS) and Financial Stability Board (FSB) (2009). *Guidance to Assess the Systemic Importance of Financial Institutions, Markets and Instruments: Initial Considerations,* https://www.imf.org/external/np/g20/pdf/100109.pdf.

Iranzo, S. (2008). *Delving into country risk,* Banco de España Occasional Papers, 0802.

Kelly, R., F. McCann, and C. O'Toole (2018). "Credit conditions, macroprudential policy and house prices", *Journal of Housing Economics,* 41, pp. 153-167.

Kilian, L., and D. P. Murphy (2014). "The Role of Inventories and Speculative Trading in the Global Market for Crude Oil", *Journal of Applied Econometrics,* 29, pp. 454-478.

Martín, C. (2017). *External stress early warning indicators,* Banco de España Working Papers, 1733.

Martínez, J., and L. Á. Maza (2003). *Analysis of house prices in Spain,* Banco de España Working Papers, 0307.

McGowan, M. A., D. Andrews, and V. Millot (2017). *Confronting the zombies: Insolvency and financial reform, corporate restructuring and productivity growth,* OECD WP prepared for the WP- October.

Mencía, J., and J. Saurina (2016). *Macroprudential policy: objectives, instruments and indicators,* Banco de España Occasional Papers, 1601.

Menéndez, Á., and M. Mulino (2019), "Results of non-financial corporations in 2018 and in the first three quarters of 2019", *Economic Bulletin,* 4/2019.

Molina, L., and F. Viani (2019). "Capital flows to emerging economies: recent developments and drivers", Analytical Articles, *Economic Bulletin,* 2/2019, Banco de España.

Moreno, A. I., and T. Caminero (2020). *Application of text-mining to the analysis of climate-related disclosures*, Banco de España Working Papers, 2035.

Muller, P., and J. Bourque (2017). *Methodology for assigning credit ratings to sovereigns,* Bank of Canada Staff Discussion Paper 2017-7.

Network for Greening the Financial System (NGFS) (2019). *A call for action. Climate change as a source of financial risk,* First comprehensive report.

Oosterloo, S., and J. de Haan (2004). "Central banks and financial stability: a survey", *Journal of Financial Stability,* 1, pp. 257-273.

Papke, L. E., and J. M. Wooldridge (1996). "Econometric methods for fractional response variables with an application to 401 (K) plan participates rates", *Journal of Applied Econometrics,* 11(6), pp. 619-632.

Regelink, M., H. J. Reinders, M. Vleeschhouwer, and I. van de Wiel (2017). *Waterproof? An exploration of climate-related risks for the Dutch financial sector,* De Netherlandsche Bank.

Restoy, F. (2020). *Central banks and financial stability: A reflection after the COVID-19 outbreak,* Financial Stability Institute, Occasional paper 16.

Röhn, O., A. C. Sánchez, M. Hermansen, and M. Rasmussen (2015). *Economic resilience: A new set of vulnerability indicators for OECD countries,* OECD Economics Department Working Papers, No. 1249, OECD Publishing.

Roncoroni, A., S. Battiston, M. D'Errico, G. Halaj, and C. Kok (2019). *Interconnected banks and systemically important exposures,* ECB Working Paper Series.

Ros, G. (2020). *The making of a cyber-crash: a conceptual model for systemic risk in the financial sector,* Occasional Paper Series No. 16, European Systemic Risk Board.

Rünstler, G., and M. Vlekke (2018). "Business, housing, and credit cycles", *Journal of Applied Econometrics,* 33, pp. 212-226.

Schelkle, T. (2018). "Mortgage Default during the U.S. Mortgage Crisis", *Journal of Money, Credit and Banking,* 50(6), pp. 1101-1137.

Sylvain, B., J.-E. Colliard, C. Hurlin, and C. Pérignon (2016). "Where the risks lie: A survey on systemic risk", *Review of Finance.*

Thomson, J. B. (1991). "Predicting bank failures in the 1980s", *Economic Review*, Federal Reserve Bank of Cleveland, 27(1), pp. 9-20.

Van Tendeloo, B. (2020). "Climate-change-related transition risk associated with real state exposures in the Belgian financial sector", National Bank of Belgium, *Financial Stability Report*.

Vermeulen, R., E. Schets, M. Lohuis, B. Kolbl, D. J. Jansen, and W. Heeringa (2018). *An energy transition risk stress test for the financial system of the Netherlands,* DNB Occasional Studies, Vol. 16-7, De Netherlandsche Bank.

World Economic Forum (WEF) (2016). *Understanding systemic cyber risk,* White Paper, October.

Appendix

Table A.1

INDICATORS TO IDENTIFY CREDIT RISK AND REAL ESTATE VULNERABILITIES

Indicator	Author	Target segment	Brief description
Vulnerability measures among indebted households	BdE (2019)	Households	Disaggregated data on households enable calculation of the fraction of households that owe more than three times their gross income, or that devote more than 40% of their gross income to debt payments
Distributional Financial Accounts	Batty et al. (2019)	Households	Quarterly series with an estimation of the distribution of assets and debts across US households (Batty et al., 2019). BdE has recently constructed distributional financial accounts by combining data on macroeconomic developments with household balance sheets
Interest coverage ratio (ICR)	Menéndez and Mulino (2019)	Non-financial corporations	The ICR is an indicator of the degree of financial pressure that firms face. In particular, when the value of this ratio remains below one over a sustained period this is considered to be a sign of vulnerability, since it implies that the firm is not capable of paying the interest on its debt out of ordinary profit in a sustained fashion. Based on this information, indicators of the proportion of debt and employment associated with Spanish firms that are subject to high financial pressure are calculated
Rating ICAS	BdE	Non-financial corporations	Credit evaluations of Spanish companies to be used in collateral eligibility for monetary policy operations
Real estate prices	—	Real Estate	Statistical approach to identify large deviations of house prices from long-term trends. Trends are obtained with Hodrick-Prescott filters to separate cyclical from long-run components. If prices are too high in relation to their trend, they could be overvalued
Over/undervaluation of residential property prices	Martínez-Pagés and Maza (2003)	Real Estate	Overvaluation of the housing market based on the deviation in pp of house prices and their long-term path estimated with an error correction model (ECM)
Misalignment indicator	ECB (2016)	Real Estate	Based on a Bayesian model, it explains real house prices using real disposable income per household, the real housing stock per capita and the mortgage rate as explanatory variables
House price-at-risk (HaR)	Adrian et al. (2019)	Real Estate	HaR measures the minimum forecast changes in real house prices (RHPI) in very adverse scenarios over a certain horizon. This methodology allows the complete distribution of future changes in the RHPI to be estimated
Lending standards (LTV, LTP…)	—	Real Estate	Based on certain characteristics of credit, which drive default probabilities in the mortgage market
Loan-to-price (LTP)	Bover et al. (2019), Galán and Lamas (2019)	Real Estate	Ratio of the principal amount of the loan to the price of the house, which represents a material driver of defaults
Residential real estate (RRE) credit-at-risk index	Banco de España (2019)	Real Estate	A synthetic indicator that estimates the risk of new mortgage operations by means of a default probability model with lending standard indicators as explanatory variables

SOURCE: Devised by authors.

Table A.2

INDICATORS TO IDENTIFY MACROECONOMIC RISKS

Indicator	Author	Target segment	Brief description
Synthetic index of the vulnerability of the most relevant emerging economies (EMEs) for Spain (SHERLOC)	Alonso and Molina (2019)	Several	A tool to detect the accumulation of risks in 25 large EMEs for three different types of crisis (sovereign, currency and banking crisis)
Economic Policy Uncertainty (EPU) index	Baker et al. (2016)	Other	It measures the frequency of articles in leading newspapers that contain certain words related to economic uncertainty
Debt Sustainability Analysis (DSA) framework	Bouabdallah et al., (2017)	Sovereings	It measures risks to fiscal sustainability by combining a deterministic analysis based on the evolution of the debt-to-GDP path as a response to economic shocks, stochastic simulations to provide uncertainty around the benchmark estimates, and the use of a set of fiscal indicators that provide information on the sustainability of public finances in the short and medium run
Growth-at-risk	Adrian et al. (2019)	Several	The forecast growth rate under an adverse scenario that occurs with a certain probability. It refers to the analysis of the left tail of the forecast GDP growth distribution
Inflation swaps	—	Several	Inflation swaps provide information on market inflation expectations at different horizons
Probability of deflation	—	Several	The Banco de España uses internal models to extract implicit probabilities of being in a situation of deflation at different horizons

SOURCE: Devised by authors.

Table A.3

INDICATORS TO IDENTIFY MARKET, FUNDING AND LIQUIDITY RISKS

Indicator	Author	Target segment	Brief description
Implied volatility indices (VIX, VVIX, MOVE, VSTOXX…)	(Chicago Board Options Exchange) CBOE-VIX-based	Several	These indices reflect the market expectations for the future volatility of the underlying asset. Their calculation is based on option prices
Price-to-earnings ratio (PER)	—	Several	It relates the risk of current or future market overvaluation to investors' future cash flow expectations. Their dynamics incorporate investors' beliefs about future cash-flows, economic activity and growth. It denotes undervaluation or overvaluation in equity markets
Cyclically Adjusted PER (CAPE)	Campbell and Shiller (1998)	Several	It smooths out the standard PER using the last ten years' average inflation-adjusted earnings in the denominator. A priori, CAPE therefore offers a less distorted view of whether an index is overvalued, as it uses information covering expansionary phases and downturns rather than current data
Implied equity risk premium	BdE	Several	Excess expected return from the equity market over the bond market. Not directly observable
Interbank Interest rate spreads (Libor-OIS, Euribor-OIS, FRA-OIS, TED-spread)	—	Interbank	It reflects the risk premia banks charge to lend to one another. A wide spread means that the interbank money markets have become less liquid
Cross-currency basis swap (CCS) spreads	—	Markets	A CCS is an agreement to borrow in one currency (for instance dollars). Its spread is an indicator of tensions in the currency of the funding market. In the case of the EUR/USD CCS, as this spread increases, swapping euros for US dollars becomes increasingly expensive; banks with large refinancing needs in US dollars and little or no access to other sources of dollar funding (e.g. deposits) are most vulnerable to fluctuations in this spread

SOURCE: Devised by authors.

Table A.4
INDICATORS TO IDENTIFY RISKS IN THE BANKING SECTOR

Indicator	Author	Target segment	Brief description
Return on Equity (ROE)	—	Banks	Ratio of profit earned to the level of capital
Return on Assets (ROA)	—	Banks	Ratio of profit earned to the level of assets. It quantifies how well shareholders’ funds are used to generate income and, contrary to the ROE, the ROA is unaffected by leverage
Net Interest Income (NII)	—	Banks	Difference between interest received for assets and interest paid on liabilities
Capital ratios	—	Banks	Indicators of banks' solvency. These ratios are either total, Tier 1 or Core Equity Tier 1 (CET1) capital to risk-weighted assets
CAMEL/CREWS	BdE	Banks	CAMELS rating-based early-warning system of risks in the banking sector. The method relies on forecasts of a logit model. Explanatory variables: individual characteristics of banks and macroeconomic variables

SOURCE: Devised by authors.

Table A.5
INDICATORS TO IDENTIFY SYSTEMIC RISK

Indicator	Author	Target segment	Brief description
Heatmaps	—	Several	Identification of risks for global financial stability. Some of them include qualitative as well as quantitative indicatos. Usually based on frequency distributions and tail risks
Financial stress indices (FSI): Composite Indicator of Systemic Stress (CISS)	Holló et al. (2012)	Markets	Aggregation of market-specific sub-indices created from individual financial stress measures. The aggregation takes into account the time-varying cross-correlations between the sub-indices. As a result, the CISS sets relatively greater store by situations in which stress prevails in several market segments at the same time, which captures the idea that financial stress is more systemic. The Systemic Risk Indicator (SRI) for the Spanish financial system follows this approach. FSIs are also calculated by the Banco de España for the usual assessment of the financial markets of almost all countries material to the Spanish banking sector
Credit-to-GDP gap	—	Banks	Difference between the credit-to-GDP ratio and its long-term trend, estimated using a Hodrick-Prescott filter
Conditional Value at Risk (CoVaR)	Adrian and Brunnermeier (2016)	Banks	It captures the change in the Value-at-Risk of the financial system conditional upon an institution being under distress, relative to the Value-at-Risk conditional upon that institution being at its median state. In other words, CoVaR measures the contribution of a financial institution to systemic risk
Marginal Expected Shortfall (MES)	Acharya et al. (2010)	Banks	Measure that estimates the expected drop in the stock returns conditional upon a poor performance of the overall system
SRISK	Brownlees and Engle (2017)	Banks	Expected capital shortfall of a bank after a substantial drop in equity markets
DebtRank algorithm	Battiston et al. (2012) and Bardoscia et al. (2015)	Several	It allows for assessment of how an initial shock could propagate through the network, whether in calm or stressed periods, and for an estimation of the influence of specific financial institutions on the network
Direct interconnectedness	—	Several	Direct exposures show holdings of assets issued by financial sectors themselves
Indirect interconnectedness	—	Several	Portfolio overlap comprises the amount of common holdings of instruments issued by both financial and non-financial sectors (calculated at the issuer level). Another indicator is the portfolio correlation coefficient of the holdings of each sector pair on each date, a measure that quantifies the extent of similarity of the distribution of the securities in the portfolios

SOURCE: Devised by authors.

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