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ORIGINAL ARTICLE

Banking stability determinants: evidence from Portugal

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Abstract

This paper aims to assess banking stability and its determinants in Portugal during the period of 2010—2019. The empirical study starts with the construction of an index, which reflects the aggregated banking stability index (ABSI), using financial soundness indicators (FSI) over the period of 2010–2019, on a quarterly basis. The ABSI is then used as the dependent variable to assess the determinants of the Portuguese banking stability. The independent variables were classified into macroeconomic and financial variables, respectively, and the ARMA conditional least square method was considered. The findings suggest an improvement in stability since 2017, and point to significant macroeconomic early warning indicators, such as the growth rate of the consumer price index (%ΔCPI), as well as financial ones, such as the ratio of the second money multiplier (M2) to gross domestic product (GDP). This paper contributes to the banking stability literature by examining the Portuguese case for the first time. The results put in evidence that both macroeconomic and financial indicators can be useful predictors of banking instability.

Keywords Banking system stability · Time series regression · Stability index · Financial soundness indicators · Macroprudential indicators · Portugal

JEL Classification C32 · C43 · G21 · E44

Introduction

The Great Recession highlighted the need for a cautious and precise assessment of the stability of the financial sector,[1] particularly of the banking sector—which is the most preponderant component. Banks mainly act as liquidity intermediaries, i.e., they transform illiquid assets into liquid liabilities [29]. Accordingly, a solid banking system is required for a good allocation of capital and subsequently for the well-functioning of the economy [28].

Over the past decade, in addition to price stability, the maintenance of financial stability has become one of the main objectives of the Eurosystem. Financial stability is defined as a condition in which the financial system—which comprises financial intermediaries, markets, and market infrastructures—is capable of withstanding shocks and the unravelling of financial imbalances. Likewise mitigates the likelihood of disruptions in the financial intermediation process that are systemic, that is, severe enough to trigger a material contraction of real economic activity [31].

Furthermore, banking system regulations have suffered alterations over time. The Basel II norms, which were implemented in 2007, relied in three pillars: Minimum capital adequacy requirements, supervisory review process, and market discipline [14]. In response to the 2008 crisis, the Basel III agreement, which was published in 2010, introduced more restricted minimum capital requirements, a new composition of Tier I equity (now subdivided into the common equity Tier I (CET-1) and the additional Tier I (AT-1)), and some new ratios (e.g., the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR)) [15].

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[1] Which has been gaining greater influence in the economy. According to Haldane et al. [37] the "growth in the financial sector value added has been more than double that of the economy as a whole since 1850" in the U.K., similar trend were observed for the U.S. and Europe.

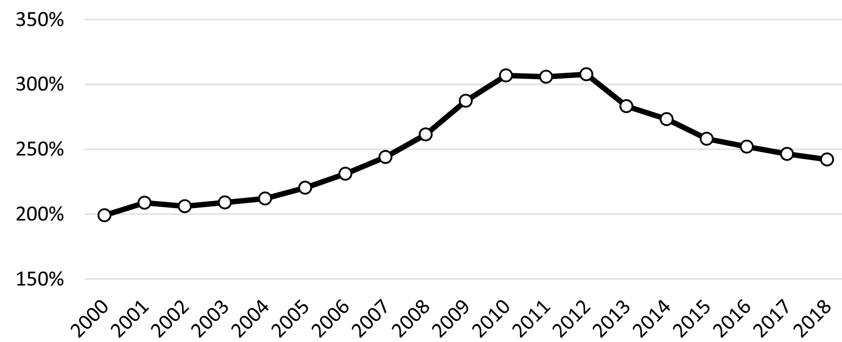

Fig. 1 Total assets of monetary and financial institutions (MFI) as a percentage of gross domestic product (GDP) for the Portuguese economy, 2000–2018. *Source*: Eurostat

This paper aims to use the aggregate banking stability index (ABSI) as a tool to assess banking stability and its determinants in Portugal. In order to do so, an index reflecting banking stability during the 2010–2019 period is first constructed, using data from the financial statements of the Portuguese banking system. Second, an analysis of the Portuguese banking system is made of to assess the impact of macroprudential indicators on the ABSI using time-series regressions, in accordance with the empirical literature on early warning indicators (EWI) (which are classified into macroeconomic and financial variables).

The paper is structured as follows: The following chapter introduces the Portuguese banking sector. The third chapter reviews the body of literature on the existing measures for financial stability and its determinants. The first section of Chapter 4 presents the data used and its treatment for the construction of the aggregated banking stability index (ABSI), while the second section carries out an analysis of the evolvement of the ABSI, as well as on the contributions of each category during the period under analysis. Chapter 5 is divided into three sections: The first deals with the choice of candidates to be determinants of the banking stability, the second presents the methodology employed in the assessment of the ABSI determinants, and the third section presents the results. Finally, Chapter 6 summarises the conclusions.

The Portuguese banking sector

Similar to Germany, Japan, or France, Portugal is considered a bank-based economy, whereas the USA and the UK are considered market-based economies. In a bank-based financial structure, financing consists mostly of institutions that conduct financial intermediation on their balance sheet. These financial institutions bear risks and generally lend through close relationships with their clients. By contrast, a market-based financial structure primarily channels savings directly to borrowers through market [16].

The banking sector is a central piece of the financial system in Portugal. The plot in Fig. 1 was achieved by calculating the ratio between two series (total assets of Portuguese monetary and financial institutions and the Portuguese gross domestic product) from Eurostat. As shown in Fig. 1, the total assets of monetary and financial institutions (MFI) as a percentage of the gross domestic product (GDP) presented an increasing trend—reaching its peak (307%) in 2012, since when it has presented a decreasing trend ever afterwards. Consequently, financial stability is highly dependent on the conditions of the banking sector—which has reported relatively good performance at the beginning of the current century [3]. The International Monetary Fund (IMF) implemented the Financial Sector Assessment Programme (FSAP) in 2006. In its report, the IMF recognises the solid Portuguese regulatory framework and the active and well-organised supervision of the Bank of Portugal. Furthermore, the results of the stress tests carried out on the Portuguese financial system enabled the IMF to conclude that the Portuguese banking system showed high resilience and is perceived to contain sufficient capital to absorb extreme, yet plausible shocks [4].

Nevertheless, the operational environment of the Portuguese banks deteriorated during the subprime crisis of 2008. This was mainly a direct consequence of the restriction on access to financing through the international debt markets and by lowering the value of the banks' portfolio of financial assets. In addition, the sovereign crisis Portugal during the following years restricted the liquidity of Portuguese banks even more.

According to Banco de Portugal (2000), 2010, 2019), 43, 40, and 30 banks were operating in January of 2000, 2010, and 2019, respectively, in Portugal.

The recent history of the Portuguese banking sector is marked by several negative events:

- In 2007, Banco Comercial Português suffered a sharp decline in its share price, as a result of suspicious practices.[2]

[2] For more information, see box 4.1 [5].

- In 2008, Banco Português de Negócios was nationalised. One month later, Banco Privado Português needed an injection of 450 million euros to survive, which was provided by a consortium of the main banking groups.[3]
- In 2014, as a result of a resolution, the Bank of Portugal took action to bail out the troubled Banco Espírito Santo (BES) (at the time the third largest bank in the system), which involved the creation of a new bank called Novo Banco, to which was transferred a significant part of Banco Espírito Santo's assets and liabilities.[4]
- In 2015, another resolution was applied to Banco Internacional do Funchal (BANIF—the seventh largest bank in the system). Most of the bank's assets and liabilities were sold to Banco Santander Totta.[5]

Literature review

Financial stability has been gaining more attention after the last global financial crisis, not only from the academics, but also from central banks and other supervisory bodies. Among the body of literature, a greater focus is devoted to the measures of banking stability, given the relevance of the banking sector in the financial system. Sect. "Financial stability measures" reviews the financial stability measures, whereas Sect. "Banking stability determinants" reviews the literature on stability determinants.

Financial stability measures

Within the literature on financial stability measures, many attempts were made to construct a stability index for the banking sector, which is the most relevant sector of the financial system. Whereas banking stability measures are principally concentrated on the banking sector, financial stability is a broader concept, which considers the entire financial system. Although a wide body of literature exists on stability measurements, there is still no standard framework. For although several methodologies exist for the construction of an index to measure stability, these vary in terms of the variables used, the weighting procedure, and the complexity of the construction.

Gadanecz and Jayaram [32] presented the various attempts of researchers to construct such an index and pointed out the most commonly variables used to assess stability in six different sectors, their frequency and signalling properties, as well as what they actually measure. Gadanecz and Jayaram [32] also emphasise the importance of the individual indicators chosen for the construction of such a composite indicator in order to capture different sources of fragility.

In an attempt to promote international comparability and the standardisation of concepts, definitions, and techniques, the IMF issued a compilation guide with a list of a set of core indicators and encouraged financial soundness indicators (FSIs) [43]. The core set of indicators for deposit takers are related to five main areas, which are compatible with the so-called CAMEL[6] methodology.

The strand of literature on EWI often makes use of binary models. For instance, Nelson and Perli [52] construct a logit model to identify periods of crisis, which uses weekly data on twelve indicators, assigning the value 0 and 1 to non-crisis and crisis periods, respectively, using three summary statistics[7] for the information of the twelve individual indicators. However, as binary models assign the values 0 and 1 for non-crisis and crisis periods, respectively, they provide less information about the developments of the economic conditions, which is not the case for an index.

Goodhart and Segoviano (2009) conceptualise the banking system as a portfolio of banks and calculate the multivariate density (BSMD) of the banking system's portfolio, from which the banking stability measures are constructed. Individual probabilities of default (PD) are first calculated, which are then used as exogenous variables for the consistent information multivariate density optimising copula function [56], which thus recover the BSMD. The objective of the stability measures presented by these authors is to assess banking stability from three different, but complementary perspectives, namely Common distress in the banks of the system, distress between specific banks, and distress in the system associated with a specific bank. The fact that the PDs were used as exogenous variables provides flexibility for the model, as PDs can be calculated using different approaches. Furthermore, BSMD captures linear and nonlinear distress dependencies among banks in the system.

Van den End [59] extends the so-called Monetary Conditions Index[8] by adding house prices, stock prices, solvency buffer, and the volatility of stock price index in terms of deviations from the trend. This measure captures the overall financial system, as it includes not only indicators from the financial institutions' balance sheets, but also indicators from financial markets. The findings suggest that this index correctly reflects the boom/bust of the business cycle.

[3] For more information, see box 4.1 [6].

[4] For more information see box 3 [10].

[5] For more information see box 2 [12].

[6] Where C stands for capital adequacy, A for asset quality, M for management soundness, E for earnings, and L for liquidity.

[7] A level indicator, a rate of change indicator, and a correlation indicator.

[8] The Monetary Conditions Index were previously developed by central banks to assess monetary policy transmission in the 1990s.

Jahn and Kick [45] construct a forward-looking composite index for the German banking system, which is comprised of three components: The individual institutions' scores (standardised PDs), the credit spread (the average bank risk premium), and a stock market index for the banking sector (the prime banks performance index). The aim of the first component is to capture idiosyncratic risk, whereas the objective of the latter two is to capture systemic risk. For major banks, the individual institutions' scores are derived from Moody's Bank Financial Strength Ratings, while the Bundesbank Hazard Rate Model is used for small banks. The framework of these authors' study consists of testing 36 combinations of weights, using a partial proportional odds model where risk profile is the dependent variable (A, B, C, and D—ranging from an 'excellent' grade, through to being a 'problem bank').

Some of the literature uses higher frequency data (usually daily, or weekly) from the financial markets (e.g., daily stock prices or exchange rates) for the construction of composite indices.

Illing and Liu [42] use daily data of the banking sector, foreign exchange market, debt markets, and equity markets of Canada to construct a financial stress index. Three different measure approaches are used, namely The standard measure, the refined measure, and generalised autoregressive conditional heteroscedasticity estimation techniques. These different measures are then combined by using different weighting schemes. The authors conclude that the standard-variable version, which is allied with credit aggregate weighting technique produces the lowest type I and II errors,[9] and that its components are simpler to interpret.

There is a trade-off from using higher frequency data. For on the one hand, the use of higher frequency data enables the rapid assessment of the improvement/deterioration of financial stability. On the other hand, higher frequency data tend to be more volatile, and accordingly, there is the possibility of them yielding false signals to decision-makers [48].

Among the body of literature, the most common weighting techniques are variance-equal (VE) and factor analysis (FA). The former approach consists of standardising the individual indicators and then assigning them equal weights based on the construction of the index. Whereas the latter approach weights individual indicators based on their common variance, i.e. the more correlated an indicator is with its peers, the greater the weight it receives. Both approaches have some shortcomings. For instance, the VE approach assumes normality of the variables and assumes that all the variables are equally important, and therefore weights are meaningless in economic terms, whereas the FA approach can generate multiple solutions [55].

The most common methods of standardisation are statistical and empirical normalisation. Statistical normalisation produces normalised indicators, which range from -3 to 3, which is calculated by:

$$I_{it}^{n} = \frac{I_{it} - \mu_i}{\sigma_i} \tag{1}$$

where $\mathrm{I}_{\mathrm{it}}^{\mathrm{n}}$ is the normalised value of the indicator i in period t, I_{it} is the value of the indicator i in period t, and μ_{i} and σ_{i} are respectively the mean and standard deviation of the indicator i for the period under analysis.

Empirical normalisation produces normalised indicators ranging from 0 to 1, and is calculated by:

$$\mathrm{I}_{\mathrm{it}}^{\mathrm{n}}=\frac{\mathrm{I}_{\mathrm{it}}-\min\left(\mathrm{I}_{\mathrm{it}}\right)}{\max\left(\mathrm{I}_{\mathrm{it}}\right)-\min\left(\mathrm{I}_{\mathrm{it}}\right)} \tag{2}$$

where $\mathrm{I}_{\mathrm{it}}^{\mathrm{n}}$ is the normalised value of the indicator i in period t, I_{it} is the value of the indicator i in period t, $\min\left(\mathrm{I}_{\mathrm{it}}\right)$, and $\max\left(\mathrm{I}_{\mathrm{it}}\right)$ are respectively the minimum and maximum value of the indicator i for the period under analysis.

Both Albulescu [1] and Cheang and Choy [23] constructed an Aggregate Financial Stability Indicator for the financial sectors of Rumania and Macau, respectively, using the VE method and empirical normalisation.

Kočišová (2016) and Gersl and Hermanek [34] construct a banking stability index by using the VE method to aggregate various FSI from the IMF core set. The former author carries out a cross-country study on a yearly basis, whereas the latter authors only consider the Czech banking sector.

Petrovska and Mihajlovska [54] construct an ABSI and a financial conditions index (FCI) for Macedonia. The ABSI is a weighted sum of the indicators that represent the main risks faced by banks.[10] Individual indicators are normalised by the empirical normalisation method and are aggregated into their category according to their source of risk. The categories are subsequently weighted based on expert judgement. The FCI is then constructed by using principal component analysis (PCA), whereby the chosen threshold of 70% for the total common variance explained was sufficient to be able to use the five principal components to summarise the data set. In conclusion, these authors further divide the resulting index by the share of total variance explained.

Using PCA, Dumičić [30] constructs two indices for the Croatian financial system, one of which reflects the accumulation of systemic risks, while the other reflects the materialisation of systemic risks. Finally, Hanschel and Monnin

[9] Type I errors represent the probability of failing to signal a crisis, whereas Type II errors are the probability of falsely signalling a crisis.

[10] Insolvency risk, credit risk, profitability, liquidity risk, and currency risk.

[38] develop a stress index for the Swiss banking sector on an yearly basis, using VE as the aggregation method.

Banking stability determinants

The empirical literature of banking stability determinants is quite extensive. The most common approaches are the signal extraction approach (non-parametric) and econometric approach (usually logit or probit models, which are parametric). Some studies use data on several countries where the crisis is represented by a binary variable (taking the value 1 in a crisis period, and 0 otherwise) and use explanatory variables (usually, macroeconomic ones), whereas other studies only focus on assessing country-specific determinants.

Gaytán and Johnson [33] present a survey of the literature on early warning systems (EWSs) for financial crises. The authors state the importance of defining the scope and certain concepts of the EWS and advocate that first it should be defined whether the EWS is aimed to assess potential individual bank failure, or that of the entire banking system. Second, based on the scope selected, the authors next propose a precise definition of crisis or bank failure. Third, a EWS requires a mechanism, which includes a set of explanatory variables and a method to obtain the predictions from those variables. Gramlich et al. [35] provide a critical review on the EWS literature and typology and also discuss the principles of how to design an efficient EWS.

Kaminsky and Reinhart [46] investigate the link between currency and banking crisis, adopting the signal extraction approach to analyse 20 economies during the period of 1970–1995. An indicator signals a crisis/distress should the value of such an indicator exceed its threshold value. Should the crisis/distress materialise during the following 12 months, then the signal is considered to be a good signal, otherwise it is a false alarm. The threshold value is chosen to minimise a noise-to-signal ratio. Based on this ratio, the authors posit that the three best indicators are: Real exchange rates, stock prices, and the ratio of public sector deficit to GDP.

Borio and Lowe [21] also use the signal extraction approach, however, instead of using individual indicators, these authors use composite indicators, which proved to improve the predictive power of their sample. Their results support that the best composite indicator for industrial countries is a combination of the credit gap with the equity price gap. On the other hand, the best composite indicator for emerging market countries is a combination of the credit gap and either the asset price gap or the exchange rate gap. Their results were further confirmed by Borio and Drehmann [20], who conclude that alongside the credit-to-GDP ratio, asset prices, and gross fixed investment, property prices also have a strong predictive power during a banking crisis.

Using the signal extraction approach, based on 12 individual indicators[11] for 13 OECD countries, Christensen and Li [24] construct three composite indicators: The summed composite, the extreme composite, and the weighted composite. Their in-sample forecasting results suggest that the three composite indicators are useful tools to predict the onset of a crisis. However, their out-of-sample forecasting results suggest that the weighted composite indicator outperforms the other two composite indicators.

Misina and Tkacz [51] use the financial stress index developed by Illing and Liu [42] to assess the possibility of credit and asset prices movements helping to predict financial stress in the Canadian economy. Their findings suggest that housing prices and business credit provide the lowest forecast errors in a two-year horizon for the Canadian economy.

Demirgüç-Kunt and Detragiache [26] apply a multivariate logit approach to assess the probability of the occurrence of a crisis through a set of explanatory variables. Their research showed that economic growth, inflation, and real interest rates all have a strong impact on the probability of a banking crisis occurring. In a posterior paper, Demirgüç-Kunt and Detragiache [27] compare the two most common approaches, suggesting the prominence of the suitability of using the logit model approach. Hardy and Pazarbaşioğlu [39] use a multivariate-multinomial logit model and define a discrete variable, which assumes the value of 1 in the year that precedes the crisis, the value of 2 in the year of the crisis, and zero otherwise. In contrast with Demirgüç-Kunt and Detragiache [26], they also include lags of the explanatory variables, which thus permits carrying out a dynamic analysis of the variables.

Hutchison and McDill [41] estimate a multivariate probit model to assess the relationship of banking problems with both a set of macroeconomic variables (real GDP growth, real credit growth, nominal and real interest rate increase, inflation, the change in a stock price index, the M2-to-reserves ratio, and exchange rate depreciation) and institutional variables (explicit deposit insurance, financial liberalisation, moral hazard, and central bank independence). Their results suggest that the best model is the one which includes all the macroeconomic and institutional variables, except for the stock prices index.

Wong et al. [60] develop a probit econometric model to identify leading indicators of banking distress for Hong Kong and other economies represented at the Executives' Meeting of East Asia–Pacific Central Banks (EMEAP). Their findings suggest that GDP growth, inflation, increase in money supply relative to foreign reserves, and asset

[11] Most of the indicators were extracted from Demirgüç-Kunt and Detragiache [26], Kaminsky [47], and Davis and Karim [25].

prices, in addition to strong credit growth are all good leading indicators of banking distress.

Pedro et al. [53] assess the main determinants of banking stability from three different perspectives: Bank-specific determinants, country-specific macroeconomic determinants, and whether regulation and supervision prevent banking crisis. At the macroeconomic level, they find that GDP growth and the inflation rate both affect the probability of having a banking crisis, and that real GDP growth is the most robust indicator, as opposed to GDP per capita, which was shown to be irrelevant in explaining a banking crisis.

Lainà et al. [50] assess 19 potential leading indicators of systemic banking crises in Europe, paying especial attention to the Finnish case and making use of the two most common methods: The signal extraction approach and multivariate logit regression. The results of the signal extraction approach suggest the prominence of the following growth rates vis-à-vis trend deviations, namely The OECD loans-to-deposits ratio, real private loans, real GDP, real house prices, real households' loans, and real private loans—which all presented a noise-to-signal ratio of less than 30%. Their multivariate logit regressions suggest that deviations from the trend are better explanatory variables for shorter term horizons (e.g. 1-year lagged variables). Real house price growth, real GDP growth, mortgage stock growth, private loan stock growth, and household loan stock growth are all appropriate indicators of a crisis.

Following Betz et al. [18] and Black et al. [19], Shijaku [58] assesses the banking stability determinants by estimating a benchmark model by means of the use of the panel ordinary least square (OLS) approach. The dependant variable is the stability indicator, which is explained by three sets of variables: A set of banking-specific variables, a set of industry-specific variables, and a set of macroeconomic variables. With regard the macroeconomic variables, GDP is shown to improve banking stability and to be statistically significant at 1% level, whereas the spread between Albanian and German 12-month T-bills has a negative effect on banking stability, although this turned out to be statistically insignificant.

Using the gap approach developed by Borio and Lowe [22], Hanschel and Monnin [38] assess the determinants of the stress index by adopting the dependent variable of the regression as the index, using the following explanatory variables (comprised of a 1, 2, 3, and 4-year lag): GDP gap, European GDP gap, share price index gap, housing price index gap, credit ratio gap, and investment ratio gap.

The second part of the study of Jahn and Kick [45] focusses on assessing the determinants of German banking stability, adopting: Three macroeconomic variables (real estate price index, the Ifo index,[12] and gross fixed investments), three financial variables (national private credit-to-GDP ratio, 3-month London Interbank Offered Rate (LIBOR), and M2-to-GDP ratio), and five structural variables (regional probability of default, regional GDP change rate, international exposure, risk aversion, and an indicator representing bank size). By using a dynamic panel data model, these authors found that in contrast to gross fixed investments, the real estate price index and the Ifo index are the leading macroprudential indicators for measuring banking stability. Furthermore, within the financial variables, the 3-month LIBOR and the national private credit-to-GDP ratio are good banking stability indicators. (However, the latter becomes less important for internationally-oriented banks.) Finally, regional probability of default and regional GDP change are only significant determinants for small cooperative banks, whereas the risk aversion indicator showed to be a prominent determinant of banking stability.

With the outbreak of coronavirus disease in 2019 (hereinafter COVID-19), at the time of this research, European Union was forced to implement extraordinary measures to contain the impact of the pandemic on the real economy. Consequently, participating member states of the European Banking Union (EBU), introduced a broad set of measures, including public guarantees, moratoria, and amendments to the European Commission State Aid framework, to contain the negative effects of the pandemic on the economy. Gulija et al. [36] analyse the COVID-19 stress impact in 2020, considered an exogenous shock to the banking system, and present findings for the Single Supervisory Mechanism (SSM) significant banks and several member states of the European Banking Union (EBU).

Aggregated banking stability index

Deriving the ABSI

Table 1 summarises the core set of FSI provided by the IMF. Most of these consist of a ratio between two underlying series. They rely on five main categories, which are relevant from the banking business perspective and provide insights about the banking system position, as the data are obtained from the banks' financial statements. Certain indicators from the core set of FSI were not included in the ABSI calculation and the two Basel III indicators (LCR and NSFR) were excluded. Being fairly recent, these two concepts are still at the implementation stage. In contrast to LCR, NFSR is not

[12] The Ifo index is an index developed by the Ifo institute for Economic Research, which measures expectations based on a survey of manufacturers, builders, wholesalers, and retailers.

Table 1 Core set of FSI for deposit takers

Category	Indicators
Capital Adequacy	Regulatory capital to risk-weighted assets
	Regulatory Tier 1 capital to risk-weighted assets
	Nonperforming loans net of provisions to capital
	CET-1 capital to risk-weighted assets
	Tier-1 capital to assets
Asset Quality	Nonperforming loans to total gross loans
	Sectoral distribution of loans to total loans
	Provisions to nonperforming loans
Earnings and Profitability	Return on assets
	Return on equity
	Interest margin to gross income
	Noninterest expenses to gross income
Liquidity	Liquid assets to total assets (liquid asset ratio) for all DTs
	Liquid assets to short term liabilities for all DTs
	Liquidity Coverage Ratio (LCR).*
	Net Stable Funding Ratio (NSFR). *
Sensitivity to Market Risk	Net open position in foreign exchange to capital.*
Real Estate Market	Residential real estate prices.*

*Excluded indicators from the ABSI calculus

Source: International Monetary Fund (2019)

Table 2 The selected FSIs and their respective weights and impacts

Category	Weight	Indicator	Impact	Data Source
Capital Adequacy	0.25	Regulatory capital to risk-weighted assets	+	BPstat
		Regulatory Tier 1 capital to risk-weighted assets	+	BPstat
		CET-1 capital to risk-weighted assets	+	BPstat
		Nonperforming loans, net of provisions to capital	–	BPstat
		Tier-1 capital to assets	+	BPstat
Asset Quality	0.25	Nonperforming loans to total gross loans	–	BPstat
		Sectoral distribution of loans to total loans	–	BPstat
		Provisions to nonperforming loans	+	BPstat
Earnings And Profitability	0.25	Return on assets	+	BPstat
		Return on equity	+	BPstat
		Interest margin to gross income	+	BPstat
		Noninterest expenses to gross income	–	BPstat
Liquidity	0.25	Liquid assets to total assets	+	BPstat
		Liquid assets to short-term liabilities	+	BPstat

Source: Prepared by the Author

yet subject to compulsory disclosure, and thus no data are available. The introduction of LCR in the construction of the ABSI would require a break in the series, which would cause a major reduction in the time window under analysis. The net open position in foreign exchange to capital and residential real estate prices were also excluded, owing to the lack of available data.

The ABSI constructed in this paper uses selected quantitative indicators of the core set of FSI of the IMF, with its calculation being tested from March 31, 2010 to March 31, 2019, on a quarterly basis. The data for the FSIs were obtained from BPstat, the Bank of Portugal database.

Table 2 presents the set of indicators used in the ABSI construction. The proposed ABSI is subdivided into four main categories, which represent the main sources of risk for banks: Capital Adequacy, Asset Quality, Earnings and Profitability, and Liquidity.

Capital adequacy ratios are the central feature of the Basel Capital Accord, as they represent insolvency risk and demonstrate a bank's capacity to deal with potential risks and also measure a bank's capital buffer to absorb expected or unexpected losses. The first is a ratio where the numerator is total regulatory capital (the supervisory definition of capital, which was developed by the Basel Committee on Banking Supervision) and the denominator is the on- and off-balance-sheet assets, weighted by risk. An increase in this ratio is therefore expected to lead to a more stable banking system. The second ratio focusses on a more specific concept of capital, Tier 1, which measures the most freely and readily available resources for absorbing losses. The third ratio is an even more restrict definition of capital, which measures a bank's capital adequacy, based on the highest-quality capital, CET-1. Both the second and the third ratios impact stability in the same way as the first ratio, as in effect they are just more restricted concepts of the first ratio. The objective of the fourth FSI is to capture the impact of those non-performing loans (NPL) that are not covered by specific provisions on capital—where the numerator is the difference between the NPL and the specific provisions, and the denominator is the regulatory capital. An increase in this ratio reflects a lower capacity of a bank's capital to withstand NPL losses and thus it has a negative impact on stability. The last capital adequacy FSI is a proxy for financial leverage, i.e., it indicates to what extent the amount of assets is funded by other capital, rather than own funds. Accordingly, an increase in this ratio reflects a lower exposure to risk, which consequently positively affects banking stability.

The aim of the asset quality indicators is to capture credit risk, which is assessed by three ratios. The first ratio is the proportion of NPL to total gross loans, which reflects the proportion of troubled loans to total gross loans. An increase in this ratio implies a poorer quality of the credit granted, which negatively impacts on banking stability. The sectoral distribution of loans to total loans ratio is calculated by taking the credit granted to the three largest economic activities as the numerator and the total gross loans as the denominator. This ratio reflects the concentration of the credit granted, where an excessive concentration of loans implies higher exposure to less activities (i.e. a less diversified loan portfolio), and therefore an increase in this ratio negatively affects banking stability. The last asset quality ratio measures the amount of NPL already covered by specific provisions, which provides information about future losses if all NPL were to be written-off. Accordingly, an increase in this ratio implies a more stable banking system.

Four FSI constitute the earnings and profitability category. Return on assets (ROA) is the ratio of net income to average total assets, which provides an insight into a bank's efficiency in managing its assets and generating earnings. Return on equity (ROE) is the ratio of net income to average book equity, which provides an insight into a bank's efficiency in using its capital to generate earnings. These two FSI are expected to positively affect stability. The interest margin to gross income ratio is the share of interest margin in gross income, which reflects the relative importance of intermediation business. The noninterest expenses to gross income ratio—which is often called the efficiency ratio—is the portion of revenues that is required to off-set operating expenses.

Liquidity management is one of the main concerns (and source of risk) of banks' activity, i.e. the ability of a bank to meet its cash outflows. The liquid assets (assets which can be quickly converted into cash) to total assets ratio measures available short-term liquidity, whereas the liquid assets to short-term liabilities ratio measures the portion of short-term liabilities that is covered by liquid assets. Both FSIs have a positive impact on banking stability.

Before final aggregation, the data passed through an adjustment process. This is necessary at a first stage because the ABSI in this study focusses on measuring banking stability, and those FSIs, which have a negative impact on the ABSI (i.e. sources of instability) need to be adjusted to ensure that they have a positive impact. Accordingly, their reciprocal value is considered (e.g.$1 - \frac{NPL}{RegulatoryCapital}$). In a second phase, all FSIs were normalised to achieve the same variance by applying the empirical normalisation method presented in Eq. 1). In this way, each indicator can thus be compared to its limit values (minimum and maximum) for the period under analysis. Movement of the ABSI towards 0 (the lower limit) represents a larger risk exposure, whereas movement towards 1 (the upper limit) means lower risk. On one hand, as this method uses the limit values for the adjustment, it can be unreliable for entire data series, whereas, on the other hand, minor date-to-date changes lead to obvious effects on the ABSI. Furthermore, the fact that this method comprises indicators in the interval from 0 to 1 provides an easy interpretation of the ABSI developments. The third step of the ABSI calculation consists of calculating each category for every quarter, by considering the arithmetic mean of the FSIs that it is composed of. Finally, based on the fact that there are four categories and that the variance-equal scheme was used, a weight of 25% for each category was allocated. The ABSI thus represents the weighted sum of the values of the four categories.

ABSI patterns

The ABSI is calculated as a weighted sum of the adjusted and normalised components of the four categories. As mentioned above, an increase in the ABSI value corresponds to an increase in stability during the period under study.

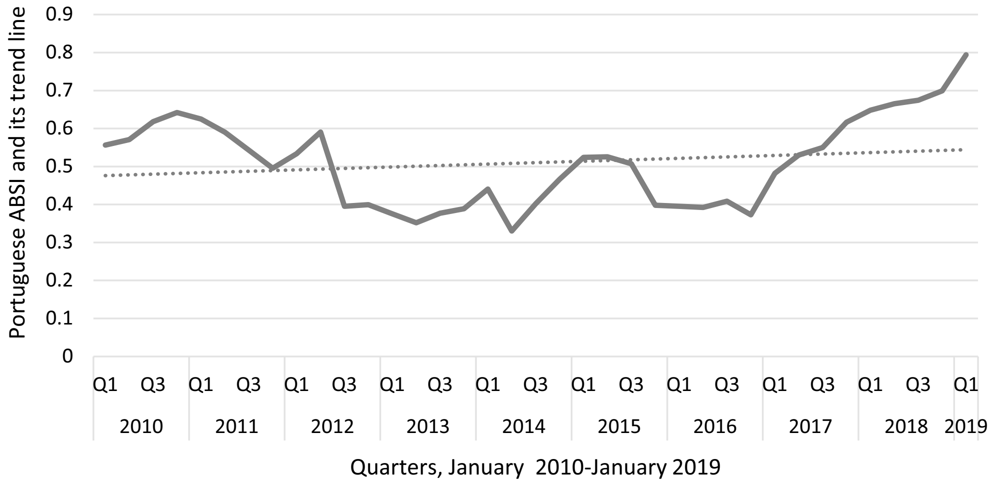

Fig. 2 Portuguese ABSI, January 2010—January 2019

Figure 2 shows the ABSI development and its average of the Portuguese banking system stability (for specific values of the ABSI, see Table 3) for the period under analysis. The ABSI was constructed on a quarterly basis, starting from the 1st Quarter of 2010 up until the 1st Quarter of 2019, presenting an average value for the entire analysed period of 0.51. The period under analysis can be divided into three stages, as follows:

- The first stage covers the period from the 1st Quarter of 2010 up until the 2nd Quarter of 2012. Even though the ABSI is greater than its average value (with the 4th Quarter of 2011 being an exception), it presented a downward trend.
- Despite the first two quarters of 2015, where the ABSI was barely greater than its average value, the second stage can be identified starting from the 3rd Quarter of 2012 up until late 2016, where the ABSI presented lower values when compared to its mean, attaining its minimum of 0.33 during the 2nd Quarter of 2014.
- The third stage covers the final period from early 2017 up until the end in the 1st Quarter of 2019. This stage is characterised by an upward trend in stability, attaining its peak of 0.79 in its final value.

Figure 3 shows the evolvements of the ABSI categories during the period under analysis (Table 4 shows all specific values). On one hand, capital adequacy was the category that presented the most remarkable improvement over time, increasing from 0.059 in the 1st Quarter of 2010 to 0.24 in the 1st Quarter of 2019. On the other hand, the liquidity category was the one that presented the worst evolvement, decreasing its contribution from 0.157 to 0.136, for the same period of time. Both the asset quality and earnings and profitability categories presented some improvement, with the former increasing from 0.163 to 0.205, whereas the latter increased from 0.178 to 0.212.

During the first stage, the improvements of the capital adequacy category were due to the more strict capital requirements ratios defined as stipulated in the Economic and Financial Assistance Programme (EFAP) [8]. This resulted in the deleveraging process undertaken by Portuguese banks to reduce their risk-weighted assets and the capitalisation ratios demanded by the European Banking Authority (EBA) for the four major banks [10]. The upward trend in capital adequacy ratios remained in 2013, due to the decline of the risk-weighted assets (RWAs) and the recapitalisation of banks, with recourse to public funds. The EBA resolution made on BES negatively influenced the capital adequacy ratios, which led to the deterioration, which was verified in 2014. Up to 2016, the negative developments in this category were due to weak profitability and the progressive elimination of the transitional provisions established in the Capital Requirements Regulation (CRR) and Capital Requirements Directive (CRD IV)—which were partially offset by the continuing decline in the RWA. The positive evolvement of capital adequacy ratios since 2016 was partly due to the increase in the banks' profitability (enabling the internal generation of capital), and also due to the continuous downward trend of the RWA, as a result of the deleveraging process and the recapitalisation processes carried out by the various banks in the system.

Credit quality presented a negative trend during the first stage. This worsening reflected the increase in the default ratios on loans either to households or to non-financial companies, due to the constant deterioration of the macroeconomic scenario: In the case of households, the rise in the unemployment and fiscal burden and the decrease in wages were the main factors, whereas in the case of non-financial companies, the contraction of domestic demand severely

Table 3 ABSI values

Year	Quarter	ABSI
2010	Q1	0.557
	Q2	0.571
	Q3	0.618
	Q4	0.642
2011	Q1	0.625
	Q2	0.590
	Q3	0.543
	Q4	0.496
2012	Q1	0.533
	Q2	0.591
	Q3	0.395
	Q4	0.400
2013	Q1	0.375
	Q2	0.352
	Q3	0.377
	Q4	0.389
2014	Q1	0.441
	Q2	0.330
	Q3	0.402
	Q4	0.466
2015	Q1	0.524
	Q2	0.525
	Q3	0.507
	Q4	0.398
2016	Q1	0.395
	Q2	0.392
	Q3	0.409
	Q4	0.373
2017	Q1	0.482
	Q2	0.530
	Q3	0.550
	Q4	0.617
2018	Q1	0.648
	Q2	0.665
	Q3	0.675
	Q4	0.699
2019	Q1	0.794
ABSI Average	0.510	

Source: Author's calculation

limited the generation of resources. The developments with respect asset quality were marked by the continuous deleveraging process and the consequent reduction of the banks' assets and by the increase in credit at risk—where the non-financial sector attained its highest credit at risk ratio at the end of 2015, which impacted this category negatively. The posterior improvements observed in this category were the result of the continuous decrease in the NPL stock (which resulted from a high flow of loan write-offs and the improved performance of non-financial companies—whose share of NPL started to decrease) and also the strengthening of impairment recognition (which was verified in the increase in the coverage ratio of NPL to provisions).

A set of non-recurring events in 2011, such as the Special Inspections Programme (SIP), which highlighted the need to reinforce the recognition of impairment losses and provisions, along with the decrease in financial operations' income led to a sharp decrease in the profitability of Portuguese banks. Part of the recovery felt in 2012 is thus due to the cessation of these non-recurring events and the slight improvement of both the operating costs and income of financial operations. The profitability of Portuguese banks continued to fall, highly influenced by the impairment costs and the contraction in the net interest margin, even when taking into account with the positive contributes of the decrease in the operation costs and the income from financial operations. The profitability of the Portuguese banking system was negatively influenced by the resolution applied to BES during the first half of 2014. Nevertheless, this episode marked a turning point in the profitability, which presents a positive trend from then onwards. 2015 was marked by the return to positive levels of profitability (which had not been seen since 2010) [11]. This positive development was facilitated by the rise in net interest income (through the reduction of interest expenses), the continued positive results of financial operations, and a reduction in the flow of impairments' costs and a continued downward trend in banks' operational costs.

The restricted access to wholesale debt markets[13] in 2010 implied a reduction of long-term bonds financing, compelling Portuguese banks to adjust their financing strategy by increasing their reliance on Eurosystem lending operations and by attracting stable deposits (with a more than 2-year maturity, e.g. savings deposits). Despite the long-term refinancing operations carried out by the European Central Bank (ECB), 2012 was marked by a significant increase in subordinated liabilities, due to the issues of contingent capital instruments subscribed by the Portuguese State, which were associated with the capitalisation needs demanded by stricter capital regulations [9].

Figure 4 displays the contributions of each ABSI category in each and every quarter of the period under analysis. Although this figure represents a combination of the information of the two previous figures, it provides a better intuition of the contribution of each category to the ABSI. During the first stage, the main contributors to maintaining the ABSI above average were liquidity, earnings, and profitability. The beginning of the second stage coincides with the sharp fall in the contribution of the liquidity category,

[13] This restriction was highly influenced by the sovereign debt crisis.

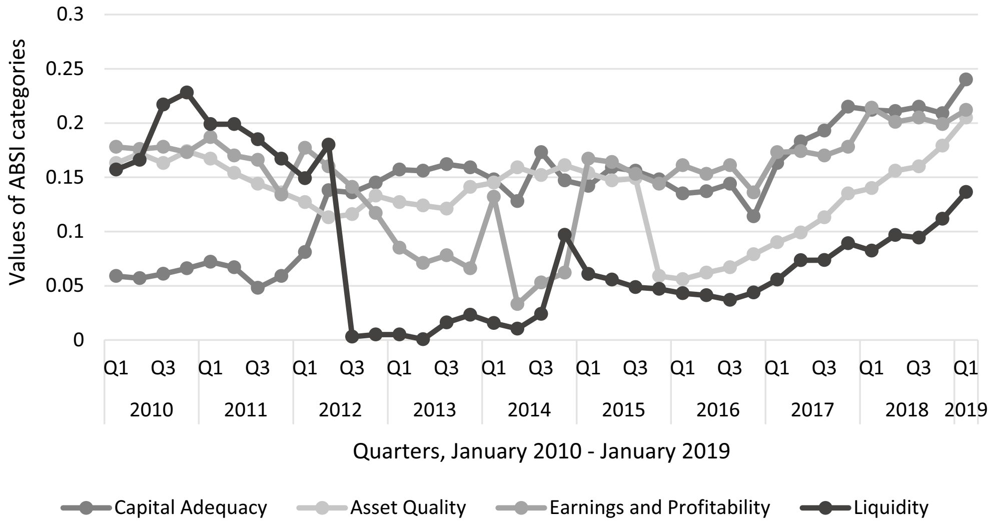

Fig. 3 Values of ABSI categories, January 2010—January 2019

which forced the ABSI below its average level, even with the increase in the contribution of capital adequacy. In addition to the sharp fall in liquidity contribution, the decreasing contribution of earnings and profitability pushed the level of the ABSI further lower, attaining its minimum level during the 2nd Quarter of 2014. The rest of the second stage was influenced by the opposite trajectories of earnings and profitability (which showed an improvement) in comparison with asset quality (which deteriorated). The third stage is characterised by the good performance of all categories, which resulted in a fairly stable improvement in the ABSI, attaining its peak during the end-period.

Aggregated stability determinants

Macroprudential leading indicators for the ABSI

The empirical work of this paper started with the construction of an index, which reflects the aggregated banking stability index (the ABSI), which will now be used as the dependent variable to assess the determinants of the Portuguese banking stability.

The descriptive statistics of all the variables (dependent and independent) used are presented in Table 5.

Regarding the dependent variable, this assessment includes 37 observations from the 1st Quarter of 2010 through to the 1st Quarter of 2019. Based on the related theoretical and empirical literature, several indicators were identified as potential candidates for the determinants of the Portuguese aggregate banking stability and were classified into macroeconomic and financial variables.

Table 6 presents the units and sources of the data of the independent variables, as well as the specifications under, which each one was calculated and their expected impact on the ABSI.

The set of macroeconomic variables comprises eight variables, which reflect the conditions of the Portuguese economy:

- The spread between domestic and German 10-year government bonds (TSPREAD) reflects the risk premium associated with Portuguese government debt when compared to German debt—the safest European debt. The high indebtedness of the Portuguese State during the financial crisis restricted the access of Portuguese banks to wholesale debt markets. Accordingly, an increase in spread is expected to harm stability, as such an increase would indicate a riskier Portuguese public debt in relation to the German debt.
- The government debt-to-GDP ratio (Debt/GDP) compares the amount the country owes, with the country on a given date. Typically, a higher debt-to-GDP ratio is associated with higher risk, as this would imply that the country would take more time to repay its debt without further refinancing. Accordingly, this regressor is expected to have a negative impact on stability.
- The real GDP growth (%ΔGDP) is the main macroeconomic indicator, where a positive value indicates an expansion period, whereas a negative value is associated with a recession and a slowdown of the economy. This indicator is thus expected to have a positive impact on banking stability.
- Theoretically, positive asset price's growth is associated with the boom phase in the business cycle. However,

Table 4 Weighted and Normalised ABSI Categories Values

Year	Quarter	Capital Adequacy	Asset Quality	Earnings and Profitability	Liquidity
2010	Q1	0.059	0.163	0.178	0.157
	Q2	0.057	0.172	0.176	0.166
	Q3	0.061	0.163	0.178	0.217
	Q4	0.066	0.174	0.173	0.228
2011	Q1	0.072	0.167	0.187	0.199
	Q2	0.067	0.154	0.170	0.199
	Q3	0.048	0.144	0.166	0.185
	Q4	0.059	0.136	0.134	0.167
2012	Q1	0.081	0.127	0.177	0.149
	Q2	0.138	0.113	0.160	0.180
	Q3	0.136	0.116	0.141	0.003
	Q4	0.145	0.133	0.117	0.005
2013	Q1	0.157	0.127	0.085	0.00507
	Q2	0.156	0.124	0.071	0.00063
	Q3	0.162	0.121	0.078	0.01607
	Q4	0.159	0.141	0.066	0.02320
2014	Q1	0.148	0.145	0.132	0.01562
	Q2	0.128	0.159	0.033	0.01043
	Q3	0.173	0.152	0.053	0.02393
	Q4	0.147	0.161	0.062	0.09679
2015	Q1	0.142	0.154	0.167	0.06077
	Q2	0.159	0.147	0.164	0.05557
	Q3	0.156	0.149	0.153	0.04865
	Q4	0.148	0.059	0.144	0.04710
2016	Q1	0.135	0.056	0.161	0.04307
	Q2	0.137	0.062	0.153	0.04123
	Q3	0.144	0.067	0.161	0.03689
	Q4	0.114	0.079	0.136	0.04379
2017	Q1	0.163	0.090	0.173	0.05568
	Q2	0.183	0.099	0.174	0.07344
	Q3	0.193	0.113	0.170	0.07358
	Q4	0.215	0.135	0.178	0.08910
2018	Q1	0.212	0.140	0.214	0.08229
	Q2	0.211	0.156	0.201	0.09678
	Q3	0.215	0.160	0.205	0.09436
	Q4	0.209	0.179	0.199	0.11170
2019	Q1	0.240	0.205	0.212	0.13637

Source: Author's calculation

large growth rates can signal the overheating of the economy, and hence future instability. Two types of asset prices are identified: Property prices—represented by the house price index (HPI), and stock prices—represented by the Portuguese stock index of the 20 major companies (PSI20). Real estate prices played an important role during the last financial crisis, as the crisis was provoked by the collapse of the real estate bubble.

- The objective of showing the variation in the consumer price index (%ΔCPI) is to proxy inflation. A positive variation in the CPI is thus associated with positive inflation. High inflation rates are usually seen to be a source of instability and their increase can lead to a contraction of the international demand for domestic products [40]. Accordingly, its estimated coefficient is expected to be negative.
- The real exchange rate with 42 trading partners (RER42) reflects international competitiveness. Thus, an increase in the real exchange rates reflects a deterio-

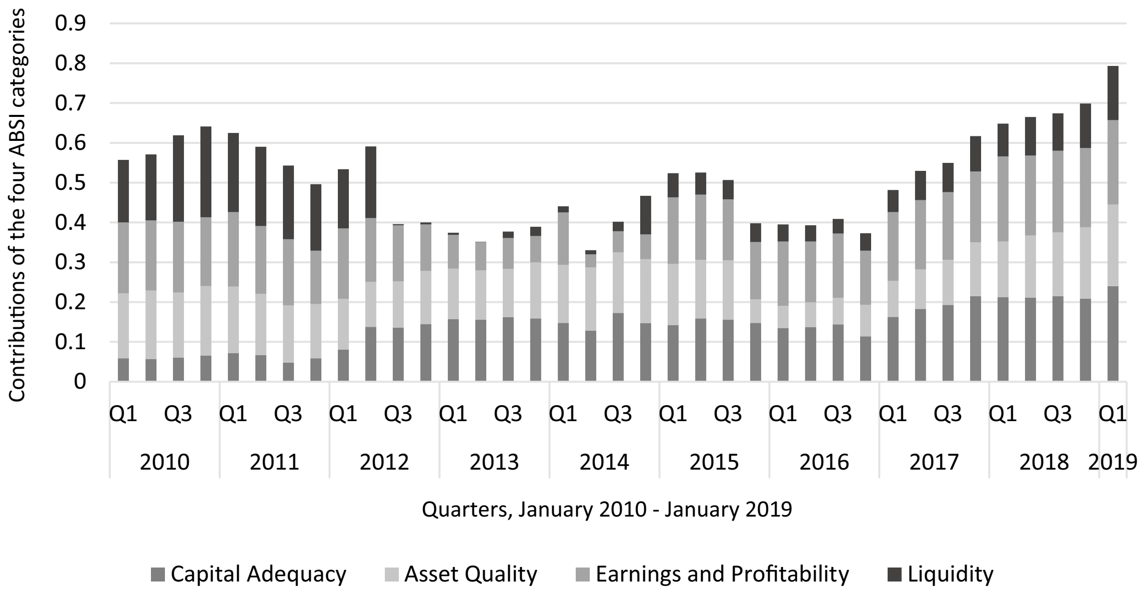

Fig. 4 Contributions of the four ABSI categories, January 2010—January 2019

Table 5 Descriptive Statistics

Variable	Mean	Median	Std. Dev	Skewness	Kurtosis	Max	Min	Obs
Dependent								
ABSI	0.510	0.524	0.116	0.343	2.254	0.794	0.330	37
Independent								
TSPREAD	3.568	2.680	2.768	1.421	4.181	11.130	0.640	41
%ΔGDP	0.090	0.400	0.793	−1.255	3.972	1.100	−2.300	41
HPI	106.188	105.450	11.649	1.050	3.348	137.140	92.250	41
%ΔPSI20	0.159	0.100	4.454	0.075	2.423	8.300	−10.200	41
%ΔCPI	0.003	0.002	0.006	1.058	4.879	0.022	0.008	41
RER42	99.154	99.280	1.912	0.326	3.046	103.260	95.450	41
ESI	96.766	100.000	11.795	0.453	1.894	112.800	75.800	41
Debt/GDP	117.607	125.400	17.737	−1.204	2.970	133.000	74.800	41
M2/GDP	3.493	3.470	0.169	0.471	2.316	3.866	3.232	41
EURIBOR3	0.309	0.206	0.613	0.700	2.303	1.635	−0.330	41
VIX Index	18.675	16.600	7.615	1.876	6.604	44.140	9.51	41

Original time series. Source: E-views 9.0 results

ration in competitiveness and is accordingly expected to have a negative estimated coefficient.

- The economic sentiment indicator (ESI) measures the confidence or expectations of economic agents. Therefore, an increase in this index reflects improvements of the agents' expectations and it is thus expected to have a positive impact on stability.

The set of financial variables is composed of three variables:

- The M2-to-GDP is a ratio where the numerator (M2) is a measure of the money supply, which includes M1 (cash and checking deposits), as well as savings deposits, money market securities, mutual funds, and other time deposits. The denominator is GDP. This ratio is a proxy for financial solidity, and it also reflects the excessive liquidity that could precede a lending boom.
- The 3-month euro interbank offered rate (EURIBOR3) is the average interest rate at which banks borrow funds from one another with 3-month maturity. If the finan-

Table 6 Description of the independent variables

Variables	Expected Impact	Unit	Observations	Source
Macroeconomic Variables				
TSpread	–	Percentage		BP
%ΔGDP	+	Chain change of rate	Seasonally adjusted, expressed as chain rate of change at constant prices of 2006	INE
HPI	±	Index, 2015 = 100	Non-seasonally adjusted	EuroStat
%ΔPSI20	±	Chain change of rate		NYSE Euronext
%ΔCPI	–	Chain change of rate		INE
RER42	–	Index, 2010 = 100		EuroStat
ESI	+	Index	End-period values taken	European Commission
Debt/GDP	–	Percentage		EuroStat
Financial Variables				
M2/GDP	±			BP
EURIBOR3	–	Percentage	End-period values taken	European Money Markets Institute
VIX Index	–	Percentage	End-period values taken	Chicago Board Options Exchange

Source: Prepared by the Author

Table 7 Correlation matrix of the original variables

Correlation	ABSI	TSPREAD	%ΔGDP	HPI	%ΔPSI20	%ΔCPI	RER42	ESI	Debt/GDP	M2/GDP	EURIBOR3	VIX Index
ABSI	1.000											
TSPREAD	−0.149	1.000										
%ΔGDP	−0.012	−0.736	1.000									
HPI	0.742	−0.496	0.382	1.000								
%ΔPSI20	0.048	−0.011	−0.107	0.027	1.000							
%ΔCPI	0.216	0.266	−0.152	0.007	0.018	1.000						
RER42	0.188	0.444	−0.341	−0.038	−0.046	0.217	1.000					
ESI	0.287	−0.862	0.734	0.684	−0.013	−0.190	−0.425	1.000				
Debt/GDP	−0.464	−0.205	0.201	−0.071	−0.168	−0.456	−0.552	0.273	1.000			
M2/GDP	0.723	−0.003	−0.015	0.832	0.043	0.109	0.240	0.240	−0.141	1.000		
EURIBOR3	0.090	0.707	−0.601	−0.448	−0.081	0.366	0.647	−0.728	−0.683	−0.138	1.000	
VIX Index	0.188	0.281	−0.261	−0.081	−0.286	−0.006	0.188	−0.334	−0.457	−0.021	0.516	1.000

Covariance Analysis: Ordinary

Sample: 2010Q1 2019Q1

Included observations: 37

Balanced sample (listwise missing value deletion)

cial environment is weak, then the 3-month Euribor should be high. Accordingly, an increase of the Euribor is expected to decrease stability and this coefficient is thus expected to be negative.

- The aim of the volatility index (VIX index) is proxy risk-aversion and uncertainty in the financial markets [17]. It is thus expected to have a negative impact on stability.

The correlation matrix of the original variables is presented in Table 7 and the correlation matrix for the de-trended variables with the respective lags is presented in Table 8.

Methodology

Many economic and financial time series exhibit non-stationarity properties resulting in spurious regressions. Therefore, before carrying out any estimation, it is necessary to check the stationarity of the series in use through the application of both the Augmented Dickey–Fuller and

Phillips–Perron unit root tests.[14] The unit root tests are to test the null hypothesis that the series has a unit root (i.e. that it is non-stationary). This procedure consists of testing all variables in levels and differentiating those that fail to reject the null hypothesis until they do so (at a minimum significance level of 10%). Accordingly, some variables enter the model in levels, some enter in the first difference (D1), and others in the second difference (D2).

To carry out this empirical study, the ARMA conditional least squares method was used,[15] with the following regressions:

$$Y_t = \beta_0 + \sum_{j=1}^{J} \beta_j \cdot X_{j,t-p} + \sum_{k=1}^{K} \beta_k \cdot Z_{k,t-q} + \varepsilon_t, \quad \text{with } t = 1,2,\dots,37\ j = 1,2,\dots,8 \text{ and } k = 1,2,3\} \tag{3}$$

$$Y_t = \beta_0 + \sum_{j=1}^{J} \beta_j \cdot X_{j,t-p} + \sum_{k=1}^{K} \beta_k \cdot Z_{k,t-q} + \varepsilon_t + ar(1) \quad \text{with } t = 1,\ 2,\ \dots,\ 37 \text{ and } k = 1,\ 2,\ 3 \tag{4}$$

$$Y_t = \beta_0 + \sum_{j=1}^{J} \beta_j \cdot X_{j,t-p} + \sum_{k=1}^{K} \beta_k \cdot Z_{k,t-q} + \varepsilon_t + ar(1) + ar(2) \quad \text{with } t = 1,\ 2,\ \dots,\ 37\ j = 1,\ 2,\ \dots,\ 8 \text{ and } k = 1,\ 2,\ 3 \tag{5}$$

$$\beta_0 + \sum_{j=1}^{J} \beta_j \cdot X_{j,t-p} + \sum_{k=1}^{K} \beta_k \cdot Z_{k,t-q} + \varepsilon_t + ar(1) + ar(2) + ar(3) \text{ with } t = 1,\ 2,\ \dots,\ 37\ j = 1,\ 2,\ \dots,\ 8 \text{ and } k = 1,\ 2,\ 3 \tag{6}$$

These econometric relationships involve the (Y_t) dependent variable, which is the ABSI calculated in Sect. 0; β_0 is the constant term; X and Z are the explanatory variables; ε_t, is the disturbance term; and $ar(1)$, $ar(2)$ and $ar(3)$ are the autoregressive components.

The term $\sum_{j=1}^{J} \beta_j \cdot X_{j,t-p}$ corresponds to the macroeconomic variables, whereas $\sum_{k=1}^{K} \beta_k \cdot Z_{k,t-q}$ corresponds to the financial variables. The lags are allowed to differ across the regressors. The β_j and β_k coefficients describe the effect of $X_{j,t-p}$ and $Z_{k,t-q}$ on Y_t and are constant across time.

When using time series, the most serious problem that can arise concerns the serial correlation. It is therefore important to check for serial correlation in the error terms for every estimation of the model. E-views tests the null hypothesis of no serial correlation through the application of the Breusch–Godfrey Serial Correlation LM test for different lag lengths. As the data are quarterly, this test was carried out for 1, 2, and 4 lags.[16] The model in Eq. (3) failed to reject the null hypothesis of no serial correlation, as it presented a p-value < 0.05. However, e-views enables this problem to be addressed by adding an autoregressive (AR) component to the equation. The models in Eqs. 4() and (5) also failed to reject the null hypothesis, indicating that $ar(1)$ and $ar(2)$ are not a good specification, as they fail to fully address serial correlation. The model in Eq. (6) rejects the null hypothesis of no serial correlation, indicating that an autoregressive process of order 3 correctly addressed the problem of serial correlation.

Heteroskedasticity problems can also arise in time series, especially in small samples. E-views enables testing for heteroskedasticity through carting out several tests. We adopted both the white test and the Breusch–Pagan–Godfrey test, as both test the null hypothesis of homoskedasticity, with both results pointing to the presence of homoscedastic errors.[17]

Results

Table 9 reports the estimation of the model for the period under analysis (2010–2019). The main results show that most of the macroprudential indicators, which are commonly used in the literature to predict banking crisis or instability are also useful key indicators for Portugal. Overall, this model presents a strong explanatory variable, as the R-squared is approximately 92% and all the regressors proved to be statistically significant at 1%, with the exception of the M2/GDP coefficient, which is significant at 5% level. Within the set of the potential determinants of stability, RER42 was the only one, which was not statistically significant, and it was thus removed from the model.

The coefficients of both TSPREAD and DEBT/GDP showed a positive impact (although they were expected to be negative) on the ABSI growth, indicating that an increase of 1 percentage point (PP) on TSPREAD growth increases the ABSI growth in the subsequent period by 0.05PP, whereas an increase of 1 unit on the variation of DEBT/GDP growth increases the ABSI growth by 0.005PP after three quarters. One possible reason for the unexpected sign of the coefficients could lie with the fact that the Portuguese government implemented various measures (e.g. bailouts

[14] Results available from the authors upon request.

[15] The estimation method used for Eq. (3) was the ordinary least squares method. ARMA conditional least squares was used to model the autoregressive components in Eqs. (4), (5), and (6).

[16] Results available from the authors upon request.

[17] "Results available from the authors upon request.

Table 8 Correlation Matrix of the detrended (D) and lagged variables (-)

Correlation	EURIBOR3(-1)	D2Debt/GDP(-3)	D1TSPREAD(-1)	D1M2/GDP (-2)	%ΔGDP(-2)	D2HPI(-2)	D1%ΔCPI(-2)	D1ESI(-1)	%ΔPSI20(-2)	VIX Index
EURIBOR3(-1)	1.000									
D2Debt/GDP(-3)	0.096	1.000								
D1TSPREAD(-1)	0.367	0.103	1.000							
D1M2/GDP (-2	0.139	0.156	0.052	1.000						
%ΔGDP(-2)	−0.462	−0.032	0.104	−0.079	1.000					
D2HPI(-−2)	−0.170	−0.026	−0.136	−0.202	−0.130	1.000				
D1%ΔCPI(-−2)	−0.188	−0.219	0.095	−0.165	0.007	0.482	1.000			
D1ESI(-1)	−0.486	−0.211	−0.365	−0.447	0.133	0.259	0.387	1.000		
%ΔPSI20(-2)	−0.152	−0.181	−0.224	−0.309	−0.071	0.098	0.130	0.179	1.000	
VIX Index	0.689	0.078	0.463	0.066	−0.271	−0.162	0.020	−0.454	−0.111	1.000

Covariance Analysis: Ordinary
Sample: 2009Q1 2019Q1
Included observations: 41

and capital injections in the banking system) to avoid major distress in the banking system. Likewise, it was possible to have both an increase in government debt and yields, which positively affect banking stability. Conversely, the coefficient of %ΔGDP presents a negative sign (contrary to what was expected), indicating that an increase of 1 pp of %ΔGDP decreases the ABSI growth by 0.034PP two periods after. One reason for this could be the low average growth rate (0.09%), combined with the negative skewness[18] that the Portuguese economy experienced during the period under analysis. Accordingly, the stability of the Portuguese banking system could have benefited from higher rates of GDP growth. The negative coefficient of %ΔCPI reflects that an increase of 1 unit in the variation of %ΔCPI decreases the growth of the ABSI by 2.161260PP after two quarters. The coefficient of the HPI shows that an increase of 1 unit in the variation of the HPI growth impacts the ABSI growth by -0.014PP during the following two periods. %ΔPSI20 presents a positive coefficient, which reflects that a 1PP increase in the %ΔPSI20 impacts the ABSI growth by 0.002PP during the two following periods. As expected, the coefficient of the ESI presents a positive sign, indicating that an increase of 1 unit in the ESI growth impacts the growth of the ABSI by 0.01PP during the subsequent period.

Turning to financial variables, the M2/GDP presents a positive sign, which indicates that an increase of 1 unit in M2/GDP growth impacts the ABSI growth by 0.144PP. As expected, the negative coefficient of EURIBOR3 indicates that an increase of 1pp in this interest rate negatively affects the ABSI growth during the subsequent period by 0.061PP. The VIX index presented a negative coefficient, also as expected, which indicates that an increase of 1 unit simultaneously affects the ABSI growth by 0.002PP.

Finally, the level of significance associated with the coefficients of the AR terms show that the model properly addresses the problem of serial correlation in the disturbance terms.

Conclusion

Over recent years, the Portuguese banking system have been experiencing some difficulties, especially after the last global financial crisis. Furthermore, there has been a continuous improvement in the regulatory and supervisory system (e.g. stricter ratios and new concepts such as the LCR and the NSFR), which obliges banks to carry out their operations in a constantly changing environment. Banks are central players in the financial system and perform a very important role

[18] A negative skewness indicates a left-sided tail, which means a larger number of observations below the average.

Table 9 Regression Output

Variable	Coefficient	Std. Error	t-Statistic	Prob
C	0.050	0.014	3.499	0.002
D1TSPREAD (-1)	0.050	0.005	9.813	0
D2DEBT/GDP(-3)	0.005	0.001	7.388	0
%ΔGDP (-2)	−0.034	0.008	−4.216	0.001
D1%ΔCPI (-2)	−2.161	0.472	−4.578	0
D2HPI(-2)	−0.014	0.002	−7.259	0
%ΔPSI20(-2)	0.002	0.001	3.064	0.006
D1ESI(-1)	0.010	0.002	6.604	0
D1M2/GDP(-2)	0.144	0.057	2.513	0.021
EURIBOR3(-1)	−0.061	0.017	−3.533	0.002
VIX_INDEX	−0.002	0.001	−2.868	0.010
AR(1)	0.585	0.178	3.281	0.004
AR(2)	0.549	0.201	2.726	0.013
AR(3)	−0.692	0.176	−3.926	0.001
R-squared	0.916	Mean dependent var	0.005	
Adjusted R-squared	0.859	S.D. dependent var	0.062	
S.E. of regression	0.023	Akaike info criterion	−4.400	
Sum squared resid	0.010	Schwarz criterion	−3.765	
Log likelihood	86.605	Hannan–Quinn criter	−4.187	
F-statistic	16.026	Durbin–Watson stat	2.116	
Prob(F-statistic)	0			
Inverted AR Roots	.74–48i	.74 + .48i	−89	
Dependent Variable: D1ABSI				
Method: ARMA Conditional Least Squares (Gauss–Newton / Marquardt				
steps)				
Sample (adjusted): 2011Q1 2019Q1				
Included observations: 33 after adjustments				
Convergence achieved after 14 iterations				
Coefficient covariance computed using outer product of gradients				

Source: E-views 9.0 estimation results

D1 and D2 indicate whether the variable enters in the first or second difference, respectively

in the financing of the economy. It is thus very important to monitor banking system stability to guarantee maintaining prosperous conditions for the economy as a whole.

Accordingly, the main objective of this paper is to assess the stability of the Portuguese banking system and to analyse whether common macroprudential key indicators are potential determinants of that stability. Therefore, an index reflecting the aggregated banking stability was constructed—the ABSI—using the FSI over the period of 2010–2019, on a quarterly basis. This index is thus in line with the attempt by the IMF to standardise the methodologies for the construction of stability indices. The findings suggest that, following a period of greater turbulence, the ABSI showed an improvement since the beginning of 2017, although this period is too short to conclude that a sustainable improvement occurred, rather than a temporary one.

Further, the ABSI was used as a dependent variable for the assessment of its determinants. By making use of time series techniques, it was possible to conclude that both macroeconomic and financial indicators can be useful predictors of banking instability. Furthermore, the regression results suggest that the determinants commonly used in the literature are also useful for the Portuguese case, except for the real exchange rate.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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