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CONTENTS

IMPACT OF PAYOUT RESTRICTIONS IN THE WAKE OF THE COVID-19 PANDEMIC ON EUROPEAN AND US BANKS' STOCK MARKET VALUATION

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Abstract

Banking prudential authorities in a large number of jurisdictions restricted payouts after the onset of the COVID-19 pandemic, with the aim of bolstering organic capital generation and strengthening banks' solvency. This paper analyses whether market reactions around the dates of the announcements of restrictions in 2020 by the main authorities in Europe and the United States were significant, using the event study methodology on bank excess returns. The results show evidence of negative excess returns only after some of the announcements by the European authorities in 2020, and uneven reactions to the different announcements are observed at individual bank level. In particular, the negative impact is confined to certain sub-samples of European banks around the first announcement of the European Central Bank (ECB) recommendations limiting dividend distributions and share buybacks. The cumulative excess returns that correlated more closely with bank characteristics were those in response to this announcement, with larger banks and banks with a lower CET1 ratio being those most affected. Results for the subsequent announcements do not show significant negative excess returns, and the analysis shows that other available information gradually prevailed over the informative content of the communications of payout restrictions themselves.

Keywords: Restrictions on payouts, excess returns, event study.

1 Introduction

One of the measures taken by banking prudential authorities in the wake of the COVID-19 pandemic was the announcement of several recommendations to limit payouts by the institutions under their supervision.[1] These measures urged institutions, in particular, to limit dividend distribution, and aimed to bolster organic capital generation and strengthen their solvency. They also sought to ensure that banks retained their capacity to extend credit amid the uncertainty generated by the pandemic.[2]

Limiting payouts increases ceteris paribus the regulatory capital available to absorb unexpected losses, but may also have an impact on stock prices and, consequently,

1 In the case of the European authorities, the requests took the form of recommendations, while the US Federal Reserve restricted payouts through reviews of institutions' capital plans.

2 Martínez-Miera and Vegas (2021) show that, in the six months following the first ECB recommendation limiting payouts (Recommendation ECB/2020/19), the Spanish banks that were able to limit their dividend distributions extended significantly more credit to non-financial corporations than those that were not able to do so. The difference in the implementation of the ECB recommendation was due to the fact that some institutions had already approved payouts in 2020 prior to its publication.

on banks' lending capacity. Payout restrictions may be perceived by investors as a negative signal, as they reduce ceteris paribus the discounted present value of bank shares.[3] Thus, bank shares could be less attractive for investors compared with other financial instruments or other shares of companies not subject to this restriction. This would make it more costly for banks to issue capital and would probably increase the financial return demanded by shareholders to provide funds.[4] It could also ultimately result in lower lending capacity, as it would be difficult to raise the required capital via the market. In other words, there would be a trade-off between higher organic capital generation through increased retention of earnings and the ability to generate capital through the financial market.

In the same vein, some studies also show that limiting dividend distribution and share buybacks would avoid agency problems between shareholders and bank debt holders stemming from the former's incentives to obtain revenue at the expense of not retaining profits or investing in riskier activities.[5] Lastly, it is worth noting that, while the literature usually finds negative stock price effects following payout reduction announcements, the signalling mechanism studied in this document is different, as the measure is driven by the authorities. In this setting, it is important to empirically determine the effect of payout restrictions on banks' market value in order to assess the appropriateness of such measures.

The aim of this paper is to explore the impact that payout restrictions during the COVID-19 crisis had on European and US banks' excess returns. To this end, an event study is used,[6] focused around the announcements of payout recommendations and restrictions made by the main banking and financial system prudential authorities in both jurisdictions during 2020. The sample of banks analysed includes 49 European banks and 49 US banks and includes both jurisdictions' largest listed banks in terms of capitalisation. In the second part of the study, the focus is on analysing which characteristics of the banks correlate, on the dates of the events, with differences in excess returns across institutions, by using cross-sectional regressions.

3 The relationship between firms' payout policies and their stock market valuation has been extensively studied in the economic and financial literature since the early work of Modigliani and Miller (1961) and Gordon (1963). Notable among the empirical literature analysing this relationship is the work of Pettit (1972) and Charest (1978), which studies the correlation between changes in firms' dividend policies and subsequent excess returns, while other papers, such as Aharony and Swary (1980), analyse the information content of corporate dividend policies through event studies. These empirical papers generally find that dividend announcements or changes in dividend policies contain information about the future performance of the firm and signal it to the market. See Baker et al. (2010) for a more recent review of the literature.

4 See Altavilla et al. (2021) and Fernández Lafuerza and Mencía (2021) for recent estimates of the cost of bank capital and its determinants. When the payout ratio is restricted, banks need to improve their financial performance to maintain the same level of dividend yields.

5 See Jensen and Meckling (1976), one of the first theoretical papers to formally characterise these agency problems between a firm's equity holders and bondholders.

6 A review of the reference literature using the event study methodology in the areas of economics and finance can be found in MacKinlay (1997).

The results show evidence of negative excess returns only after some of the announcements by the European authorities in 2020, and uneven reactions to the different announcements are observed at the individual bank level. Thus, a closer examination on an event-by-event basis shows that the negative impact is confined to around the time of the ECB's first announcement on payout restrictions (indicating that this was the announcement that provided the most information to the market) and, within this event, to the sample of European institutions in particular, excluding Greek banks. Other subsequent announcements generally do not reveal significant and robust excess returns in different windows of days around the event dates. This seems to indicate that the information in subsequent announcements was largely expected and may have already been included in institutions' capital plans. Moreover, cross-sectional regressions indicate that the cumulative excess returns that correlated most closely with bank characteristics were those following the first ECB announcement, with larger banks and banks with a lower CET1 ratio being those most affected. Therefore, taking into account the heterogeneity of the impacts, the results suggest that the set of payout restrictions had a modest aggregate effect on stock prices, noticeable only over a limited time horizon and with notable differences across institutions. The paper also highlights that other developments, such as the announcement of strong economic policy support measures around the time of the restriction announcements, may have offset their impact on the market. It should be borne in mind that this study documents the impact of these on stock prices during an extraordinary period, in terms of the scale of the crisis and the degree of government intervention, and that such restrictions could have different effects when used under normalised conditions or recurrently.

This paper contributes to the literature that analyses the effect of payout recommendations and restrictions during the COVID-19 crisis on stock prices. Hardy (2021) describes the impact of the announcements on European and US banks, finding that they had a negative effect in the short term on larger banks, consistent with the results obtained in this study for European banks. Kroen (2022) shows that, minutes after the first announcement by the Federal Reserve, the stock price of the US banks subject to the restriction fell relative to the stock price of other firms not subject to the measure.[7] In the case of European banks, Andreeva et al. (2021) examine market reactions to the announcements of the first ECB restriction and the two subsequent extensions through difference-in-differences regressions. Using intraday frequency data, they find that the first announcement had a negative impact on stock prices in a narrow window around the time of the announcement. The effect was strongest for euro area banks that paid dividends and, within this group, for those that failed to generate returns commensurate with shareholder

7 Using daily data for the ten days around the announcement, this study also shows that yields and CDS premia on the unsecured bonds of these banks fell relative to those of other financial firms not subject to the restriction. This could indicate that limiting payouts reduced the market's perception of the riskiness of these banks' bonds, as it increased their capital buffer. The study finds that after the restriction is eased the effects are reversed.

expectations.[8] Unlike those papers, this document analyses a longer period, which allows it to examine the continuing importance of the announcements, and uses cross-sectional regressions to analyse a different set of determinants of excess returns, including the CET1 capital ratio, return on assets (ROA) and size.

The remainder of this article is structured as follows. Section 2 sets out the payout recommendations and restrictions announced during 2020 that will be studied in the paper. Section 3 concisely explains the database used in the analysis and the methodology for obtaining the excess returns for each bank and event. Section 4 analyses the significance of excess returns for each event and the correlation of banks' characteristics with excess returns in the events where market reactions have been most important. Section 5 sets out the main conclusions of the paper.

2 Recommendations and restrictions on payouts

This paper analyses the three recommendations issued by the ECB in 2020 seeking to limit distributions out of 2019 and 2020 earnings and share buybacks aimed at remunerating shareholders. The first recommendation,[9] published on 27 March 2020, is considered event *ECB 1* in this paper. The recommendation limited dividend distributions and share buybacks until at least 1 October 2020. The second ECB recommendation,[10] of 28 July 2020, announced an extension of the restriction until 1 January 2021 and is considered event *ECB 2* in the analysis. As for the third ECB recommendation,[11] published on 15 December 2020, it called on institutions to refrain from or limit payouts until 30 September 2021. Specifically, this third ECB recommendation, referred to as *ECB 3,* indicates that dividends and share buybacks must remain below 15% of accumulated 2019-2020 profits and not be higher than 20 basis points (bp) of the CET1 ratio. These limits entailed a certain easing of the more general limitation of previous announcements, but, at the same time, the period during which the recommendation applied was extended.

Three Federal Reserve restrictions on payouts are likewise analysed. First, the Federal Reserve announcement in the afternoon of 25 June 2020 limiting payouts by large banks for the first time *(FED 1* event) is analysed, along with the publication of its bank stress test report.[12] This first restriction prohibited share buybacks and limited dividend payouts in 2020 Q3 to the 33 institutions participating in the Dodd-

8 The banks that failed to generate returns commensurate with shareholder expectations are those whose estimated cost of equity (COE) is higher than their return on equity (ROE).

9 See ECB press release and ECB Recommendation of 27 March 2020 on dividend distributions during the COVID-19 pandemic (ECB/2020/19).

10 See ECB press release and ECB Recommendation of 27 July 2020 on dividend distributions during the COVID-19 pandemic (ECB/2020/35).

11 See ECB press release and ECB Recommendation of 15 December 2020 on dividend distributions during the COVID-19 pandemic (ECB/2020/62).

12 See Federal Reserve press release dated 25 June 2020.

Frank Act Stress Test (DFAST) 2020, based on their recent income, capping them to the amount paid in Q2 that year. Subsequently, on 30 September and on 18 December the Federal Reserve announced two extensions of the restrictions, until 2020 Q4 and 2021 Q1, respectively, the latter of which allowed share buybacks but limited to an amount based on the previous year's income.[13] These two announcements are dubbed here *FED 2* and *FED 3,* respectively.

An additional contrasting event is analysed (event *D. FED),* which refers to the statements by the Chair of the Board of Governors of the Federal Reserve System, Jerome Powell, on 9 April 2020 (at the start of the pandemic), stating that at the time there was no need for US banks to suspend dividend payouts to preserve capital, citing high solvency levels.[14] However, the signals subsequently sent to the market by the Federal Reserve were contradictory, as in a press article published on 16 April 2020[15] the President of the Federal Reserve Bank of Minneapolis encouraged banks not to pay dividends and to increase their capital to ensure their resilience in the face of the COVID-19 crisis.

Lastly, the recommendations issued by the European Systemic Risk Board (ESRB) on EU system-wide restraints on dividend payments, share buybacks and other payouts are considered. First, an analysis is conducted of the impact of the recommendation published on 8 June 2020 (event *ESRB 1)*[16] together with the second set of ESRB measures in response to the coronavirus emergency.[17] The recommendation aims to achieve a uniform approach in relation to capital distribution restrictions in the EU and in the different sectors of the financial system. The dates surrounding this event coincide with relevant updates to the macroeconomic scenarios of various economies and with an extension of the purchase programme to alleviate the effects of the coronavirus crisis (PEPP).[18] It should also be highlighted that this announcement by the ESRB preceded the extension of the ECB recommendations considered under event *ECB 2.* Secondly, the extension on 18 December of the application period of the recommendation

13 See Federal Reserve press release of 30 September 2020 and press release of 18 December 2020 on the extension of the restrictions on payouts.

14 See Westbrook (2020).

15 See Kashkari (2020).

16 See ESRB Recommendation of 27 May 2020 on restriction of distributions during the COVID-19 pandemic (ESRB/2020/7).

17 See ESRB press release dated 8 June 2020. The second set of measures in response to the coronavirus emergency, approved on 27 May 2020, is aimed at strengthening the oversight, analysis and coordination among the competent authorities across five priority areas: (i) implications for the financial system of guarantee schemes and other fiscal measures to protect the real economy; (ii) market illiquidity and implications for asset managers and insurers; (iii) procyclical impact of debt downgrades on markets and financial institutions; (iv) system-wide restraints on dividend payments, share buybacks and other payouts; and (v) liquidity risks arising from margin calls.

18 The ECB's macroeconomic scenarios were published on 4 June 2020, the same day that the institution announced the extension of the pandemic emergency purchase programme. The Banco de España published its revised macroeconomic scenarios on 8 June and the US Federal Reserve published its macroeconomic projections on 10 June.

until 30 September 2021 (event *ESRB 2),*[19] which coincided with event *FED 3,* is considered.

In support of its first recommendation, the ESRB published a report[20] analysing several arguments that should be borne in mind when limiting payouts by financial institutions, and included an event study on the market reaction to the first ECB announcement (of 27 March 2020) on the restriction of dividend distributions, using intraday data. Among the arguments in favour of payout restrictions on banks, the ESRB highlights their critical function in the economy and the need to mitigate pro-cyclicality in lending during recessions. As for the arguments against restrictions, the ESRB cites the possible disruptions to resource reallocation and the negative signals to investors. However, the results of its event study show that the market response to the first ECB announcement on the restriction of payouts was relatively limited in general, although it was more significant for larger banks and banks operating in jurisdictions without applicable bans on short selling.

3 Stock valuation of the main European and US banks and excess returns

This first stage of the analysis uses a database with daily stock prices for 49 European banks (eight of which are Spanish) and 49 US banks. The sample of banks analysed includes both jurisdictions' largest listed banks in terms of capitalisation.

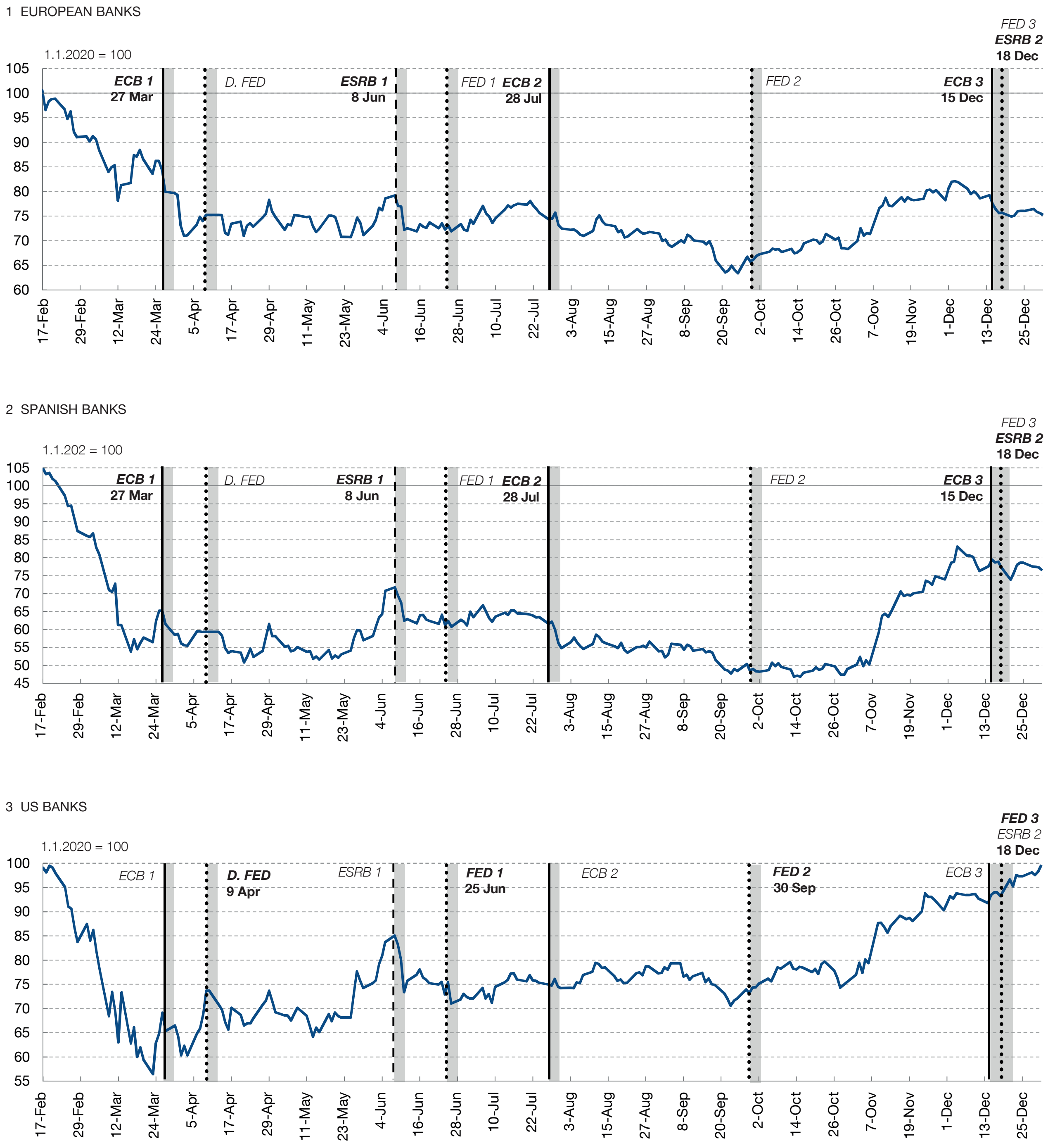
Chart 1 shows the stock price indices weighted by the market value of each European, Spanish and US bank. It can be seen that the stock prices of the main European banks fell around the dates of the ECB announcements (which are marked with continuous vertical lines). Chart 1.3 also indicates that there were slight declines in the stock prices of the main US banks in the days following the first payout restriction announcement by the Federal Reserve. Table A.1 in the Annex shows how the indices changed around the reference dates. The chart also reveals that the performance of the markets analysed differed, since at end-2020 the weighted stock price index for the US banks in the sample had returned to its pre-pandemic level, while the index for European banks stood at around 75% of its level at the start of the period under study.

However, stock market indices fluctuate continuously, reacting to the flow of information and to market players' shifting financial goals. In order to analyse whether there were significant market reactions on the dates of the event (i.e. higher or lower than average normal fluctuations) the excess returns for each trading day and for each bank in the sample are obtained as the residual of a one-factor model. The

19 See ESRB press release of 18 December and ESRB recommendation of 15 December 2020 amending Recommendation ESRB/2020/7 on restriction of distributions during the COVID-19 pandemic (ESRB/2020/15).

20 See ESRB (2020).

Chart 1
INDEX OF MAJOR BANKS' STOCK PRICES



SOURCE: Banco de España.
NOTE: Stock price indices weighted by each bank's market value. The continuous vertical lines indicate the dates of the ECB announcements, the dotted vertical lines indicate the Federal Reserve's announcements and signals to the market and the dashed lines indicate the ESRB announcements. Events FED 3 and ESRB 2 occurred at the same time. The shaded areas cover the period of the day of the event and the two subsequent days.

model regresses the time series of the returns (changes in the stock prices) on the return of the market index, and is estimated for each bank (i) and each day (t) separately. For each of the estimations on date t, the sample period is the 200 days spanning from t-210 to t-11.

$$AR_{it} = R_{it} - \left(\alpha_{it} + \beta_{it} R_{mt}\right) \qquad [1]$$

AR_{it} is the excess return of bank i on day t and R_{it} is the return of bank i on day t. The market index (R_{mt}) considered for European banks (and for the sub-sample of Spanish banks) is the EURO STOXX 600, while the S&P 500 is used in the case of US banks. The parameters of the estimated relationship between R_{it} and R_{mt} are dubbed α_{it} and β_{it}. The part of each bank's performance not explained by the performance of the relevant market in its jurisdiction is obtained from equation [1].

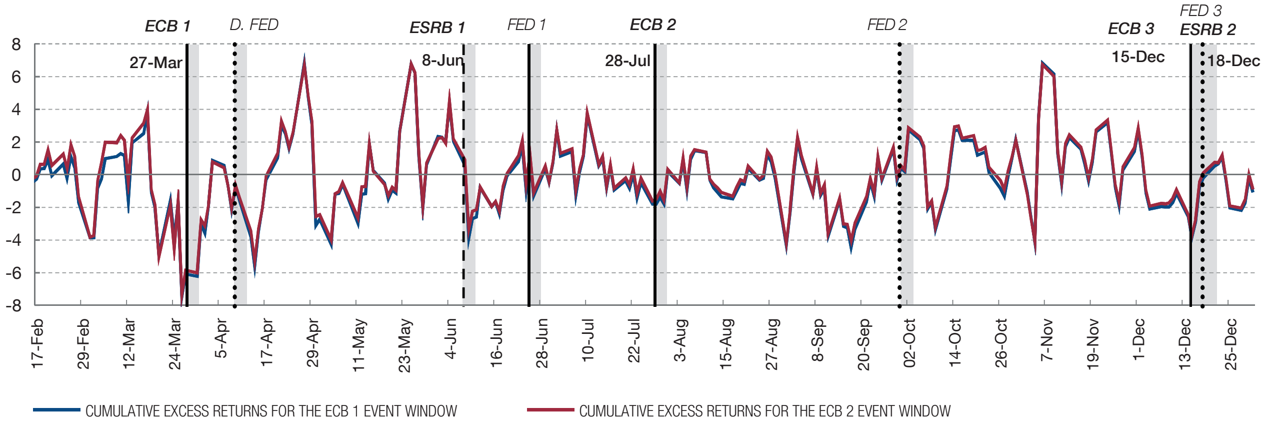
Chart 2 shows the time series of the resulting cumulative excess returns for three-day windows (t, t+1, t+2).

A first study is then conducted to verify whether the joint impact of the announcements on the market was relevant, through a dummy variable analysis on the panel of daily excess returns in 2020 estimated for each bank (see Table 1). In the analysis, variables d_event_eur and d_event_US take the value 1 on the days of the payout restriction announcements and on the following two days (t^*, t^*+1, t^*+2). If these variables are statistically significant, they would indicate that the set of events analysed in the jurisdiction had a differential effect in days (t^*, t^*+1, t^*+2), compared with the rest of the trading days in 2020. The possibility that some of the individual events do not have a significant impact is not studied here. Variable d_jurisd takes the value 1 if the institution is in the United States and shows the existence of differential effects between jurisdictions. The Driscoll-Kraay (1998) estimator is used, which makes it possible to correct for the cross-sectional correlation bias that often occurs in daily series of market variables.

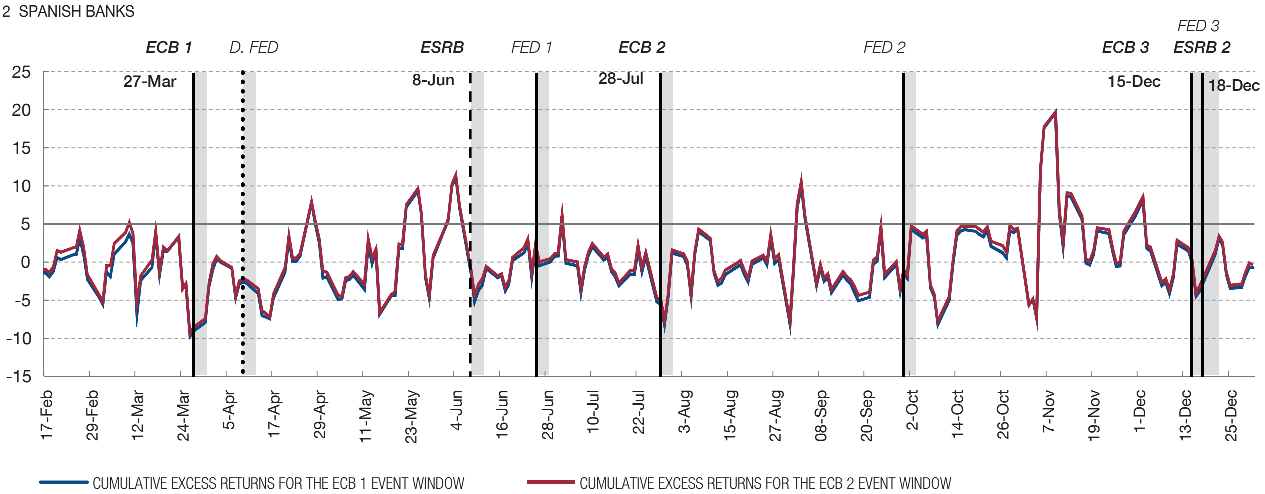
Specification (1a) shows evidence that the European authorities' announcements had a negative joint impact on the excess returns of the banks in this jurisdiction, as there is a significant negative differential effect on variable d_event_eur. Specification (2a) extends the sample to include the US banks and finds that their excess returns were also negative on the dates of the European policy announcements. Although the excess returns of the banks in the US jurisdiction were larger than those of the European banks, the difference is not significant. The remaining specifications, which take into account the Fed's announcements of restrictions, do not yield significant results or differential effects between both jurisdictions. However, this methodology is agnostic as to the causes of the deviations detected and there may be heterogeneity across events and institutions. Thus, the following sections compare the impact for each event and for different sub-samples of banks.

Chart 2
CUMULATIVE EXCESS RETURNS IN THREE-DAY WINDOWS

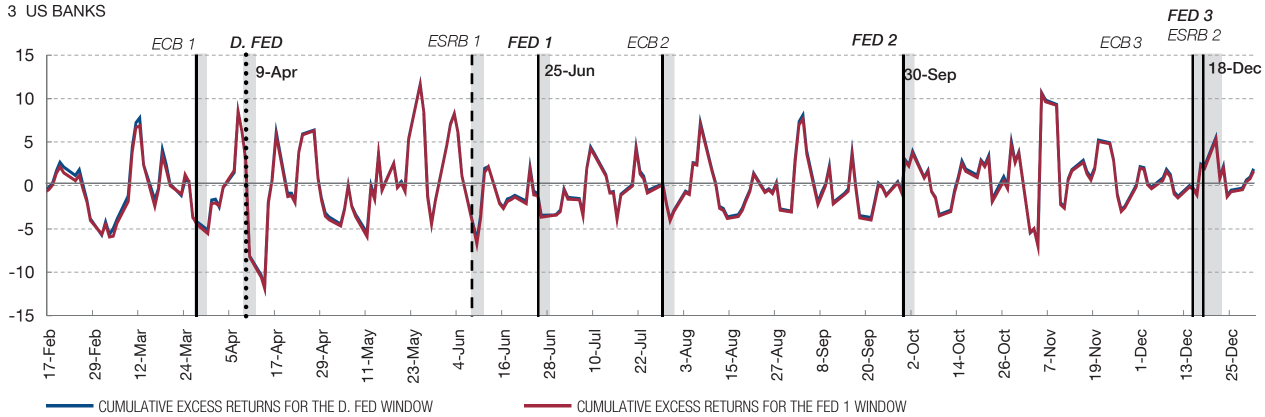
1 EUROPEAN BANKS



2 SPANISH BANKS



3 US BANKS



SOURCE: Datastream and Banco de España.
NOTES: Excess returns weighted by each bank's market value. In particular, the estimated cumulative excess returns for various 200-day windows are shown (the windows spanning from t*-210 to t*-11 for events ECB 1 and ECB 2 in the charts for European and Spanish banks and the windows spanning from t*-210 to t*-11 for events D. FED and FED 1 in the chart for US banks). The continuous vertical lines indicate the dates of the ECB announcements, the dotted vertical lines indicate the Federal Reserve's announcements and signals to the market and the dashed lines indicate the ESRB announcements. Events FED 3 and ESRB 2 occurred at the same time. The shaded areas cover the period of the day of the event and the two subsequent days.

Table 1
JOINT IMPACT OF THE ANNOUNCEMENTS

	Announcements by the European authorities		Announcements by the US authorities	
	Sample of European banks	Entire sample	Sample of US banks	Entire sample
	(1a)	(2a)	(1b)	(2b)
d_event_eur	-0.770**	-0.770**		
	(0.365)	(0.365)		
d_event_EEUU			0.473	0.006
			(0.445)	(0.226)
d_jurisd.		0.013		0.003
		(0.102)		(0.099)
d_event_eur · d_jurisd.		0.113		
		(0.465)		
d_event_EEUU · d_jurisd.				0.468
				(0.416)
Constant	0.057	0.057	0.015	0.012
	(0.092)	(0.092)	(0.134)	(0.098)
No. of banks	49	98	49	98
No. of observations	12.838	25.546	12.708	25.546

SOURCE: Banco de España.
NOTE: The estimations in (1a) and (1b) correspond to models $AR_{it} = \theta_i + p$ $d\_event\_eur_t + \varepsilon_{it}$ and $AR_{it} = \theta_i + p$ $d\_event\_EEUU_t + \varepsilon_{it}$, respectively. The variables are the excess returns (AR_{it}), a dummy for European events ($d\_event\_eur_t$), a dummy for US events ($d\_event\_EEUU_t$) and the residual of the model(ε_{it}). For (2a) and (2b) the estimates correspond to specifications $AR_{it} = \theta_i + p$ $d\_event\_eur_t + \delta$ $d\_jurisd_i + \vartheta$ $d\_event\_eurt \cdot d\_jurisd_i + \varepsilon_{it}$ and $AR_{it} = \theta_i + p$ $d\_event\_EEUU_t + \delta$ $d\_jurisd_i + \vartheta$ $d\_event\_EEUU_t \cdot d\_jurisd_i$. Variable d_jurisd. takes the value 1 for US banks. The estimation period is 2020. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.

4 Significance of excess returns in different bank sub-samples and explanatory factors

In order to analyse whether market reactions around the dates of each of the events were significant, the Kolari-Pynnönen (2010) test is used for different sub-samples of European and US banks (see Section 4.1). Lastly, the factors explaining the excess returns surrounding each significant event identified are analysed (see Section 4.2).

4. 1 Kolari-Pynnönen test for excess returns

The Kolari-Pynnönen (2010) test shown below compares the null hypothesis of a zero value[21] for cumulative and standardised returns surrounding each event, corrected by the average cross-correlation of banks' excess returns:[22]

21 Note that the significance of the dummy variables in Table 1 indicate the existence of differential effects on days (t*, t*+1, t*+2) for all the events as a whole relative to other trading days, or differential effects between jurisdictions, in the panel of excess returns in 2020. Conversely, the Kolari-Pynnönen (2010) test is used to determine whether the excess returns were significantly different from zero for each group of banks around each event.

22 This correction is applied to prevent bias in the test results due to the common movements of banks' excess returns.

Table 2
EVENT STUDY - [T*, T*+2] WINDOW: KOLARI-PYNNÖNEN (2010) TEST.
FIRST ANNOUNCEMENTS AND STATEMENTS

		ECB 1	*ESRB 1*	*FED 1*	*D. FED*
		ECB announcement 27 March 2020	ESRB announcement 8 June 2020	FED announcement 25 June 2020	J. Powell speech 9 April 2020
Euro area banks	Full sample (37 banks)	-1.613	0.304	0.324	-0.283
		±2.028	*±2.028*	*±2.028*	*±2.028*
	P/B > median P/B	**-2.338**	-0.115	0.930	0.085
		±2.11	*±2.11*	*±2.11*	*±2.11*
	P/B < median P/B	-0.979	0.709	0.066	-0.858
		±2.101	*±2.101*	*±2.101*	*±2.101*
	Excluding Greek banks	**-2.336**	0.160	1.255	-0.090
		±2.037	*±2.037*	*±2.037*	*±2.037*
Spanish banks	Full sample (8 banks)	-1.808	0.149	1.031	-0.214
		±2.365	*±2.365*	*±2.365*	*±2.365*
European banks	Full sample (49 banks)	-1.776	0.417	0.387	0.022
		±2.011	*±2.011*	*±2.011*	*±2.011*
	Excluding Greek banks	**-2.352**	0.309	1.222	0.180
		±2.015	*±2.015*	*±2.015*	*±2.015*
US banks	Full sample (49 banks)	-1.219	**-3.446**	0.165	1.164
		±2.011	*±2.011*	*±2.011*	*±2.011*
	Subject to the restriction	-1.129	**-3.952**	-0.620	1.887
		±2.093	*±2.093*	*±2.093*	*±2.093*
	Not subject to the restriction	-1.207	**-2.997**	0.969	0.836
		±2.048	*±2.048*	*±2.048*	*±2.048*

SOURCE: Banco de España.
NOTES: For each event and bank group, the statistic (above) and its critical level (below and in italics) are shown for a significance of α = 5% (since this is a two-tailed test, the critical values correspond to $\alpha/2$ = 2.5%). Significant results are shown in bold.

$$t_{KP} = \frac{\overline{era}}{\sigma_{\overline{era}} \sqrt{\frac{1+(n-1)\overline{r}}{n}}} \qquad [2]$$

where $\overline{era}$ is the average (in the cross-section) of the cumulative excess returns in the event window, considering the day of the event and the two subsequent trading days [t*, t*+2]. As proof of robustness in view of the fact that markets may have anticipated the announcements, the Annex (see Tables A.2 and A.3) shows the results including the two previous days, giving rise to five-day windows [t*-2, t*+2]. The statistic also takes the following into account: n, number of banks in the sample; $\sigma_{\overline{era}}$, standard deviation of the cumulative excess returns; and $\overline{r}$, average cross-correlation of banks' excess returns in the period [t*-210, t*-11].

The results of Table 2 show that excess returns are negative in the *ECB 1* event for all bank groups, but they are only statistically significant for the euro area in the group of banks with a high price-to-book (P/B) ratio or after excluding the Greek banks. This result for banks in the euro area based on their P/B ratio is unexpected a priori, since banks with a lower P/B ratio tend to pay out more dividends[23] (Gambacorta et al. (2020)) and, therefore, it could be expected that their stock market price would be more affected.

However, the banks with the highest P/B ratio in the European sample are generally the largest ones, which, in turn, suffered a greater stock market price correction.[24] The sample of European banks with the lowest P/B ratio includes the Greek banks, whose valuation in these event dates was affected by favourable news for them. In particular, the dates surrounding the *ECB 1* event coincide with the ECB's announcement on 18 March 2020[25] of the launch of the purchase programme to alleviate the effects of the COVID-19 crisis, which grants a waiver of the eligibility requirements for Greek sovereign bonds under this programme. Chart A.1 shows Greek banks' stock prices, which started to perform favourably in the second half of March. Other events that could have positively affected Greek banks' market valuation were the news about the first transfers of securitised NPLs within the Hercules Asset Protection Scheme (HAPS).

The first announcements of the ESRB (event *ESRB 1)* and of the Federal Reserve (event *FED 1)* were not significant in their respective jurisdictions,[26] nor is a significant positive reaction observed in the US markets with regard to the optimistic statements of the contrasting event (event *D. FED).* The significantly negative excess returns of US banks in the *ESRB 1* event could be reflecting a negative market sentiment following the publication of the Federal Reserve's less favourable macroeconomic outlook (10 June 2020). Also, as seen in Table A.2, which considers five-day windows around the events, the impact of other information can be substantial, as in the case of the announcement of the extension of the PEPP for the euro area and of the Paycheck Protection Program[27] for the United States.

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23 When the stock market valuation is substantially lower than book value, shareholders may have incentives to increase their dividends to extract value from the bank; therefore, it is to be expected that banks with low P/B values would be more affected by the dividend payout restriction. The literature also notes the signalling mechanism whereby the distribution of dividends at banks with a lower P/B ratio is an indication of financial health or future growth opportunities (see Forti and Schiozer (2015)).

24 This result is consistent with the European Systemic Risk Board (2020) study, which reveals a negative differential impact for banks with a greater asset volume.

25 See ECB press release of 18 March 2020, on the announcement of a pandemic emergency purchase programme (PEPP).

26 In the *FED 1* event, the value of the statistic is negative for the US banks of the sample that are subject to the restriction, but positive for the other US banks. However, the impact is not statistically significant in either case. The impact has also been analysed by differentiating US banks with a P/B value above and below the median, with no significant effects having been found (the results are not shown but are available from the authors upon request). This test does not directly analyse whether the excess return differences between different groups of banks are statistically significant; it analyses whether the excess returns in each bank group are statistically different from zero. When no bank group differs from zero, this provides some evidence that there are no differences between them. Using a dif-in-dif methodology between banks subject to the restriction and other firms, Kroen (2022) estimates a negative differential effect for banks. In our study, excess returns use, by construction, the differences between each group of banks analysed and the set of firms in the market index, which are the control group.

27 See US Small Business Administration (SBA) press release of 3 April 2020, on the announcement of the launch of the SBA's Paycheck Protection Program for Small Businesses Affected by the Coronavirus Pandemic.

Table 3

EVENT STUDY - [T*, T*+2] WINDOW: KOLARI-PYNNÖNEN (2010) TEST. EXTENSION OF THE RESTRICTIONS

		ECB 2 ECB announcement 28 de July 2020	*FED 2* FED announcement 30 September 2020	*ECB 3* ECB announcement 15 December 2020	*FED 3 and ESRB 2* FED and ESRB announcements 18 December 2020
Euro area banks	Full sample (37 banks)	-0.940 *±2.028*	0.030 *±2.028*	-0.971 *±2.028*	-1.588 *±2.028*
	P/B > median P/B	-1.795 *±2.11*	-0.098 *±2.11*	-1.145 *±2.11*	-1.459 *±2.11*
	P/B < median P/B	-0.457 *±2.101*	0.094 *±2.101*	-0.795 *±2.101*	-1.740 *±2.101*
	Excluding Greek banks	-0.836 *±2.037*	0.154 *±2.037*	-0.987 *±2.037*	-1.530 *±2.037*
Spanish banks	Full sample (8 banks)	-0.121 *±2.365*	-0.214 *±2.365*	-0.165 *±2.365*	-2.306 *±2.365*
European banks	Full sample (49 banks)	-1.115 *±2.011*	0.293 *±2.011*	-1.165 *±2.011*	-0.909 *±2.011*
	Excluding Greek banks	-1.025 *±2.015*	0.412 *±2.015*	-1.175 *±2.015*	-0.812 *±2.015*
US banks	Full sample (49 banks)	0.599 *±2.011*	**2.256** *±2.011*	-0.639 *±2.011*	-0.154 *±2.011*
	Subject to the restriction	0.337 *±2.093*	**1.943** *±2.093*	-0.777 *±2.093*	0.503 *±2.093*
	Not subject to the restriction	0.727 *±2.093*	**2.516** *±2.093*	-0.562 *±2.093*	-0.571 *±2.093*

SOURCE: Banco de España.
NOTES: For each event and bank group, the statistic (above) and its critical level (below and in italics) are shown for a significance of α = 5% (since this is a two-tailed test, the critical values correspond to $\alpha/2$ = 2.5%). Significant results are shown in bold.

As regards the subsequent announcements on the extension of restrictions, no significant results are observed overall (see Table 3). Of note is the market volatility in the last week of December 2020, since day t*+2 of the *ESRB 2* and *FED 3* events (22 December) was the first trading day following the approval of the Pfizer vaccine in the European Union, and European bank excess returns generally became positive. The significantly positive excess returns in the *FED 2* event were probably due to the Federal Reserve's announcement on 1 October of the extension of temporary measures aimed at increasing the availability of intraday credit/liquidity for banks under its jurisdiction.[28]

The announcements of payout restrictions in March, April and June 2020 (first announcements, see Table 2), which appear as significant, coincided with the arrival

28 See Federal Reserve press release of 1 October 2020, on the extension of temporary actions aimed at increasing the availability of intraday credit extended by Federal Reserve banks.

of fresh information on the unfolding of the crisis, which may have prevailed over the informative content of the announcements themselves. Although subsequent events (see Table 3) might have had less interference from other important information for the market, they may also have been more easily anticipated by the markets, and no significant reaction is observed.

4.2 Determinants of excess returns

The results of the Kolari-Pynnönen (2010) test suggest that there is heterogeneity in the excess returns of the different sub-samples, particularly in the case of European banks. These differences are explored in this second phase of the analysis, examining the correlation with possible determinants of the three-day window cumulative excess returns surrounding each event for individual banks. In particular, excess returns are used as the dependent variable of cross-sectional regressions, using the variability of reactions between banks to analyse their correlation with bank characteristics. The explanatory factors included in the regressions to reflect the characteristics of each bank are: ROE, CET1 capital ratio, dividend yield (dividend per share over 12 months/share price) and total assets.[29]

Explanatory factors generally relate to the quarter prior to that of the event to be analysed. This is because such variables are constructed using data from the income statements published at the end of each quarter, which are not known by the market during the event quarter. For instance, for the *ECB 1* event of 27 March 2020, the explanatory variables used refer to 2019 Q4, for the *FED1* and the *ESRB 1* events of 25 June 2020 and 8 June 2020, respectively, they refer to 2020 Q1 and for the event of 9 April 2020, they refer to 2019 Q4, since the 2020 Q1 data had not yet been published at that date. Table 4 shows the most significant results, which are obtained for the *ECB 1* event's three-day window cumulative excess returns [t*, t*+ 2].[30]

The results reveal that European banks' excess returns have a negative (and generally significant) correlation with bank size, which is in line with the findings of previous papers (see Andreeva (2021) and Hardy (2021)). The results also indicate that the markets valued bank solvency in the *ECB 1* event positively (the coefficient of the CET1 capital ratio is positive and significant). Table 4 also shows the differential effect for Spanish banks (specification 2) and takes into account whether the decision to make distributions out of 2019 earnings had already been approved in their respective General Meetings[31] (specification 3). However, this separation of Spanish

29 The P/B ratio has been analysed but has not been included in the regression shown because there is substantial collinearity with ROE. This is because the price in the P/B ratio reflects the market perception of future profitability.

30 The explanatory variables are more correlated with excess returns and more statistically significant when the returns are accumulated for the three-day window (t, + 2 days). The Annex shows the results using the five-day window around the *ECB 1* event.

31 Significant institutions eliminated the interim dividend out of 2020 earnings.

Table 4
EXPLANATORY FACTORS FOR THE CUMULATIVE EXCESS RETURNS IN THE THREE-DAY WINDOW FOLLOWING EVENT *ECB 1* [T*, T*+2]

	European banks, excluding Greek banks			US banks
Variables	(1)	(2) + ES dummy	(3) +ES dummy payout restrictions	(4)
ROE	-0.265	-0.276*	-0.286*	-1.324
	(0.160)	(0.159)	(0.165)	(1.264)
CET1 ratio	0.707*	0.860*	0.869*	0.541*
	(0.406)	(0.460)	(0.469)	(0.271)
Dividend yield	0.022	-0.012	-0.021	-0.191
	(0.347)	(0.366)	(0.369)	(0.518)
Log. Total assets	-1.894***	-1.701**	-1.754**	-0.278
	(0.645)	(0.649)	(0.647)	(0.400)
ES dummy		1.873		
		(2.067)		
Interaction ES* dummy no payout restrictions			1.428	
			(2.356)	
Interaction ES* dummy payout restrictions			3.213	
			(2.086)	
Constant	19.320	13.160	14.100	-1.117
	(16.450)	(17.190)	(17.180)	(7.170)
Observations	45	45	45	49
R^2	0.360	0.373	0.376	0.056

SOURCE: Banco de España.
NOTES: Event *ECB 1* corresponds to the first ECB announcement on payout restrictions (March 2020). Robust standard errors within brackets. *** p<0.01. ** p<0.05. * p<0.10.

banks does not show significant differential effects. Nor are significant effects observed with regard to other events.

5 Conclusions

The impact on the market of the bank payout recommendations and restrictions was significantly negative only in specific sub-samples of European banks, in response to the ECB's first announcement of restrictions in March 2020. Following that first event, European banks' excess returns showed no significant reactions around the dates of the subsequent announcements extending those measures. The impacts of the Federal Reserve's announcements of restrictions were not significant for US banks' excess returns either. The results obtained from the cross-sectional analysis confirm that there is heterogeneity across banks, particularly in response to the

ECB's first announcement of restrictions, whose effect was most significant for the excess returns of larger banks and banks with lower capital levels.

The results of the analysis suggest that the impact of these events, compared with others, was not large enough to dominate the changes in banks' stock market value during the most acute phase of the COVID-19 crisis in 2020. As detailed throughout this paper, other equally or more important information available around the time of the events could have had a greater impact on the market than the events themselves. In this connection, the negative impact of the ECB's first announcement is only identified after excluding Greek banks, which were affected by the optimistic sentiment following the ECB's announcement of the launch of the pandemic emergency purchase programme or the news on the start of the HAPS.

It is important to note that the limited impact of the payout restrictions on banks' stock market prices in 2020 is reasonably associated with this being a temporary measure, with the announcement of this limited temporary extension being plausible for the markets and with it being part of a broad set of economic policy support measures. These results are thus useful to measure the costs of these types of measures in terms of banks' stock market value in an extraordinary crisis situation. However, announcements of related more recurrent measures, disconnected from other economic policy actions, could have a different impact and would require a specific analysis to estimate their differential effects with respect to the experience during the COVID-19 crisis.

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Table A.1
INDEX OF MAJOR BANKS' STOCK PRICES

1.1.2020 = 100

		European banks	Spanish banks	US banks
ECB 1 ECB announcement of 27 March 2020	25-Mar	86.2	65.2	64.9
	26-Mar	84.3	65.2	69.1
	27-Mar	80.0	61.5	65.4
	30-Mar	79.7	58.5	66.5
	31-Mar	79.2	58.8	64.2
ECB 2 ECB announcement of 28 July 2020	24-Jul	75.6	63.4	75.3
	27-Jul	74.3	61.5	74.9
	28-Jul	74.5	62.2	74.7
	29-Jul	75.7	59.9	76.1
	30-Jul	73.2	56.3	74.5
ECB 3 ECB announcement of 15 December 2020	11-Dec	78.6	76.3	92.7
	14-Dec	79.2	77.6	91.8
	15-Dec	77.4	79.5	93.5
	16-Dec	76.4	78.7	94.0
	17-Dec	75.6	78.9	94.0
ESRB 1 ESRB announcement of 8 June 2020	4-Jun	76.2	64.3	80.9
	5-Jun	78.6	70.8	83.7
	8-Jun	79.2	71.7	85.1
	9-Jun	77.1	69.4	83.3
	10-Jun	76.9	67.4	80.1
FED 1 FED announcement of 25 June 2020	23-Jun	73.5	64.1	75.5
	24-Jun	72.2	61.2	72.9
	25-Jun	73.1	62.3	75.4
	26-Jun	71.9	60.7	71.0
	29-Jun	73.3	62.6	71.8
FED 2 FED announcement of 30 September 2020	28-Sep	66.7	50.4	73.9
	29-Sep	65.7	48.6	73.2
	30-Sep	66.2	49.0	74.3
	1-Oct	66.9	48.3	74.4
	2-Oct	67.2	48.2	75.1
FED 3 - ESRB 2 FED and ESRB announcements of 18 December 2020	16-Dec	76.4	78.7	94.0
	17-Dec	75.6	78.9	94.0
	18-Dec	75.6	77.3	93.2
	21-Dec	74.9	73.8	96.6
	22-Dec	75.1	75.8	95.2
D. FED J. Powell's statement of 9 April 2020	7-Apr	74.8	59.4	65.9
	8-Apr	74.0	59.3	68.9
	9-Apr	75.2	59.3	73.6
	10-Apr	75.2	59.3	73.6
	13-Apr	75.2	59.3	70.7

SOURCE: Banco de España.
NOTE: Stock price index weighted by each bank's market value.

Table A.2
EVENT STUDY - [T*-2, T*+2] WINDOW: KOLARI-PYNNÖNEN (2010) TEST.
FIRST ANNOUNCEMENTS AND STATEMENTS

		Event 1 *ECB 1* ECB announcement 27 March 2020	Event 5 *ESRB 1* ESRB announcement 8 June 2020	Event 3 *FED 1* FED announcement 25 June 2020	Event 4 *D. FED* J. Powell speech 9 April 2020
Euro area banks	Full sample (37 banks)	-1.379	**2.700**	0.747	0.588
		±2.028	*±2.028*	*±2.028*	*±2.028*
	P/B > median P/B	-2.078	**2.327**	1.045	0.539
		±2.11	*±2.11*	*±2.11*	*±2.11*
	P/B < median P/B	-0.838	**2.844**	0.530	0.541
		±2.101	*±2.101*	*±2.101*	*±2,101*
	Excluding Greek banks	**-2.365**	**2.481**	1.327	0.389
		±2.037	*±2.037*	*±2.037*	*±2.037*
Spanish banks	Full sample (8 banks)	-1.540	**2.472**	1.154	0.225
		±2.365	*±2.365*	*±2.365*	*±2.365*
European banks	Full sample (49 banks)	-1.469	**2.614**	0.927	0.670
		±2.011	*±2.011*	*±2.011*	*±2.011*
	Excluding Greek banks	**-2.226**	**2.442**	1.512	0.505
		±2.015	*±2.015*	*±2.015*	*±2.015*
US banks	Full sample (49 banks)	-0.787	0.553	-0.912	**2.504**
		±2.011	*±2.011*	*±2.011*	*±2.011*
	Subject to the restriction	-1.144	0.234	-0.853	**2.163**
		±2.093	*±2.093*	*±2.093*	*±2.093*
	Not subject to the restriction	-0.615	0.704	-0.933	**2.513**
		±2.048	*±2.048*	*±2.048*	*±2.048*

SOURCE: Banco de España.
NOTES: For each event and bank group, the statistic (above) and its critical level (below and in italics) are shown for a significance of α = 5% (since this is a two-tailed test, the critical values correspond to α/2 = 2.5%). Significant results are shown in bold.

The results are consistent with those obtained for the three-day window. However, the results of the test for the *ESRB 1* event in the five-day window shown in this annex are likely due to other relevant information for the institutions published in the days leading up to the event. In particular, these results could be reflecting the ECB's announcement on 4 June 2020 of the extension of the PEPP and the relative underperformance of other sectors in the stock market following the macroeconomic scenario review. The significant reactions to event *D. FED* are probably due to the announcement of the launch of the Paycheck Protection Program on 3 April, several days prior to J. Powell's statement.

Table A.3
EVENT STUDY – [T*-2, T*+2] WINDOW: KOLARI-PYNNÖNEN (2010) TEST. EXTENSION OF THE RESTRICTIONS

		ECB 2 ECB announcement 28 de July 2020	*FED 2* FED announcement 30 September 2020	*BCE 3* ECB announcement 15 December 2020	*FED 3* and *ESRB 2* FED and ESRB announcements 18 December 2020
Euro area banks	Full sample (37 banks)	-1.229	-0.346	-0.604	**-2.681**
		±2.028	*±2.028*	*±2.028*	*±2.028*
	P/B > median P/B	-2.022	-0.347	-1.101	**-3.119**
		±2.11	*±2.11*	*±2.11*	*±2.11*
	P/B < median P/B	-0.881	-0.324	-0.308	**-2.462**
		±2.101	*±2.101*	*±2.101*	*±2.101*
	Excluding Greek banks	-1.221	-0.219	-1.486	**-2.950**
		±2.037	*±2.037*	*±2.037*	*±2.037*
Spanish banks	Full sample (8 banks)	-0.190	-0.890	-0.432	**-3.447**
		±2.365	*±2.365*	*±2.365*	*±2.365*
European banks	Full sample (49 banks)	-1.365	0.176	-0.865	**-2.313**
		±2.011	*±2.011*	*±2.011*	*±2.011*
	Excluding Greek banks	-1.361	0.289	-1.575	**-2.435**
		±2.015	*±2.015*	*±2.015*	*±2.015*
US banks	Full sample (49 banks)	-0.259	1.892	-1.057	-0.693
		±2.011	*±2.011*	*±2.011*	*±2.011*
	Subject to the restriction	-0.615	1.721	**-2.320**	-0.182
		±2.093	*±2.093*	*±2.093*	*±2.093*
	Not subject to the restriction	-0.127	**2.190**	-0.615	-1.067
		±2.048	*±2.048*	*±2.048*	*±2.048*

SOURCE: Banco de España.
NOTES: For each event and bank group, the statistic (above) and its critical level (below and in italics) are shown for a significance of α = 5% (since this is a two-tailed test, the critical values correspond to $\alpha/2$ = 2.5%). Significant results are shown in bold.

European banks' excess returns were significantly negative in the days around the extension of the restrictions recommended by the ESRB (event *ESRB 2).* However, the effect of this event is difficult to isolate, as the two previous days overlap with the ECB announcement of 15 December. Moreover, the result is blurred if only the day of the ESRB announcement and the two subsequent days, when the impact of the approval was strongest, are taken into account, as explained in Section 4.

Chart A.1

STOCK MARKET PRICE OF THE GREEK BANKS IN THE SAMPLE

SOURCE: Banco de España.
NOTE: Stock price indices weighted by each banks' market value.

Table A.4

EXPLANATORY FACTORS FOR THE CUMULATIVE EXCESS RETURNS IN THE FIVE-DAY WINDOW CENTRED AROUND EVENT *ECB 1* [T*-2, T*+2]

	European banks, excluding Greek banks		US banks
	(1)	(2) + ES* dummy payout restrictions	(3)
ROE	0.056	0.054	-0.607
	(0.372)	(0.400)	(1.413)
CET1_ratio	0.156	0.351	-0.239
	(0.552)	(0.667)	(0.478)
Dividend yield	0.378	0.345	0.381
	(0.518)	(0.532)	(0.635)
Log. total assets	-1.577**	-1.243	-0.761*
	(0.705)	(0.774)	(0.424)
Interaction ES* dummy no payout restrictions		3.153	
		(2.690)	
Interaction ES* dummy payout restrictions		0.718	
		(2.847)	
Constant	18.140	8.477	14.480*
	(18.530)	(21.810)	(8.286)
Observations	45	45	49
R^2	0.098	0.118	0.093

SOURCE: Banco de España.
NOTES: Event *ECB 1* corresponds to the first ECB announcement on payout restrictions (March 2020). Robust standard errors in brackets. *** p<0.01. ** p<0.05. * p<0.10.

STRUCTURAL RISK INDICATORS FOR THE SPANISH BANKING SECTOR

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Abstract

Structural risks are long-term non-cyclical risks stemming from the structural characteristics of the financial system and the wider economy. In this respect, the systemic risk buffer (SyRB) is a fairly flexible macroprudential instrument that aims to address such risks. However, the European Union (EU) legislation is still flexible regarding the indicators for activating or releasing this buffer. Although a clear definition of these indicators is key to enabling the early detection of vulnerabilities that may lead to a crisis, in practice, each national authority determines its own set of indicators. This article has a dual aim. First, to select a set of indicators that are relevant for regularly monitoring the Spanish banking sector's structural risks and, second, to develop a heatmap of structural indicators comparing variables for Spain with those for the EU. The empirical evidence suggests that the Spanish banking sector shares most of its structural features with those of the EU economies. According to the analysis, no structural risks are identified at present that might threaten the Spanish banking sector.

Keywords: macroprudential policy, systemic risk, structural indicators, heatmap.

1 Introduction

The prevention and mitigation of systemic risk is a key objective for macroprudential authorities. Broadly speaking, systemic risk can be analysed in two dimensions: cyclical and structural (see European Systemic Risk Board (ESRB) (2013)). This article addresses this second structural (or cross-sectional) dimension of systemic risk, which stems from different characteristics of the financial system that could make it more vulnerable in the event of a potential adverse shock and more prone to spread throughout the system. In the European Union (EU) legislation, the three main macroprudential tools to prevent these non-cyclical risks are the buffer for global systemically important institutions (G-SIIs), the buffer for other systemically important institutions (O-SIIs) and the systemic risk buffer (SyRB). While the two SII buffers address the externalities caused by these large and interconnected individual institutions, the SyRB can be applied to the mitigation of risks stemming from the structural features of the financial system and the wider economy.[1]

1 Article 128(5) of the Capital Requirements Directive (CRD) defines the SyRB and its use is further specified in Article 133 of the CRD. Accordingly, the SyRB can be interpreted as a residual macroprudential instrument that targets structural systemic risks not covered by other measures specified in the Capital Requirements Regulation (CRR) and cyclical risks not addressed by the countercyclical capital buffer (CCyB). It is worth noting that in the latest amendments to the EU prudential framework for the banking sector (the CRD V and CRR II amendments), the application of the SyRB is no longer restricted to long-term non-cyclical systemic risks and can also be applied to sectoral exposures.

The structural features of the financial system are very diverse in nature and include the banking sector's structural characteristics, such as its size and concentration, the degree of interconnectedness among domestic credit institutions or with foreign counterparties, and the level of common exposures in lending or funding. In addition, certain structural features of the economy, such as the composition and size of non-financial private sector and public sector indebtedness, could also pose risks to the financial system. The analysis of an appropriate set of indicators to identify structural risks is crucial,[2] not only to identify such risks but also to guide macroprudential policy decisions that may have to be adopted on the SyRB.[3] However, compared with SII buffers, the EU's CRD[4] is less prescriptive regarding the set of indicators to guide the decisions on the SyRB. The ESRB Handbook (see ESRB (2018)) specifies a taxonomy of three risk categories to be addressed by the SyRB and a non-exhaustive list of indicators. As the identification framework for using the SyRB in the EU is not clear-cut, in practice there is no homogeneous approach to be adopted by national macroprudential authorities to define and classify the indicators of structural systemic risk. In this respect, the ESRB expects that national authorities determine the risks to be addressed by the SyRB and the selected indicators to be regularly monitored (see ESRB (2013), (2017)).

Choosing the most relevant indicators for each economy is not straightforward either. There is an enormous cross-country variation in the structural systemic risk assessment between Member States. National authorities typically use their own metrics to identify the structural vulnerabilities of their financial systems.[5] This circumstance complicates the assessment and the undertaking of comparisons among EU countries, not least because of the unique structural features of each national financial system.[6] Moreover, it is not always easy to distinguish between the cyclical and the structural dimensions of systemic risk, as some structural metrics, such as exposure concentration and asset commonality, are also monitored to detect the emergence of cyclical risks.

The aim of this article is to propose a comprehensive set of structural indicators for the Spanish banking sector. As proposed by the ESRB, the taxonomy of structural risks should be based not only on the current structure and state of the particular economy, but also on a sufficiently broad amount of information to target a wide range of potential risks (see ESRB (2017)). In this spirit, the metrics proposed in this

2 Among other authors, Cerruti, Claessens and McGuire (2012) and Gambacorta and van Rixtel (2013) show the importance of having better information on structural systemic risks to appropriately monitor risks.

3 In fact, the ESRB recommends the use of appropriate indicators to monitor risks and guide the application of macroprudential instruments. See ESRB/2013/1 Recommendation C.

4 Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013 on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms, amending Directive 2002/87/EC and repealing Directives 2006/48/EC and 2006/49/EC.

5 And only a few authorities, including Finland (see Suomen Pankki – Finlands Bank (2022)), disclose the list of specific indicators used in the assessment methodologies of their SyRB frameworks.

6 In this regard, Mæhlum and Riiser (2019) provide a summary of the main vulnerabilities and indicators used for the activation of the SyRB in countries that apply this buffer, which illustrates the cross-country heterogeneity.

article address not only the financial sector's structural features themselves, but also channels through which these vulnerabilities may amplify systemic risk within the system, as well as characteristics of the economy that could trigger the shocks, as suggested in ESRB (2018). Once the complete set of variables is selected, a heatmap is put forward to assess the level of these structural features for the Spanish banking sector with respect to its EU peers and to historical figures, i.e. a cross-sectional and a time series analysis of the data is performed. This tool could be regularly updated on an annual basis for monitoring purposes that could be useful to inform policy decisions regarding SyRB activation.

After describing the ESRB's taxonomy of structural risks, a set of structural indicators is defined and estimated as inputs for a proposed heatmap. This is followed by an assessment of the main structural characteristics of the Spanish banking system and a study of some selected structural variables by means of a pairwise analysis based on scatterplots. Finally, the article tries to disentangle whether the performance of some of these variables has some impact on growth or on growth volatility.

2 Taxonomy of structural risks and relevant indicators

An accurate assessment of structural systemic vulnerabilities should include a broad set of indicators that reflects the most relevant features of the banking sector. However, there are only a few examples of institutions that have developed empirical analysis to assess the structural features that could serve as reference. For instance, the central banks of four countries – namely, Finland, France, Norway and Sweden – have developed empirical research on this topic,[7] and the ESRB regularly updates a set of structural variables for the EU financial system in its Risk Dashboard.[8] Apart from not being widespread among institutions, analysis of the structural variables is not standardised across national macroprudential authorities either.

The proposed set of structural indicators specific to the Spanish banking sector relies on the taxonomy of structural risks in ESRB (2017, 2018). According to this classification, long-term non-cyclical risks could be classified into the following three categories:

1 *Structural characteristics of the financial sector.* This category reflects the systemic role of the aggregate banking system in its interplay with the real economy. The main indicators of this group relate to the size and concentration of the domestic banking sector and its importance for the financing of the

7 For more details, see Suomen Pankki – Finlands Bank (2022), Gabrieli and Jimborean (2020), Krygier and van Santen (2020) and Mæhlum and Riiser (2019), respectively. Specifically, Suomen Pankki – Finlands Bank uses a set of eleven structural indicators for the Finnish financial system and compares them with the median values of the corresponding indicators for the EU countries and the Finnish historical average.

8 For further details, see the ESRB Risk Dashboard on the ESRB website.

economy. This category also covers the funding and liquidity structure of the banking sector, as well as its constraints on intermediation capacity, such as solvency, profitability and efficiency.

2 *Amplification channels.* This group of indicators includes measures to analyse possible channels of amplification and propagation of shocks within the financial system. It addresses not only direct channels of transmission, such as interconnectedness and intra-financial linkages, but also indirect channels, such as common exposures and business model commonalities. In addition, this category also encompasses cross-border banking, such as dependence on foreign intermediaries and exposures to external sources of macroeconomic volatility.

3 *Financial structure of the real economy.* Finally, there could be broad macroeconomic shocks, as well as shocks that originate from specific economic sectors in distress, that could lead to losses for the banking sector. The spectrum of characteristics of the real economy that make it more vulnerable to such shocks are country-specific and encompass, among others, a persistently high level of private and public debt, as well as external debt.

Once the taxonomy is set, a selection is made of 20 banking sector indicators that are representative of these three categories and ten subcategories of metrics proposed by the ESRB. The chosen set of indicators is linked to the structural features of the banking sector, as well as the financial system vulnerabilities and those characteristics of the economy that may amplify systemic risk. Table 1 lists and describes these indicators and their calculation methodology. Next, the article briefly discusses the reasons why each indicator subcategory is relevant for monitoring structural vulnerabilities.

2.1 Structural characteristics of the financial sector

The first group of indicators on the structural features of the financial sector consists of four subcategories – namely, banking sector size and importance, concentration, funding and liquidity structure, and constraints on intermediation capacity. First, banking sector *size and importance* represents a relevant characteristic to be monitored as, when a banking sector is large and important as a provider of financial services, serious difficulties experienced by this sector could adversely affect financial intermediation and have a negative impact on the real economy (see Laeven, Ratnovski and Tong (2016)).

Concentration measures are also relevant for analysing structural risks. There is a long-standing debate among theoretical and policy economists about the relationship

Table 1
STRUCTURAL RISK TAXONOMY (a)

Category	Subcategory	Indicator	Calculation methodology
1 Structural features of the financial sector	Size and importance	Banking sector size	Total bank assets as a % of the four-quarter sum of nominal GDP
		Bank lending to the NFPS	Loans provided by the domestic banking sector as a % of total loans to the domestic NFPS
	Concentration	Concentration ratio (CR5)	The five largest banks' share of the domestic banking sector's total assets
		Herfindahl index of total bank credit	Sum of the squares of the market shares of all the credit institutions in the banking sector (b)
	Funding and liquidity structure	Loan-to-deposit (LTD) ratio	Total loans granted by the banking sector as a % of total deposits excluding the European System of Central Banks
		Bank funding by central banks	Banks' deposits vis-à-vis the Eurosystem (for euro area countries) or the national central bank (for other EU countries) as a % of banking sector total liabilities
		Share of variable-rate mortgage loans	New loans for house purchase with a variable rate or an initial rate fixed for a period of up to 1 year as a % of total new loans to households for house purchase
	Constraints on intermediation capacity	CET1	CET1 capital as a % of the total risk exposure amount
		RoA	Total banking sector profit as a % of banking sector total assets
		Cost-to-income ratio	Ratio of total operating expenses to total operating income
2 Amplification channels	Common exposures	Share of mortgage loans	Loans for house purchase as a % of total loans and debt securities granted to the domestic NFPS
		Share of construction and real estate loans	Loans for construction and real estate activities as a % of banking sector total assets
		Exposure to domestic sovereign	General government loans and debt securities as a % of banking sector total assets
	Intra-financial contagion	Share of interbank loans	Interbank loans as a % of banking sector total loans
	Cross-border banking	Share of foreign ownership	Total assets held by foreign subsidiaries and foreign branches as a % of banking sector total assets
		Cross-jurisdictional assets	Share of cross-jurisdictional assets, i.e. all except domestic assets, as a % of banking sector total assets
3 Financial structure of the real economy	Private sector indebtedness	Household indebtedness	Household loans as a % of household gross disposable income
		NFC indebtedness	NFC debt securities and loans as a % of the sum of nominal GDP
	Public sector indebtedness	Public sector debt	Government debt as a % of the four-quarter sum of nominal GDP
	Foreign indebtedness	Net external debt	Net external debt as a % of the four-quarter sum of nominal GDP

SOURCES: Devised by authors drawing on ESRB (2018), ESRB Risk Dashboard and ECB Statistical Data Warehouse.

a NFPS = non-financial private sector; NFC = non-financial corporation; CET1 = Common Equity Tier 1 ratio; RoA = Return on assets.
b See the exact definition from the Banking Structural Statistical Indicators (SSI) dataset from the SDW.

between bank concentration and financial stability (see Beck, De Jonghe and Mulier (2022)).[9] At high levels of banking concentration, the excessive reliance on a few

9 This analysis relies on two widely used indicators of banking concentration, namely the concentration ratio of the five largest banks (CR5) and the Herfindahl-Hirschman Index (HHI) of total bank credit. Alternatively, Beck, De Jonghe and Mulier (2022) propose a metric that summarises three dimensions of bank sectoral concentration – degree of specialisation, deviation from peer banks and direct interconnectedness.

banks to finance the economy could lead to significant shortcomings in the provision of financial services under difficulties experienced by this low number of banks, so that replacing their services would require significant capital and other capacity from other credit institutions (see Calice and Leonida (2015)).[10] However, concentration has various dimensions and other authors – such as Giannetti and Saidi (2019) – find that higher concentration may favour financial stability.[11]

Indicators on the funding and liquidity structure of the banking system show how its business, primarily lending, is financed and whether it is capable of repaying its investors and depositors. The loan-to-deposit (LTD) ratio is a commonly used indicator of stable funding and liquidity mismatch (see Van den End (2016)).[12] When the LTD ratio is too high, it suggests that the banking system may not have enough liquidity to cover any unforeseen funding requirements in an adverse scenario, the so-called funding gap. In this situation, banks often access funding from their central bank, so that a high dependence on central bank funding could signal a shortage of private funding. The extent to which banks rely on such support is proxied by borrowing from the central bank as a percentage of total bank liabilities. In addition, the sensitivity of funding costs to external shocks is measured by the proportion of variable-rate loans.[13,14] The cost of financing of variable-rate loans fluctuates throughout the life of the loan due to policy rate changes, but also to other types of disturbances, such as shocks in financial markets. This adds uncertainty regarding its future course: if investor confidence in banks is undermined, banks' funding costs may become higher.

Finally, the subcategory related to the *constraints on intermediation capacity* includes indicators of bank solvency, profitability and efficiency. While bank solvency indicators – such as the Common Equity Tier 1 (CET1) ratio – measure the loss absorption and precautionary means to protect the economy from a financial crisis, profitability metrics – such as the return on assets (RoA) – provide information about the overall efficiency of the banking system and its capacity to generate income and capital. Finally, the cost-to-income ratio is used to measure banking efficiency. This indicator captures the relative performance of cost management with respect to income generation.[15]

10 According to these authors, at low levels of concentration, a higher concentration could improve banking system stability via profitability, so that an intermediate level of concentration may be optimal in terms of welfare.

11 Giannetti and Saidi (2019) conclude that credit concentration may enhance financial stability as it affects the way in which industry shocks are transmitted along the supply chain and become systemic.

12 The LTD ratio measures the share of the loan book that is covered by deposits received from customers.

13 In the case of variable interest rate loans, the changes in the revenue on these loans are tied to the changes in their funding costs. This is because the latter are renewed more frequently, in line with interbank market yields, given the prevalence of short-term loans.

14 The proportion of variable-rate loans could be interpreted as two-tailed. Thus, a high proportion of variable-rate loans on banks' balance sheets could indicate a potential vulnerability in the case of a sudden interest rate rise, as this will affect borrowers' debt servicing capacity and could lead to an increase in impairments. On the other hand, a high proportion of fixed-rate loans issued at low rates with long maturities in the event of rising rates could put pressure on interest income, unless properly hedged against these events.

15 The cost-to-income ratio takes into account not only purely operational performance, but also other more structural factors affecting both components, such as provisioning linked to asset quality, challenges in income generation and rigid cost structures.

2.2 Amplification channels

The second group of indicators, amplification channels, includes representative metrics of three subcategories: common exposures, intra-financial contagion and cross-border banking.

First, high levels of *common exposures* concentrated in specific sectors across the banking system, such as in real estate, increase the likelihood of simultaneous distress. Serious disruptions to these sectors could pose a direct or indirect threat to the functional capacity of a number of credit institutions and the system as a whole (see ESRB (2016)). Mortgage loans and construction and real estate loans as a percentage of total loans are used to monitor these developments. In this subcategory the exposure of the banking system to domestic sovereign debt is also considered. Banks' exposures to sovereign debt were one of the channels through which the sovereign-bank nexus operated during the euro area sovereign debt crisis.

Regarding *intra-financial contagion,* a closely interconnected banking system offers a network to absorb liquidity shocks through diversification, but it also allows these shocks to propagate and sometimes it may amplify them, spreading financial weaknesses throughout the banking system (see Rochet and Tirole (1996), Brunnermeier (2009) and Elliot et al. (2014)).[16] A higher value for the selected interconnectedness indicator, defined as interbank loans as a percentage of total bank loans, means larger transmission channels between banks, which may produce contagion in an adverse scenario.

The *cross-border banking* subcategory includes two complementary indicators. The first one – the share of foreign ownership – quantifies the importance of foreign banks in the banking sector in terms of balance sheet size. This indicator is a proxy of the ability of the banking sector to finance the economy and channel domestic savings. There is no general conclusion as to whether foreign banks amplify systemic risk or not. Rather, the question relates to the substitutability of activities performed by foreign banks in the event of propagation of foreign-originated shocks.[17] In addition, management misalignments between a parent and its subsidiaries and branches may create additional vulnerabilities. The second indicator, cross-jurisdictional assets as a percentage of total assets, measures the exposure and vulnerability of the banking system to foreign shocks, which may be associated with non-synchronised business cycles, more complex monitoring and compliance, and geopolitical or country-specific risks. A higher value for this indicator could denote potential higher structural systemic vulnerabilities, as the banking system is more exposed to shocks beyond its borders. In terms of macroprudential policy

16 For instance, funding problems in one bank can spread to other banks and amplify losses in the banking sector.

17 There is evidence that foreign-owned banks may be more procyclical regarding credit supply in crisis times and amplify credit constraints (see Albertazzi and Bottero (2014)).

effectiveness, it is important to consider both indicators, as they could provide insight into the level of exposure and the degree of possible inward and outward cross-border spillover effects (see European Central Bank (ECB) (2020)).

2.3 Financial structure of the real economy

Finally, the third category of risk indicators includes features related to the financial structure of the real economy, namely private and public sector indebtedness and external debt. Shocks to the financial system may originate outside the banking sector, and the risk of such shocks could also depend on the vulnerabilities of other participants, such as households, non-financial corporations (NFCs) and the public sector. Regarding *private sector debt,* under persistently high levels of household and NFC indebtedness, even a small shock might negatively affect borrowers' debt servicing capacity. In addition, indicators that measure *public indebtedness* address the potential risk of spillovers from the sovereign to the banking system. This impact between both sectors might be driven by shocks to revenues and interest rates when repaying debt and to the unavailability of funds for debt refinancing or for issuing new debt.

Finally, high *external debt* is also an element of vulnerability as it exposes issuers to a potential rollover risk and higher financing costs if the conditions for accessing international markets tighten or become more expensive. More generally, external indebtedness is a measure of external leverage (see Krygier and van Santen (2020)). Previous research has shown that large current account deficits have often preceded financial crises (see ECB (2019)). Similarly, persistently elevated levels of net external debt could raise economies' dependence on global financial markets and accentuate their vulnerability to swings in investor sentiment.

3 Data and methodology

To provide an assessment of the Spanish banking sector's structural risks and its relative position within the EU, a set of 20 indicators is obtained (see Table 1). The data source is the aggregate balance sheet information from the ECB's Statistical Data Warehouse (SDW). Some of the indicators were obtained from this source directly, while others require some calculations.[18] The data set runs from 1997 Q3 to 2021 Q4 and the country sample consists of the 28 EU Member States.[19] The panel is unbalanced as not all the indicators are available for all countries from the

18 Nine indicators (CR5, HHI, LTD ratio, proportion of variable-rate loans, CET1, RoA, cost-to-income ratio, share of interbank deposits and public sector indebtedness ratio) can be directly obtained from the SDW, while the remaining metrics require some calculations.

19 From 2019 Q4 the country sample consists of 27 countries as the UK data series was discontinued in the SDW as a result of Brexit.

beginning of the sample period. Most indicators (16 out of 20) are quarterly. For those variables that are not available at a quarterly frequency annual data are used instead.[20] Following ESRB (2017, 2018), it is assumed that all indicators are one-tailed, so that a higher level of the indicator represents higher vulnerability.[21]

Next, a heatmap is constructed to identify the potential build-up of structural risks in the Spanish banking sector. Heatmaps are data-based monitoring tools that offer a visual assessment of the values of large panels of indicators. This instrument consists of a two-dimensional table that assigns to each indicator a colour code linked to its current position on the percentile scale of its corresponding frequency distribution. Colour codes tend to range from red to green, the former being associated with higher risk and the latter with a normal range of values.

Given their simplicity and straightforward interpretation, heatmaps are broadly used to monitor the emergence of systemic risks by central banks and other institutions. Among others, for instance, the IMF regularly monitors in its *Global Financial Stability Report* (GFSR) a broad set of indicators in a matrix defined by types of macro-financial imbalances across types of lenders and borrowers (see Adrian, He, Liang and Natalucci (2019)). Other institutions, such as the Federal Reserve Board (see Aikman, Kiley, Lee, Palumbo and Warusawitharana (2017)) or Norges Bank (see Arbatli and Johansen (2017)), also use heatmaps as a monitoring tool. In the case of Spain, Mencía and Saurina (2016) propose a heatmap to identify potential systemic risks to the Spanish banking system. Additionally, 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. 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.

To address the evolution of these indicators in their time-series dimension, a heatmap is built using a methodology similar to that in Mencía and Saurina (2016). Additionally, as in Alonso and Molina (2021), the proposed heatmap for structural risks also covers the cross-sectional dimension, which allows us to analyse the extent to which the structural characteristics of the Spanish banking system are similar to those of other EU countries.

After obtaining 20 indicators, a heatmap for structural variables is developed in two steps. First, threshold values are estimated to represent the different warning levels for each indicator that allow us to assess the structural risk level of all the EU national

20 There are three indicators that are not available at a quarterly frequency: CR5, HHI and the share of interbank deposits. RoA is conveniently analysed at an annual frequency, although it can also be assessed at a quarterly frequency.

21 In theory some of the indicators, such as the proportion of variable-rate loans, could be two-tailed. However, for simplicity purposes and to ensure comparability with other indicators, in this empirical work it is assumed that all indicators are one-tailed.

banking sectors, before shifting the focus of our attention to the particular case of Spain. For each indicator three sets of thresholds – corresponding to three different exercises – are computed. The first one is obtained from the cross-section sample only for the last available observation, that is, 2021 Q4. Then, the second set of warning threshold levels is based on the entire sample period, so that the indicators' entire time series is needed to perform the assessment. Finally, a third set of thresholds from the last five years of the sample (from 2017 Q1 to 2021 Q4) is obtained so as to take into account the most recent evolution of the indicators that could signal the build-up of systemic imbalances. For these three sets of thresholds, three percentiles of the distribution of the indicators are calculated, namely p75, p90 and p95.[22] All the percentiles are calculated using the interpolation approach.[23] In any case, given the structural nature of these characteristics, these indicators tend to be rather stable, so that these percentiles are quite sensitive to small variations.

Second, a comparison is made between the current levels of the 20 structural indicators for the Spanish banking sector as of 2021 Q4 and the warning levels. To this end, a colour code linked to the position of each indicator on the percentile scale of its frequency distribution distinguishes four different levels of risk. If the level of an indicator is below p75 it is interpreted that it is within a normal range of values (green colour coding). Then, as the indicator departs from the normal range, the level of risk increases from moderate risk (yellow; p75-p90), to medium risk (orange; p90-p95) and, lastly, to the maximum level of risk (red; p95 and above).[24] In any case, the structural risk assessment obtained with this heatmap only provides information about the relative position of the variables. Therefore, departures from normal ranges should not be interpreted as early warning signals of future risks, as the properties of these indicators as leading indicators must be further analysed.[25] Consequently, this analysis should be complemented by expert judgement.

4 Assessment of the Spanish banking system's main structural risks

The results of the heatmap for the 20 structural indicators for the Spanish banking sector are summarised in Table 2. The overall comparison across the three exercises suggests that most indicators are green coloured, so that they are in a normal range, both in terms of their own time series and in comparison with European peers.

22 For the CET1 ratio and RoA, the percentiles p25, p10 and p5 are used in the reverse order to signal vulnerabilities.

23 If the *k-th* percentile does not correspond to a specific data point, the interpolation between points is performed to determine the value at the *k-th* percentile. The range of percentiles is between 0 and 100, inclusive. For more details, see NIST/SEMATECH (2022).

24 These intervals include the lower bound, but not the upper bound.

25 Indeed, the definition of the normal range depends on the distribution considered for each exercise and variable. The main advantage of this approach is that it takes into account the average range for the euro area, while allowing us to monitor developments in domestic banking sectors over time.

Table 2
STRUCTURAL RISKS HEATMAP FOR 2021 Q4

Category	Subcategory	Indicator	Cross-section 2021 Q4	Panel 2017 Q1 - 2021 Q4	Panel 1998 Q4 - 2021 Q4
1 Structural features of the financial sector	Size and importance	Banking sector size	Yellow	Yellow	Green
		Bank lending to the NFPS	Yellow	Yellow	Green
	Concentration	CR5 ratio	Green	Green	Green
		Herfindahl index of total bank credit	Green	Green	Green
	Funding and liquidity structure	LTD ratio	Green	Green	Green
		Bank funding by central banks	Orange	Red	Orange
		Share of variable-rate mortgage loans	Green	Green	Green
	Constraints on intermediation capacity	CET1 ratio	Red	Orange	Orange
		RoA	Green	Green	Green
		Cost-to-income ratio	Green	Green	Green
2 Amplification channels	Common exposures	Share of mortgage loans	Green	Green	Green
		Share of construction and real estate loans	Green	Green	Green
		Exposure to domestic sovereign	Green	Green	Green
	Intra-financial contagion	Share of interbank loans	Green	Green	Green
	Cross-border banking	Share of foreign ownership	Green	Green	Green
		Cross-jurisdictional assets	Yellow	Yellow	Orange
3 Financial structure of the real economy	Private sector indebtedness	Household indebtedness	Green	Green	Green
		NFC indebtedness	Green	Green	Green
	Public sector indebtedness	Public sector debt	Yellow	Yellow	Orange
	Foreign indebtedness	Net external debt	Orange	Yellow	Yellow

SOURCES: ECB Statistical Data Warehouse and devised by authors.
NOTE: For each indicator, the colours indicate the position of the Spanish banking sector relative to the thresholds, which are calculated from each sample and correspond to three percentile scores: p75, p90 and p95. Green indicates no risk, yellow indicates moderate risk, orange indicates high risk and red indicates severe risk.

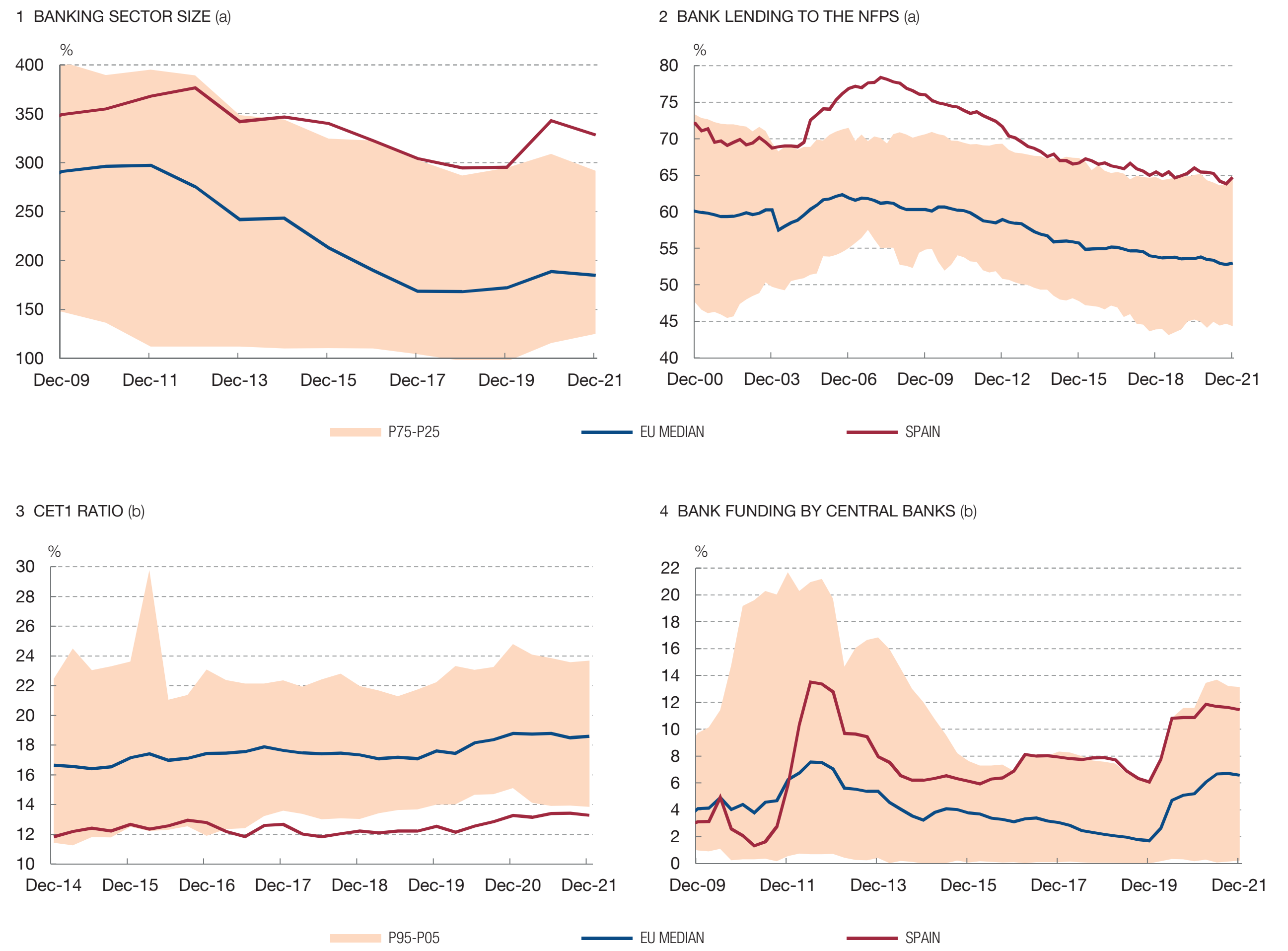
4.1 Structural features of the financial sector

The analysis of the first risk category (structural features of the financial sector) shows that four out of the ten indicators, namely, banking sector size, bank lending to the NFPS, bank funding by central banks and the CET1 ratio, are relatively high both in the time and in the cross-sectional dimensions. Chart 1 shows the evolution of these four variables in Spain and in the EU.

When the entire historical perspective is considered (see the third column of Table 2) the size and importance for the NFPS signal no potential structural risk. However, in the exercises that analyse the cross-section of countries and the short sample panel (see the first and second columns of Table 2), these indicators suggest a moderate level of risk. Thus, as illustrated in Charts 1.1 and 1.2, although both variables are above p75 with respect to the European countries in the last six years of the sample, both variables exhibit a downward trend (since 2012 in the case of banking sector size and since 2007 in that of bank lending to the NFPS). Additionally, in the case of lending to the NFPS, the

Chart 1

STRUCTURAL FEATURES OF THE BANKING SECTOR: INDICATORS THAT DEPART FROM THEIR NORMAL RANGE



SOURCE: Own calculations drawing on the ECB Statistical Data Warehouse.

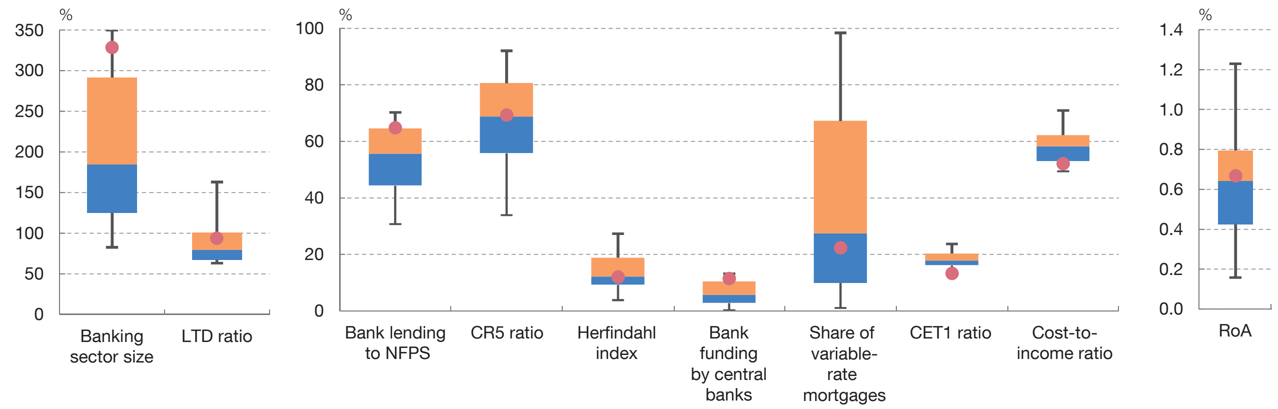
a The median and the interquartile range of the EU distribution – that is, the difference between the third and the first quartile –, are calculated in each quarter.

b The median and the range between the 95th (p95) and the 5th (p05) percentiles of the EU distribution are calculated in each quarter.

downward trend for Spain has been steeper than that for the rest of the countries, while the starting point was well above p75 in 2006, but converged to it during 2013-2014.

The other two indicators – bank funding by central banks and the CET1 ratio –, suggest potential structural vulnerabilities to some extent in the three exercises. Regarding the bank solvency indicator, in 2021 Q4 the CET1 ratio of the Spanish banking system was below percentile p5 of the EU distribution. That is, in terms of its CET1 ratio the Spanish banking industry ranks among the lowest. This difference could be related to Spanish banks' higher risk weight densities and structural factors such as the more widespread use of the standardised approach to calculate capital requirements for credit risk (see Banco de España (2022)). In addition, the CET1 ratio has been increasing in recent years, as shown in Chart 1.3, so that although the level of CET1 of Spanish banks

Chart 2
DISTRIBUTION OF STRUCTURAL INDICATORS IN THE EU: STRUCTURAL FEATURES OF THE FINANCIAL SECTOR (a)



SOURCE: Own calculations drawing on the ECB Statistical Data Warehouse.

a For each indicator, the red dots indicate the position of the Spanish banking sector. The colour boxes represent the interquartile range, the upper whisker corresponds to p95 and the lower one to p5. Data as of 2021 Q4.

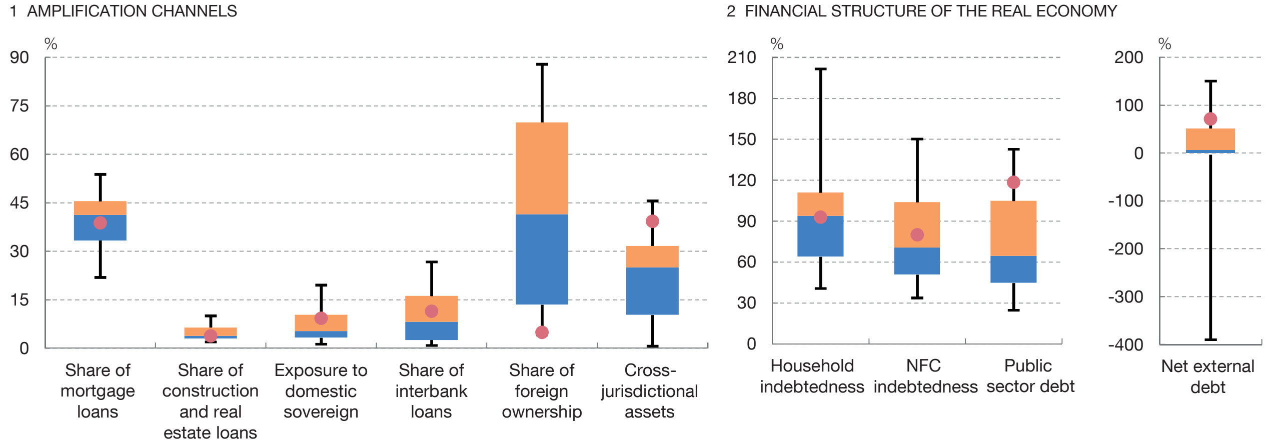
remains relatively low, their solvency is gradually becoming sounder. Regarding bank funding by central banks, central bank funding as a percentage of total Spanish banking system funding increased during the sovereign debt crisis between 2011 and 2012, as illustrated in Chart 1.4. As sovereign debt concerns receded, the reliance on this type of funding slowly decreased, alongside similar developments in the rest of the EU. However, the onset of the COVID-19 pandemic led to an increase in this indicator throughout the EU.

Chart 2 shows the box-and-whiskers plots of each variable as of 2021 Q4. This chart provides further details on the distribution of the metrics of the structural features of the financial sector category. Each box represents the interquartile range and the median, while the whiskers characterise the range between the p95 and p5 percentiles. The red dots indicate the position of the Spanish banking system. On the negative side, as reported in the heatmap in Table 2, the Spanish banking system is in the tail of the distributions of the four metrics showing some warning signals. On the plus side, the banking efficiency indicator (the cost-to-income ratio) is in the first quartile, which suggests a favourable performance of Spanish banks compared with other EU countries. In addition, four of the indicators for structural features exhibit a relative position of the Spanish banking sector that is close to the EU median (namely the two concentration measures, the share of variable-rate mortgage loans and RoA).

4.2 Amplification channels and financial structure of the real economy

All the indicators of the second category of structural risks (amplification channels) in the heatmap are in a range considered to be normal, except for the cross-

Chart 3
DISTRIBUTION OF STRUCTURAL INDICATORS IN THE EU: AMPLIFICATION CHANNELS AND FINANCIAL STRUCTURE OF THE REAL ECONOMY (a)



SOURCE: Own calculations drawing on the ECB Statistical Data Warehouse.

a For each indicator, the red dots indicate the position of the Spanish banking sector. The colour boxes represent the interquartile range, the upper whisker corresponds to p95 and the lower one to p5. Data as of 2021 Q4.

jurisdictional assets indicator. This metric exceeds warning levels under the three metrics shown in Table 2. Specifically, this indicator has historically been somewhat higher than the percentile p90 of the EU distribution. However, the latest data suggest that the relative position of Spanish banking sector exposure to cross-jurisdictional assets has been gradually decreasing and is currently just above the percentile p75. This fact highlights the potential vulnerability of the Spanish banking system to cross-border banking activities, specifically to the asset holdings of Spanish banks abroad. However, this result should be qualified given the structure of independent subsidiaries in the specific case of the Spanish banking sector.

Finally, the indicators of the third category of structural risks, which correspond to risks arising from the real economy, confirm that the high levels of public and external debt are outside their normal range in the three exercises. The increased public and foreign indebtedness make the economy more sensitive to the tightening of financing conditions that could spill over to the banking system as well. On a more positive note, indicators of private indebtedness do not show signs of structural vulnerability, potentially due to the correction that took place after the global financial crisis.

Chart 3 depicts the distribution of the indicators in the amplification channels and financial structure of the real economy categories. Most of these indicators are within the interquartile range, which denotes values comparable to the majority of other EU banking sectors. It is worth noting that the share of foreign ownership is relatively low – below percentile p5 –, so that this indicator evidences the minor role of foreign-owned banks in Spain. However, as previously mentioned, the cross-jurisdictional assets indicator shows relatively high exposures compared with those of the European peers. Regarding the financial structure of the economy indicators, household and NFC indebtedness are around the EU median.

5 Pairwise analysis of the selected structural indicators

The structural characteristics of the banking system analysed in this article are not necessarily independent. Some vulnerabilities may be intensified if they tend to simultaneously coexist with others. To explore potential interrelations, this section analyses some pairs of variables linked to the profitability, liquidity and the portfolio risk concentration of banks, as well as their degree of interconnectedness. Chart 3 shows the scatterplots of these structural indicators that represent the cross-section of the selected indicators as of 2021 Q4 for the EU countries. This pairwise analysis is not exhaustive. The objective is to highlight the usefulness of this combined study of individual variables.

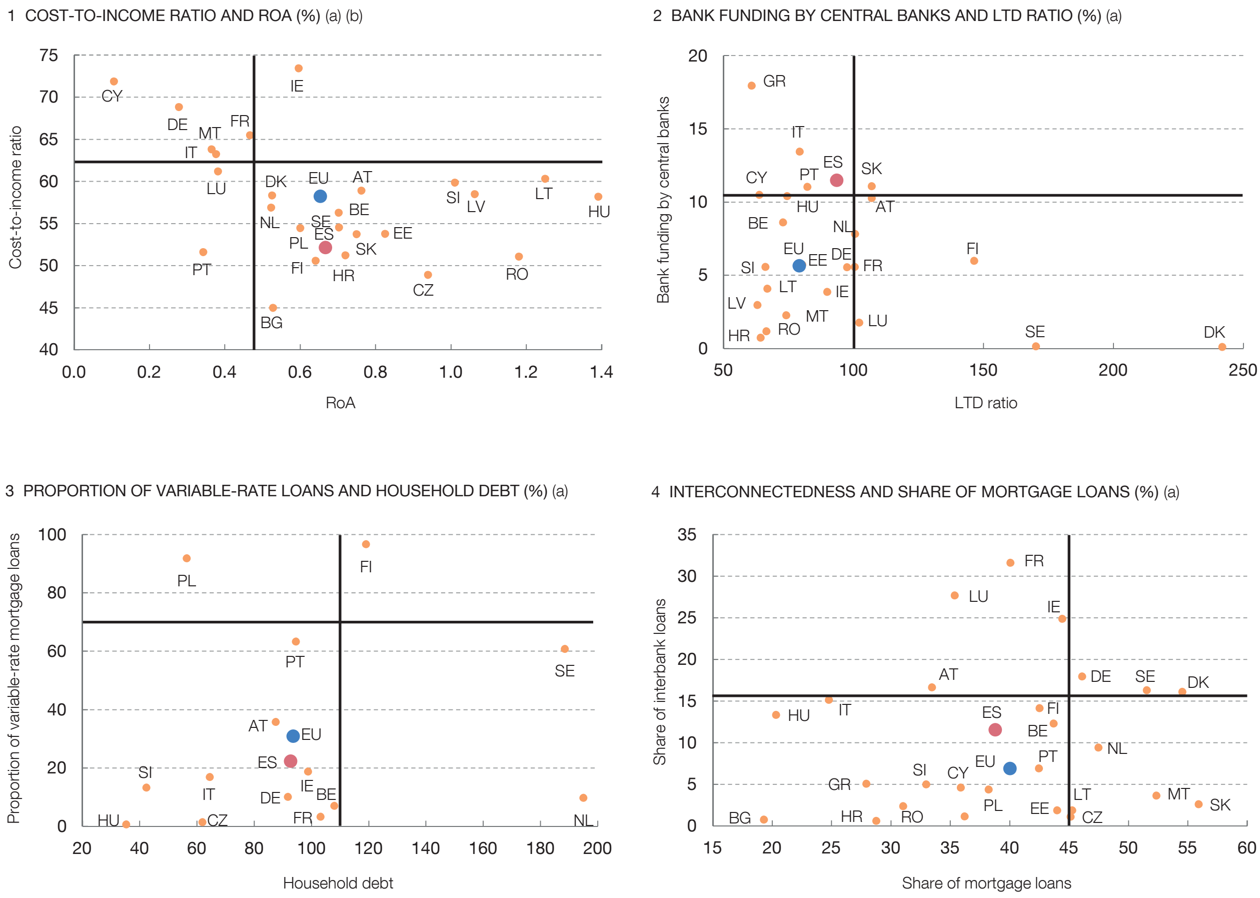
First, Chart 4.1 shows the distribution of the cost-to-income ratio and RoA across the EU countries. Low structural profitability and low cost efficiency could pose a notable vulnerability for the more traditional banking business models. In the particular case of the Spanish banking sector, its profitability is just above the EU median, while its efficiency is one of the highest, corresponding to a low cost-to-income ratio, far from any sign of vulnerability.

Next, Chart 4.2 displays the distribution of the share of bank funding by central banks and the LTD ratio. Typically, banks collect deposits to finance their lending, but when they find themselves in trouble they opt for central bank funding. The onset of the COVID-19 pandemic was associated with higher liquidity risk, so that central bank funding as a precautionary measure was increasingly used by banks. The relative position of the Spanish banking sector is in the highest quartile of the cross-country distribution for both indicators, which might indicate a potential vulnerability. It is likely that, in the current context of monetary policy normalisation in the EU, deposits from central banks will decrease.

Regarding portfolio risk concentration, Chart 4.3 shows the scatterplot of the share of variable-rate mortgage loans and household indebtedness. The combination of high household indebtedness and an elevated proportion of variable-rate loans makes the banking system particularly vulnerable to both a decline in household income and higher interest rates. In the cross-country comparison, the Spanish banking sector is in the lowest quartile of the distribution for both indicators, and the proportion of variable-rate loans is below the EU median.[26] Therefore, no vulnerability is identified after combining both dimensions.

26 Since 2016 the ratio of variable-rate mortgage loans in the Spanish banking sector has been decreasing, against the backdrop of ‘low for longer’ interest rates and increasing competition among banks as well as from non-banks.

Chart 4
SCATTERPLOTS OF KEY STRUCTURAL INDICATORS



SOURCE: Own calculations drawing on the ECB Statistical Data Warehouse.

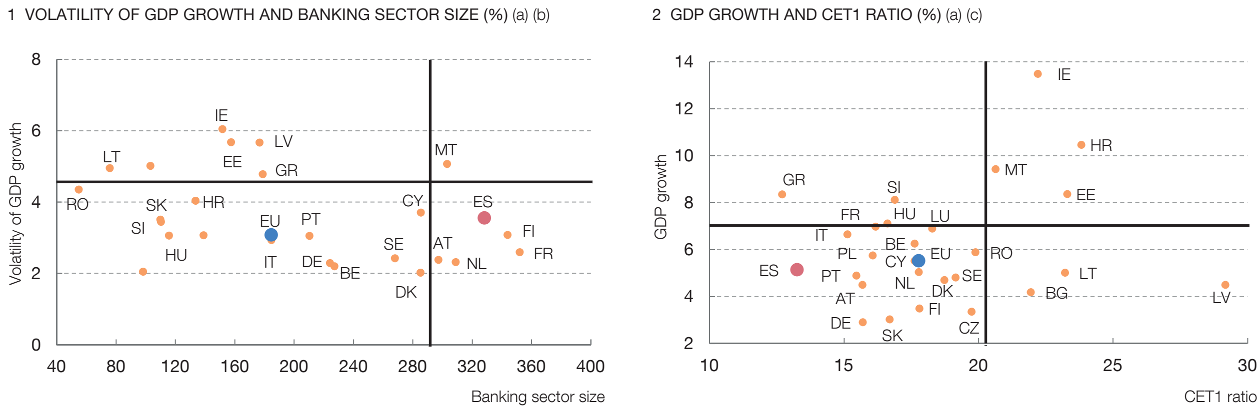
a Each orange dot represents a value of the indicator for the banking sector of one EU country. The red dot corresponds to Spanish data and the blue dot represents the EU median. The solid lines stand for the third quartile of the EU distribution of each indicator.
b The solid line in the horizontal axis represents the first quartile of the EU distribution of RoA.

Finally, Chart 4.4 shows the share of interbank loans, which proxies interconnectedness, and the share of mortgage loans for the sample of EU countries. Concentration risk, such as that in mortgage portfolios, and interconnectedness may jointly amplify risks of shock propagation. According to the distribution of these indicators, the Spanish banking sector is in the lowest quartile for both, while it is above the EU median for the share of interbank loans.

6 Structural risks indicators and growth

The macro-financial environment is also related to the structural characteristics of the banking system. Thus, in a context of weakening economic conditions and economic deterioration, structural vulnerabilities in banking systems would also be

Chart 5
STRUCTURAL RISK INDICATORS AND GROWTH



SOURCES: Own calculations drawing on the ECB Statistical Data Warehouse and the World Bank indicators.

a Each orange dot represents a value of the indicator for the banking sector of one EU country. The red dot corresponds to Spanish data and the blue dot represents the EU median. The solid lines stand for the third quartile of the EU distribution of each indicator.
b GDP growth volatility is calculated from 1997 to 2021. Banking sector size is the average from 1997 to 2021.
c Data as of Q4 2021.

affected and might affect credit and growth in turn. For instance, while lower growth puts a general drain on bank profitability via reduced asset quality across all business models, a lower interest rate environment would pose a more severe challenge to banking systems with business models largely relying on net interest income (NII) paired with a strong maturity mismatch. On the other hand, under interest rate increases there would be improvements in profitability, but such higher interest rates could pose risks to the debt servicing capacity of highly indebted agents, which could negatively impact growth.

In the literature, the link between the financial structure of the economy and economic growth has also been studied. In particular, Gambacorta, Yang and Tsatsaronis (2014) and Law and Singh (2014) discuss how the determinants of the financial sector might affect economic growth. They conclude that there is a positive correlation between the size of the financial system and economic growth. However, there is a point of negative returns so that, beyond it, additional banking intermediation is associated with lower growth. Furthermore, a large and well-capitalised banking sector could support the real economy during economic downturns, especially if the crisis is exogenous to the financial system.

Chart 5.1 displays the correlation between the size of the banking sector and GDP growth volatility. In line with Gambacorta, Yang and Tsatsaronis (2014), there is higher output volatility among countries with smaller banking sectors. Chart 5.2 suggests a positive correlation between the CET1 ratio and GDP growth. One possible interpretation of this result is that favourable economic conditions could provide more room to the banking system to increase its resilience that could protect the economy during bad times.

7 Conclusions

This article puts forward a set of 20 indicators that could be relevant for regularly monitoring the Spanish banking sector's structural risks. In addition, a heatmap of these structural indicators is developed to compare the variables for Spain with those for the EU as a whole. The empirical evidence suggests that the Spanish banking sector shares most of its structural features with those of the EU economies.

However, some of the indicators for the Spanish banking sector depart from their normal range, both compared with our European peers and with their historical range. Yet the relatively high level of some indicators cannot be interpreted as posing a risk to financial stability. As a result, the analysis should be complemented with expert judgement. For instance, its relatively large banking sector (in terms of GDP) is mostly due to a high international presence, which increases exposure and vulnerability to foreign shocks and could negatively impact the domestic banking system. Further, Spanish banks' deposit deficit was one of the largest in the EU, but it has decreased sharply over the last decade. Next, the share of central bank funding, which has increased since 2012 and is above the EU median, is expected to decrease amid higher interest rates. Solvency and profitability are cross-cutting structural vulnerabilities that affect the whole European banking system. Finally, high public and foreign indebtedness make the economy more sensitive to the tightening of financing conditions that could have spill-over effects on the banking system as well.

From a policy perspective, the set of indicators and methods discussed in this article represent a helpful tool to analyse the existence of potential structural vulnerabilities in the Spanish banking sector, as well as to inform the activation of macroprudential instruments that could address structural systemic risks, such as the SyRB.

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DIGITAL RESILIENCE AND FINANCIAL STABILITY. THE QUEST FOR POLICY TOOLS IN THE FINANCIAL SECTOR

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Abstract

As a result of the sweeping transition to a digitalised financial system, digital resilience is a fundamental pillar of financial stability. Achieving digital resilience poses a broad range of regulatory challenges, to respond to the complex combination of risks, essentially consisting of cyber (in)security and the concentration of computer resources in the cloud. This article presents the guiding principles of the new regulatory logic needed in the microprudential and macroprudential fields, highlighting its special features and its relationship to the exceptional combination of risks at stake in the area of digital resilience. It also discusses the need for instrumental innovations, such as greater use of circuit breakers, the singular role of cooperation in cybersecurity regulation and the unique challenges raised by the regulatory perimeter of digital resilience.

Keywords: Operational resilience, cyber resilience, cyber security, cloud.

1 Introduction

Digital resilience ranks high in the set of concerns across industries worldwide. But the new breed of risks that accompany widespread digitalisation are particularly worrying in combination with others. The concerns are magnified when considering the tight connections between traditional financial risks in the financial sector and the dangers surrounding information and communication systems (ICTs) employed for provision of financial services. Cyber space, i.e. the software-based medium that drives the “intelligence” of the services provided is often singled out as particularly challenging. Some even conceive scenarios where cyber risks are the root of the next major financial crisis (Schuermann and Mee (2018)).

Dealing with cyber and ICT risks in the financial sector or, in short, risks to digital resilience, requires new tools and metrics adapted to the interaction effects arising and the singular features of some of the new risks. These tools should complement the already broad and growing range of policies mainly dealing with technology prerequisites for successful adaptation and with the microprudential objective of developing appropriate digital risk management practices within the context of broader operational resilience programmes (BCBS (2021)).[1] This paper thus examines

1 The Basel Committee on Banking Supervision (BCBS) is following a programme to develop a coherent framework to deal with risks to basic working processes. Under the umbrella of operational resilience, the programme covers traditional operational risk management, business continuity planning and testing, third-party dependency management, incident management and resilient cyber security and ICT (here captured as digital resilience).

the ongoing quest for tools and metrics to address the risks emerging at the interface between technology and financial risks from a macroprudential vantage point. The system-wide perspective suits both the broad-based interaction and correlation effects between technology and financial vulnerabilities taking place and the level of interconnectedness that prevails.

The paper highlights the comparatively singular nature of the macroprudential measures required to deal with the interaction effects between technology and financial fragilities. In turn, it argues that these peculiarities arise largely from some singular features of shocks to digital resilience. In particular, the paper argues that the deep uncertainty regarding the probability of and losses from cyber threats calls for a stronger role for circuit breakers as a tool to contain any induced impact on financial stability. Generalised circuit breakers are intended as "time-out" rules aimed at pausing the normal course of intermediaries' business in situations where cyber incidents may put financial stability at risk.

Another noteworthy macroprudential specificity in the context of cyber risks is the comparatively greater role of cooperative tools that strengthen the ability of the community as a whole to defend itself and to recover from attacks. Providing collective IT buffers and sharing of information are two examples of collaboration highlighted. Nonetheless, traditional macroprudential instruments that limit the build-up of systemic risks in the first place like systemic risk buffers are also argued to potentially play a role provided that sound metrics have been developed for the problem.

The technological interconnectedness brought about by the new computing environments employed in the provision of digitised financial services links micro- and macro-oriented policies in singular ways. The adoption of the cloud, as the computing environment of choice by intermediaries, and the critical role played by a limited set of cloud service providers (CSPs) both elevates the systemic relevance of microprudential ICT policies and endows macroprudential ones with connotations of market structure regulation. The need to ensure a system-wide functionality that exhibits fault tolerance to individual breakdowns in a concentrated market inevitably links the micro and macro concerns in a way that blurs the ordinary limits of regulation.

The paper is organised as follows. Section 2 initially sets the scene by presenting relevant definitions and a discussion of the general nature of cyber and ICT risks, as a prelude to a discussion of the interaction between financial stability and digital resilience. Section 3, frames the various sorts policy measures (framework, micro- and macro-prudential) for dealing with digital resilience in the financial sector and examines the adequacy of traditional macroprudential tools. Then, section 4 elaborates on the need for singular macroprudential tools like circuit-breakers, collective IT buffers and rules on structure. The paper concludes by emphasising some of the challenges still besetting the quest for tools and, most notably, measurement and standardisation.

2 Digital resilience: the relevance and peculiarities of cyber and ICT risks

The importance of digital resilience is a natural outcome of the advance of digitalisation (World Economic Forum (2022)) and of two of its associated challenges, cyber and ICT risks. Cyber risk refers, broadly speaking, to the absence of cyber security in the conduct of digital operations, i.e. to risks to the confidentiality, integrity and availability of information and/or information systems (the basic triad of cyber security or “CIA”) due to a cyber attack. ICT risk refers to ICT-related operational disruptions that may also put the CIA triad at risk for reasons (mostly engineering ones) unrelated to attacks.

The frequency, diversity and magnitude of some cyber incidents have led to the current situation being likened to a pandemic (Accenture (2022)). Despite the difficulties in measuring the problem, the overall phenomenology is well known in terms of scope and drivers. Both public and private, financial and non-financial entities are targets for cyber attacks by both state and non-state actors. Cases of attacks to sovereigns, health institutions, critical infrastructures abound, as revealed by existing trackers (see CSIS (2022)). Cyber incidents have kept on growing across geographical areas (see Chart 1.1) and have adapted their methods based on the pursuit of exploitive, disruptive or mixed effects (see Chart 1.2, based on the taxonomy proposed by Harry and Gallagher (2022)). Breaches compromise some or all the components of the CIA triad (see Chart 2.1). The US Congress “Solarium” report has declared that “the country is at risk, not only from a catastrophic cyber attack, but from millions of daily intrusions disrupting everything from financial transactions to the (…) electoral system” (King and Gallagher (2020)). The diversity of cyber risks is also broad as regards the business models (targeted and profit driven, attacks-as-a-service, ransomware driven, destruction driven…), the nature of the threat actions involved in the attacks (malware, hacking, social…), the attack vectors (supply chain, mobile connectivity, web services…).[2] The assets compromised exhibit a relatively stable composition over time, with incidents impacting online (servers) more intensively, followed by user and networking devices.

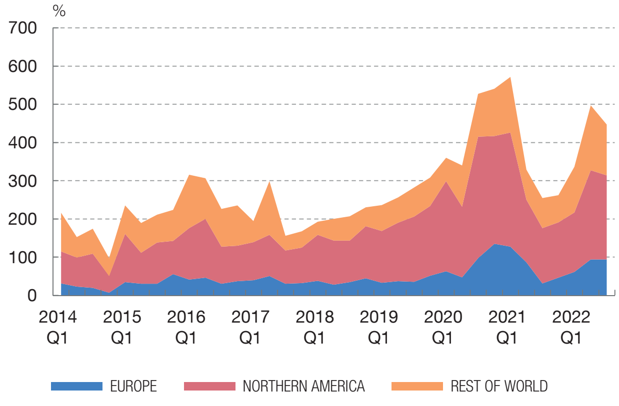
The basic distinction between cyber and ICT risks, based on the degree of intent behind their crystallization, does not imply that they are entirely independent. In addition to compromising the availability of computing resources or data, the widespread adoption of cloud computing makes this an environment that is particularly sensitive to risks, because of the concentration and interconnectedness that their scale-based business model entails.

2 The term “actions” refers to how the security incident or breach plays out. In turn, “attack vector” refers to a path that a hacker takes to exploit cybersecurity vulnerabilities. Digitalisation leads to an unavoidable expansion of the attack surface, i.e. the number of the attack vectors.

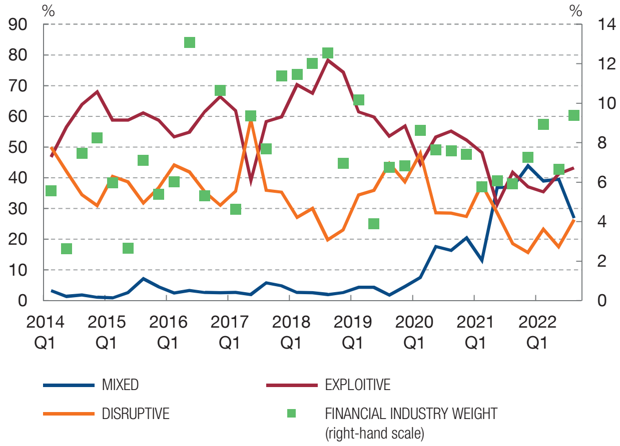
Chart 1

CYBER ATTACKS: INTENSITY AND MODALITIES

1 NUMBER OF PUBLICLY REPORTED CYBER ATTACKS ON A QUARTERLY BASIS (a)



2 DYNAMICS OF CYBER ATTACK MODALITIES ACROSS INDUSTRIES AND RELATIVE VULNERABILITY OF THE FINANCIAL SECTOR (b)



SOURCE: CISSM Cyber Events Database (University of Maryland).

a Number of breaches per quarter across geographical areas and time. See CISS (2022) and Harry and Gallagher (2022).
b Weight of exploitive, disruptive and mixed breaches in the quarterly total. See CISS (2022) and Harry and Gallagher (2022). Rhs: weight of breaches in the financial sector over the total number across sectors. A modality of attack with mixed effects can be "ransomware", the dynamics of which lately conform to those of an epidemic.

2.1 What is special about cyber shocks

The main distinctive feature of cyber shocks is the logic of intent that guides their occurrence, timing and magnitude. Their life-cycle and impact are thus crucially influenced by the original intent of the attack and its potential mutation if it is not neutralised. The traditional diffusion-based model of shock propagation, characteristic of credit and market risk models, fails to grasp the sense of purpose, intent and ingenuity that drives cyber attacks. In fact, one of the conceptual methods that is useful for quantitatively scoring the severity of cyber threats gauges the presence of such attributes (Talon (2022)).

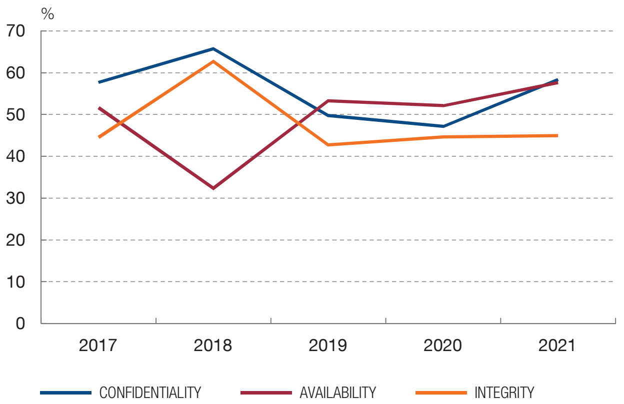
The evolution of cyber attacks may thus include special features like “smart” latency, contagion through “directed percolation”[3] and reactions to any response and/or deterrence by the victims. “Smart” latency refers to the lapse of time between system breaches and their identification, materialisation or neutralisation of economic consequences based on the attackers’ strategic calculations. Latency can achieve outstanding levels as illustrated by the endemic character attributed to some threats such as those to Log4j declared endemic despite the availability of patches (CSRB (2022)). NotPetya, one of the most damaging attacks ever recorded, is argued to have been present for several weeks in the targeted hardware. Chart 2.2 illustrates non-

3 Percolation theory describes the behaviour of clustered components in random networks.

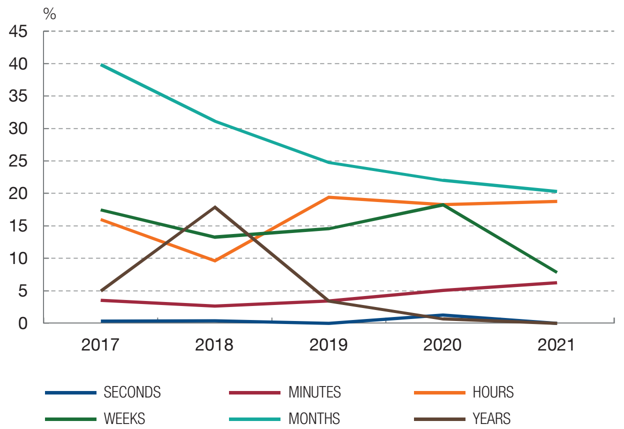
Chart 2

CYBER ATTACKS: COMPROMISED VALUES AND TIME LAG TO DISCOVERY

1 SECURITY BREACHES. BREAKDOWN BASED ON THE CIA TRIAD ACROSS TIME (a)



2 DISTRIBUTION OF TIME LAG TO BREACH DISCOVERY ACROSS YEARS (b)



SOURCE: *2022 Verizon Data Breach Investigation Report.*

a Weight of Confidentiality, Availability and Integrity breaches based on Verizon (2022).
b Percentage of breaches whose discovery takes place with various lags after occurrence. See Verizon (2022).

negligible time required to discover some breaches (Verizon (2022)). The term "percolation" describes the special process of cyber risk propagation: cyber threats are directed by attackers to transit through weak spots both within and across borders of institutions. Importantly, the percolation process exhibits an intrinsic asymmetry between defenders and attackers. The latter just need to trespass controls once to succeed in their mission. Response to and deterrence of cyber shocks shape the defensive capability to combat cyber shocks, a feature much less common in other types of shocks that also proves to be relevant to shape singularities.

The described atypical profile of cyber shocks shapes many of the challenges that explain the evolution of policies, mitigation and defence practices across sectors as well as the continuing lack of appropriate data. This evolution started with the growth of the cybersecurity industry when the first "worms" embedded in code written in the 1980s threatened early information technology users, both individual and corporate. The development of a private industry to protect IT resources has subsequently evolved in parallel to military solutions to also keep in check attacks and, in the opposite direction, to the development of a full-fledged business model for extortion and destruction even on a state-sponsored basis (Brooks (2022)). But the need to invest in private solutions to gain protection against the complexity of attacks has arguably faced the specific challenges posed by the market for security technology (Dixon (2020)). In this view, the complexity of cyber risks and cyber security would determine an information asymmetry between buyers and vendors that leads to a market breakdown (Akerlof effect) in the absence of standards and certification. Microeconomic policies that establish horizontal frameworks for the proper functioning of security technology markets are thus instrumental for overcoming uncertainty and industry fragmentation (ECS (2021)).

Broad-based information security policies are instrumental for recognising and addressing cyber threats both as an individual and as an overall concern. In particular, they prove instrumental in overcoming the reluctance of victims to disclose information on incidents, to increase awareness and to measure the impact of breaches (Kopp, Kaffenberger and Wilson (2017)). The phenomenological characterisation of threats and impact provided by various vendors (inter alia Verizon (2022) and IBM (2022)) has helped to raise awareness although this still falls short of satisfying the need for more ambitious policy goals like those of macroprudential policies in the financial sector. Standardisation, measurement and harm quantification beyond just counting events still remain a fundamental weakness in cyber security.

The study of the transmission of cyber risks also requires new modelling approaches that could inform adapted policy approaches. Thus, the dynamics of cyber threats within a population has been found to match features of both epidemiological (Schrom et al (2021)) and securitisation market models of risk transmission (Atlantic Council (2014)). The epidemiological view of cyber risks as contagion through the exchange of code emphasises the role of collective defence and recovery whereas the securitization market analogy stresses the value of cyber design principles for security, like "zero trust" operations and transparent reporting, as a way to contain the percolation of threats. To some extent, novel policy measures against cyber risks borrow *mutatis mutandis* from similar institutions in the epidemiological and securitisation spheres. The responsibility assigned to victims in some jurisdictions to report any incident promptly to their direct partners in the supply value chain, parallels *(mutatis mutandis)* the risk retention philosophy engineered as a solution to the broad-based distribution of embedded risks characteristic of originate-to-distribute securitisation markets.

2.2 ICT and cyber risks in the financial sector

2.2.1 Digitalisation "on steroids"

Digital resilience has acquired enhanced relevance in the financial sector. The intense digitalisation of the sector together with the criticality of its services and the interconnections prevailing reinforce the concerns raised by both cyber risks and ICT outages. The accumulation of wealth managed by financial intermediaries and the general expectations that they have an unrestrained ability to offer transaction services and to preserve their vast holdings of confidential information makes of them an attractive value proposition for attackers[4] and particularly sensitive to ICT breakdowns.

4 In a nutshell, the special relevance of cyber risk for the financial sector follows the same logic as the dictum "bank robbers rob banks 'because that is where the money is'".

The frequency, diversity and magnitude of the cyber incidents in the financial sector confirms the relevance of the problem despite its moderate weight in the overall picture of attacks across sectors (see Chart 1.2). The notable efforts to quantitatively track attacks to the financial and other sectors still have to rely on publicly reported evidence based on anecdotal evidence. The Carnegie Endowment for International Peace (CEIP) compiles a tracker of publicly disclosed cyber attacks that illustrates their worldwide breadth and the moving targets (see (CEIP (2022)). The CISSM Cyber Events Database (see CISSM (2022)) attempts to lay the basis for a systematic approach to capture the effect of cyber attacks.

But expressions of concern from the industry confirm the severity of an issue where we just capture the “tip of the iceberg”. The Norwegian Investment Fund puts cyber risk ahead of market risks in its list of concerns after experiencing, on average, 100,000 attacks a year, of which 1% are serious. In the field of regulators, the FCA notes a 52% increase in reports of “material” cybersecurity incidents in 2021 and expects the uptrend to continue. The public resonance of the assets compromised in some prominent cases has further raised public awareness. Significant examples of confidentiality breaches include the Target Corp. and Equifax.[5] The theft of funds in the central bank of Bangladesh epitomises the criminal high-end attack to a financial institution in an international context (Popowicz (2022)). The US also registered a massive denial of service attack and campaigns against financial messaging systems attributed respectively to Iran and North Korea.

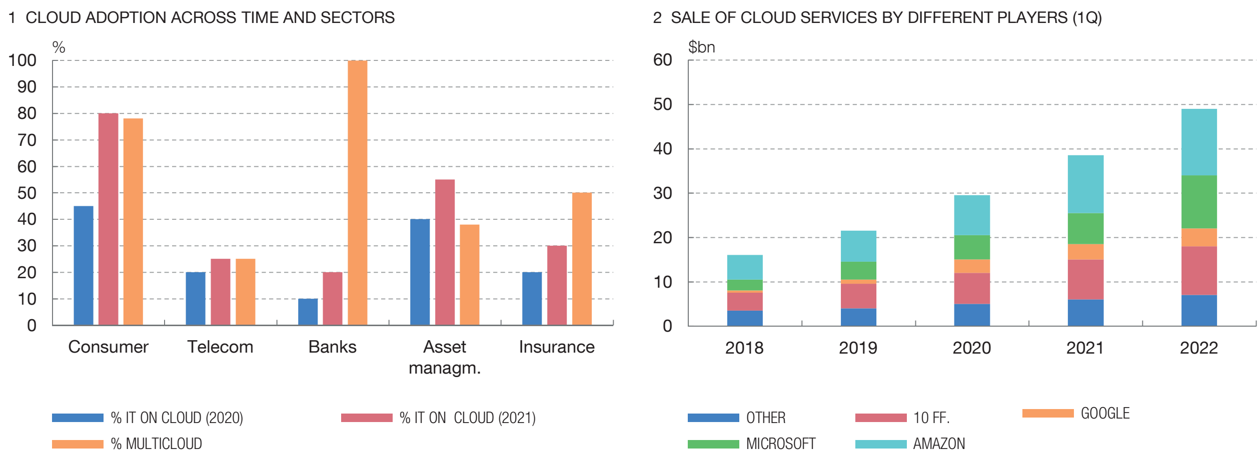
Data availability problems specifically hinder a robust estimation of financial losses due to cyber risks and impede the advancement of the cyber insurance industry. Bouveret (2018) delves into the problems while modelling aggregate losses based on a mix of actuarial and operational risk concepts. The results, based on a mix of proprietary data on losses from a consortium of banks (ORX) and on frequency of cyber attacks from a different provider, illustrates the potential for significant losses (close to 9 percent of banks’ net income globally) but exclude large-scale events. However, both the methodology and the bias of the data on losses towards smaller losses (see Aldasoro et al. (2020)) limit the significance of the quantitative estimates provided, although the thrust of the analysis remains valid.

ICT-related risks have also gained prominence in the financial sector as a result of the widespread adoption of cloud computing. Cloud computing is an ICT infrastructure model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort of service provider interaction (NIST (2011)). In a nutshell, cloud computing attempts to scale up to an external context the

5 In the Target Corp case, 41 million customers’ payment card accounts were breached by criminals using the credentials of 61 million Target customers that were stolen from a third-party vendor. The Equifax case sparked momentum in policy by engaging the US Senate, the CFPB and the NYDFS. 143 million US consumers had been compromised by criminals exploiting a US website application vulnerability.

Chart 3

CLOUD SERVICES: INCREASING ADOPTION AND CONCENTRATION



SOURCE: Moody's Survey and Synergy Research Group.

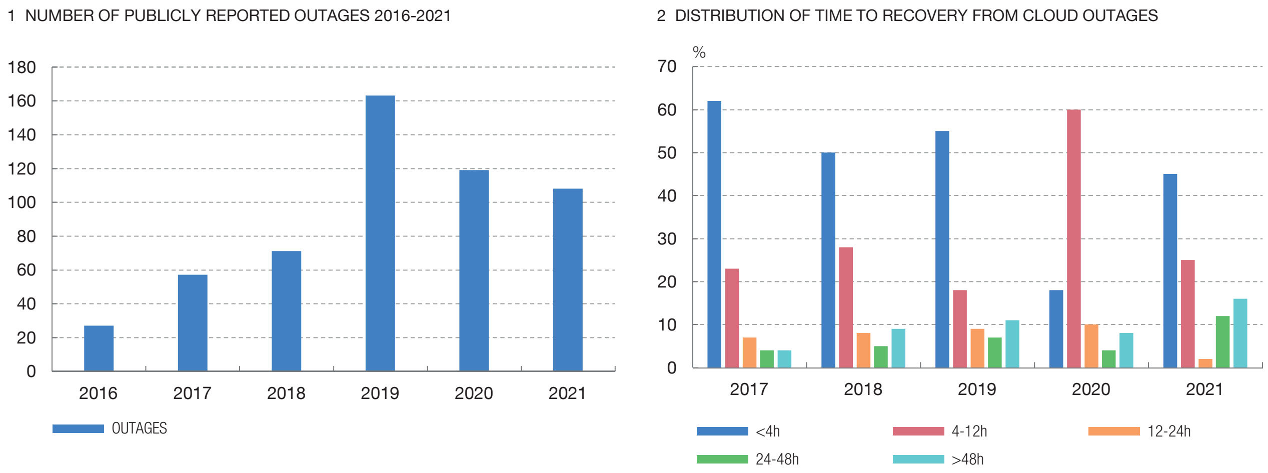
benefits of sharing software and servers among users, thus leading to advantages like flexibility and reduction of operating costs (CAPCO (2021)). The adoption figures in the financial sector are telling (see Chart 3.1). Data compiled by (McKinsey (2021)) show that by 2024 the average company aspires to have cloud spend represent 80 percent of its total IT-hosting budget.

Cloud computing happens to crucially condition the digital resilience of financial companies on several grounds. The concentration in the market for the provision of cloud services play a prominent role in most cases (see Chart 3.2). The market power and lock-in effects that accrue to the benefit of large third-party service providers (hyper-scalers) create an asymmetry in customers' negotiating power which could impair the ability to enforce service-level agreements that limit availability risks at reasonable costs. Choices regarding risks retained in various dimensions (service modality, control framework[6], handling of critical data[7] or handling of critical functions) can be decisive. But the basic problem of concentration through physical scaling can

6 The service modality and the control framework refer to the involvement of customers in the exploitation of the stack (SaaS, PaaS, IaaS) and to their control rights (public, private, hybrid) over the computing facility, respectively. In SaaS (software as a service) providers' applications run on cloud infrastructure and are accessible from various client devices through web/API interfaces. The consumer neither manages nor controls the underlying cloud infrastructure including network, servers, etc. In IaaS (infrastructure as a service), there is a provision of computer processing, storage, networks, and other fundamental computing resources for the consumer to deploy and run arbitrary software, including operating systems as well as applications. The consumer neither manages nor controls the underlying cloud infrastructure but has control over operating systems, storage, and deployed applications, and possibly some control of select networking components. PaaS (platform as a service) provides ability to deploy consumer-created applications created using programming languages, libraries, services, and tools. The consumer neither manages nor controls the underlying cloud infrastructure including network, servers, etc. operating systems, or storage but has control over the deployed applications.

7 The "location" of data influences jurisdictional powers and responsibilities arising from the CIA triad.

Chart 4
CLOUD OUTAGES: NUMBER AND TIME TO RECOVERY



SOURCE: *Uptime Intelligence 2022 Outages Report.*

also crucially affect the engineering risks of the service (density of servers, power security, cooling and site construction features). Cloud adoption transfers some but not all of organizations' cyber risk since the strong security capabilities of cloud service providers must also be matched by adequate controls by providers and customers.

The advance of cloud storage and computing thus entails a comingling of ICT and cybersecurity risks with potential systemic impact. In fact, the contribution to this outcome from the mix of physical and cyber risks described in the previous paragraph has to be supplemented by that made by the complexification of the cloud market (Rogers (2022)). The recourse to multi-cloud and virtualisation techniques to mitigate the risks stemming from physical concentration and consolidate computing sites in different availability zones, leads to new risks due to an uncoordinated control of distributed computing processes. To some extent, this complexification is driven by a demand of multi-cloud multi-service choices. In a nutshell, the satisfaction of economic, functional and regulatory requirements has led to complex "cloud computing menus" that accommodate the various combinations of computing elasticity requirements and management capacity through different service modalities and control frameworks (see footnote 6).

The overall combined picture regarding digital resilience (ICT + cyber + complexification) is not entirely reassuring either in terms of clarity or risks. The increasing recourse to audits and ratings to build a picture of digital resilience in the financial sector still lacks an integrated view. But the most accurately measured component of the incidence of ICT risks (physical outages) does not provide entirely reassuring signals. Chart 4.1 drawn from a cloud services audit firm (Uptime Institute (2022)) shows the non-negligible number of publicly recorded outages, to the point that 80% of cloud customers have experienced an outage in the past three years, with about one in five of those surveyed experiencing severe outage during the same timeframe. Significantly, the frequency and/or duration of outages might be increasing due to climate-change and energy cost reasons, inter alia (see Chart 4.2 for evidence regarding duration provided by UptimeInstitute). The lack of statistical robustness for the existing evidence does not diminish the importance of the concerns that raise the prospect of an increasingly fragile cloud industry when its use is pervasive.

2.2.2 Interplay between cyber risks and financial stability

The confluence of fragilities in digital and financial spaces heightens the significance of the former for financial sector companies. Shocks to the CIA cyber triad can trigger financial sector fragilities that largely pivot around liquidity, leverage and trust. Table 1 depicts an analytical representation of linkages between digital resilience and financial stability risks in order to guide the following discussion. Conceptually, the depicted links may operate causal effects both from the left side – i.e. technology shocks leading to the crystallisation of financial risks – and from the right, i.e. financial features inducing technological vulnerabilities. However, this paper takes the view that the former are more relevant than the latter, although section 3.2 highlights a model that stresses a role for the reverse link.

Systemic risks can unfold in this hybrid setting under a broad range of scenarios. This is essentially due to the fact that contagion effects can work now at various layers operating both in parallel and through cross-interaction. At the digital layer, digital interdependencies resulting from cyber and/or ICT connections can spread out broadly at very high speeds at the same time as they activate regular contagion channels in the financial sector. But this broader range of routes to systemic risk also exhibits a varied propensity to result in extreme effects. This diversity is largely accounted for by, for example, the lower severity of shocks to C (i.e, to data confidentiality) in comparison to shocks to I (i.e. data integrity) or to A (i.e. availability of data and systems to operate financial services). Systemic risks thus need to be qualified and not just measured.

The operation of non-linear effects further limits the chances of coming to straightforward conclusions as regards the likelihood of major events. For example, broad-based risks to data confidentiality could still damage confidence and deter the adoption of efficient financial servicing channels, causing real losses for society as a whole that exceed the outright costs of data leakages. But for this to happen, an appropriate chain of behavioural reactions among agents must take place. Although of limited use so far, agent-based models provide a general toolkit to model the endogenous reactions to attack/failure that translate various CIA shocks into liquidity and/or market value perturbations of affected intermediaries. Harmon et al. (2020) adopt this modelling framework to analyse concentration risks in the cloud. Cyber and ICT stress tests can ideally thus be grounded on micro foundations.

Table 1

INTERACTING VULNERABILITIES AND POLICIES AT THE JUNCTURE BETWEEN TECHNOLOGY AND FINANCE

The table represents two pillars of variables (technology and purely financial ones) shaping the performance and vulnerabilities of financial services. The variables in each pillar influence financial stability through their impact on vulnerabilities and amplification mechanisms of various shocks. The table intends to highlight the interaction effects between the technology and financial pillars that justify the adoption of hybrid measures, including macroprudential ones when the regular conditions of interconnection and substitutability warrant it.

	TECHNOLOGY			FINANCIAL		
	Policy	Operational	Fragility	Vulnerability	Behavioural	Policy
AMPLIFIERS	Fragmented regulation	Miopia	Complexity (supply)	Leverage	Herd behaviour	Regulatory Arbitrage
AMPLIFIERS	Geopolitical confrontation	Free riding	Interconnec-tedness	Liquidity Transformation	Miopia	Market Value Accounting
AMPLIFIERS	Incomplete reg. perimeter	Complexity (demand)	Attack surface	Points of Failure	Variation Margin	Regulatory Fragmentation
AMPLIFIERS	Insufficient standarisation		Cloud consolidation			
DAMPENERS	Intl. Law	Cyber Governance	Encryption	Risk limits	Arbitrage	CCyRW
DAMPENERS	Government umbrella	Cyber Ratings	Tokenisation	Capital requirements	Initial Margin	Deposit Insurance
DAMPENERS	Regulatory Harmonisation	Cyber Frameworks	Cloud	Disclosure		Activity Restrictions
DAMPENERS	National registers	Cooperation	IT Standards	Circuit Breakers		Liquidity Requirements
DAMPENERS			AI	Government Support		Third Party Sector Providers

SOURCE: Own adaptation from Healey et al. (2021).

The need for agent-based models to grasp the routes to systemic instability is illustrated by the unusual outcomes taking place in shocks at the interface between the technology and financial spheres. For example, a severe cyber shock may incentivise bank creditors to run on their bank but at the same time it may disable its capacity to physically service the claims made by the customers. But such apparent neutralisation of contagion from the technology realm to the financial realm is on closer inspection only a mirage. A more granular perspective on the options available to the customers (e.g. joining the "digital queue" of bank runners, raiding other banks' operating services in anticipation of their ulterior paralysis or runs on other banks…) shows that the disruption of the supply chain caused by the cyber attack only hides the routes of contagion from the surface.

The non-linear risks associated with supply chain disruptions in the financial sector have been dealt extensively in the past in the policy space in the context of services provided by critical infrastructures. But the widespread transformation process of financial institutions adapting to the digital reality and deeper interconnections has heightened the need to deal with supply chain disruptions of regular intermediaries consistently across the financial system. The increased interconnectivity of processes resulting from cloud computing, networking and shared software vulnerabilities brings to the forefront a distributed sense of critical arrangements in the financial system as a whole. In other words, to avoid destabilising general gridlocks in some financial functions, the reliability of individual intermediaries does not have to be absolute, but sufficient to ensure that, jointly with a quick capacity to recover from shocks, those important financial system functions do not break down. The typification of ICT processes based on their relevance for financial sector functions and the operation of intermediaries under strict reliability tolerances thus becomes a must to statistically limit knock-on effects from cyber and ICT shocks.

Widespread loss of confidence is a direct avenue linking bank fragilities and cyber-ICT shocks. The provision of liquidity services based on demand-deposit contracts is well known to be susceptible to runs driven either by panic (Diamond and Dybvig (1983)) or by fundamentals (Goldstein and Pauzner (2005)). Analysis conducted by (Duffie and Younger (2019)) and by (Koo et al. (2022)) on the ability of liquidity buffers built up under existing general regulations such as the Liquidity Coverage Ratio (LCR) and/or the current monetary policy stance to serve as a backstop has not yet sounded the alarm. But the lack of signals may be misleading due to a combination of factors, especially the ample liquidity in the banking system in the sample dates of both studies. The deposit runoff rates contained in the LCR regulations certainly provide benchmarks for assessing, based on reverse stress tests, the first-order capacity of liquidity buffers to cover outflows due to cyber shocks. More importantly, a realistic analysis of confidence shocks needs to factor in the strategic behaviour of agents.[8]

3 Policy and instruments

The importance of digital resilience warrants intense work by regulators and supervisors on both the technology and the financial side of the problem. This section provides an overview of regulatory initiatives in various dimensions. More specifically, section 3.1 briefly describes the evolving fragmentary landscape of micro-oriented rules, while section 3.2 provides the setting for macroprudential rules.

3.1 Framework and micro-oriented tools

Micro-oriented tools refer here to measures devised with individual institutions' digital “health” in mind and often arising in the context of broader operational and due diligence guidance. In turn, framework policies provide basic specifications regarding network and system operations that underpin implementations conducive to digital health. The recent accumulation of risks to digital resilience have generally

8 Eisenbach et al. (2022) make this point in the context of a shock to the operation of the Fedwire system.

led to a swift overhaul of framework rules in the US and the EU, at the same time as specific sectoral policies in the financial sector have been strengthened to deal with the relevance of digital resilience for banks. In the international context, the G7, the FSB, the Basel Committee and CPMI-IOSCO have prepared the ground by developing action principles in the quest for digital resilience[9].

Some recent landmarks of this process in Europe are the adoption of a review of rules on the security of network and information systems like NISD 2 (see EP (2022)), almost simultaneously with the agreement on the Digital Operational Resilience Act (DORA). The ECB was the front-runner in the rule-making process, with detailed guidance of cyber resilience oversight expectations for financial market infrastructures (see ECB (2018)), while the European Banking Authority has provided guidelines on ICT risk assessment (EBA (2019)), that feeds into the Supervisory Review and Evaluation process envisaged in the capital requirements Directive.[10]

The presence and mechanisms of the interaction effects between the technology and financial vulnerabilities besetting the financial sector are captured in Table 1, which represents two pillars of technology and financial variables (policies, behavioural features and vulnerabilities) that drive both the performance and vulnerabilities of financial services. The variables in each pillar influence financial stability through their impact on vulnerabilities and amplification mechanisms of various shocks. The table highlights, in particular, the potential contribution of technology policies to improve financial stability as well as the potential role of aggregate-based financial policies (inter alia macroprudential policies) aimed at feeding back in terms of a less fragile technology setup. Policy rules could thus dampen, in a hybrid fashion, the dynamics of vulnerabilities and behavioural features.

The range of relevant policy measures at horizontal level is very broad. It certainly exceeds the number of rows in Table 1 and the object of this article. Nonetheless, it helps to illustrate the plurality of rule types and even of authorities involved. Specifically, in the networks domain, the International Telecommunications Union (ITU) highlights due diligence measures and norms covering technical issues, organizational aspects, capacity-building, cooperation and legal backing that feed into comparative indexes of base country cyber resilience.[11] Unsurprisingly, such a broad landscape of cyber security frameworks and ICT rules is beset by complexity and intrinsically creates a need to provide arrangements to deal with it. Thus, the build-up of a first line of defence around technology requires certification and standardisation of solutions. Their take-up by firms requires a mix of market mechanisms and cyber hygiene regulations to build a kind of public-private partnership. In the process, the number of “framework” authorities involved increases and the coordination needs to respond

9 See G7 (2016); BCBS (2021); CPMI-IOSCO (2016).

10 See ECB (2018); EBA (2017). Calliess, C. and A. Baumgarten (2020) review the overall legislative process in Europe.

11 See ITU (2020).

swiftly to this. Computer Security Incident Response Teams (CSIRTs) and security operation centres (SOCs) are core pieces in these arrangements. Some jurisdictions have attempted to facilitate coordination with the consolidation of the multiple agencies involved within national cybersecurity centres.

Against this complex horizontal background, financial regulators and supervisors have separately strengthened their involvement in the of digital resilience policy process based on their privileged access to boards and overseers of risk management governance. The thrust of the new emerging rules applicable to cyber risks in the financial sector have thus been crafted in many respects as sector-specific rules. Nonetheless, their scope is moving beyond just due diligence considerations that target the survival of individual intermediaries to failures of entire critical functions. The new emerging regulatory notion of operational resilience encapsulates a forward-looking and functionally oriented goal to ensure fault tolerance, as opposed to the backward-looking and bag-of-risks philosophy characteristic of traditional operational risk regulations (see Peihani (2022) and Crisanto and Prenio (2017)). This new principles-based approach is facilitating the adaptation of the precise sense of rules to a complex and dynamic environment, although its commitment-based approach limits its further application from a system-wide perspective of risk. The specification of targets for key ultimate operational performance metrics (e.g. time to recovery of normal functioning) can serve the survival of individual intermediaries but be less useful from a systemic risk perspective (Prenio and Restoy (2022)).

The assurance of individual resilience has thus acquired a supervisory flavour that reflects difficulties in measuring, integrating and comparing metrics of internal performance (Venables (2022)). Against this backdrop, penetration stress testing (i.e. red team testing[12] or controlled cyber attack “simulation” like TIBER-EU) has become the most robust tool to make end-to-end security audits and supervisory assessments (Gaidosch et al. (2019)). The use of breach and attack simulation exercises has even become a commercial service for companies to remain alert on a continuous basis. Holistic rating-like tools that assess and integrate the potential for internal network risks, employee-generated risks, social engineering attacks, cloud-based attacks or third-party threats also inform the assessments.

However, cybersecurity rules aimed at individual institutions cannot avoid also pursuing the common good. Incident reporting and information sharing rules have long been deemed to be crucial to build a common defence, to the point that each EU authority concerned had its own policy (EBF (2020)). Against this backdrop, already touching upon macroprudential issues, one of the first initiatives of the European Systemic Risk Board (ESRB) in the cyber security space has been the recommendation for the establishment of a pan-European systemic cyberincident coordination framework (see ESRB (2022b)).

12 The mechanics of red team testing is described in Prenio et al. (2021).

In the EU, DORA has introduced important new orientation and harmonisation in the regulation of digital operational resilience in the EU. In particular, the sectoral contours of regulation and supervision have been pierced by the recognition and treatment of critical third-party service providers and any future guidance from supervisors on digital resilience has been strengthened with legal provisions to the effect. Thus, in addition to provisions that specify conditions formulated as *lex specialis* on cyberincident reporting and information-sharing, DORA also contains rules to strengthen the ability to deal with ICT third-party risks encountered in cloud business models. The attribution of audit rights over cloud service providers (CSPs), the strengthening of negotiating powers for service-level agreements (SLAs) with CSPs or the threat-based penetration testing of critical entities also belong to the new ample package of tools included in DORA.

3.2 Macroprudential tools

The increasing abundance of micro-focused rules for digital resilience, as outlined in section 3.1, has started to address systemic risk indirectly, through guidelines that affect critical players, like some big tech CSPs. But a robust working of the system as a whole also requires macroprudential policies addressing the externalities and interconnections arising in a fragile financial system that interacts with a brittle digital sphere.

This section elaborates on the need for tools to fight system-wide instabilities caused by the interaction of vulnerabilities on two fronts: digital and financial. The discussion on this topic in the following part of the paper must be qualified by three general observations. First, the tools considered should help prevent crisis but do not cover the deployment of crisis management tools to redress the effect of operational resilience breakdowns. Still, the preservation of incentives to manage digital resilience should remain a constraint when granting liquidity assistance in operational breakdowns, as discussed for the Bank of New York case by (Ennis and Price (2015)). Second, the nature of the macroprudential tools may vary according to the nature of shocks to digital resilience, i.e. cyber shocks and ICT shocks. Third, the suitability of regular macroprudential tools may be limited whilst new singular tools like circuit breakers, cooperative arrangements and structural measures acquire more prominence.

3.2.1 Main externalities at stake

External effects among a set of agents refers to the non-internalised and mostly indirect economic interconnections that may facilitate the propagation of shocks. They provide the basic mechanism that can lead to the transformation of more or less localised shocks into widespread systemic disruptions. The following analytical list of external effects highlights relevant behavioural mechanisms potentially conducive to spreading of risks on the digital-financial fronts:

a) The cyber free rider problem

System-wide cyber security is a public good whose “production” depends not only on public but also on sufficiently widespread private initiatives. In fact, the maximum level of ex-ante security achievable by the community as a whole depends on the efforts made by the weakest member of the community. An imperfect substitute for the ex-ante protection granted by the recourse to cyber defence is a resilience strategy targeting just expost business continuity. But the cost undertaken to build such a strategy in terms of redundancy of resources and recovery capabilities only delivers a private good.

Anand, Duley and Gai (2022) analyse the economics of cyber contagion in a setting where a budgetary restriction on the side of intermediaries gives rise to a trade-off between the public and the private good versions of cybersecurity investment. Furthermore, they assume that the size of cyber investments by banks may also be influenced by the magnitude of their financial (rollover) risks through a relaxation-based (lower rollover risk would lower investment in cyber security) channel that might even dominate free-riding on cyber security when the liquidity risks are high.

The regulatory implications of the model are as follows. The model establishes a direct link between bank liquidity rules and investment in cyber security that creates a trade-off between the liquidity coverage ratio (LCR) and cybersecurity investment. But in the presence of heterogeneity only liquidity requirements customised to the cybersecurity profile of individual banks can be efficient. Alternatively, where free-riding prevails, regulators could achieve the efficient outcome by the imposition of appropriate duty of care penalties. Implicitly, constraining the investment in private-good resilience (pure redundancy) to a low level is also argued to lead to efficiency in the presence of closely monitored cyberhygiene guidelines or stress tests that increase incentives to invest.

b) Cyber epidemics and confidence breakdowns

Public opinion is a subtle medium as regards its role in shaping situations of systemic risk. Users of financial services can too easily experience confidence breakdowns when cyber attacks exceed thresholds of tolerance, especially if exacerbated by a state of public opinion alarm. Wolff and Demtzis (2019) depict a hypothetical but not unrealistic case of a hybrid cyber event where pure technology events and manipulation of public opinion could unleash systemic effects.

c) Short-sighted view of risks and/or uncoordinated response to cyber shocks

The feasibility of a continuum of cyberrisk/financial risk scenarios, ranging from scattered effects to major confidence breakdowns, broadens the spectrum of analytical and policy tools required. ESRB (2022 and 2022a) opt for testing the cyber resilience of the financial system through scenario analysis to ascertain how systemic institutions in the financial system would respond to and recover from a severe but plausible cyberincident scenario. Agent-based models can provide a methodological platform to improve these techniques based on desktop analysis.

Furthermore, the ability to undertake coordinated defence or even deterrence is a distinctive feature of cyber shocks. But a basic precondition for these strategies to succeed is the readiness to share information about the risks and attacks. However, reputational costs incurred in the process of information revelation or a lack of coordination between stakeholders can limit success in the defence of the common good. ESRB (2022) explains the vision of the EU macroprudential authority on how an incident coordination framework would facilitate an effective response to a major cyber incident.

d) Cloud contagion

The increasing reliance on a limited number of CSPs may bring about concentration risks for both individual intermediaries and for the financial sector as a whole. Two broad mechanisms underlying the magnification of IT risks in the cloud are correlated and cascading failures of servers. The achievement of tolerance to individual server faults has advanced based on increasing levels of redundancy and load balancing across servers (see Scott et al (2021)).

Correlation risks arise due to common factors that can eventually render redundancy useless. Segmentation of redundant servers across so-called availability zones can mitigate the risk to infrastructure features like power, cooling and network. But clouds still have an important non-infrastructure common driver: software. A oftware bug or attack can lead to correlated server failures in a distributed system. Common dependencies like DNS services are also a critical vector of attack. The isolation of workloads in individual servers may contain the direct risk of contagion and breakdown. But correlation risk through cascading failures may also create problems, i.e. computing underperformance resulting from the accumulation of backlogs of processing work across servers and delays.

Regardless of the channels through which correlation risk arises, the assessment of its likelihood and consequences in the financial sector requires active involvement of financial authorities to keep systemic risk under check (Prenio and

Restoy (2022)). The calibration of reset times after failures is a single operational resilience parameter relevant not only at the individual services provider level but also for the financial system as a whole. For example, the chaining of payments implemented through cloud micro-services can be made robust to failures capped in their duration.

3.2.2 The traditional macroprudential toolkit and cyber risks

The application of a macroprudential perspective to the regulation of digital risks in financial services provision requires adaptations to the conventional framework. The general goal of setting a system-wide safety standard with a top-down perspective in such a way that spill-overs are somehow neutralised still applies. But traditional macroprudential tools (see Krishnamurti and Lee, 2014)) do not suit the nature of the externalities at stake.

Capital buffers sensitive to cyclical patterns in the line of countercyclical capital buffers or outright exposure limits to digital risk factors cannot be operationalised to contain the external effects at play. The inertial dynamics that enables the role of cyclical buffers to curb herding behaviour does not work when the main externality at stake is free-riding. In turn, the imposition of outright limits to digital risk factors, like the ones applied under so-called borrower-based measures, can be unduly blunt and intrusive.

Arguably, a cross-sectional perspective to the design of macroprudential tools might still be useful, provided that a consistent set of indicators was available to quantify system-wide cyberrisk factors jointly with individual losses. As happens with systemic risk buffers, the logic here would be to penalise at any point of time the individual allocations of cyberrisk contamination capabilities in a manner that discourages contagion and generation of tail risks. The nature of the analysis thus relies on some mapping of internal and external cyber interconnections and dependencies. But the practical feasibility of the approach seems far-fetched at present.

4 Macroprudential tools for a singular combination of risks

This section will argue that the special profile of shocks to digital resilience warrants new approaches to macroprudential policies. In particular, this section examines the role of circuit breakers to contain contagion, the inclination to cooperate in the pursuit of system-wide stability (including through the collective provision of IT buffers) and broadening the perimeter of financial regulation beyond the financial sector.

4.1 Circuit breakers

In regulatory jargon, circuit breakers refer to provisions restricting the validity of ordinary rules during limited periods of time. Circuit breakers have found widespread application in stock market trading settings but have been much less common in banking until the introduction of resolution regimes. The main reason for this is their general association with traumatic crisis in situations where traditional shocks can unleash bank runs. This was a hindrance identified by Ize et al. (2005), who discussed whether circuit breakers in banking, i.e. temporary, efficient, and pre-programmed suspension of the convertibility of deposits could help with the management of liquidity risks of highly dollarised banking systems.

The singular nature of some large-scale cyber incidents affecting banks might also justify the interruption of the ordinary course of business in order to contain confidence breakdowns and self-fulfilling runs. The activation of a special regime linked to a large-scale cyber attack would limit in an organised, transparent and predictable way the convertibility of deposits when the event entails loss of control over the assets and the timing of recovery remains clouded by uncertainty.

Cybersecurity circuit breakers would thus complement the tepid network of regulatory, supervisory, resolution and insurance institutions that currently underpin the fragility of demand deposits. In fact, cyber-oriented circuit breakers follow a similar rationale to moratoria in recovery and resolution, i.e. the need for a pause to gather evidence on the magnitude and persistence of the damage after serious attacks.

Indeed, servicing bank deposits in non-sequential ways that limit runs is not alien to either theory or practice. Goldstein and Pauzner (2005) study the way in which general settlement rules and intermediary commitment affect the probability of runs and welfare. Under discretion over suspension of convertibility, the sequential service emerges as the optimal outcome when liquidity needs are very valuable and the liquidity of assets backing the deposits is high. The regulatory choices faced under a run, i.e. pay, stay or delay have in fact already been recognised in the context of rules on redemption gates that may ration liquidity withdrawals from money market funds under stress.

Circuit-like breakers are not entirely alien to practice or law in some jurisdictions either. Authorities can call bank moratoria in conditions unrelated to resolution proceedings and mercantile contracting frameworks worldwide also envisage clauses to deal with situations beyond the control of the parties that affect the incentives to maintain the contract unaltered. In commerce, “force majeure” clauses supersede the ordinary course of business relationships under events whose effects cannot be reasonably anticipated or controlled. A party claiming “force majeure” would need to prove that their ability to meet the contract was “impaired” or made “impossible” due to one of the events agreed in the contract based upon the “force majeure” clause. Indeed, “force majeure” is not entirely alien to banks. For example, various trade finance model contracts issued by the International Chamber of Commerce contain such clauses adapted to and supporting the banking services at stake. Common to all these clauses is the fact that they assume that the business of the affected bank is interrupted and/or that the bank is closed for business as could happen in a large-scale cyber breach.

Admittedly, the eligibility of cyber attacks as force majeure events is not an undisputed technique to gain time after a shock. In a general commercial contracting setting one needs to exclude that the arrangement does not gives rise to moral hazard. In a cybersecurity context, the unpredictability and severity of cyber incidents might not be sufficient reason to call a pause if cyber due diligence could have avoided the damage (see Rogers and Bahar (2017)). But the capability to contain bank run contagion after large-scale cyber shocks can be sufficient justification for adding circuit breakers to the arsenal of bank regulators.

4.2 Cooperative arrangements: general incentives and shared ICT buffers

Cyber risks intrinsically entail a sort of prisoner’s dilemma for targeted companies. They have both incentives to cooperate in the defence and recovery from the attack but also to follow the selfish dictates of competition. Tilting the balance between both forces typically requires the deployment of institutions by public authorities. But this endeavour faces an additional dilemma, now affecting the relationship between private and public players. Namely, the general benefits of public-private partnerships, which entail a minimum of information sharing, may also encounter reluctance among private stakeholders if they perceive that the information provided could have other non-cooperative uses (e.g. enforcement actions).

Cooperation stands out both as a significant attitude and policy orientation in the pursuit of the stability of the system as a whole in the context of cyber risks (see Rondelez (2018)). The overwhelming advance of the underlying technology threats would already justify cooperation among small to medium firms. But the alignment of incentives and the deployment of facilitating measures does not flow smoothly even in critical sectors like the financial system. Atkins and Lawson (2021) examine the faltering evolution of the public-private partnership model that deals with cyber risks in the US financial system. They document how the achievement of the current level of advance has required both the pressing force of big threats as well as a sustained and broad range of policy initiatives. But the existence of information and knowledge-sharing hubs with a broad constituency of financial sector firms, like FS ISAC, and even a selective constituency of firms dealing with systemic risk issues, like FS ARC, is a testament to the progress towards a sounder overall system.

Beyond supporting the process, Atkins and Lawson (2021) highlight the specific contribution of US regulatory policies which harmonise disparate cybersecurity standards (including on information reporting) and replace checklist-based compliance requirements with resilience judgements. A similar path may need to be covered at the international level. The dearth of standardised and complete information on threats and breaches has led to a focus on incident reporting both in Europe (ENISA (2018)) and internationally (see FSB (2021)).

An alternative based on the insurance of cyber risks by public authorities would fail to align incentives between the private and public sector. Reasons similar in nature to the ones underlying the underdevelopment of the insurance market for cyber risks would thwart the functioning of a cyber federal insurance corporation as suggested by Disparte (2017). The supporting role that public authorities have played by undertaking deterrence (see Herpig (2022)) and providing umbrella protections cannot substitute private due diligence and incentives to prevent and react to attacks.

The provision of collective ICT buffers is an example of a cooperative measure with distinct beneficial systemic effects. Collective ICT buffers can enable a significant reduction in the time needed to reboot the provision of services even after a destructive event that oversteps redundant resources built by adhering banks. A macroprudential rule that fosters the collective provision of technology buffers would compel to fund them in proportion to metrics of performance and use.

The provision of collective ICT buffers in the context of systemic risks is not an entirely new idea. In the aftermath of the global financial crisis, the systemic risks associated with the US tri-party repo system led to various reform proposals. One that finally did not come to fruition was precisely the incorporation of a shell bank (the so-called New Bank) owned by the whole industry to backstop the provision of tri-party repo services by the clearing banks.

But the provision of an extra layer of security for consumer bank accounts in the US has resulted in the provision of mutually owned infrastructure to mitigate cyberrisk effects on data availability. Sheltered Harbor is an LLC that operates under the umbrella of FS-ISAC to enhance the industry's resilience in the event of a major cybersecurity event (Nelson (2018)). In a nutshell, should a financial institution adhered to Sheltered Harbor be unable to recover from a cyber attack in timely way, it would still enable its customers to access their accounts from another member bank. The venture demonstrates in practice the strength of cooperation incentives to combat cybersecurity risks. The adoption of common data formats, secure storage of customers' data in data vaults and agreed operating processes to store and restore data overnight limits the risks from cybersecurity incidents.

4.3 Systemic technology providers and the perimeter of macroprudential policy

Macroprudential regulation cannot easily avoid overstepping its original financial sector perimeter. The framework agreed after the global financial crisis to deal with too-big-to-fail problems focused on the regulatory issues raised by both systemic banks and non-bank financial institutions (SIFIs). Emerging systemically important technological institutions (SITIs) have started to acquire increasing public policy focus as their anti-trust, sociological and/or technological externalities have gained prominence. But the interconnections between the business models and risks of financial sector intermediaries and large SITIs, like cloud “hyperscalers”, implicitly broaden the institutional perimeter of macroprudential concern to SITIs.

The bonds between macroprudential oversight and technology underpinnings of financial services provision have strengthened. Prenio and Restoy (2022) envisage various alternatives to address the resulting challenges although their analysis leads them to prefer the submission of the relevant SITIs to macroprudential oversight, an approach that oversteps its traditional perimeter and that is already present in DORA and in the draft concept paper outlining supervisory powers of UK authorities in connection with third-party service providers. As a matter of fact, the alternatives also amount to a kind of intervention by financial authorities in the cloud services market. In a nutshell, and drawing on some of the service types discussed in section 2.2.1, alternative options could be to enhance the (own or external) assessments of critical providers, to promote multi-cloud services (prevailing practice nowadays) or to promote the recourse to private clouds. The winning approach will depend on new international consensus on a revamped and broader notion of the meaning of systemic and strategic that goes beyond this discussion.

The rationale to intervene in the market in the pursuit of macroprudential goals can also be demonstrated in the cybersecurity space. Kashyap and Wetherilt (2019) highlight the interest in encouraging firms to avoid common vulnerabilities and to make more diverse infrastructure (e.g. the multi-cloud argument made before) or software choices. A conceptual solution would be to penalise taking on shared risks, for example, through a concentrated use of the same software. But intervening in the market to force diversification is challenging for financial regulators. The suggested introduction of penalties in stress testing exercises based on the concentration of choices regarding software sounds more problematic than helpful.

5 Concluding remarks

Financial sector digital resilience regularly tops the rankings of systemic risk concerns. The concentration and interconnectedness of risks prompted by a shift towards cloud computing services and the pervasive intensification of cyber risks has stimulated a broad programme of policy and regulatory measures. This paper examines the quest for tools and metrics to deal with the interaction between financial stability and technological vulnerabilities and, more specifically, it addresses the singular features of macroprudential policy for digital resilience.

The significant challenges to bolstering the individual soundness of financial intermediaries against shocks to cyber and ICT shocks through regulation have been addressed recently with intense policy impetus. In the EU, NISD 2 and DORA epitomise this trend to strengthen the basic tools and incentives of individual players to address cyber and digital operational resilience, including measures to handle the challenges posed by critical third-party service providers. Despite the proliferation of authorities involved, financial regulators and supervisors can play a crucial role in this complex regulatory process at the frontier of technology and finance thanks to their direct access to boards and their influence on financial intermediaries' risk management. But in this endeavour they still face basic measurement and standardisation problems that shape part of their regulatory agenda in the area.

The macroprudential agenda constitutes a less advanced component of the mix of concurrent tools required to ensure systemic stability. Although microprudentially oriented rules like DORA already address systemic concerns through their treatment of critical service providers, the range of externalities at stake in the cyber and ICT space raises the need for tools to address non-internalised system-wide concerns in those areas. Moreover, the singular nature of cyber and ICT risks rules out most ordinary macroprudential tools and calls for new tools or, at least, new approaches, to be considered to advance the toolkit.

Specifically, the paper examines and/or makes exploratory proposals on the potential role of circuit breakers to fight daunting large-scale cyber attacks in banking, on the opportunities raised by the distinct cooperative nature of cyber defence and on the challenges posed by the mix of cyber and ICT problems for the definition of regulatory and supervisory perimeters.

Against this backdrop, a checklist-like approach to macroprudential regulation still looks elusive. Mechanical ratios for weighting a performance metric and existing IT or financial buffers have to wait until metrics and standards are more advanced. Stress testing remains a flexible tool to accommodate both microprudential and macroprudential goals. In any event, for the macroprudential agenda, the promotion of cooperation is a productive avenue of work. The harmonisation, standardisation and enforcement of incident reporting rules should feed into the next steps for advancement. In more advanced jurisdictions, cooperation has even reached the level of building shared IT buffers.

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UNWRAPPING BLACK-BOX MODELS: A CASE STUDY IN CREDIT RISK

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Abstract

The past two decades have witnessed the rapid development of machine learning techniques, which have proven to be powerful tools for the construction of predictive models, such as those used in credit risk management. A considerable volume of published work has looked at the utility of machine learning for this purpose, the increased predictive capacities delivered and how new types of data can be exploited. However, these benefits come at the cost of increased complexity, which may render the models uninterpretable. To overcome this issue a new field has emerged under the name of explainable artificial intelligence, with numerous tools being proposed to gain an insight into the inner workings of these models. This type of understanding is fundamental in credit risk in order to ensure compliance with the existing regulatory requirements and to comprehend the factors driving the predictions and their macro-economic implications. This paper studies the effectiveness of some of the most widely-used interpretability techniques on a neural network trained on real data. These techniques are found to be useful for understanding the model, even though some limitations have been encountered.

Keywords: Machine learning, interpretability, explainable artificial intelligence (AI), credit scoring, credit risk modelling.

1 Introduction

1.1 Overview of the problem

Machine learning is a subfield of artificial intelligence which exploits the patterns present in data to construct mathematical models. This type of model has proven to be very successful for diverse tasks such as optimization, data processing and estimating unknown variables. The origins of the discipline date back to the 1950s, but it has not been until recently, fuelled by the rise of big-data and the access to faster and cheaper computational capacities, that machine learning has emerged as a disruptive technology.

The field of credit risk has a long tradition in the use machine learning techniques, since well before the current boom. Among the most widespread applications are credit scorecards for estimating the probability of loan default. These models, typically based on logistic regressions using a reduced set of variables, have simple mathematical representations and are easy to understand.

However, the development of more advanced techniques is changing the landscape in credit risk modelling. Several academic studies have revealed the potential benefits of using more complex models, with a particular emphasis on the greater accuracy of these alternatives and on the possibility of incorporating new types of data. This trend can also be seen in the financial industry, with institutions showing an increasing interest in the deployment of more powerful methodologies, both for internal management and for the computation of regulatory capital requirements.

This migration towards more complex techniques is having an impact on the interpretability of the models, and in some cases we end up with what are called black-box models, where it is no longer possible to understand a model's underlying logic, or at least it is not possible for the naked eye of an analyst. The challenge of understanding the inner workings of complex machine learning models is not exclusive to credit risk, and a whole new field of research (explainable artificial intelligence or XAI) has emerged in recent years. While many different methodologies have been proposed, how useful or limited these techniques are remains an open question. In this regard it is important to note just how different models for image classification, natural language processing and credit scoring based on tabular data can be.

Nonetheless, the relevance of interpretability in machine learning models in the context of credit risk estimation is well worth highlighting, especially when used for lending and for the quantification of capital requirements. These activities have profound implications for economic growth and financial stability, and there are various regulations in place that require an understanding of the inner logic of the models used for these purposes.[1] Moreover, an understanding of the role of variables sensitive to macro-economic conditions within the models is vital for assessing the fluctuations of capital requirements and the resulting funding needs.

The goal of this paper is to analyse the utility and limitations of some of the most widely-used interpretability tools on a realistic credit risk estimation model. Using data from CIRBE,[2] a neural network for estimating probability of default has been constructed, and several interpretability techniques have been applied to it. The resulting explanations are analysed and discussed.

1.2 Related literature

The use of advanced machine learning techniques for credit risk purposes has garnered significant attention in recent years, generating an extraordinary volume of

1 Some of the most relevant European Union regulations in this regard are the Capital Requirements Regulation (EU) 575/2013, the General Data Protection Regulation (EU) 2016/679, the Guidelines on Loan Origination and Monitoring (EBA/GL/2020/06) and the Artificial Intelligence Act, a Proposal for a Regulation currently before the European Commission.

2 CIRBE stands for *Central de Información de Riesgos del Banco de España* (the Banco de España's Central Credit Register).

published work. Providing an overview of this vast literature is therefore a challenge in itself. One of the issues that has drawn most attention is the comparison of traditional logistic regressions with more advanced approaches to credit scoring (see Alonso and Carbó (2020) and references therein). But other more ambitious approaches have also been considered, e.g. incorporating new sources of information which require more sophisticated architectures (see Babaev et al. (2019), who use recurrent neural networks to process transactional data; or Korangi et al. (2021), who apply transformers to time-structured accounting and pricing data), or in other secondary tasks of the modelling process (see Engelmann and Lessmann (2020), who use generative adversarial networks for data preparation; or Liu et al. (2021), who apply deep neural networks to define the set of explanatory variables).

This trend towards more complex techniques has been closely monitored, and various publications have analysed the implications and set out recommendations and guidance. In the paper by Yong and Prenio (2021), the Financial Stability Institute examines a selection of policy documents on machine learning issued by financial authorities in nine jurisdictions, together with other governance guidance, and flags interpretability as one of the major concerns in the use of these technologies. Similar conclusions have been expressed in other publications, such as the Deutsche Bundesbank and BaFin consultation paper (2021), the Bank for International Settlements working paper (Doerr et al. (2021)) and the European Banking Authority discussion paper (2021).

Within the field of XAI, among the most relevant methods proposed in the literature are partial dependence plots (see Friedman (2001)), individual conditional expectations (see Goldstein et al. (2014)), accumulated local effects (see Apley and Zhu (2019)), local interpretable model-agnostic explanations (see Ribeiro et al. (2016)) and Shapley additive explanations (see Lundberg and Lee (2017)). These tools are examined in this paper, and are described in Section 3. Other popular XAI techniques that may also be of interest for evaluating credit scoring models are anchors (see Ribeiro et al. (2018)), prototypes and criticisms (see Kim et al. (2016)), trust scores (see Jiang et al. (2018)) and contrastive and counterfactual explanations (see Stepin et al. (2021) for a survey of these type of methods).

Last, but not least, is the question of how successful these techniques are in delivering adequate, useful explanations of the models. While a number of analyses have been carried out to address this question, the answers obtained are specific to the types of models and data considered. With the goal of interpreting credit scoring models in mind, some of the most relevant papers are: Ariza-Garzón et al. (2020), who evaluate the effectiveness of SHAP on a credit scoring model based on XGBoost; Demajo et al. (2020), who apply anchors along with two other methods[3] to a credit scoring model based on XGBoost; Visani et al. (2020), who assess the stability of

3 GIRP, introduced in Yang et al. (2018), and ProtoDash, introduced in Gurumoorthy et al (2019).

LIME on a credit scoring model based on XGBoost; and Cascarino et al. (2022), in which accumulated local effects, along with two other methods,[4] are applied to a logistic regression and a random forest to analyse their differences.

1.3 Contribution of the paper

A neural network has been constructed for estimating probability of default using tabular data on real mortgages extracted from CIRBE. The dataset has been defined so as to be representative of those used for credit scoring, in terms of size, number of explanatory variables and type of information (debtor and loan characteristics).

Some of the most popular interpretability techniques have then been applied to this neural network, contrasting all of the explanations obtained and assessing their utility and limitations. The focus has been placed on so-called model agnostic explanations (interpretability techniques which can be applied to any type of predictive model) and on techniques which can be used to interpret the neural network as an estimator of the probability of default, which is how credit scoring models are generally used.

1.4 Outline of the paper

The paper is structured as follows: Section 2 introduces the notion of model interpretability using a logistic regression as an example. Section 3 describes the interpretability tools analysed in the paper. Section 4 summarizes the data and the model to which the interpretability tools are applied. Section 5 shows some of the explanations obtained and the analyses performed to evaluate their consistency and appropriateness. Section 6 presents the conclusions drawn from the analyses carried out. The appendix contains further details on the dataset used, the model constructed and the software used.

2 When is a model interpretable?

The logistic regression models usually used in credit scoring are an illustrative example of an interpretable model. These models are constructed using a reduced set of features[5] with low correlation between them. The features used are typically loan characteristics (e.g. loan-to-value ratio, maturity, etc.), debtor characteristics (e.g. income, age, etc.) or macro-economic information (e.g. interest rates, gross

4 A method based on permutations to quantify the importance of each feature and a local method based on Shapley values introduced in Štrumbelj and Kononenko (2014).

5 In machine learning, the term *feature* is frequently used to refer to the explanatory variables used in a model.

domestic product, etc.). A realistic example could use 10 features, which are denoted as X_j, and would require the calibration of 11 parameters β_j (the sensitivity of the model to each feature plus a constant term or bias). In this setting, the probability of default estimated by the model is given by the following two equations:

$$z = \beta_0 + \sum_{j=1}^{10} \beta_j X_j$$

$$\hat{P}\left[\text{default}\right] = \frac{1}{1+e^{-z}}$$

The first important aspect to note is that the second equation, which provides the estimated probability of default in terms of z, is monotonically increasing and involves no parameters. Thus, understanding the first equation, which is a linear equation, provides a full picture of the internal logic of the model. In other words, understanding a logistic regression is pretty much the same as understanding a linear regression.

In particular, note that the following information can be directly obtained from the coefficients:

- If $\beta_j > 0$, feature j is positively correlated with the output of the model, and an increase in the value of the feature always leads to an increase in the predicted value.

- Given an observation x, if $\left|\beta_j x_j\right| > \left|\beta_k x_k\right|$, feature j is more influential than feature k in the prediction obtained for this particular observation.

- If the features are standardised[6] and $\left|\beta_j\right| > \left|\beta_k\right|$, feature j is more influential than feature k in the overall model.

Moreover, we can obtain further understanding of these models by applying well-established statistical tools, such as tests to assess the significance of the coefficients (e.g. the Wald test) or measures of goodness of fit (e.g. pseudo R^2 measures). In short, logistic regressions are models which rely on simple relationships between the inputs and the output, can be fully described from the specification of a small set of coefficients and a simple analysis of such coefficients delivers a detailed understanding of the model.

In contrast, more complex models, such as gradient boosting machines or neural networks, lack any of these properties. These models involve thousands of parameters and there is no clear relationship between the inputs and outputs. Gaining insight here requires the use of specific, sophisticated tools, most of which

6 There is no loss of generality in this assumption, as features can be standardised before training the model.

have been recently developed. The next section describes some of the most popular interpretability tools, which are evaluated in our case study.

3 Interpretability tools

This section describes the interpretability tools used in the assessment of our model. These tools can be local, describing how the model generates a particular observation, or global, explaining the overall behaviour of the model across all observations. In some cases, local explanations can be aggregated together to obtain a global understanding of the model.

3.1 Feature influence plots

Different types of plots can be constructed to display the influence of a feature on the model. Some of the most popular techniques of this nature are Individual Condition Expectations (ICE), Partial Dependence Plots (PDP) and Accumulated Local Effects (ALE).

ICE and PDP show a model's prediction for each possible value of the feature under examination. ICE displays the relationship for a particular observation, providing a local explanation of the model, while PDP shows the average relationship across all observations, and therefore provides a global explanation. In the computation of these plots, the feature examined is rewritten considering all the values in its range, while the rest of the features are left unchanged. This can produce unrealistic data instances,[7] where the predictions obtained from the model may not be representative of those obtained from actual observations.

ALE plots were introduced by Apley and Zhu (2019) as an alternative to PDP to address the unrealistic data issue. These plots are computed separately on each sub-range of values, considering only observations with a similar value, and evaluating how the output of the model changes as a result of small perturbations to the values of the feature. A drawback of ALE plots is that these are defined only for numerical features.

3.2 LIME

A local surrogate is an auxiliary interpretable model (such as a linear model with few features) which accurately approximates the behaviour of the original model on a

7 For example, if a model uses the initial maturity and the remaining maturity as features, rewriting only one of them may yield a combination of values where the remaining maturity is longer than the initial one, which is not a realistic data instance.

subset of similar observations. We can understand why our model delivers a specific prediction by fitting a local surrogate around the observation and interpreting it. One of the most successful approaches to building local surrogates is Local Interpretable Model-agnostic Explanations (LIME), introduced in Ribeiro et al. (2016).

LIME first generates an auxiliary, synthetic dataset by randomly perturbing the actual observations in the sample.[8] Then, a local surrogate is trained to replicate the predictions generated by the true model on the synthetic data. In order to obtain a surrogate which explains the model in the vicinity of a specific observation, the training procedure uses a weight function that gives more relevance to the synthetic observations which are closer to it.

Perhaps the most relevant drawback of LIME is that the method requires the specification of several parameters, and there is no silver bullet when selecting them. Some of these parameters are needed to specify the weighting function which defines the notion of vicinity, while other parameters, such as the number of features used, are needed to define the structure of the surrogate model. One of these parameters allows for the application of a discretization on continuous features, in order to obtain comparable coefficients and avoid double negations. However, it is our understanding that discretization should be used with care, as the resulting surrogate model could be non-monotonic and hard to interpret.

3.3 SHAP

Shapley values are a concept that originated in the field of game theory, and have been proposed in machine learning for defining the contribution of each feature of a model to a specific prediction. In order to define them, let F be a model with n features as inputs, let F_S denote a version of the model which uses only the subset of features S, and let x be the observation whose prediction we want to analyse. The Shapley value φ_j for the feature j is defined as

$$\varphi_j(x) = \sum_{S \subseteq \{x_1, x_2, \dots, x_n\} \setminus \{x_j\}} \left(F_{S \cup x_j}(x) - F_S(x)\right) \frac{|S|!\left(n - |S| - 1\right)!}{n!}.$$

Shapley values allow us to decompose the prediction of the model by

$$\sum_{j=1}^{n} \varphi_j(x) = F(x) - \mathbb{E}\left[F(X)\right]$$

where $\mathbb{E}\left[F(X)\right]$ is the average prediction of the model (across all observations).

8 The random perturbation used assumes that the features are independent.

The main challenge of using Shapley values is their computational cost, since they require a different version of the model for every possible subset of features. This can be unfeasible even for a moderate number of features, as the number of subsets grows exponentially.

One of the most influential works based on Shapley values are Shapley Additive ExPlanations (SHAP), introduced in Lundberg and Lee (2017). In this paper and in the software library released by the authors a number of methods for estimating Shapley values are proposed, some of which are model-specific, while others are model-agnostic. These methods rely on different definitions of the terms F_S, which do not require a model to be trained for each subset of features, and on approximations to address the computational cost. Perhaps the most relevant theoretical downside of SHAP is that some of the methods proposed, including the model-agnostic ones, assume that the features are independent. However, this assumption is usually not satisfied, and it is not clear beforehand what impact the dependence present in our data has on the quality and reliability of the explanations obtained.[9]

4 Model developed

The dataset is composed of mortgages at January 2018, with no additional guarantor and denominated in Euro, containing 3,184,956 observations. The January 2018 snapshot was chosen as it was the most recent one available not affected by the Covid-19 pandemic.

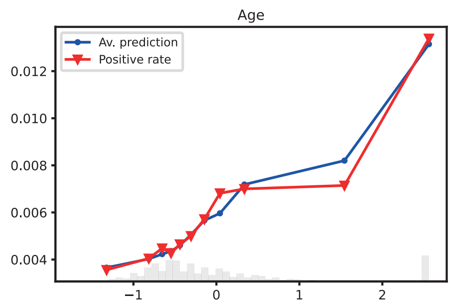
The model uses 19 features, containing both numerical and categorical data, and covering loan and debtor characteristics. The objective variable is the indicator of default at January 2019, and its rate of positive values is 0.61% (i.e. the observed default rate). The model constructed is a neural network with two hidden layers, with 128 neurons in each layer, and the total number of parameters is 24,577. The performance of the model, measured using the area under the receiver operating characteristic curve (AUC) on a validation sample, is 89.96%. See Appendix 1.3 for more details on the characteristics of the model.

5 Unboxing the model

The tools described in Section 3 are now applied to the model constructed. A few examples of the explanations obtained are presented to understand the how these tools work and what their utility and limitations are. In order to assess how intuitive

9 See, for example, Aas et al. (2020) and Frye et al. (2021) for more details on this issue.

Chart 1
AUXILIARY PLOT EXAMPLE



SOURCE: Devised by the author.

the explanations obtained are, the graph in Chart 1 will be useful as an auxiliary tool.

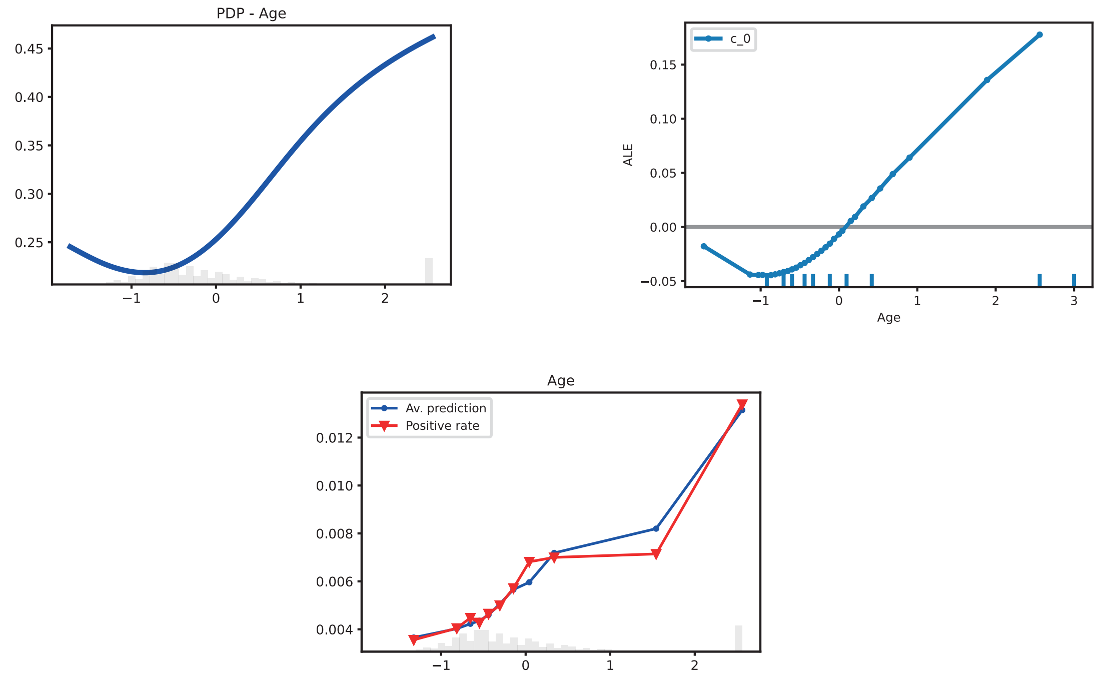
In this graph we can see the average prediction of the model for different values of a feature. In order to compute the graph above, buckets are defined with an equal number of observations by discretizing the feature under analysis and the average prediction of the model for the observations in each bucket is computed. The average default rate in each bucket is also computed, and both graphs are placed on a common scale to improve comparability. It is important to note that this plot does not reflect a cause-and-effect relationship between the feature and the outcome of the model (the plot could be constructed for a feature that is not used in the model and still reveal a dependence).

5.1 Feature influence plots

In the graphs below, the x-axis is not at its natural scale for the continuous features, as the features have been normalized to facilitate the training of the model. Similarly, due to the use of weights to mitigate the class imbalance in training,[10] the predictions of the model (the y-axis of the PDPs) are not on the same scale as the default rates.

10 When constructing a classifier where one of the categories is far more frequent than the other, this can hinder the training of the model. This issue can be addressed by introducing a weight function that gives more relevance to the minority class.

Chart 2
INFLUENCE PLOTS FOR FEATURE AGE



SOURCE: Devised by the author.

5.1.1 Age

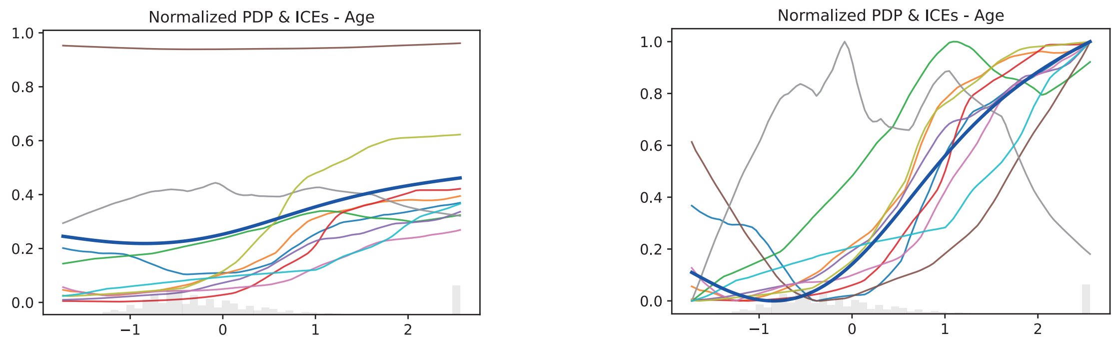
In Chart 2 we can see the PDP (left), the ALE (right) and the average prediction (bottom) of the model for the feature *Age.* The concentration of mass of the density of the feature on the large, positive values corresponds to missing or erroneous values, as the value of the age is capped at 100.

Note that PDP and ALE coincide in how the feature influences the model, which suggests that the PDP for this feature is not distorted by possible out-of-distribution issues as a result of overwriting the values of *Age.* Moreover, both graphs are aligned with the average prediction and with the default rate, which makes these explanations intuitive.

In order to study whether the general influence captured by the PDP is representative of the influence on specific, individual observations, we can plot PDP and ICE jointly.

In chart 3 the left plot shows the PDP and ICEs on their natural scales and the right plot shows them on a common scale to enhance comparability. We can see that the

Chart 3
PDP AND IC FOR FEATURE AGE



SOURCE: Devised by the author.

influence of the feature is similar in some observations, and is aligned with the average influence captured by the PDP, albeit not in all of them.

5.1.2 Principal amount

In Chart 4 we can see the PDP (left), the ALE (right) and the average prediction (bottom) of the model for the features *Initial principal amount* and *Remaining principal amount.*

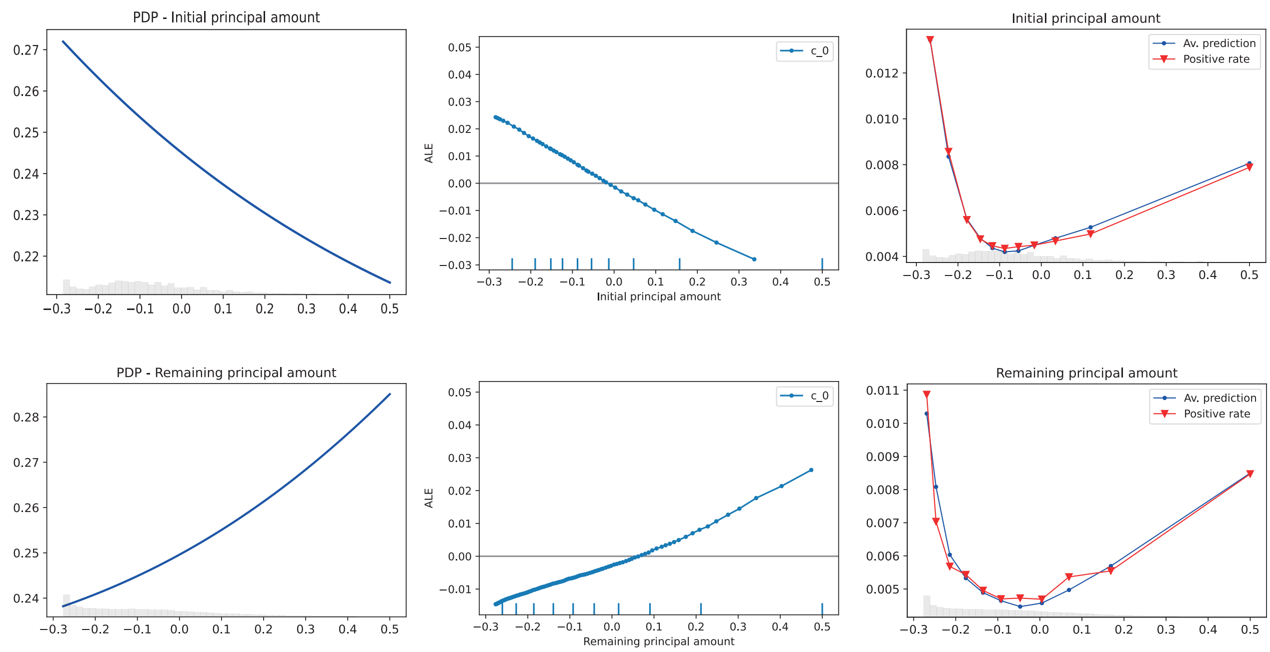
It is worth noting that the PDPs and the ALEs coincide for these two features, although the pattern revealed by the two graphs is not aligned with the average prediction and the default rate. As both of these features are based on the principal outstanding amount of the loan, there is a strong dependency between the two, and it may be the case that this interdependence is behind this misalignment. The joint influence of both features in the model can be studied using a bivariate PDP[11] (see Chart 5) to see if this sheds more light on the matter, but this plot does not seem to offer any further insight.

In order to study the representativeness of the PDP for specific, individual observations, the PDP and the ICE are plotted jointly, yielding graphs in Chart 6.

It is difficult to compare the influence of the features on different observations, as the ICEs are on different scales and normalization of the graphs to a common scale

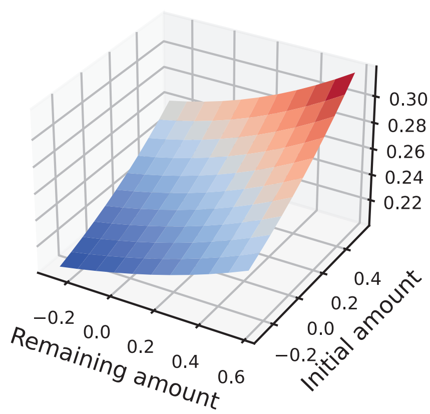
11 Bivariate PDP are a straightforward extension of PDP where the average prediction of the model is plotted for every combination of values of the features examined, while the values of the remaining features are left unaltered.

Chart 4
INFLUENCE PLOTS FOR INITIAL PRINCIPAL AMOUNT AND REMAINING PRINCIPAL AMOUNT



SOURCE: Devised by the author.

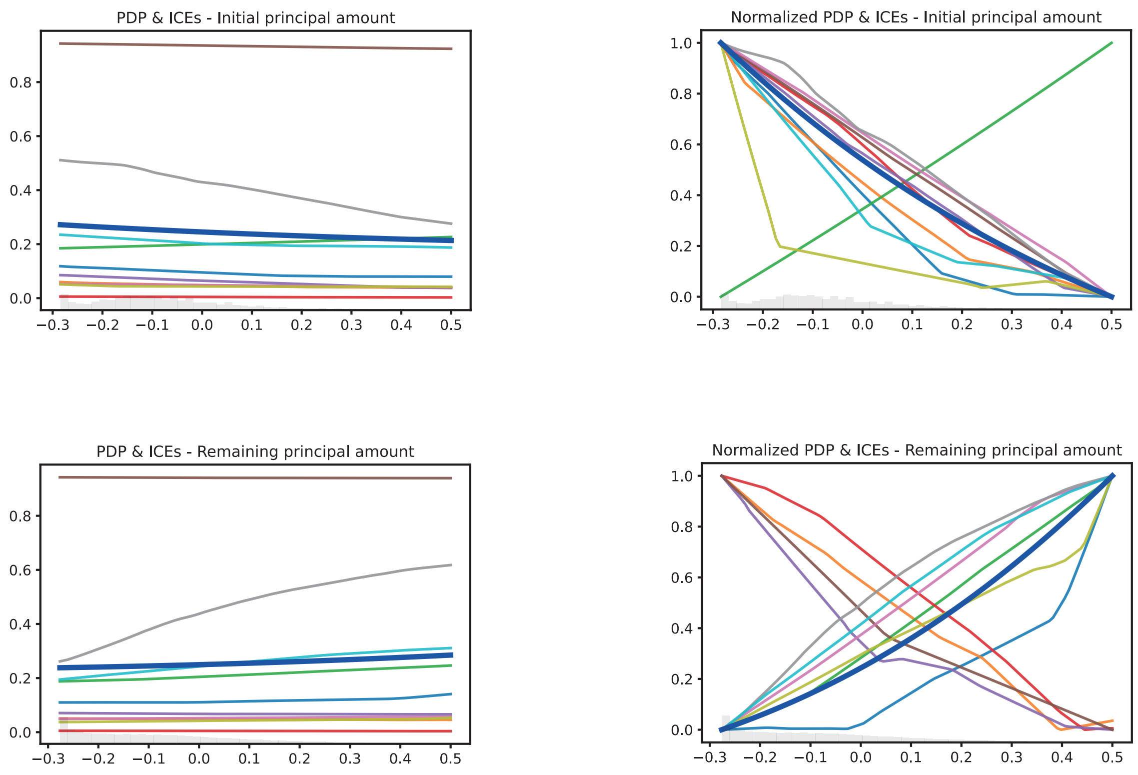
Chart 5
BIVARIATE PDP FOR INITIAL PRINCIPAL AMOUNT AND REMAINING PRINCIPAL AMOUNT



SOURCE: Devised by the author.

can be problematic, since the influence is very small in some observations. On the feature *Initial principal amount,* there seems to be a closer alignment between the ICEs and the PDP (a negative effect with small impact). On the feature *Remaining principal amount,* the pattern across the ICEs is less clear, and the PDP may not be as representative of the influence in individual cases.

Chart 6
PDP AND ICE FOR INITIAL PRINCIPAL AMOUNT AND REMAINING PRINCIPAL AMOUNT



SOURCE: Devised by the author.

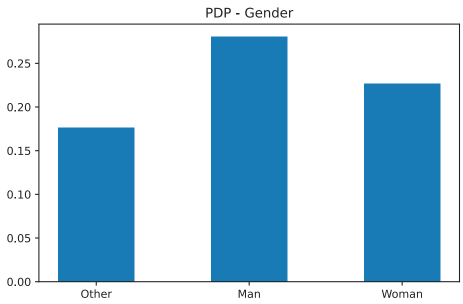
In short, the auxiliary plots show that there is a non-monotonic relationship between these features and the default rate and the average prediction, although the PDP and the ALE do not show an influence of this type in the model; a bivariate PDP has been used to analyse both features jointly, albeit without offering any further insight. Regarding the question of whether the influence is homogeneous across observations, it is difficult to draw any conclusions of this nature based on the ICEs due to the different scales of the plots and the fact that the influence of these features in the model appears small.

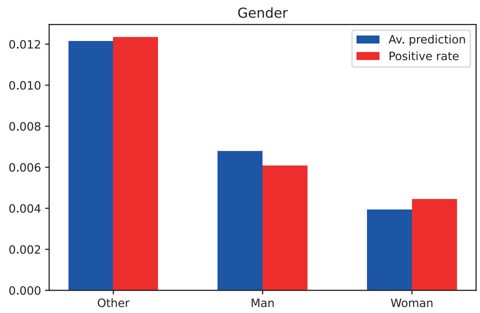
5.1.3 Gender

PDP can be applied to categorical features in a straightforward manner using bar-plots. In Chart 7 we can see the PDP and the average prediction of the model for the feature *Gender.*

The PDP shows the influence of the category *Other,* which is the opposite of the model's average prediction for the observations in this category. This misalignment may be due to the fact that this category contains the missing values of the feature,

Chart 7
INFLUENCE PLOTS FOR FEATURE GENDER





SOURCE: Devised by the author.

Table 1
JOINT DISTRIBUTION OF MISSING VALUES OF AGE AND GENDER

	Missing *Age*	Informed *Age*
Missing *Gender*	15.203	338,969
Informed *Gender*	0	2,830,784

SOURCE: Devised by the author.

and that the occurrence of missing values is correlated across features. An example of this correlation between the missing values is shown in Table 1.

5.2 Local explanations

5.2.1 LIME

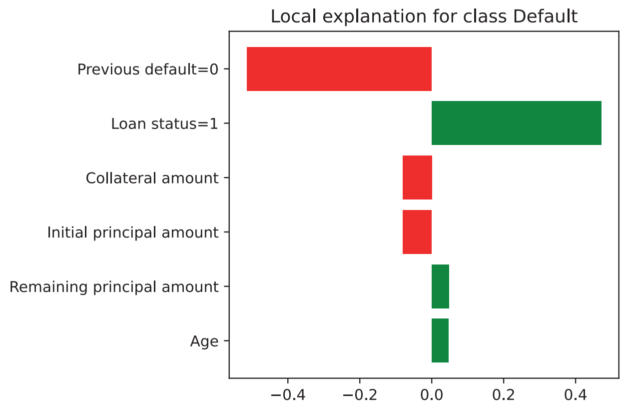
This section analyses the explanations provided by LIME, studies its stability with respect to the choice of parameters and evaluates the noise stemming from the random sampling.

Example

The graph in Chart 8 displays an explanation given by LIME based on the 6 most significant features. The values shown correspond to the weight of each feature in the local linear model.[12]

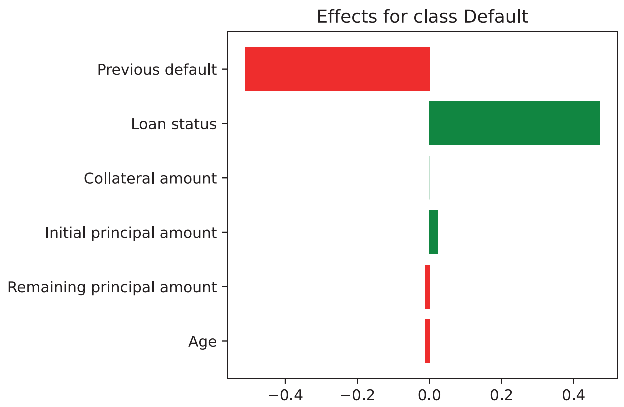
12 For categorical features the value reflects the weight of belonging to the category of the explained observation.

Chart 8
LIME EXAMPLE



SOURCE: Devised by the author.

Chart 9
EFFECTS IN THE LOCAL SURROGATE



SOURCE: Devised by the author.

Even though all of the numerical features are normalized, since LIME focuses on the vicinity of a specific observation, the features are no longer normalized, and the coefficients are not therefore fully comparable. A complementary analysis can be conducted to study the net effect of the features in the prediction, which can be computed by multiplying the weights of the explanation and the values of the features, and has the advantage that these values are comparable across features. The figure in Chart 9 shows the effects of the same features and the same observation as in the plot in Chart 8.

This second plot shows that some care is required when interpreting the first one. Note that even though *Collateral amount* is the third most influential variable in the

Table 2
DISPERSION OF THE LIME COEFFICIENTS

Feature	Mean	Std
Loan status	-0.280	0.018
Loan purpose	0.083	0.009
Resident type	-0.049	0.007
Economic activity	-0.047	0.006
Previous default	-0.043	0.001
Real guarantee coverage	0.043	0.003

SOURCE: Devised by the author.

local model, it has no effect on this particular prediction (since the value of this feature is zero). Note also that the influences observed can have an effect in the opposite direction (where the value of a feature is negative).

Estimation error

The sensitivity of the explanations to the random sampling is assessed by computing the explanation of a specific prediction multiple times.[13] Table 2 shows the mean and dispersion of the coefficients of the most relevant features.

We can see that the explanations obtained are fairly stable with respect to the randomness stemming from the random sampling.[14]

Sensitivity to the choice of parameters

In order to assess the sensitivity of the method to the choice of discretization applied to the numerical features, Table 3 compares the explanations obtained using different discretization criteria on the same observation.[15]

We can see that the choice of the discretization method affects the explanation obtained, as the most significant features in the explanation vary. In particular, note that *Age* does not appear in the explanation using deciles and *Remaining principal amount* is not present when no discretization is applied.

It is important to note that the coefficients with different signs for the features *Initial principal amount* and *Original maturity* are not contradictory, since the value of these

13 1,000 simulations, using kernel width 3, no discretization on the continuous features and 5,000 observations for fitting each local model (default value).

14 A similar question has been considered in Visani et al. (2020), where they find that the stability of LIME depends upon the choice of parameters, even though a quantification of the instability found is not provided.

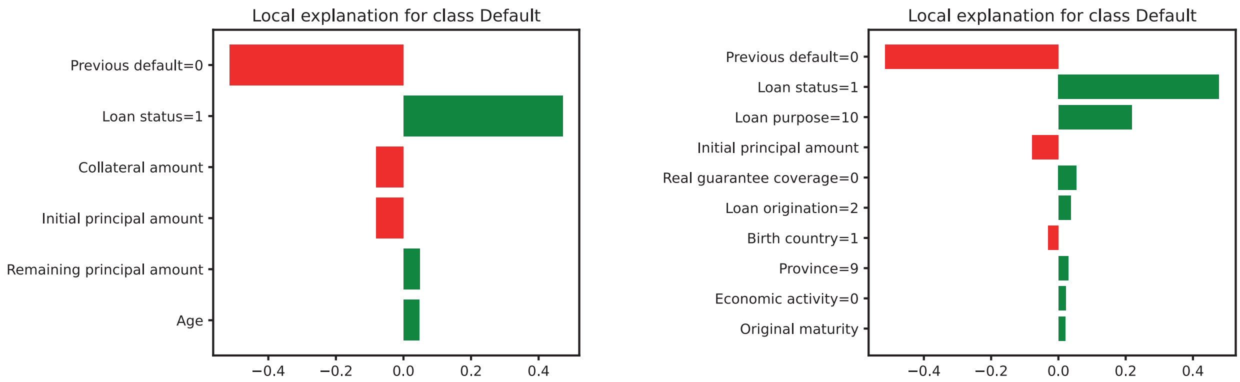
15 Using kernel width 3 and 100,000 observations.

Table 3
LIME EXPLANATIONS DEPENDING ON THE DISCRETIZATION

Quartiles		Deciles		No discretization	
Feature	Value	Feature	Value	Feature	Value
Previous default	-0.548	Previous default	-0.551	Previous default	-0.519
Loan status	-0.521	Loan status	-0.519	Loan status	-0.476
Age	0.130	Real g. c.	-0.062	Initial p. a.	-0.076
Real g. c.	-0.061	Birth country	-0.040	Real g. c.	-0.055
Remaining p. a.	-0.048	Remaining p. a.	-0.028	Age	0.048
Initial p. a.	0.044	Gender	-0.025	Birth country	-0.029
Birth country	-0.033	Loan origination	-0.024	Loan origination	-0.024
Gender	-0.025	Original maturity	-0.021	Gender	-0.017
Original maturity	-0.025	Loan purpose	-0.020	Original maturity	0.014
Loan origination	-0.019	Initial p. a.	0.019	Personal g. c.	0.014

SOURCE: Devised by the author.

Chart 10
LIME EXPLANATIONS WITH DIFFERENT NUMBER OF FEATURES



SOURCE: Devised by the author.

features is negative in this observation. Thus, in all of the tree explanations obtained, the influence of these features results in a decrease in the prediction.

The graphs in Chart 10 show the impact of modifying the number of features in the explanation. We can see that the explanations differ significantly, except for the two most relevant features, which play the same role in both explanations. The source of this divergence seems to be that LIME adopts a different strategy for selecting which features are the most relevant depending on the number specified.[16]

16 The forward method is used when the number of features is six or less. Otherwise, the weight of each feature is used (see https://cran.r-project.org/web/packages/lime/vignettes/Understanding_lime.html).

We have also studied the stability of the results with respect to the size of the kernel, and we have not found any relevant deviations.

5.2.2 SHAP

This section analyses the explanations provided by SHAP and studies the noise generated from the random sampling. The explanations have been computed using the default method,[17] which does not require any relevant parametrization.

Example

The graph in Chart 11 shows an explanation provided by SHAP for a given observation. Each row represents the contribution of a feature to the prediction generated by the model. The sum of the contributions of all of the features is equal to the difference between the prediction obtained on this observation and the average prediction across all observations.

Estimation error

In order to assess the noise introduced by the random sampling, the explanation of a specific prediction has been computed 20 times. There are two sources of sampling error in the method, one due to the choice of the background sample and the other to a simulation performed within the method. In order to understand the impact of each source, two analyses have been carried out, using the same background sample in one and different background samples in the other.[18] Table 4 summarizes the distribution of the most significant features.

We can see that the volatility of the estimations, relative to their average value, is not negligible in either case. In order to gain further insight into the contributions the different noises make, the same computation has been carried out with a smaller sample (see Table 5).[19]

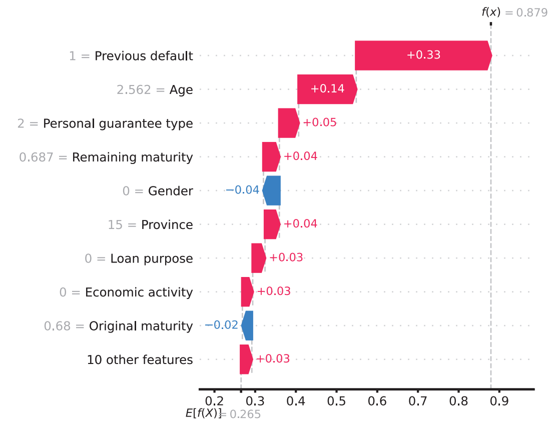
Using a smaller background sample does not appear to significantly affect the explanations obtained in either case.

17 The default model agnostic explainer is the so-called permutation explainer.

18 The results shown have been computed with background samples of 4,000 observations.

19 Background samples of 1,000 observations.

Chart 11
SHAP EXAMPLE



SOURCE: Devised by the author.

Table 4
SIMULATION WITH THE SAME BACKGROUND (LEFT) AND WITH DIFFERENT BACKGROUNDS (RIGHT). SAMPLE SIZE 4,000

Feature	Mean	Std.	Feature	Mean	Std.
Loan origination	-0.0447	0.0096	Loan origination	-0.0523	-0.0523
Province	0.0363	0.0099	Province	0.0367	0.0367
Age	0.0330	0.0050	Gender	-0.0340	-0.0340
Gender	-0.0259	0.0062	Previous default	-0.0286	-0.0286
Original maturity	-0.0277	0.0110	Age	0.0229	0.0229
Previous default	-0.0250	0.0012	Remaining maturity	-0.0152	-0.0152

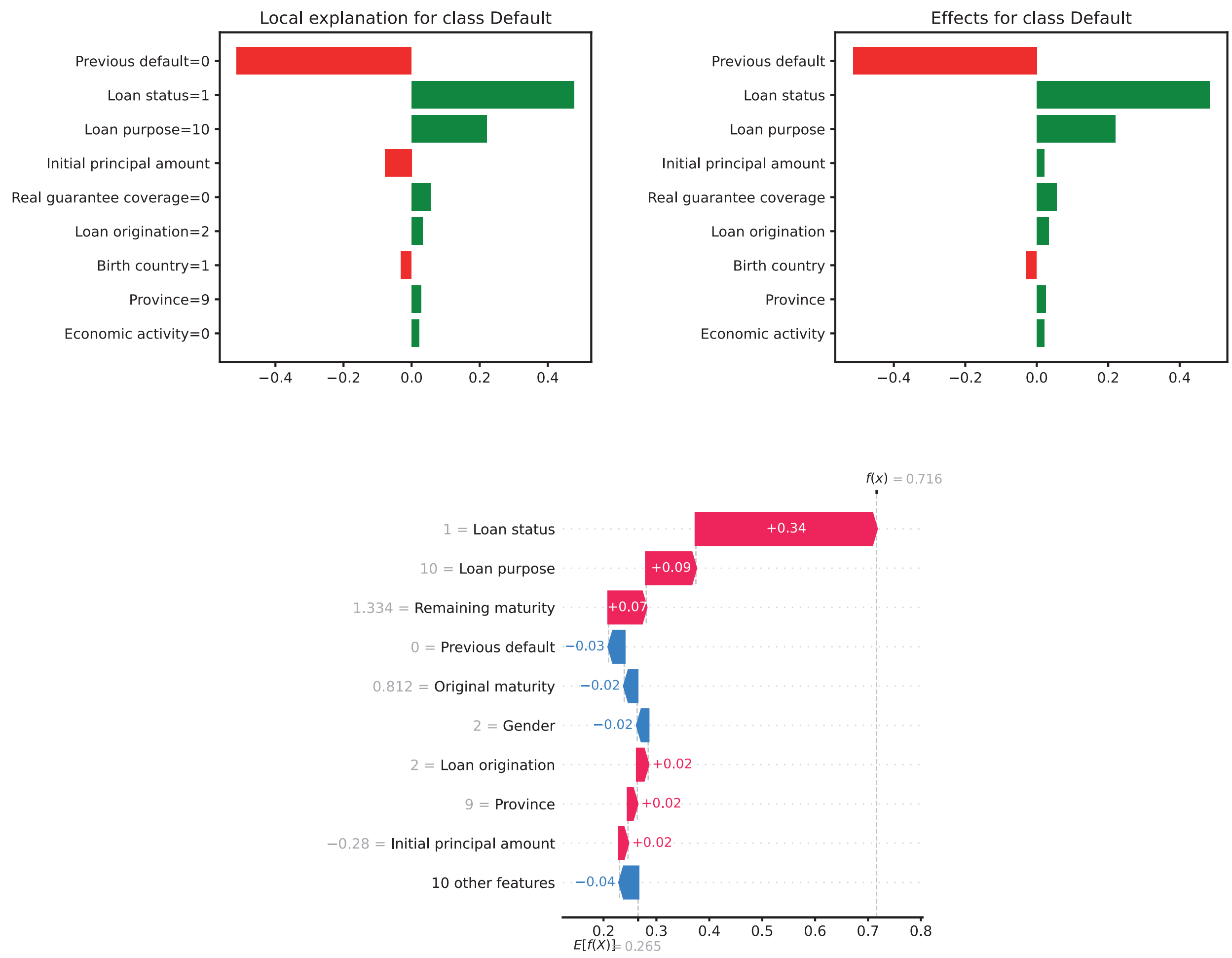
SOURCE: Devised by the author.

Table 5
SIMULATION WITH THE SAME BACKGROUND (LEFT) AND WITH DIFFERENT BACKGROUNDS (RIGHT). SAMPLE SIZE 1,000

Feature	Mean	Std.	Feature	Mean	Std.
Province	0.0496	0.0085	Loan origination	-0.0476	0.0140
Loan origination	-0.0425	0.0107	Province	0.0368	0.0134
Age	0.0303	0.0062	Gender	-0.0319	0.0127
Gender	-0.0293	0.0076	Previous default	-0.0291	0.0123
Original maturity	-0.0222	0.0090	Age	0.0267	0.0096
Remaining maturity	-0.0155	0.0124	Original maturity	-0.0149	0.0086

SOURCE: Devised by the author.

Chart 12
LIME VS SHAP



SOURCE: Devised by the author.

5.2.3 Comparison

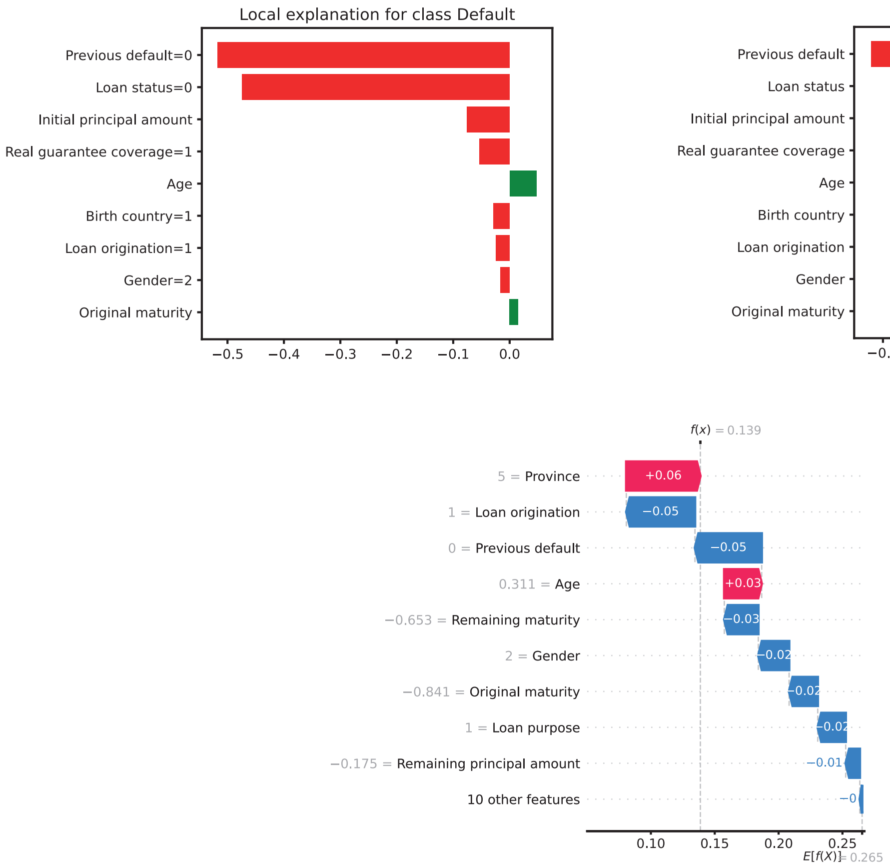
This section compares the explanations obtained using LIME and SHAP, both on an individual observation basis and on an aggregate basis.

Individual level

In Chart 12, the top two graphs show the explanation obtained using LIME (the left plot shows the output of the method, corresponding to the coefficients of the surrogate regression, while the right plot shows the effect of each feature) and the bottom graph shows the explanation obtained from SHAP.

The explanations obtained do not seem incompatible, since they coincide in several of the features on which they rely and the effects are aligned in all cases. However,

Chart 13
LIME VS SHAP



SOURCE: Devised by the author.

there are also significant differences, especially with respect to the feature *Previous default,* which is the most significant feature for LIME, but does not appear among the relevant features for SHAP. Chart 13 shows the same comparison when made with a different observation.

The conclusions in this case are the same. The two explanations do not seem to be incompatible, though there are relevant differences between them, especially with respect to the feature *Loan status,* which plays a major role for LIME but is not relevant for SHAP.

Aggregated level

Table 6 compares the importance given by LIME and SHAP to each feature,[20] and includes two additional metrics. The column marginal contribution refers to the

20 Defined as the average absolute value of the LIME and SHAP effects on a sample of 4,000 observations.

Table 6
IMPORTANCE OF THE FEATURES

Feature	Information value	Marginal contribution	Lime score	SHAP Score
Age	0.158	0.266	0.349	4.417
Country of birth	0.121	0.107	0.297	0.951
Collateral amount	0.114	0.171	0.100	0.871
Economic activity	0.311	0.606	0.235	3.486
Gender	0.115	0.256	0.402	3.071
Initial principal amount	0.154	0.042	0.124	1.225
Loan origination	0.033	0.030	0.343	1.444
Loan purpose	0.417	0.475	0.245	3.653
Loan status	0.903	1.224	4.615	0.718
Number of holders	0.003	0.033	0.001	0.001
Original maturity	0.110	0.330	0.146	2.754
Personal guarantee coverage	0.034	0.031	0.123	0.591
Personal guarantee type	0.044	0.068	0.058	0.668
Previous default	1.304	7.071	5.089	6.854
Province	0.060	0.252	0.280	3.737
Real guarantee coverage	0.108	0.334	0.551	2.910
Remaining maturity	0.022	0.227	0.094	1.731
Remaining principal amount	0.079	0.165	0.092	1.214
Resident type	0.015	0.049	0.101	0.485

SOURCE: Devised by the author.

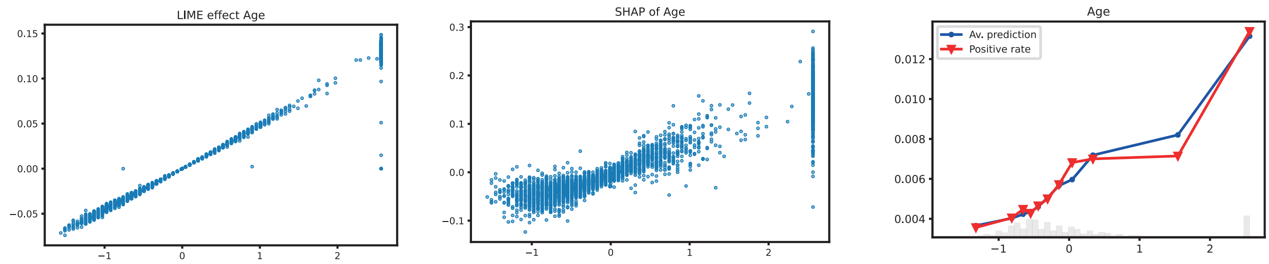
influence of a feature in the model with all other features present (the measure as the decay in the predictive capacities of the model when the feature is removed[21]). The idea is to provide a complementary view to the information value, which assesses the predictive capacity of each feature on a standalone basis.

There are notable differences in the importance given to the features by the two explanations, the most notable being *Loan status,* which is of very little relevance for SHAP, but is the second most significant feature for LIME and the other two measures.

The scatter plot in Chart 14 shows how the effects of the feature *Age* are distributed. The distribution is very similar in both methods and is aligned with the results obtained using PDP and ALE (see Section 5.1.1). We can see how the influences estimated by LIME are less volatile than those of SHAP. The volatility observed in the SHAP explanations could be explained, at least partially, by the estimation error (see Section 5.2.2), but it could also be the result of the explanations' greater dependence

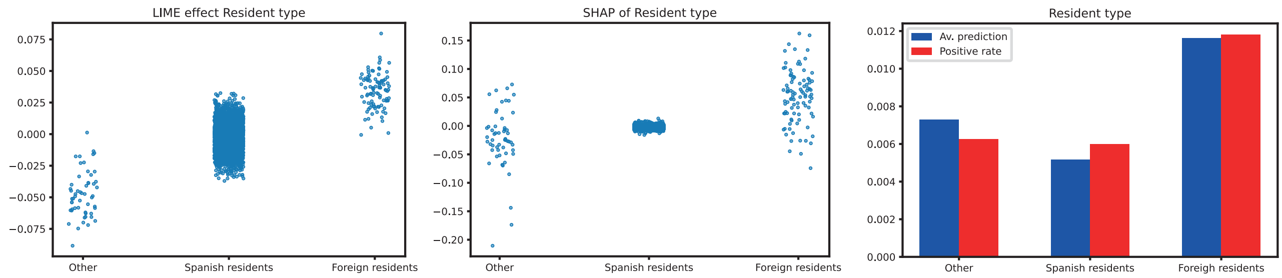
21 We have used the average AUC between training epochs 100 and 300 in order to stabilise the measure, as in most cases the decrease in the AUC is small and can be masked by the randomness of the AUC on a fixed epoch.

Chart 14
DISPERSION OF LIME AND SHAP EFFECTS



SOURCE: Devised by the author.

Chart 15
DISPERSION OF LIME AND SHAP EFFECTS



SOURCE: Devised by the author.

on the values of the other features (two observations with the same value for the feature *Age,* having different explanations and different contributions for this feature).

The plot in Chart 15 shows the contribution of the feature *Resident type* to the model estimated by LIME and by SHAP depending on the value of the feature. For this feature, we can see that there is an alignment between both methods and the PDP. In this case, the explanation of LIME shows greater volatility.

6 Conclusions

The interpretability techniques analysed are useful for gaining an insight into the model, and the explanations provided by the different techniques are, in general, compatible with each other. However, the explanations obtained require a careful assessment and, in some cases, may not lead to a complete understanding. Specifically, aggregating the information obtained from the different techniques, and obtaining a sufficient understanding of the theoretical basis of the tools, are by no means trivial tasks and can be laborious.

Influence plots provide plausible and robust explanations for some features, but they do not work well in all cases. For some features the ICE shows different model behaviours depending on the observation, which can make the information provided by PDP hard to interpret. Also, in some cases there are deviations between the influence revealed by these plots and the actual average predictions, and it is not clear what the implications of this divergence are or how to determine its cause.

The LIME and SHAP methods seem useful for delivering local explanations, though both methods also have their limitations. The most relevant are the sensitivity of LIME to the choice of parameters and the fact that SHAP has failed to capture the influence of a very relevant feature according to other measures. Also, the local explanations obtained with these two methods can differ significantly in some cases.

It is our understanding that there are certain aspects of our dataset that adversely affect the performance of the interpretability tools:

— A large proportion of categorical features, which makes it harder to define the vicinity of an observation.

— A strong dependency between the features, which contravenes the independence assumption on which some of these methods rely.

— A non-negligible amount of missing values in some of the features.

It is important to note that these characteristics are usually present, to a greater or lesser extent, in credit datasets, and caution should therefore be taken when using these tools on credit scoring models.

It is also worth pointing out that the work has been greatly facilitated by the open-source libraries available, some of which have been implemented and released by the authors of the methods themselves. Nevertheless, newcomers should be aware that some of these libraries are still being developed and complete documentation may not be available, and they can therefore be laborious to use.

This work should be complemented with other studies to determine how dependent the results drawn here are on the specificities of the dataset, the selection of the features and the choice of the model. It would also be interesting to extend the analysis to other techniques, considering other model-agnostic tools as well as model-specific ones.

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Appendix 1 Details of the implementation

1 Dataset

The features used in the model are the following:

- Real guarantee coverage: The extent of funded credit protection.
- Personal guarantee type: The type of unfunded credit protection.
- Personal guarantee coverage: The extent of unfunded credit protection.
- Loan origination: How the loan was originated.
- Loan purpose: The type of residential asset financed by the loan.
- Loan status: Indicates if the payments are up to date.
- Province: The province where the residential asset financed by the loan is located.
- Previous default: Indicates if there has been a previous default in the previous 2 years.
- Initial principal amount: The initial principal amount of the loan.
- Remaining principal amount: The remaining principal amount of the loan.
- Collateral amount: The value of the collateral.
- Initial maturity: The maturity of the loan at origination.
- Remaining maturity: The remaining maturity of the loan.
- Number of holders: The number of holders of the loan.
- Resident type: The residential status of the debtor.
- Economic activity: The economic sector of the debtor.
- Age: The age of the debtor.
- Country of birth: The country where the debtor was born.
- Gender: The gender of the debtor.

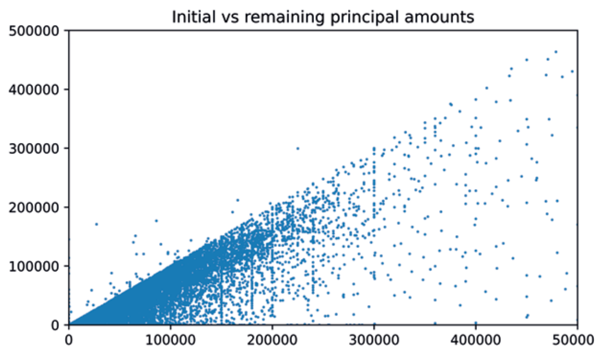
Table A1.1
PEARSON'S RANK CORRELATION BETWEEN THE FEATURES

%

	Real guarantee coverage	Previous default	Remaining principal amount	Initial principal amount	Remaining maturity	Initial maturity	Number of holders	Collateral amount	Loan status	Age	Country of birth
Real guarantee coverage	100.0	5.8	1.0	1.1	-1.4	0.7	-2.3	-0.6	-5.0	-4.9	-0.5
Previous default	5.8	100.0	0.7	0.4	0.3	1.3	-0.2	-0.3	16.8	6.1	-6.6
Remaining principal amount	1.0	0.7	100.0	87.1	7.8	2.5	0.4	47.2	2.3	11.8	-12.9
Initial principal amount	1.1	0.4	87.1	100.0	0.4	-1.5	0.5	46.3	1.9	15.8	-15.0
Remaining maturity	-1.4	0.3	7.8	0.4	100.0	83.5	0.1	-2.1	6.2	-39.4	15.2
Initial maturity	0.7	1.3	2.5	-1.5	83.5	100.0	-0.2	-3.4	4.2	-40.6	23.3
Number of holders	-2.3	-0.2	0.4	0.5	0.1	-0.2	100.0	0.0	1.0	0.3	-2.8
Collateral amount	-0.6	-0.3	47.2	46.3	-2.1	-3.4	0.0	100.0	1.2	11.3	-9.0
Loan status	-5.0	16.8	2.3	1.9	6.2	4.2	1.0	1.2	100.0	8.4	-7.0
Age	-4.9	6.1	11.8	15.8	-39.4	-40.6	0.3	11.3	8.4	100.0	-66.9
Country of birth	-0.5	-6.6	-12.9	-15.0	15.2	23.3	-2.8	-9.0	-7.0	-66.9	100.0

SOURCE: Devised by the author.

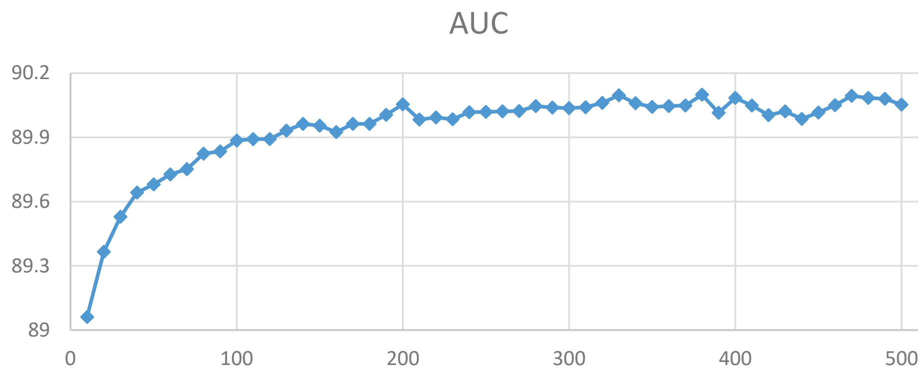
Chart A1.1
JOINT DISTRIBUTION OF INITIAL PRINCIPAL AMOUNT AND REMAINING PRINCIPAL AMOUNT



SOURCE: Devised by the author.

There are two aspects concerning this dataset worth highlighting with respect to their potential impact on the interpretability techniques. First, of the 19 features used, 7 are numerical and 12 are categorical (of which 4 are binary). Second, some of these features have a strong dependency between them. This can be seen in Table A1.1, which displays the Pearson's correlation matrix (on the numerical variables and the binary variables), and in Chart A1.1, which shows the joint distribution of the two most correlated features, *Initial principal amount* and *Remaining principal amount.*

Chart A1.2
VALIDATION SAMPLE AUC AT EACH TRAINING EPOCH



SOURCE: Devised by the author.

2 Data pre-processing

Categorical features are represented using one-hot-vector encodings. Provinces have been grouped by autonomous communities and, for the rest of the categorical features, categories containing less than 1% of the observations have been grouped together. In order to prevent numerical instabilities in the training of the model, the values of the numerical features have been truncated at their 0.01% and 99.99% percentiles. All the features have been normalized to facilitate the training process.

3 Structure of the model

The model is a feedforward fully-connected neural network with no leaping connections. The activation function is the ReLu in the hidden layers and the sigmoid in the output. The model has been trained using weights to address class imbalance and with drop-out regularization. The hyperparameters used are:

— Number of hidden layers: 2.

— Number of neurons per layer: 128.

— Drop-out rate: 0.4.

— Optimizer: ADAM.

— Learning rate: 1e-2.

— Batch size: 2048.

The values of the hyperparameters have been chosen by minimizing the error in the validation sample, taking a sample split of 80% for training and 20% for validation. We trained the model for 300 epochs, where the performance of the model, measured using the AUC, stabilizes (see Chart A1.2).

4 Software and hardware used

The model, accuracy metrics and interpretability tools have been implemented in python using the libraries Tensorflow 2.5.0, Keras 2.5.0, Numpy 1.19.2, Sklearn 0.24.1, Matplotlib 3.4.2, Shap 0.39.0, Lime 0.2.0.0 and Alibi 0.6.0.

All the computations have been carried out on a laptop with an Intel Core i5-10210U processor, 16 GB of RAM and no GPU or TPU.

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