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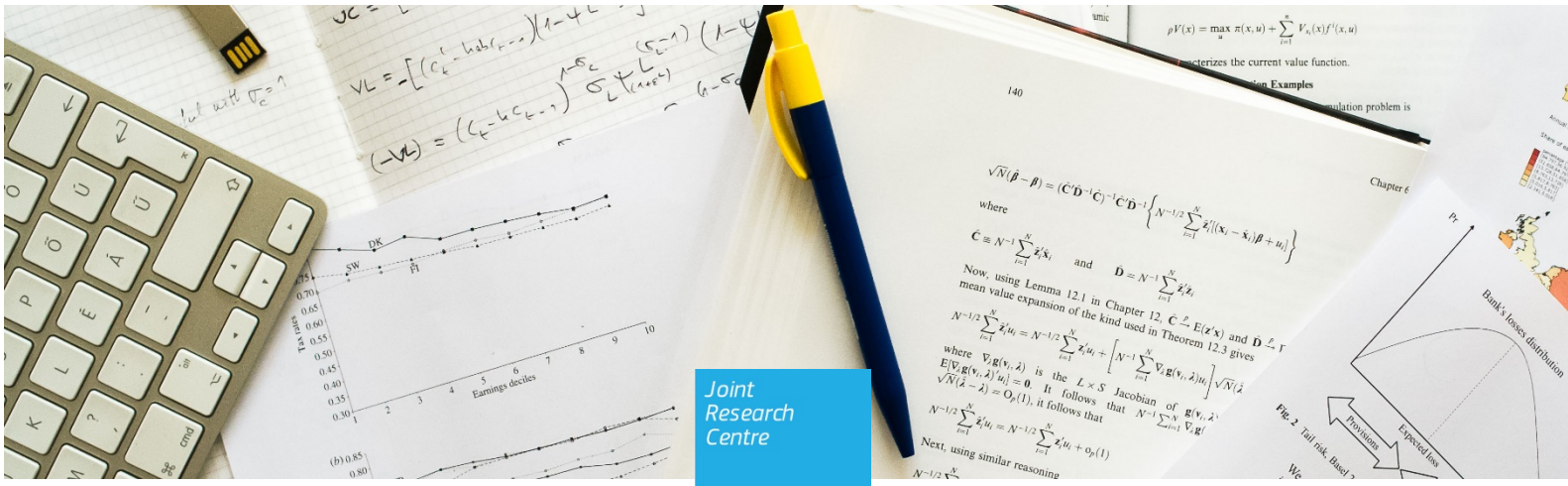

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What drives bank coverage ratios: Evidence from the euro area

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Abstract

We analyse micro and macro drivers of coverage ratios in a cross–country sample of euro area banks. Among the former, we find that coverage ratios increase with the reliance on deposit funding and when asset quality is very poor. Among the latter, coverage ratios increase with GDP growth and with more stringent supervision and macro–prudential policies, as well as with deeper NPL secondary markets. Finally, we find evidence of peer imitation behaviour, as banks with below country average coverage ratios increase coverage ratios to catch up with their peers. As for the prevalent mechanism, banks tend to enhance coverage ratios primarily by increasing loan loss reserves rather than by resolving NPLs.

Keywords: loan loss reserves, non–performing loans, loan loss coverage

JEL Classification: G21, G28, M41

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1. Introduction

One of the most debated issues in Europe since the financial and sovereign debt crises concerns the accumulation of large stocks of non–performing loans (NPLs). The relevance of the issue has attracted the attention of both European and national regulators and policy makers with the objective of reducing troubled assets both via micro and macro supervisory initiatives (Draghi 2017; ECB, 2017a; and ESRB, 2019). Although these assets have decreased by one third over the last three years, they still amounted to over 700 billion euros in September 2018, with large variation across banks and countries (EBA, 2018).

Several of these actions entailed measures on how to enhance coverage ratios, i.e., the share of loan loss reserves (LLRs) to total NPLs, as a measure of how much the credit risk associated with a given loan is covered through provisions. As such, over the last years this variable has gained relevance as a key supervisory metric to assess banks' soundness (ECB, 2017a).

Notwithstanding the pressure to foster the accumulation of LLRs, coverage ratios vary remarkably across banks and countries. According to official statistics, at the bank level, large institutions have commonly reported lower coverage ratios than small and medium–sized banks. At the country level, the average coverage ratio in Europe is nearly 46%, but it ranges from 24% in Finland to nearly 70% in Hungary. What is more striking is that many of the countries with the highest level of NPLs report below–average coverage ratios (EBA, 2018).

Despite the policy focus on loss coverage for NPLs, there is little, if any, empirical evidence on coverage ratios and the factors driving them. Previous work on related topics has focused on explaining loan loss provisions (LLPs) through managerial discretion (Liu and Ryan, 2006; Bushman and Williams, 2012; Norden and Stoian, 2013; Beatty and Liao, 2014, and literature therein) and their timeliness and contribution to procyclical lending (Leaven and Majoni, 2003; Beatty and Liao, 2011; Nicoletti, 2018).

Although they are related, provisioning policies are only partially correlated with coverage ratios (see Table 1) and thus, previous findings on the determinants of provisioning cannot fully explain the dynamics of coverage ratios, which is a more comprehensive indicator of balance–sheet strength.

Our paper aims to fill this void by focusing on the accumulation of coverage ratios and their drivers, both at the micro and macro level. The focus on the euro area (EA) provides an interesting case study given the high level of NPLs and substantial bank and country heterogeneity in the region (EBA, 2018). The analysis covers the euro sovereign crisis and the post–crisis years, a relatively long period marketed with a slow recovery. Both circumstances outline why the coverage ratio has

gained importance as a measure of balance sheet strength, and why it is relevant to explore its determinants.

Our work differs from the existing literature in various respects. First, our main variable of interest is the stock of LLPs accumulated over the years (i.e., LLRs or loan loss allowances) in percentage of NPLs rather than the flow of LLPs. As argued above, one area of renewed interest for banking authorities is the appropriate level of loan loss reserve to face the growing risk emerging from the lending business. Coverage ratios, however, still exhibit large variation both at the bank and at the country level.

Second, we explore additional bank and country factors affecting coverage ratios relative to those analyzed in the existing literature on provisioning. For example, among bank characteristics, we explore the role of funding structure in addition to that of managerial discretion, which has dominated previous studies (see, e.g., Beatty and Liao, 2014, and Beck and Narayanamoorthy, 2013 for a review). Funding structure is a potential relevant driver of coverage ratios because, for example, banks more exposed to market scrutiny, such as those relying on wholesale funds, may have greater incentives to build large loan loss reserves so to protect their balance sheets.

Among the country variables, we analyse the importance of the institutional framework as captured by the strength of supervision and macro-prudential policies as well as by the development of a secondary market for NPL assets, in addition to the typical focus on GDP growth and pro–cyclicality in previous studies. This allows us to exploit the richness of country characteristics and thus, better explain the large variation in coverage ratios across countries.

Finally, as we focus on coverage ratios rather than loss loan provisions, we are able to explore the mechanisms (i.e., changes in LLRs versus changes in asset quality) through which banks protect themselves against credit losses and adjust their coverage ratios in response to shocks. This allows us to better gauge the ability or willingness of banks to shield their balance sheets against variations in asset quality and to draw some conclusions on which policy measures could enhance coverage ratios.

To investigate dynamics as well as micro and macro drivers of coverage ratios, we use a sample of around 570 large and medium–sized banks in the EA over the period 2010–2016. We first employ a panel fixed–effect model to understand to what extent credit risk considerations matter for coverage ratios as opposed to other micro–level factors unrelated to the riskiness of the loan portfolio.

Results from the micro–level analysis show the relevance of asset quality and funding structure, while, unlike in previous studies, earnings and capital motives do not appear to be significant. This finding can be explained by the fact that our analysis covers a period of economic

downturn, when discretionary earnings management to smooth income may have become undesirable, if not unfeasible.

In our baseline specification, we first find higher coverage ratios in banks with better asset quality. Interestingly, the relationship between asset quality and the coverage ratio is not linear, suggesting that banks build up large loan loss reserves only once their assets deteriorate substantially. Moreover, we do not find evidence that banks more exposed to market scrutiny show greater protection through larger loan loss reserves. On the contrary, we uncover higher coverage ratios in banks more reliant on customer deposits. This result may reflect a more cautious approach in more traditional banks.

In an extension of our baseline analysis, we study how banks adjust their coverage ratios in response to major events that occurred in Europe in the period of analysis: the euro sovereign crisis in 2010–2012 and the introduction of the single supervisory mechanism (SSM) in November 2014. We find that banks decreased coverage ratios during the euro sovereign crisis. In an attempt to inspect the mechanisms behind this result, we disentangle the components of coverage ratios, i.e., LLRs and NPLs. We uncover that coverage ratios decreased primarily as an effect of higher NPLs, with no visible variation in LLRs. This finding, contrary to prior evidence on pro–cyclical provisioning (e.g., Laeven and Majnoni, 2003), supports the view that, in bad times, banks tend to postpone adjustments in provisioning. This is consistent with the idea that banks may want to limit the drawbacks of higher LLPs, namely that of reducing earnings and capital ratios (Andries et al., 2017). Moreover, our finding may reflect regulatory forbearance in downturns, consistent with prior research (Huizinga and Laeven, 2012; Yang, 2017; Gallemore, 2018).

By contrast, the tightening of banking supervision due to the inception of the SSM in 2014 is associated with higher coverage ratios in supervised banks relative to the others, but the mechanism by which supervised banks achieve higher coverage ratios is not clear. Overall, our finding is consistent with the evidence that stricter supervision stimulates banks to reduce their risk profile (e.g., Gropp et al., 2017; Fiordelisi et al., 2017).

As a last exercise in the pure micro–level setup, we investigate whether and how banks change their coverage ratios to catch up with their peers. Benchmarking is a common practice among practitioners and supervisors to assess the "adequacy" of a bank's performance. We find that, independently of their specific characteristics, banks with coverage ratios below their country average increase their respective ratios, and this effect is stronger for banks that are farther away from the average. This result is in line with anecdotal and empirical evidence that market pressure and benchmarking play an important role in banks' provisioning policies (e.g., Rajan, 1994). In terms

of mechanism, we uncover that banks adjust coverage ratios by both increasing LLRs and resolving NPLs.

In the second part of the analysis, we exploit cross–country discrepancies by replacing country fixed effects with macro variables to account for institutional specificities at the country level that we deem relevant in a context of high NPLs. We first find that coverage ratios increase with GDP growth. This evidence complements our findings on coverage–ratio dynamics during the euro debt crisis and confirms that the business cycle is an important driver of bank behaviour.

To measure regulatory intervention, we include the macro–prudential index from Cerutti et al. (2017) and its subcomponents. We find some evidence of a positive association between tighter macro–prudential regulation and coverage ratios.

In particular, coverage ratios are higher in banks located in countries with more restrictive limits on bank borrowers and (to a lower extent) with dynamic loan loss provisions, while they are lower for banks in countries with higher capital buffers on significant financial institutions (SIFI). A possible explanation of this last finding is that banks subject to tight regulation, as in the case of SIFI, can be constrained in setting aside more LLPs, as this would reduce the possibility of using retained earnings to enhance capital ratios (Andries et al., 2017).

We then exploit the large cross–country variation in asset quality by focusing on banks from countries with NPLs ratios above the sample mean. On the one hand, banks from countries more exposed to risky assets should be more reactive to tighter regulation. On the other hand, these banks may find it more costly to adjust their coverage ratios to stricter rules (Andries et al., 2017), also because of their weaker institutional settings (Aiyar et al., 2015; ECB, 2016 and 2017b). In the restricted sample of banks from high–NPLs countries, we find that measures to enhance provisioning and taxes on financial institutions are important drivers of coverage ratios, while limits on bank borrowers and capital buffers lose significance.

In another extension, we take into account the degree of development of the NPL secondary market. According to European central authorities (see, e.g., Fell et al. 2016 among others), a well developed market for NPLs is an important structural feature to resolve troubled assets effectively. Reporting adequate level of coverage ratios is key to make the loan disposal more likely, because this would reduce the bid–ask spread between sellers and buyers, and limit the actual loss for the seller in case of asset disposal (Constâncio, 2017). We find higher coverage ratios in banks from countries where secondary markets for distressed debt are larger. This suggests that in more developed secondary markets, banks have stronger incentives to increase their coverage ratios, so as to lower the net loan book values, reduce the potential loss deriving from the asset disposal, and henceforth, enhance the marketability of their loans.

Finally, we allow for some of the most recent actions to tackle NPLs taken by national jurisdictions, as documented in the ECB's "Stocktake of national supervisory practices and legal frameworks related to NPLs" (ECB, 2016 and 2017b). We find that banks report higher coverage ratios when more measures to reinforce the judicial and legal system are in place.

Our main findings are robust to several checks. We show that results are robust to employing alternative measures of asset quality, capitalisation, funding structure, profitability, and regulatory stringency. To mitigate potential concerns about endogeneity, we lag all bank–level covariates by one period. Then, we estimate a GMM model as a robustness check in order to be sure that our model does not suffer from endogeneity. In addition to that, we saturate our model by including a full set of bank–, time– and country–time fixed effects, to control for potential omitted variables at the bank and country level, which could otherwise bias the coefficient estimates of our variables of interest. This is important because EA countries show several specific features at the institutional level that can influence the way banks resolve NPLs or accumulate LLRs. Finally, we try to exploit these cross–country discrepancies by replacing country–time fixed effects with macro variables to account for national specificities at the institutional level that we deem relevant to our purposes.

To the best of our knowledge, this is the first empirical analysis on drivers of coverage ratios in Europe. Providing comprehensive evidence on the dynamics of coverage ratios across banks and countries and their determinants contributes to both the academic and the policy debate. Concerning the former, we contribute to the vast literature on determinants of provisioning by placing renewed interest on the accumulation of LLRs as a means to protect bank balance sheet in a context of increased credit risk. Credit risk considerations seem to matter more than managerial discretion in explaining the way banks adjust coverage ratios. While we do not find any direct relation between bank capital, profitability and coverage ratios, however, our evidence points to the fact that banks tend to reduce coverage ratios in bad times, and to increase them in good times. This is suggestive of a countercyclical behaviour in accumulating LLRs. It also suggests that in downturn banks might be unable or unwilling to accumulate large LLRs, in order to preserve earnings and minimize the negative impact of income decline on equity capital, and that maybe this behaviour was incentivised by supervisory forbearance, in line with Huizinga and Laeven (2012).

To the benefit of current debate, our results on the role played by macro drivers of coverage ratios could help policy makers in clarifying which levers may be the most effective to reach the desired level of loss coverage. We show that, overall, the main mechanism by which banks reinforced their coverage ratios is by shaping LLRs, i.e., by increasing the numerator of the ratio. This finding points to the importance of comprehensive measures to tackle the NPL problem in Europe.

Stricter supervision is relevant but addressing other structural sources of inefficiencies (e.g., by developing the secondary market for loans or reinforcing the legal framework) is at least equally important in order to provide banks with further tools for the disposal of legacy assets. These would help banks enhance coverage ratios by enabling them to reduce the denominator of the ratio more quickly and at a lower cost.

The remainder of the paper is structured as follows. Section 2 provides some background details on the main measures taken to enhance loss coverage for NPLs and the reasons why, in a context of high NPLs, it is important for banks to build up adequate coverage ratios. It also presents stylized facts on recent dynamics of NPLs and coverage ratios. Section 3 illustrates the data and provides descriptive statistics for our sample. Section 4 and 5 investigate empirically the main sources of discrepancies in coverage ratios. We first focus on micro–level factors (Section 4) and then extend the analysis by using macro–level data (Section 5). In both sections we include several extensions to our baseline specifications. Section 6 concludes.

2. NPLs and coverage ratios: institutional background

2.1 Recent measures to enhance loss coverage for NPLs

NPLs have recently become a concern for macro–prudential authorities in Europe because of the potential negative externalities associated with large stocks of troubled assets (ESRB, 2019). High NPLs are potentially detrimental to individual banks and the financial system for several reasons. First, an unresolved stock of NPLs may have negative externalities on the perception of the health of the financial system, making bank funding more expensive and discouraging banks from new lending. Second, lending can be impeded as banks with poorer asset quality may seek to regain adequate capital ratios by deleveraging and cutting back on lending rather than by raising new equity. Third, high NPL ratios can also distort managers' incentives if troubled loans increase moral hazard and favour excessive risk taking because of eroding bank capital (Bruno and Marino, 2019).

NPLs in European banks skyrocketed to unprecedented levels in the wake of the global financial crisis, making them more vulnerable than their international peers to the repercussions of poor asset quality. The European supervisors have reacted fiercely to resolve the problem of legacy assets. As a result of these actions, according to ECB statistics, the NPLs ratio of significant EA institutions has decreased from 8% as of mid–2015 to nearly 4% as of the third quarter of 2018. Nevertheless, discrepancies across banks and countries still persist and the aggregate level of NPLs in EA banks remains very high, especially when compared to their international peers: according to World bank data, the NPL ratio is nearly 1% in both the US and Japan as of end 2017 (Figure 1).

Several of these actions entailed measures on how to enhance provision coverage of NPLs. In March 2017, the ECB released guidelines on how to manage and provision for problem loans, complemented with quantitative indicators, mainly based on the vintage and the degree of collateralisation of the non–performing exposures, as well as and on the minimum levels of prudential provisions (see the Addendum to the NPLs guidance as of March 2018). In July 2018, the ECB announced the decision to set bank–specific supervisory expectations for the provisioning of NPLs as part of the supervisory dialogue.[1] In March 2018, the European Commission adopted a comprehensive package of measures. This included a proposal to introduce common minimum coverage levels for newly originated loans that become non–performing.

To complete the picture, the accounting standard IFRS 9, introduced as of January 2018, has changed the impairment recognition by requiring banks, in essence, to make larger and timelier provisions.[2] Ideally, provisions should anticipate deteriorating economic conditions that may affect borrowers' ability to repay. In such a way, they could be effectively used to cover expected losses, while bank capital serves as a buffer against unexpected losses (Laeven and Majnoni, 2003). However, until the introduction of IFRS 9, banks in most European countries accumulated provisions according to a backward–looking approach, reflecting "incurred" rather than "expected" credit losses (Cohen and Edwards, 2017).

2.2 Why is it desirable to have high loss coverage?

In this section we aim to clarify the main reasons why it is desirable for regulatory and supervisory purposes to promote high loan loss coverage.

The question is not trivial. First of all, at least before the introduction of the IFRS9 as of January 2018, there is a sort of trade–off between the goals of accounting standard setters, who emphasize transparency of financial statements, and the goals of regulators and supervisors who emphasize safety and soundness. Given the accounting rules, LLPs have a significant, detrimental effect on earnings and regulatory capital (Liu and Ryan, 2006; Andries et al., 2017). Because LLPs are at the discretion of bank managers, there is potential for banks to provision more or less than necessary as a way to smooth their income. From an accounting perspective, this would introduce discretionary modifications to earnings and reduce comparability across firms (Walter, 1991).

[1] More precisely, the aim is to achieve the same coverage of NPL stocks and flows over the medium term through bank–specific expectations, guided by individual banks' current NPL ratio and their main financial features in a consistent way across comparable banks.

[2] There are some exceptions. Notably, Spanish bank regulators introduced a forward–looking provisioning regime in 2000, meant to address procyclicality issues, which led to more timely and higher general provisions (de Lis et al., 2001; Jiménez et al., 2017).

On the other hand, from a prudential perspective, higher provisioning may reflect a more cautious approach to building up large reserves prior to future losses. In fact, adequate coverage ratios can help banks mitigate most of the concerns associated with high NPLs, by enhancing balance sheet strength, by increasing balance sheet transparency, and by making troubled asset disposal more likely.

Coverage ratios as tools to strengthen bank balance sheets

The first reasons for regulators to promote high coverage ratio is that adequate loan loss allowances enhance banks' safety and soundness (Wheeler, 2019). In fact, provisioning is a credit risk management tool through which banks alleviate credit risk by setting aside a given amount (LLP) as a buffer to absorb expected losses associated with a loan. LLPs allow banks to recognise the estimated loss in their profit and loss account, even before the actual loss can be determined with accuracy and certainty. The stock of LLPs accumulated over years is referred to as loan loss reserves or allowances (the numerator of the coverage ratio). When loan losses eventually materialise, banks can ideally draw on these reserves, thereby absorbing the losses without impairing capital. This would preserve banks' capacity to provide credit to the economy (Beatty and Liao, 2011).[3]

By construction, the coverage ratio is complementary to the book value of the loan, as larger LLRs correspond to lower (net) book value of loans. Hence, the lower the coverage ratio, the higher the carrying amount of the loan as well as the credit risk faced by the bank.

In principle, low coverage ratios do not necessarily imply under–provisioning or delayed recognition of losses, as they might reflect rigorous lending practices or strong insolvency frameworks (EP, 2016). In practice, however, especially in a context of high NPLs and generalised poor asset quality, low coverage ratios represent a potential source of instability in that any future loss on the loan portfolio, if not sufficiently provisioned for, would be covered by bank capital. This would make banks with large volumes of NPLs and moderate coverage ratios more vulnerable to negative shocks affecting borrowers' credit quality, especially in crisis years.

Coverage ratios as tools to enhance banks' transparency and loan marketability

High coverage ratios are also important instruments to make banks' balance sheet less opaque. In the traditional banking literature, loans are illiquid and untraded contracts (Diamond and Dybvig, 1983). In the absence of a true market price, the loan fair value is approximated through the process of provisioning. The process of accumulating provisions is, in fact, equivalent to reducing the

[3] The NPL Guidance stresses the importance of timely provisioning and write–off practices related to NPLs, as "these serve to strengthen banks' balance sheets, enabling them to (re)focus on their core business, most notably lending to the economy" (ECB, 2018).

face value of the loan to its present value, taking into account the allowance built up over time (Song, 2002). Thus, if loan loss allowances were underestimated, bank assets and capital ratios would be overvalued and balance sheets would be distorted. Because high loan loss coverage corresponds, *de facto*, to low loan net book value, it follows that reporting high coverage ratios is also a precondition to make the asset disposal more likely and reduce the bid–ask spread between sellers and buyers (Fell et al., 2016).

2.3 Some stylised facts on NPLs and coverage ratios

Despite the benefits associated with high coverage ratios, there still exists large variety across banks and countries in Europe. Figures 2 to 7 explore trends in NPLs and coverage ratios in our sample of EA banks in 2010–2016 (details on the dataset used in the analysis are provided in Section 3). Figure 2 shows that the average coverage ratio in the EA has trended up since the sovereign debt crisis in 2010–2012 and, again, after the entrance of the SSM in 2014. Figure 3 shows that overall LLRs increased relatively more (or decreased less) than NPLs, probably as an effect of prudent provisioning associated to more intense NPL resolution in the most recent years. This evidence suggests that, on average, European banks have progressively increased their coverage ratios, partly as a managerial response asset quality deterioration, partly due to stricter supervisory and market scrutiny.[4]

However, Figures 4 to 7 confirm the presence of large cross–sectional variability in asset quality and coverage ratios, both across countries and across banks within the same country. The comparison between Figure 5 and 6 shows that, on average, there is no full correspondence between countries with low (i.e., below the sample average) asset quality and those with high (i.e., above the sample average) coverage ratios. Figure 7 shows the evolution of the average coverage ratio for banks in high–NPL countries, i.e. those with NPL ratios above the sample mean. Although generally lower than the average in the euro area, coverage ratios in high NPL countries have trended up in the aftermath of the euro sovereign crisis and especially since the inception of the single supervisor in 2014.

Overall, the comparative analysis of coverage ratios and NPLs suggests that heterogeneity in European banks' coverage ratios is not fully explained by differences in asset quality.[5] Differences in coverage ratios may depend on other bank–specific factors as well as on characteristics of the

[4] "This may have been due to stricter supervisory and regulatory scrutiny in relation to the AQR exercise, increased market pressure, as well as a deterioration of collateral values (Council of the European Commission, 2017).

[5] An EBA report on NPLs also shows that the correlation between these assets and coverage ratios is low over time, with a correlation coefficient close to 0 at least since September 2014 (EBA, 2016).

national legal, judicial and supervisory/regulatory framework.[6] In the next section, we will empirically explore the relationship between coverage ratios and some of these characteristics.

3. Data and summary statistics

We collect annual bank–level data from the S&P Global Market Intelligence Platform (S&P Global).[7] The dataset spans the years 2010–2016 and covers all EA countries.

We apply a careful cleaning procedure to the dataset in order to ensure to have as homogeneous a sample as possible. In doing so, we closely follow Eber and Minoiu (2016). To begin with, we only keep the statements with the highest level of consolidation. To avoid including too small banks that could introduce noise, we only keep banks that are being classified as medium–sized and large according to the ECB definition in 2016.[8] Given the purpose of the analysis, we delete institutions whose commercial banking business is negligible, i.e., we delete those with a loan–to–asset ratio and a deposit–to–asset ratio smaller than 20%. For the same reason, we filter out institutions not classified as 'bank' or 'savings bank/thrift/mutual', as well as those that, although being classified as banks by S&P Global, may operate not in a pure commercial manner because for example of ownership (e.g., government–owned banks) or scope (e.g., asset management companies). Finally, all micro–level variables are winsorised at 2.5% and 97.5%, respectively. Nevertheless, our findings are robust to different levels of winsorisation.

We also identify the banks that were part of the Comprehensive Assessment, which the European Central Bank carried out in 2014 and use this sample when analyzing the role of the institutional supervisory setting in explaining banks' coverage ratios.[9] In doing this, we remove the subsidiaries, parents, and ultimate parents of these banks, as they could have also changed their provisioning policies in anticipation of the assessment or after it, while not formally showing up as banks under SSM supervision.

The final sample contains 570 banks, representing around 70% of the EA banking assets. Descriptive statistics for the main variables are shown in Table 2. The average sample bank is medium–sized according to the ECB definition with assets amounting to nearly euro 10 billion; and is a traditional commercial bank, whose core business is lending (the average loan to asset ratio is 64%) and whose main source of funds are customer deposits (the deposits to assets ratio averages

[6] The ECB has taken stock of these differences and produced a report on national supervisory practices and legal frameworks related to NPLs. So far, the ECB has published two reports: the first one as of September 2016 and the second as of June 2017.

[7] This database has formerly been known as SNL Financial.

[8] The ECB labels as large those institutions with assets greater than 0.5% of total consolidated assets of European Union banks and medium–sized as those with assets between 0.5% and 0.005%.

[9] In doing this, we remove the subsidiaries, parents, and ultimate parents of these banks, as they could have also changed their provisioning policies in anticipation of the assessment or after it, while not formally showing up as banks under SSM supervision.

66%). As far as bank asset quality is concerned, the NPL to total asset ratio averages about 4% and the mean NPL to total loan ratio is 6.4%. The average coverage ratio is nearly 50%, with large variation across banks, the minimum coverage ratio being 14.5% and the maximum 87%. These numbers are comparable to those reported in aggregate statistics (IMF, 2015; ECB, 2016).

Looking at measures of bank capitalisation, the CET 1 regulatory capital ratio is close on average to 14%, well above the Basel III minimum requirement of 8.5% including the capital conservation buffer. Note that the European banking sector has taken a number of steps to strengthen its resilience since the onset of the euro debt crisis. The average levels of ROE and ROA (3% and 0.24%, respectively) confirm that low profitability remains a major source of concerns for European banks according to central authorities (Constâncio, 2017). The comparison between the average ROA and the pre–impairment profits over total assets ratio (about 1%) suggests that allowances associated with the riskiness of lending have indeed eroded over three quarters of revenues generated by the whole banking business. This supports the view that high NPLs have been an important cause of low profitability in European banks (Altavilla et al., 2018).[10]

4. Exploiting the cross section of banks: micro–level analysis

In this section, we exploit our sample heterogeneity to explore the link between coverage ratios and bank–specific characteristics that seem more relevant to our purposes. There are several factors that, in principle, can justify variation in coverage ratios. Some of them relate to loan portfolio characteristics others to features unrelated to credit risk considerations. We illustrate these factors and formulate hypotheses. Because higher coverage ratios may entail larger provisions, we will also draw on the literature on determinants of LLPs when investigating the drivers of coverage ratios.

4.1 Baseline specification, variables and testable predictions

We test whether bank level characteristics have an impact on NPL coverage ratios by estimating the following panel fixed effects model:

$$\left(\frac{LLR}{NPL}\right)_{ik,t} = \lambda_t + \mu_i + \gamma_{k,t} + \beta X_{ik,t-1} + \varepsilon_{ik,t}, \qquad (1)$$

[10] "The return on equity remains below the cost of equity with legacy assets, cost–efficiency and banks' business models still being some of the main obstacles towards reaching sustainable profitability levels". (EBA, Risk Dashboard as of Q1 2018)

where i = 1, …, N, k = 1, …, K and t = 1, …, T, with i being the bank, k being the country, and t being the year. The vector $X_{ik,t-1}$ includes bank–level covariates and all explanatory variables, which are lagged by one year to mitigate concerns about reverse causality. The equation includes time, bank and country–time fixed effects (λ_t, μ_i and $\gamma_{k,t}$, respectively). The latter accounts for country–time–specific characteristics, which we will investigate in depth in Section 5.

Our key variable is the coverage ratio, i.e., the amount of LLRs over the stock of NPLs.[11] In additional regressions, to better understand the mechanisms by which banks adjust their coverage ratios, we decompose the coverage ratio and use its components, the log(LLR) and the log(NPL), as dependent variables. In an extension to our baseline analysis, we also replace the level with the change in coverage ratio.

We include a set of controls for the main balance sheet items we consider being potential drivers of coverage ratios. The first plausible driver of coverage ratios is the quality of the loan portfolio. *Ceteris paribus*, one may expect poorer asset quality to be associated with higher coverage ratios as banks with lower asset quality should be more prone to increase loss coverage for the reasons discussed in the previous sections. Our preferred measure of asset quality is the ratio of NPL over total assets; for robustness, we replace this indicator with the NPL to total loans ratio (see Table A.1). In an extension to the baseline analysis, we also include the high–NPL bank dummy to exploit variation across banks and account for potential non–linear effects of asset quality.

The literature on drivers of LLPs also points to profitability and capitalisation as factors affecting provisioning policy. Bank managers may exploit discretion in provisioning to smooth income and to manage capital (see, among others, Liu and Ryan, 2006 and Better and Liao, 2014, and literature therein). The income–smoothing hypothesis in loan loss provisioning states that banks provision during times of higher earnings in order to smooth profits over time: when earnings are low, provisions are deliberately understated to mitigate the adverse effect of other factors on earnings, in contrast to situations when earning are thought to be high. Therefore, under this income–smoothing behaviour, banks' provisioning policy may be used to minimise the variance of reported earnings. The systematic under (over) provision in banks with low (high) profits should be reflected in lower coverage ratios.

We account for the potential influence of profitability on coverage ratios and test the income–smoothing hypothesis by using the return on assets (ROA). For robustness checks, we also include the return on equity (ROE) and the pre–impairment operating profit over TA (see Table A.1).

The role played by capitalisation is less clear. Two related arguments point to a positive association between capitalisation and coverage ratios. The first one draws on the traditional view

[11] NPLs include the subcategories of bad loans, unlikely–to–pay exposures and past–due exposures. Unfortunately, the amounts of the subcategories are not available for several banks in our sample.

on accounting discretion and capital management, according to which capital–constrained banks may have the incentive to use provisions to achieve regulatory capital targets (Andries et al, 2017). This occurs because provisions, by reducing earnings, have a mechanical negative effect on banks' capital. Hence, weak banks would have the incentive to hold back on LLPs in order to preserve regulatory capital. If this is the case, lower capitalisation should be associated with reduced provisions that would progressively lead to lower coverage ratios.[12] The second argument relies on the fact that an increase in NPLs mechanically pulls down coverage ratios. When asset quality deteriorates substantially, only well capitalised institutions can afford the cost of a substantial increase in provisions to restore adequate levels of LLRs.

Contrary to these arguments, an alternative view would justify the existence of a negative nexus between coverage ratios and capitalisation. In this view, the two variables are substitutable buffers against potential losses. When raising capital is too costly, lower capitalised banks may have the incentive to increase coverage ratios to partly compensate for their lack of capital (Norden and Stoian, 2013). Or, to change perspective, better capitalised banks would be in a more comfortable position to absorb shocks prompted by the deterioration of the loan portfolio. As such, these banks should have less incentives to increase coverage ratios.

To test these different views, we control for capitalisation by using the CET 1 capital ratio. The ability to absorb unexpected losses makes common equity the highest quality and most costly component of banks' regulatory capital. Later, for robustness, we replace the CET1 ratio with two alternative measures: the Tier 1 ratio and the CET1 over NPLs ratio (see Table A.1).

Banks' funding structure could also influence coverage ratios in that low asset quality might compromise banks' ability to borrow by making them more risky and opaque (Bruno and Marino, 2019). As discussed in the background section, higher coverage ratios can mitigate the concerns associated with NPLs by buffering risk and enhancing transparency. We therefore expect that banks more exposed to market discipline have more incentives to report higher coverage ratios compared to banks less subjected to investors' scrutiny. To capture the role of funding structure, we focus on the ratio of customer deposits to assets to gauge the importance of traditional sources of funds. We assume banks that are more reliant on traditional deposits are less exposed to market scrutiny and, therefore, have less need to report high coverage ratios compared to banks more reliant on wholesale funding.

[12] Measuring the actual impact of LLPs on regulatory capital is not trivial, as this depends (among other factors) on the way banks measure risk weights. For banks under the standardised approach for calculating regulatory capital ratios, the provisions regime varies across jurisdictions, building on the distinction between specific and general provisions. The former refers to identified problem loans for which trigger events (e.g., due payment) exist; the latter is made against a portfolio of loans, and the computation of it varies significantly across countries (ESRB, 2017).

We control for size (log of total assets) because aggregate statistics show that smaller banks tend to report higher coverage ratios, although variation in bank asset size has declined progressively over time (EBA, 2018). More generally, prior research proved that size is a relevant factor affecting lending and risk taking (see Kishan and Opiela, 2000, among others), and therefore it may also explain banks' provisioning policies.

We also control for the loan to asset ratio, because previous studies on the determinants of bank provisioning find a positive association between the relevance of the lending business and loan loss provisioning behaviours (see, among others, Bouvatier and Lepetit, 2012).

4.2 Baseline results

Table 1, Column 1 presents our main results for the baseline investigation on the main micro drivers of coverage ratios. Only few bank–specific characteristics have statistical significance. We find that banks with poorer asset quality in the previous year (i.e., a higher share of NPL/TA) exhibit lower coverage ratios, while banks with a larger base of customer deposits show higher coverage ratios. Columns 2 and 3 present results on the components of coverage ratios. Not surprisingly, we find strong evidence that banks with lower asset quality report increasing LLRs. We also uncover that less profitable and less capitalized banks show larger share of LLR, although the coefficients on the ROA and CET1 are significant at the 10% level (Column 2); this last finding does not support the view of banks' discretionary behavior to smooth income and manage regulatory capital. We also find higher level of NPLs in larger banks as well as in banks with lower capital ratios (Column 3), consistent with risk taking and moral hazard hypotheses (Keeton and Morris, 1987; Berger and De Young, 1997). Interestingly, funding structure seems to be unrelated to LLRs and NPLs.

We run several tests to prove robustness of the results. In Table A.1., we account for alternative measures of asset quality, bank capitalisation and profitability. We first re–estimate Eq. (1) by replacing our preferred indicator of asset quality with the NPL ratio (i.e., the share of NPLs to total loans) which is the most commonly used measure of lending portfolio quality (Column 1). With respect to capitalisation, we replace the CET 1 ratio by the share of CET 1 capital over the stock of NPLs (Column 2) and by the Tier 1 ratio (Column 3). As for profitability, to test the earning smoothing hypothesis, we alternatively use the return–on–equity (Column 4) and the earnings before taxes and LLPs to total assets ratio (Column 5). The baseline results are confirmed across the various specifications.

To mitigate endogeneity concerns, we lag all bank–level covariates by one year. In addition to that, we estimate our baseline model using GMM (see Table A.2). The GMM estimator provides consistent estimates in the presence of different sources of endogeneity, including unobserved

heterogeneity, simultaneity, and dynamic endogeneity (Wintoki et al., 2012). Results from the GMM estimation are qualitatively comparable to those of the panel fixed effects model.

4.3 Investigating non–linearity: Low asset quality, low deposit, and low capitalised banks

As discussed in the background section, building up adequate coverage ratios would serve the purpose of strengthening balance sheet and ensuring transparency, to the benefit of bank regulators and investors. We now aim to investigate whether any of these features drive banks' behavior, by exploring the way banks with very low asset quality, low deposits and low capital adjust their coverage ratios.

Specifically, in Table 4 (Column 1) we first extend our baseline regression by including the high NPL bank dummy that equals 1 if the NPL to total asset ratio is in the top decile of the sample distribution, and zero otherwise. We find that the nexus between asset quality and coverage ratio is not linear. While the coefficient for the linear measure of asset quality is positive and significant at 1% level, the coefficient for the very risky banks turns positive and statistically significant at 1% level.

This finding suggests that coverage ratios are somewhat sticky. A possible explanation of the mechanism is that when NPLs increase, coverage ratios mechanically decrease because banks are unable or unwilling to adjust loan loss reserves at the same pace as loan quality deteriorates. The mechanism changes for banks facing high level of credit risk, as they tend to restore adequate level of coverage ratios by increasing loan loss allowances.

We then include the low customer deposit dummy that equals 1 for banks with a customer to total asset ratio in the bottom decile of the sample distribution, and zero otherwise (Column 2). Contrary to our expectations, we find no evidence of higher coverage ratios in banks presumably more exposed to investors' scrutiny. In untabulated results, available upon request, we further explore the role of funding structure by replacing the customer deposit with the high wholesale funding bank dummy. In an additional test, we include the dummy listed banks. As in the main specification, we do not find higher coverage ratios in banks more exposed to investors' scrutiny and market discipline (in both robustness checks, the coefficients are statistically insignificant).

To explore the non–linear effect of capitalisation, we then include the low CET 1 ratio bank dummy taking the value of 1 for banks in the bottom decile of the CET 1 distribution, and zero otherwise (Column 3). Consistent with results in Column 1, capitalisation does not seem to be a relevant driver of coverage ratios. In Column 4, we saturate the specification by adding all the three dummies. Results are confirmed.

For robustness, in unreported regressions, we modify the thresholds, to allow for banks with asset quality, funding and capitalization ratios above (below) either the mean value or the median

value. The coefficient for banks with NPL ratios above the sample average and median is negative (significant at the 10% level). This confirms that banks increase coverage ratios only when asset quality is substantially deteriorated, as occurs with banks with a NPL to total asset ratio in the top decile of the distribution. Consistent with our baseline results, the coefficient for banks with deposits and CET 1 ratios below the mean/median value remain insignificant.

4.4 The euro sovereign crisis and the advent of the SSM

In this subsection we explore the role played by two major events that occurred in Europe between 2010 and 2016: the euro sovereign crisis years (2010–12) and the commencement of the SSM as of November 2014. Both events may have affected the way banks adjust their coverage ratios differently and, hence, they may explain variation in coverage ratios across banks.

During the euro sovereign crisis, NPLs skyrocketed as an effect of the prolonged recession that started in the aftermath of the global financial crisis. The question is whether and the extent to which in very harsh times, EA banks were able or willing to adjust their coverage ratios by increasing LLRs to offset higher NPLs.

To take into account the role of the euro sovereign crisis years explicitly, in Table 5 (Column 1) we remove country–year and year fixed effects and include the dummy euro area crisis that equals 1 in 2010–2012, and zero otherwise. We find that in crisis years banks reduced their coverage ratios. We interpret this result as an effect of the business cycle on default rates and non–performing loans (the denominator of coverage ratios). Notoriously, deterioration in macroeconomic conditions constitute a key factor explaining the sharp increase of NPLs (see among others Nkusu, 2011, Beck et al., 2013 and literature therein). Consistently, when the economy slows down, non–performing loans tend to increase. Because most countries and banks in Europe use backward–looking provisioning practices, changes in coverage ratios should be associated with the identification of troubled loans, which exhibit a cyclical pattern (Laeven and Majnoni, 2003; Bouvatier and Lepetit, 2012).

We argue, however, that because in times of severe distress it is more difficult (costly) for banks to accumulate large provisions to offset increased bad loans, one may expect coverage ratios to decrease. Results from Table A.3 on the components of the coverage ratio (Columns 3 and 4) confirm this interpretation; during the sovereign crisis years, NPLs increased remarkably with no significant variation in terms of LLRs. While our finding challenges the thesis of pro–cyclical provisioning, it is consistent with the evidence in Huizinga and Laeven (2012) that regulators tend to be more lenient in bad times and that discretion over accounting rules combined with regulatory

forbearance may lead banks to understate balance sheet stresses by under–provisioning to preserve bank capital.

Indeed, the stringency of supervision is a potential relevant driver of the way banks build up loan loss coverages. According to an IMF survey on obstacles to NPL resolution, the robustness of coverage ratios appears to be linked to the stringency of supervision (Aiyar et al., 2017).[13] Empirical evidence confirms that supervisory and regulatory practices influence provisioning and loan loss allowances (Barth et al., 2013; Laurin, Majnoni, 2003; Yang, 2017; Nicoletti, 2018; Gallemore, 2018).

Supervisory practices have varied largely among European countries. [14] One of the reasons behind the switch to the single supervisor was that "common supervision across the euro area could meet high standards and reassure citizens and markets in the aftermath of the euro debt crisis" (EC, 2012).

The introduction of the single supervisor in Europe can be considered a case of tightening in banking supervision under several respects (Eber and Minoiu, 2016). For example, the introduction of the SSM was preceded by an asset quality exercise leading to additional provisions of euro 48 billion (+12%), as an effect of the consistent application of the EBA restrictive approach to defining non performing exposures and the credit file review (ECB, 2014). In addition, as discussed in Section 2, SSM has recently introduced several new measures promoting more prudent provisioning and higher coverage ratios.

In Table 5 (Columns 2 to 4), we take into account this additional factor and test whether the shift to the single supervisor triggered higher coverage ratios in supervised banks, relative to banks not subject to the ECB supervision. We remove bank and year fixed effects and include progressively the dummy SSM taking the value 1 for banks under direct control of the SSM in 2014 (Column 2), the dummy POST taking value 1 from 2014 onwards (Column 3), and the interacted term SSM x POST (Column 4). As expected, the coefficient on the interacted term is positive and statistically significant at 5% level, while the coefficient on the dummy post is insignificant. This finding confirms that supervised banks, after the inception of the SSM, increased their coverage ratios by more than non–supervised banks over the same time spam.

4.5 Do banks catch up to their peers?

In this subsection, we want to explore whether banks adjust coverage ratios due to peer imitation behaviour. Anecdotal and empirical evidence suggests that banks modify their coverage

[13] The survey focuses on countries where the aggregate NPL ratio over 2008–2014 exceeded 10% and reflects the views of authorities as well as banks operating in those countries. See Aiyar et al. (2015) for the main outcomes of the survey.

[14] See the ECB reports (2016 and 2017) for a stocktaking of different national supervisory practices and legal frameworks related to NPLs in Europe.

ratios "to catch up to their peers", and therefore, for reasons unrelated to the quality of their loan portfolios.

Financial reports for banks are widely published, so determining the amount of reserves held by peer banks is a simple matter (Walter, 1991). Peer comparison is, in fact, one of the most widely used methods of assessment employed by professional analysts as well as by individual investors. Supervisors tend to monitor and assess banks against their peers; in doing so they favour imitating behaviour.[15] Empirical analysis also confirms that herding in financial markets is a common phenomenon (see Rajan 1994, among others).[16] If herding behaviour occurs, one reason why banks adjust their coverage ratios is to be aligned to their peers.

To test this hypothesis, we replace our preferred dependent variable to include the change in coverage ratio. We measure peer imitation behaviour in terms of deviation of a given bank's coverage ratio to a benchmark represented by country average coverage ratio. To calculate the average coverage ratio in each country we rely on official ECB statistics rather than on our sample country average due to underrepresentation of banks in some countries. This is to ensure that the average that we are using is not biased towards larger banks as data availability is usually better for those.

The regression model, then, becomes the following:

$$\Delta\left(\frac{LLR}{NPL}\right)_{ik,t} = \lambda_t + \mu_i + \gamma_{k,t} + \beta_1 Dev_{ik,t-1} + \beta_2 Below_{ik,t-1} + \beta_3 |Dev_{ik,t-1}| \times Below_{ik,t-1} + \varepsilon_{ik,t}, \quad (2)$$

where $\Delta\left(\frac{LLR}{NPL}\right)_{ik,t}$ is the change in coverage ratio, defined as $\left(\frac{LLR}{NPL}\right)_{ik,t} - \left(\frac{LLR}{NPL}\right)_{ik,t-1}$. On the right hand side, the variable $Dev_{ik,t-1}$ is the deviation of a bank's coverage ratio to its country average; $Below_{ik,t-1}$ is a dummy that equals 1 for banks with their coverage ratios below their respective country average; $|Dev_{ik,t-1}| \times Below_{ik,t-1}$ is the interacted term between the absolute deviation and the below country average dummy.

In Table 6, Column 1, we first include the relative deviation of the single bank's coverage ratio to the country average. We find lower distance from the country average to be associated with a positive change in coverage ratios. Because banks may behave differently according to whether their coverage ratio is below rather than above their target, in Column 2 we focus on banks with a below average coverage ratio. We find that the coefficient of the below country average dummy is

[15] For example, in its guidance on NPLs (ECB 2017), the ECB claims that best practices "are intended to constitute ECB banking supervision's expectation" (p. 5) and that "where possible, indicators related to the NPL ratio/level and coverage should also be appropriately benchmarked against peers in order to provide the management body with a clear picture on competitive positioning" (p. 30).

[16] Rajan (1994) find evidence of herding behaviour in loan loss provisioning and charge offs in New England banks over 1986–1992, after correcting for changes in observable fundamentals.

positive and significant at 1% level. To better understand the mechanism, in Column 3, we include the absolute deviation to the country average and its interaction with the below country average dummy. We first find that when the absolute distance increases, coverage ratios tend to decrease. However, the coefficient on the interacted term $|Dev| \times Below_{ik,t-1}$ shows that banks with below country average coverage ratios tend to increase their coverage ratios the more they are distant to their target (i.e., the more the coverage ratio in a given year is below the country average). This suggests that banks in a more unfavourable position try to catch up, and the more so the more they are distant from their target. In the Appendix (see Table A.3, Columns 7 and 8), we explore the mechanism by which imitating behaviour occurs. We find that banks with below average coverage ratios tend to approach to their target by both increasing LLRs and resolving NPLs.

5. Exploring macro–level data

In this section we focus on country–level factors by replacing country–time fixed effects with time–varying country–level variables. First, to control for the business cycle, we include the real GDP growth rate (source Eurostat) defined as the percentage change with respect to the previous year. Second, to complement the analysis on the role played by supervision and regulation (see Section 4.4), we include the 2018 update of the country–specific prudential measures derived from the Cerutti et al. (2017) macro–prudential policy dataset. We start with the broadest index available in the dataset, the so–called Macroprudential Index. It covers three borrower–targeted and nine financial–institution–targeted instruments, therefore taking on values between 0 and 12, where 0 means that none of the instruments is in place and 12 means that all of them are in place. Hence, the higher the index, the more stringent the regulation in the respective country. We then substitute the index by some of its subcomponents, focusing on those ones that are more likely to affect banks' coverage ratios.

We focus on components that, consistent with our institutional framework, seem to be more relevant for incentivizing banks to change coverage ratios. These components correspond to measures on provisioning policies, capital buffers, taxation, and limits to borrowers' loan–to–value ratio.

Thus, the model becomes:

$$\left(\frac{LLR}{NPL}\right)_{ik,t} = \lambda_t + \mu_i + \beta X_{ik,t-1} + \theta Y_{k,t} + \varepsilon_{ik,t} \qquad (3)$$

where $\boldsymbol{X_{ik,t-1}}$ includes lagged bank–level variables as illustrated in previous sections and $\boldsymbol{Y_{k,t}}$ is comprising time–varying macro–level factors. We saturate the specification with time and bank–level fixed effects.

Table 7, Column 1 contains the results from estimating Eq (3). First, results confirm that funding structure is a highly significant drivers of coverage ratios. Unlike previous tests, the share of loans rather than NPLs is now significantly and negatively correlated with loan loss coverage. Second, in terms of general macroeconomic conditions, we find that GDP growth enters with a positive and significant coefficient, in line with our findings on the dynamics of loss coverage during the euro sovereign crisis. Third, the coefficient on our main measure of macro–prudential regulation is insignificant. A plausible explanation is that this is a too broad measure unable to capture what is relevant for banks on how to adjust coverage ratios. In line with anecdotal evidence (Walter, 1991) and prior research on the effects of macro factors on banks provisioning (Jiménez et al., 2017 and Andries et al., 2017, among others), we then split the index to focus on interventions that are plausibly better able to shape the change in coverage ratios. Specifically, we add an indicator on time–varying/dynamic loan–loss provisioning, which indicates whether banks in a certain country are required to provision more during upturns (Column 2). The second variable indicates if systemically important financial institutions are required to hold a higher capital level than other financial institutions (Column 3). The third variable tracks the tax regime of financial institutions in a certain country (Column 4). The fourth indicator shows if banks are subject to caps on the loan–to–value ratio (Column 5).

Not surprisingly, the indicator on time–varying/dynamic loan–loss provisioning is positive and significant (Column 2). This suggests that when specific measures to address pro–cyclical provisioning are in place, banks are better able to build up high loan loss allowances to face asset quality deterioration. Increasing taxation on financial institutions is also associated with higher coverage ratios (Column 4), plausibly because the higher deductions associated with larger provisions can reduce taxable income, and thus encourage banks to build more timely provisions and henceforth, higher LLRs (Andries et al., 2017).[17]

We also find that setting limits to borrowers' loan–to–value ratios (namely, by increasing loan collateralisation) is associated with higher coverage ratios (Column 5). One possible explanation is that collateral and coverage ratios are complementary rather than substitute tools to strengthen bank balance sheets.[18]

[17] Although at different rates, the majority of EA countries "acknowledge tax deductions for LLPs, write-offs9 and collateral sales". (ECB, 2016 and 2017b).

[18] We are aware of the fact that the characteristics of collateral, and the actual ability to enforce such collateral are additional elements that can influence coverage ratios (Constancio, 2017; Bruno and Carletti, 2017). Due to lack of data, we are unable to control for these aspects explicitly.

Interestingly, setting higher capital buffers in large institutions (SIFI) is associated with lower coverage ratio (Column 4). As discussed in Section 4.1, there are two potential (and not mutually exclusive) reasons explaining a negative association between capitalisation and coverage ratios. First, bank losses can be absorbed either through a capital buffer or by drawing down loan loss allowances. As such, capital and coverage ratio can be deemed as substitute tools. Second, increasing coverage ratios and raising capital are both costly strategies. In particular, one potential drawback of increasing LLRs includes lower current earnings (due to higher LLPs) that reduce banks' capital buffer (Andries et al., 2017). Consistently, banks subject to stricter binding capital rules (such as SIFIs) would have more incentive to retain earnings to comply with higher capital requirements rather than to increase provisioning in order to accumulate higher LLRs and coverage ratios.

In Column 6 we saturate the specification by including all the subcomponents of the macro-prudential index. Results on the role played by capital surcharges, provisioning and collateralisation in driving coverage ratios are overall confirmed.

5.1 Exploiting cross–country variation in asset quality

In this subsection, we exploit asset quality variation across countries and focus on banks from jurisdictions with high levels of NPLs. We define high NPLs countries as those reporting NPL ratio above the sample average.

We argue that, all things being equal, banks from countries affected by high levels of NPLs may behave differently from the average sample bank for a number of reasons. First, most of the countries affected by high NPLs levels have weak institutional frameworks, where for instance foreclosure procedures are particularly lengthy and costly (Aiyar et al., 2015; ECB, 2016). This translates into reduced ability to resolve NPLs, which would require banks to overprovision in order to maintain loss coverage at an adequate level. Moreover, national and supranational supervisors may exercise more severe scrutiny on banks from high–NPL jurisdictions, and require them to make more effort to strengthen their balance sheet.[19] As such, the way banks adjust their coverage ratios against changes in the business cycle may vary according to whether they are located in high–NPL countries or not.

Table 8 replicates the analysis from estimating Eq (2) in banks from high NPL countries. This leads to a drop in the number of banks from over 400 to above 180. As in Table 7, we first include the overall macroprudential index (Column 1) and, then each of its main subcomponents (Column 2 to 5). In Column 6 we saturate the specification by including all the sub–indices.

[19] The policies and practices in jurisdictions not afflicted by high NPLs "are not expected to be as prescriptive or coordinated as those in jurisdictions currently reacting to high levels of NPLs". ECB (2016)

Among bank characteristics, funding structure and, to a lower extent, size turn out to be the most relevant. Similarly to previous tests, banks from countries with high legacy assets tend to increase coverage ratios when they rely more on deposit funding. In addition, as in official statistics, larger banks show smaller coverage ratios. Interestingly, as for the larger sample, the coefficient on the NPL to asset ratio loses some of its significance (Columns 1 to 3), while we find a negative association between the coverage ratio and the loan to asset ratio that is significant in four out six specifications, meaning that when the lending business expands, banks tend to reduce their coverage ratio.

In terms of macro variables, interestingly, we do not find any significant association between coverage ratios and the business cycle (the sign of the coefficient is positive but insignificant); this may be explained by the limited variation in the economy conditions in this sub sample. Concerning macroprudential measures, the most effective ones seem to be those related to increased provisioning and more stringent tax rules on financial institutions, as they both lead to higher coverage ratios (Column 6), in line with Andries et al. (2017).

5.2 Additional checks

In this section, we try to further explore the role played by the institutional framework to explain variation across coverage ratios. To this end, we first replace our macroprudential index with indices on the stringency of the supervisory and legal and judicial framework at national level. We construct these additional indices based on specific measures taken recently by national supervisors and governments to better cope with NPLs. Second, we investigate the role played by NPLs secondary markets.

The role of specific measures to strengthen the supervisory and legal framework

As we have discussed, EA countries differ under several institutional aspects that could be relevant for explaining the way banks adjust their coverage ratios (Bruno and Carletti, 2017). Interestingly, several jurisdictions (most of which featured by high–NPLs) have taken actions and implemented strategies to reduce these discrepancies and better cope with the NPL issue. The ECB published two reports (as of September 2016 and as of June 2017) to take stock "of national supervisory practices and legal frameworks related to NPLs" (ECB, 2016 and 2017b). Based on these reports, we construct two additional synthetic indices. The first one captures the "Supervisory regime and practices." It is composed of five sub–indexes, which reflect the following features: i) additional supervisory guidance on NPL recognition and classification (beyond current regulation); ii) supervisory guidance on provisioning (beyond accounting standards); iii) supervisory guidance on collateral valuation (beyond current regulation); iv) detailed supervisory guidance on NPL governance/workout (beyond current regulations); v) some features of on–site and off–site

supervisory practices and methodologies. Each sub–index takes on a value between 0 and 1, where one indicates that all measures listed in the ECB report under this particular sub–index are in place, and zero indicates that none is in place. The overall index on "Supervisory regime and practice" is the average value of the five sub–indexes.

The second index contains information on the "Legal, judicial and extrajudicial framework." It is comprised of the following seven sub–indexes: i) main features of the sale portfolios; ii) main features of debt enforcement/foreclosure; iii) main features of the corporate insolvency and restructuring framework; iv) main features of the household insolvency and restructuring; v) main features of the judicial system; vi) main features of the tax regime; vii) overall perception of the quality and comprehensiveness of the information framework. The construction of the index is analogous to the one in the previous paragraph.

The ECB report represents a snapshot of the institutional framework; as such, values for our indexes are time–invariant and capture the year 2016. As in Eq (3), we also include GDP growth and saturate the model with time FEs.

Results, available in Table 9, confirm that the most relevant bank specific factors remain asset quality and funding structure. If we include the two indices separately (Columns 2 and 3), we find a positive relation between coverage ratios and the recent measures introduced at the supervisory and juridical/legal level, significant at the 5 and 1% level, respectively. When we saturate the specification by including both indices (Column 3), we find higher coverage ratios only in countries featured by higher level of the legal, judicial, and extrajudicial index (the coefficient on this index is positive and significant at the 1% level). This finding suggests that measures to reinforce the legal and judicial framework seem particularly effective in incentivising banks to build up high coverage ratios. Although interesting, the results should be interpreted somewhat with caution given the time–invariant nature of the two indices and the fact that several measures tracked by the ECB report have been implemented only recently.

The role of the NPL secondary market

Although still underdeveloped, NPLs transactions have progressively increased over the last years, varying from 11 billion euros in 2010 to nearly 100 billion euros as of end 2016, according to PwC reports.[20] Transactions are concentrated in a few countries, i.e., the UK, Germany, Spain, Ireland, and more recently, Italy (the largest market place since 2016). Figure 9 shows the value of NPL transactions by countries in 2010–2016.

The level of development and liquidity of the secondary markets for distressed loans is another feature that may explain variation in coverage ratios. The secondary market for troubled assets is a market for lemons à la Akerlof, being characterised by high information asymmetries and

[20] The EC's package of measure to tackle high NPLs presented in March 2018 includes initiatives to encourage the development of secondary markets, such as a proposal for a directive aiming to harmonize requirements and create a single market for credit servicers and buyers.

large bid–ask spreads between sellers and buyers (Fell et al., 2016). Deeper markets incentive banks to accumulate larger reserves and henceforth higher coverage ratios, as a pre–condition to access the market (see also the discussion in Section 2).

In Table 10, we expand our micro–macro baseline regression to account for the relevance of the NPL secondary market in a given country. We measure the share of NPL transactions over the total banking assets at country level to proxy the degree of development of the market (Column 1). Due to the negligible volume of trades in most European countries, data on secondary NPL market mostly refer to Ireland, Spain, Germany and Italy, where transaction have taken place in 2010–2016 (source PwC reports).[21]

We find that more intense activity in the NPL secondary market is associated with higher coverage ratios. This is not surprising, as information asymmetry concerns help explain the need for higher coverage ratios to mitigate lemon problems and make NPLs more marketable. Moreover, higher level of coverage ratios correspond to lower net loan book value and, *ceteris paribus*, to lower losses in case of asset disposal.

When we look at the change in coverage ratios (Column 2), we find that the bigger the NPLs market is the smaller the change in coverage ratios. A possible interpretation is that, in progressively more liquid and developed markets, there would be relatively less information asymmetry concerns and hence, relatively less need for accumulating large LLRs.

6. Conclusions

This paper explores the main drivers of coverage ratios, an indicator of bank balance sheet strength that has gained increasing importance in Europe in the last few years.

Using a sample of over 500 medium and large sized banks in the EA, we try to disentangle micro and macro factors affecting coverage ratios. Our analysis reveals some interesting findings.

First, we find that asset quality and funding structure are the main bank specific drivers of coverage ratios, and that the relation between NPLs and coverage ratio is not linear in that it becomes positive only when banks hold very large stock of troubled assets. We also document that, independently of these characteristics, banks adjust their coverage ratios to catch up with their peers, and the more so, the more they are distant (below) from their target. This confirms that benchmarking is a common practice, even with respect to the creation of loss coverage.

Second, we find that the build-up of loss coverage decreased during the euro–sovereign crisis, suggesting that banks were either unable or unwilling to offset the increase of NPLs through adequate provisioning.

[21] The dataset also includes transactions for France (2012), Belgium (2013), Netherlands (2013, 2015 and 2016), and Greece (2016) but for more limited amount.

Third, a more stringent supervisory and regulatory framework may serve the purpose of increasing coverage ratios. Results, however, are not always consistent across specifications. Specifically, the shift to a stricter supervisory approach after the inception of the SSM in 2014 is associated with higher coverage ratios in supervised banks. When we introduce country specific indicators of macro–prudential policies, results change according to the policy measure and to whether we analyse the whole sample compared to the subsample of high NPL countries.

We also examine specific institutional features or country characteristics that matter in a context of high NPLs. We document a positive relation between coverage ratios and (1) recent national measures to strengthen the judicial and the legal framework and (2) more developed NPLs secondary markets.

The main message of our paper is that banks are not always able to compensate higher credit risk with more adequate loan loss allowance and that there are reasons beyond asset quality that explain discrepancies in coverage ratios. Country specificities matter, pointing to the fact that addressing inefficiencies at the institutional level may help create higher coverage ratios through a faster resolution of NPLs or, in perspective, may enable banks to operate with relatively lower level of loan loss coverage without compromising their balance sheet strength.

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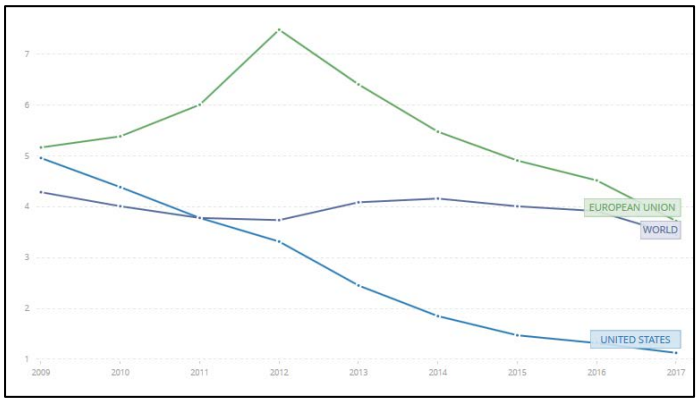
Figures and Tables

Figure 1. International comparison on NPL ratios (2009–2017)



Source: World Bank

Figure 2: Average coverage ratio for EA banks (2010 – 2016)

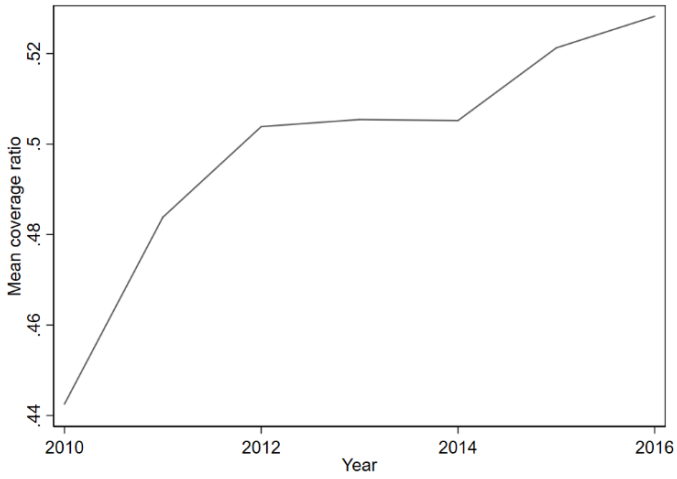


Figure 3: Components of the coverage ratio (2010 – 2016, in millions of EUR)

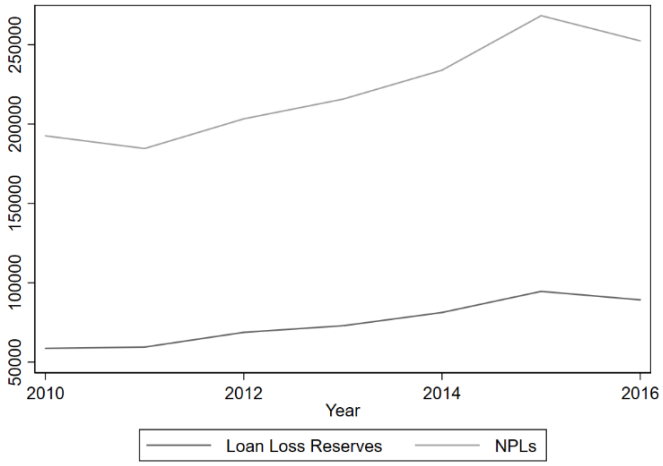


Figure 4: Average NPL/TA and average NPL/TL by country

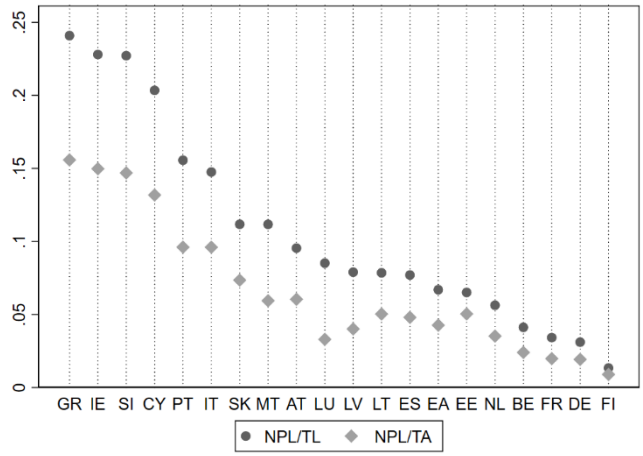


Figure 5: Range and average NPL/TA

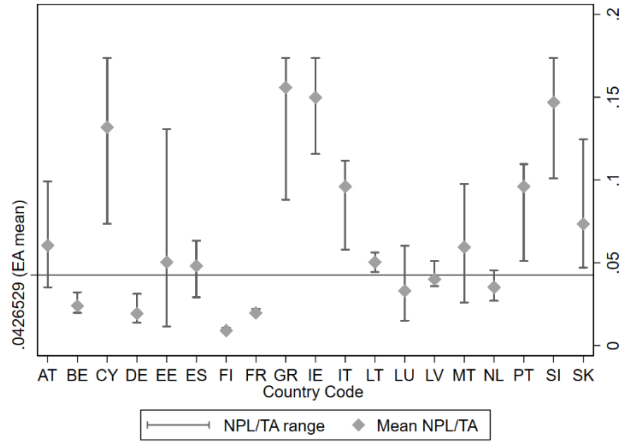


Figure 6: Range and average coverage ratio

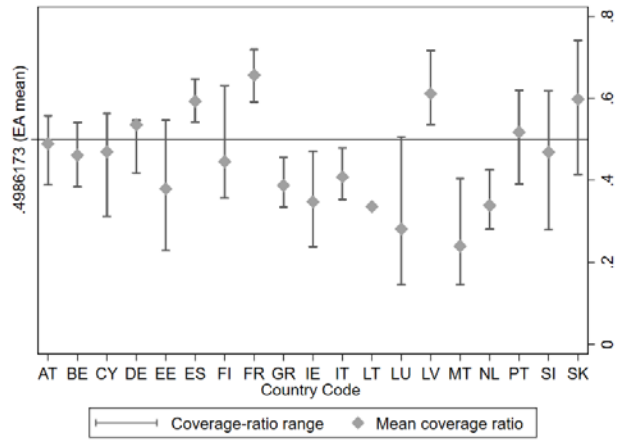


Figure 7: Average coverage ratio for EA banks in high–NPL countries (2010 – 2016)

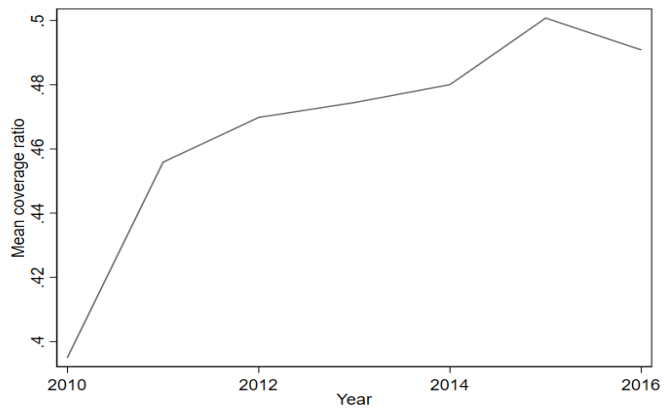


Figure 8: Secondary loan market transaction data (2010–2016, source: PwC)

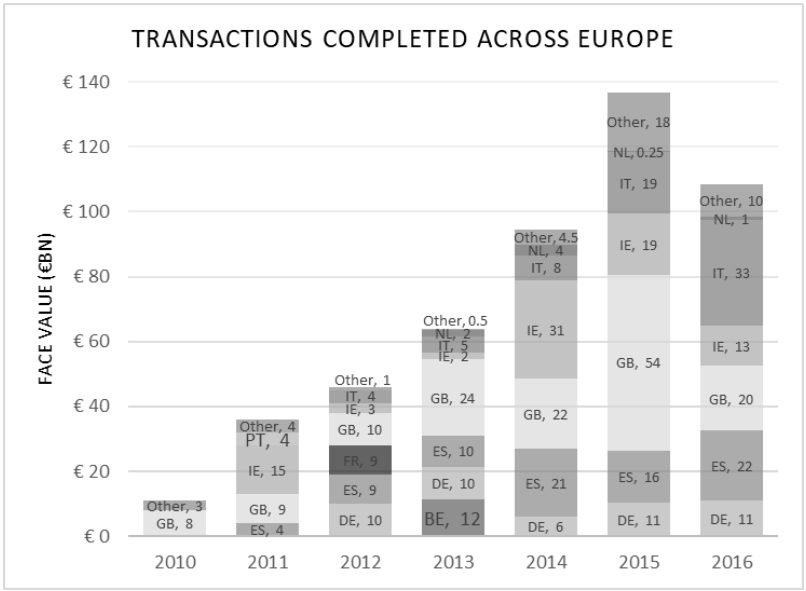


Table 1: Correlations between LLP/TA and coverage ratio. Correlations with a * are significant at the 5% level.

	LLPs	LLPs(t–1)	LLPs(t–2)	Coverage ratio	Coverage ratio (t–1)	Coverage ratio (t–2)
LLPs	1					
LLPs(t–1)	0.9116*	1				
LLPs(t–2)	0.8661*	0.9161*	1			
Coverage ratio	–0.1054*	–0.1126*	–0.1035*	1		
Coverage ratio (t–1)	–0.091	–0.0902	–0.0742	0.9122*	1	
Coverage ratio (t–2)	–0.1412*	–0.1234*	–0.0977	0.7993*	0.9092*	1

Table 2: Summary statistics. This table gives summary statistics for the baseline regression sample.

	Mean	**Std. dev.**	**Min**	**p10**	**p50**	**p90**	**Max**
Coverage ratio	50,77%	16,22%	14,47%	30,57%	50,06%	72,97%	86,84%
NPL / TA	4,08%	4,49%	0,12%	0,60%	2,26%	11,10%	17,37%
Gross loans_/_TA	63,81%	13,62%	29,16%	45,21%	65,10%	80,36%	87,37%
NPLs / gross loans	6,45%	6,92%	0,24%	1,04%	3,60%	16,95%	27,77%
CET1	13,87%	4,27%	7,13%	9,06%	13,33%	19,08%	34,41%
Total capital ratio	16,42%	4,46%	3,76%	11,92%	15,62%	21,78%	51,66%
Total Assets (in thousands)	9958858	11723879	1670832	1885038	4112080	36402000	36402000
Deposits / TA	65,75%	15,77%	33,28%	38,47%	70,40%	82,44%	89,37%
ROAA	0,24%	0,36%	–0,79%	0,02%	0,21%	0,61%	1,35%
ROAE	3,00%	4,32%	–9,70%	0,30%	2,60%	8,02%	13,78%
Net income before taxes / TA	0,43%	0,44%	–0,89%	0,06%	0,43%	0,88%	1,66%
Profits / average assets	0,97%	0,45%	0,11%	0,45%	0,91%	1,58%	2,24%
Pre–impairment profits / TA	0,96%	0,44%	0,10%	0,45%	0,90%	1,54%	2,21%

Table 1: Micro–level regressions baseline: Determinants of coverage ratios and components of coverage ratios. This table reports estimation results from the panel fixed–effects micro–level regressions. The dependent variables are the coverage ratio (1), log(LLR) (2), and log(NPLs) (3) at the bank level. Coverage ratio is defined as LLR/NPLs. Time, country–time, and bank dummies are included in each regression. Robust standard errors are clustered at the bank–level and reported in parentheses. Significance at the 1, 5 and 10% level is denoted by *, **, and *** respectively.

	(1)	(2)	(3)
	Coverage ratio	Log(LLR)	Log(NPLs)
NPL/TA (t–1)	–1.119***	3.694***	6.778***
	(0.393)	(1.034)	(1.343)
Gross Loans/TA (t–1)	–0.111	–0.163	0.16
	(0.100)	(0.317)	(0.319)
Log (TA) (t–1)	–0.038	0.511***	0.663***
	(0.044)	(0.137)	(0.131)
Deposits/TA (t–1)	0.145**	0.244	0.023
	(0.061)	(0.241)	(0.239)
ROAA (t–1)	0.007	–5.946*	–5.131
	(0.968)	(3.453)	(3.230)
CET1 (t–1)	0.128	–0.922*	–1.402**
	(0.177)	(0.555)	(0.565)
Constant	1.096	3.19	1.487
	(0.716)	(2.253)	(2.143)
Observations	1471	1471	1471
No. of banks	409	409	409
Within R–squared	0.037	0.081	0.154
FE Bank	yes	yes	Yes
FE Country * Year	yes	yes	Yes
FE Year	yes	yes	Yes

Table 4: Micro–level regressions outliers: Determinants of coverage ratios. This table reports estimation results from the panel fixed–effects micro–level regressions. The dependent variable is the coverage ratio, defined as LLR/NPLs. Time, country–time, and bank dummies are included in each regression. Robust standard errors are clustered at the bank–level and reported in parentheses. Significance at the 1, 5 and 10% level is denoted by *, **, and *** respectively.

	(1)	(2)	(3)	(4)
	Coverage ratio	Coverage ratio	Coverage ratio	Coverage ratio
NPL/TA (t–1)	–1.471***	–1.129***	–1.114***	–1.465***
	(0.441)	(0.397)	(0.394)	(0.444)
Gross Loans/TA (t–1)	–0.113	–0.103	–0.108	–0.104
	(0.098)	(0.100)	(0.100)	(0.099)
Log (TA) (t–1)	–0.046	–0.032	–0.04	–0.042
	(0.044)	(0.044)	(0.044)	(0.044)
Deposits/TA (t–1)	0.143**	0.171***	0.141**	0.165***
	(0.061)	(0.062)	(0.061)	(0.062)
ROAA (t–1)	–0.062	0.067	0.053	0.043
	(0.957)	(0.971)	(0.975)	(0.968)
CET1 (t–1)	0.159	0.114	0.18	0.192
	(0.175)	(0.174)	(0.170)	(0.166)
High NPL dummy	0.042***			0.041***
	(0.015)			(0.015)
Low Deposits Dummy		0.022		0.022
		(0.015)		(0.015)
Low CET1 Dummy			0.011	0.010
			(0.014)	(0.014)
Constant	1.237*	0.982	1.13	1.149
	(0.722)	(0.710)	(0.716)	(0.714)
Observations	1471	1471	1471	1471
No. of banks	409	409	409	409
Within R–squared	0.043	0.040	0.038	0.047
FE Bank	yes	yes	yes	yes
FE Country * Year	yes	yes	yes	yes
FE Year	yes	yes	yes	yes

Table 5: Micro–level regressions extensions: Influence of the single supervisory mechanism and EA crisis. This table reports estimation results from the panel fixed–effects micro–level regressions. Robust standard errors are clustered at the bank–level and reported in parentheses. Significance at the 1, 5 and 10% level is denoted by *, **, and *** respectively.

	(1)	(2)	(3)	(4)
	Coverage ratio	Coverage ratio	Coverage ratio	Coverage ratio
NPL/TA (t–1)	–0.701***	–0.947***	–0.697***	–0.730***
	(0.232)	(0.274)	(0.234)	(0.236)
Gross Loans/TA (t–1)	0.021	0.045	0.004	0.002
	(0.048)	(0.051)	(0.049)	(0.049)
log(TA) (t–1)	0.001	0.011	0.011	0.01
	(0.007)	(0.010)	(0.010)	(0.010)
Deposits/TA (t–1)	0.101*	0.068	0.08	0.079
	(0.057)	(0.059)	(0.057)	(0.058)
ROAA (t–1)	0.493	–0.266	0.058	–0.122
	(1.821)	(2.040)	(1.771)	(1.786)
CET1 (t–1)	0.223	0.222	0.208	0.19
	(0.158)	(0.165)	(0.156)	(0.157)
Euro Area Crisis Dummy	–0.024**			
	(0.010)			
SSM Bank Dummy		–0.04	–0.046*	–0.070**
		(0.026)	(0.026)	(0.028)
Post SSM (1)			0.021**	0.014
			(0.009)	(0.010)
*SSM Bank Dummy * Post SSM (2)*				0.041**
				(0.018)
Constant	0.417***	0.271*	0.274*	0.292*
	(0.134)	(0.164)	(0.161)	(0.162)
F–test statistic: (1) + (2) = 0				11.18
p–value				0.001
Observations	1570	1550	1570	1570
No. of banks	487	486	487	487
Within R–squared	0.047	0.05	0.053	0.056
FE Country * Year	no	yes	no	no
FE Country	yes	no	yes	yes
FE Year	no	Yes	no	no

Table 6: Micro–level regressions herding behaviour: Determinants of changes in coverage ratios. This table reports estimation results from the panel fixed–effects OLS micro–level regressions. The dependent variable is the change in coverage ratio, defined as LLR/NPLs (t) – LLR/NPLs (t–1). Time, country–time, and bank dummies are included in each regression. Robust standard errors are clustered at the bank–level and reported in parentheses. Significance at the 1, 5 and 10% level is denoted by *, **, and *** respectively.

	(1) Delta Coverage Ratio	(2) Delta Coverage Ratio	(3) Delta Coverage Ratio
NPL/TA (t–1)	–0.073	0.682***	–0.004
	(0.246)	(0.207)	(0.221)
Gross Loans/TA (t–1)	–0.169**	–0.204***	–0.169**
	(0.067)	(0.067)	(0.066)
log(TA) (t–1)	–0.019	–0.008	–0.017
	(0.034)	(0.033)	(0.033)
Deposits/TA (t–1)	0.093**	0.091*	0.101**
	(0.045)	(0.049)	(0.044)
ROAA (t–1)	1.279*	1.963**	1.371*
	(0.752)	(0.861)	(0.746)
CET1 (t–1)	0.341***	0.502***	0.332***
	(0.124)	(0.124)	(0.122)
Deviation from Country Avg. (t–1)	–0.498***		
	(0.044)		
Below Country Avg. Dummy (t–1)		0.061***	0.022***
		(0.007)	(0.007)
Absolute Deviation from Country Avg. (t–1) (1)			–0.496***
			(0.048)
*Abs. Deviation * Below Country Avg. Dummy (t–1) (2)*			0.850***
			(0.107)
Constant	0.355	0.089	0.308
	(0.543)	(0.526)	(0.540)
F–test statistic: (1) + (2) = 0			19.154
p–value			0
Observations	1460	1471	1460
No. of firms	406	409	406
Within R–squared	0.279	0.116	0.287
FE Bank	yes	yes	yes
FE Country * Year	yes	yes	yes
FE Year	yes	yes	yes

Table 7: Micro–macro regressions: Determinants of coverage ratios. This table reports estimation results from the panel fixed–effects micro–macro regressions. The dependent variable is the coverage ratio at the bank level. A set of bank and time dummies is included in each regression. Robust standard errors are clustered at the bank–level (all sample). Significance at the 1, 5 and 10% level is denoted by *, **, and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Coverage ratio	Coverage ratio	Coverage ratio	Coverage ratio	Coverage ratio	Coverage ratio
NPL/TA (t–1)	–0.493	–0.515*	–0.511*	–0.666**	–0.764**	–0.865***
	(0.303)	(0.303)	(0.303)	(0.315)	(0.315)	(0.324)
Gross Loans/TA (t–1)	–0.271***	–0.282***	–0.270***	–0.227**	–0.175*	–0.159
	(0.094)	(0.094)	(0.095)	(0.094)	(0.096)	(0.098)
log(TA) (t–1)	–0.02	–0.023	–0.014	–0.024	–0.032	–0.03
	(0.045)	(0.045)	(0.046)	(0.045)	(0.045)	(0.046)
Deposits/TA (t–1)	0.230***	0.227***	0.232***	0.207***	0.193***	0.198***
	(0.068)	(0.069)	(0.070)	(0.068)	(0.067)	(0.068)
ROAA (t–1)	0.392	0.376	0.344	0.348	0.252	0.208
	(1.086)	(1.075)	(1.089)	(1.091)	(1.047)	(1.065)
CET1 (t–1)	0.089	0.079	0.067	0.089	0.134	0.117
	(0.173)	(0.173)	(0.172)	(0.170)	(0.169)	(0.167)
Real GDP growth rate per country	0.006**	0.007**	0.007***	0.005*	0.006**	0.005**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Macroprudential Index	0.008					
	(0.007)					
Time–Varying/Dynamic Loan–Loss Provisioning		0.040*				0.039*
		(0.022)				(0.023)
Capital Surcharges on SIFIs			–0.037**			–0.033*
			(0.015)			(0.019)
Levy/Tax on Financial Institutions				0.033***		0.02
				(0.013)		(0.012)
Loan–to–Value Ratio Caps					0.053***	0.046***
					(0.015)	(0.015)
Constant	0.819	0.896	0.756	0.874	0.978	0.935
	(0.749)	(0.747)	(0.758)	(0.749)	(0.743)	(0.759)
Observations	1494	1494	1494	1494	1494	1494
No. of banks	411	411	411	411	411	411
Within R–squared	0.049	0.05	0.05	0.058	0.071	0.076
FE Bank	yes	yes	yes	yes	yes	yes
FE Year	yes	yes	yes	yes	yes	yes

Table 8: Micro–macro regressions: Determinants of coverage ratios. This table reports estimation results from the panel fixed–effects micro–macro regressions for high–NPL countries, defined as countries with NPL ratios above the sample mean. The dependent variable is the coverage ratio at the bank level. A set of bank and time dummies is included in each regression. Robust standard errors are clustered at the bank–level (high–NPL countries). Significance at the 1, 5 and 10% level is denoted by *, **, and *** respectively.

	(1) Coverage ratio	(2) Coverage ratio	(3) Coverage ratio	(4) Coverage ratio	(5) Coverage ratio	(6) Coverage ratio
NPL/TA (t–1)	–0.404	–0.389	–0.369	–0.595*	–0.588*	–0.761**
	(0.315)	(0.317)	(0.320)	(0.346)	(0.346)	(0.369)
Gross Loans/TA (t–1)	–0.265**	–0.269**	–0.259**	–0.214*	–0.188	–0.179
	(0.115)	(0.119)	(0.119)	(0.119)	(0.116)	(0.117)
log(TA) (t–1)	–0.126*	–0.125*	–0.124*	–0.117*	–0.118*	–0.115*
	(0.065)	(0.065)	(0.066)	(0.065)	(0.063)	(0.064)
Deposits/TA (t–1)	0.275***	0.251**	0.258**	0.238**	0.217**	0.202**
	(0.099)	(0.105)	(0.105)	(0.100)	(0.106)	(0.102)
ROAA (t–1)	–1.385	–1.111	–1.154	–1.219	–1.217	–1.21
	(1.608)	(1.577)	(1.574)	(1.612)	(1.549)	(1.578)
CET1 (t–1)	0.003	–0.043	–0.043	–0.032	0.042	0.029
	(0.207)	(0.211)	(0.212)	(0.209)	(0.215)	(0.216)
Real GDP growth rate per country	0.001	0.003	0.003	0	0.002	0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Macroprudential Index	0.019*					
	(0.010)					
Time–Varying/Dynamic Loan–Loss Provisioning		0.052**				0.064***
		(0.024)				(0.024)
Capital Surcharges on SIFIs			–0.001			–0.001
			(0.021)			(0.030)
Levy/Tax on Financial Institutions				0.041**		0.039**
				(0.018)		(0.017)
Loan–to–Value Ratio Caps					0.041**	0.029
					(0.019)	(0.019)
Constant	2.401**	2.462**	2.432**	2.294**	2.314**	2.253**
	(1.064)	(1.056)	(1.070)	(1.056)	(1.023)	(1.053)
Observations	603	603	603	603	603	603
No. of banks	184	184	184	184	184	184
Within R–squared	0.078	0.071	0.064	0.086	0.082	0.107
FE Bank	yes	yes	yes	yes	yes	yes
FE Year	yes	yes	yes	yes	yes	Yes

Table 9: Micro–macro regressions: Determinants of coverage ratios: national supervisory practices and legal frameworks related to NPLs. This table reports estimation results from the OLS micro–macro regressions. The dependent is the coverage ratio at the bank level. A set of time dummies is included in each regression. Robust standard errors are clustered at the bank–level. Significance at the 1, 5 and 10% level is denoted by *, **, and *** respectively.

	(1)	(2)	(3)
	Coverage ratio	Coverage ratio	Coverage ratio
NPL/TA (t–1)	–1.108***	–1.217***	–1.214***
	(0.166)	(0.166)	(0.170)
Gross Loans/TA (t–1)	0.056	0.06	0.06
	(0.055)	(0.053)	(0.053)
log(TA) (t–1)	0.008	0.005	0.005
	(0.007)	(0.007)	(0.007)
Deposits/TA (t–1)	0.053	0.115**	0.117**
	(0.057)	(0.052)	(0.055)
ROAA (t–1)	–0.425	–2.529	–2.592
	(1.839)	(1.760)	(1.774)
CET1 (t–1)	0.257	0.25	0.248
	(0.165)	(0.158)	(0.158)
Real GDP growth rate per country	0.002	0.003	0.003
	(0.003)	(0.003)	(0.003)
Index: Supervisory regime and practices	0.147**		–0.008
	(0.071)		(0.077)
Index: Legal, judicial and extrajudicial		0.430***	0.438***
		(0.096)	(0.109)
Constant	0.252**	0.081	0.081
	(0.124)	(0.126)	(0.126)
Observations	1570	1570	1570
No. of banks	487	487	487
Within R–squared	0.111	0.14	0.14
FE Year	yes	yes	yes

Table 10: Micro–macro regressions: Determinants of coverage ratios, secondary NPL market transactions. This table reports estimation results from the OLS micro–macro regressions. The dependent is the coverage ratio at the bank level. A set of time dummies is included in each regression. Robust standard errors are clustered at the bank–level. Significance at the 1, 5 and 10% level is denoted by *, **, and *** respectively.

	(1)	(2)
	Coverage ratio	Delta Coverage ratio
NPL/TA (t–1)	–0.729**	0.916***
	(0.334)	(0.151)
Gross Loans/TA (t–1)	–0.226**	–0.179***
	(0.095)	(0.068)
log(TA) (t–1)	–0.035	0.008
	(0.045)	(0.031)
Deposits/TA (t–1)	0.181***	0.018
	(0.066)	(0.059)
ROAA (t–1)	0.244	1.604*
	(1.059)	(0.918)
CET1 (t–1)	0.133	0.434***
	(0.168)	(0.132)
Real GDP growth rate per country	0.007**	0.000
	(0.003)	(0.001)
Secondary market transactions over country TA	4.178***	–3.665***
	(1.556)	(1.131)
Constant	1.064	–0.104
	(0.748)	(0.508)
Observations	1494	1494
No. of banks	411	411
Within R–squared	0.066	0.052
FE Bank	yes	yes
FE Year	yes	yes

APPENDIX

Table A.1: Micro–level regressions robustness: Determinants of coverage ratios. This table reports estimation results from the OLS micro–level regressions with bank, year, and country–year fixed effects. The dependent variable is the coverage ratio, defined as LLR/NPLs. Robust standard errors are clustered at the bank–level and reported in parentheses. In Column 1 NPL/TA is replaced with NPLs over gross loans (NPL/GL), which is the most commonly used measure of lending portfolio quality. With respect to capitalisation, we replace the CET1 ratio by the share of CET1 capital over the stock of NPLs (Column 2) and the Tier 1 ratio (Column 3). As for profitability, we alternatively use the return–on–equity (Column 4) and the earnings before taxes and LLPs to total assets ratio (Column 5). Significance at the 1, 5 and 10% level is denoted by *, **, and *** respectively.

	(1) Coverage ratio	(2) Coverage ratio	(3) Coverage ratio	(4) Coverage ratio	(5) Coverage ratio
NPL/Gross Loans (t–1)	–0.560**				
	(0.259)				
NPL/TA (t–1)		–1.102***	–1.373***	–1.126***	–1.117***
		(0.394)	(0.381)	(0.395)	(0.389)
Gross Loans/TA (t–1)	–0.179*	–0.114	–0.127	–0.118	–0.118
	(0.094)	(0.100)	(0.110)	(0.100)	(0.100)
log(TA) (t–1)	–0.037	–0.039	–0.038	–0.04	–0.039
	(0.046)	(0.044)	(0.044)	(0.044)	(0.045)
Deposits/TA (t–1)	0.134**	0.146**	0.149**	0.143**	0.137**
	(0.060)	(0.061)	(0.065)	(0.061)	(0.061)
ROAA (t–1)	–0.037	0.094	0.129		
	(1.011)	(0.972)	(0.943)		
CET1 (t–1)	0.121			0.128	0.127
	(0.177)			(0.178)	(0.177)
CET1 / NPLs (t–1)		1000.493			
		(1613.873)			
Tier 1 Capital Ratio (t–1)			–0.017		
			(0.190)		
ROAE (t–1)				0.015	
				(0.078)	
Pre–impairment operating profit / TA (t–1)					1.013
					(1.173)
Constant	1.124	1.14	1.131	1.146	1.122
	(0.754)	(0.713)	(0.718)	(0.721)	(0.724)
Observations	1471	1471	1573	1468	1471
No. of banks	409	409	419	409	409
Within R–squared	0.82	0.822	0.814	0.822	0.822
FE Bank	yes	yes	yes	yes	yes
FE Country * Year	yes	yes	yes	yes	yes
FE Year	yes	yes	yes	yes	yes

Table A.2: GMM Micro–macro regressions. Significance at the 1, 5 and 10% level is denoted by *, **, and *** respectively.

	(1)	(2)	(3)
	Coverage ratio	log(LLRs)	log(NPLs)
Coverage ratio (t–1)	0.433***		
	(0.047)		
log(LLRs)(t–1)		0.768***	
		(0.070)	
log(NPLs)(t–1)			0.218***
			(0.073)
NPL/TA	–0.848*	0.753	7.489***
	(0.493)	(1.407)	(1.626)
Gross Loans/TA	–0.08	–0.043	0.604
	(0.180)	(0.477)	(0.584)
log(TA)	–0.001	–0.329	0.257
	(0.088)	(0.246)	(0.265)
Deposits/TA	0.231	–1.209	–0.324
	(0.246)	(0.743)	(0.759)
ROAA	–5.966**	–1.285	–17.278**
	(2.829)	(7.533)	(7.573)
CET1	0.717**	–0.174	–1.08
	(0.310)	(0.827)	(0.904)
Observations	1608	1608	1608

Table A.3: Inspecting the mechanism: the components of coverage ratios. Significance at the 1, 5 and 10% level is denoted by *, **, and *** respectively.

	Non–linear behaviour		Euro crisis		SSM		Peer behavior		NPL Secondary Market	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	log(LLR)	log(NPLs)	log(LLR)	log(NPLs)	log(LLR)	log(NPLs)	Delta log(LLR)	Delta log(NPL)	log(LLR)	log(NPLs)
NPL/TA (t–1)	4.938***	8.729***	16.160***	18.387***	16.187***	18.373***	–3.213***	–3.257***	5.355***	7.836***
	(1.101)	(1.390)	(1.355)	(1.150)	(1.363)	(1.195)	(0.698)	(0.631)	(0.922)	(1.015)
Gross Loans/TA (t–1)	–0.121	0.165	–0.14	–0.385	–0.056	–0.163	–0.011	0.205	–0.903***	–0.293
	(0.304)	(0.310)	(0.250)	(0.250)	(0.258)	(0.241)	(0.175)	(0.192)	(0.291)	(0.280)
log(TA) (t–1)	0.561***	0.705***	0.979***	1.047***	0.932***	0.915***	–0.169*	–0.185*	0.464***	0.570***
	(0.134)	(0.128)	(0.040)	(0.036)	(0.049)	(0.039)	(0.087)	(0.098)	(0.127)	(0.111)
Deposits/TA (t–1)	0.344	0.008	–1.543***	–1.858***	–1.432***	–1.594***	–0.133	–0.313**	0.387*	0.152
	(0.245)	(0.242)	(0.326)	(0.302)	(0.309)	(0.272)	(0.147)	(0.151)	(0.220)	(0.231)
ROAA (t–1)	–5.397	–4.837	22.414***	19.514***	23.994***	24.233***	1.618	0.45	–2.937	–2.552
	(3.469)	(3.125)	(7.505)	(6.608)	(7.623)	(6.572)	(2.354)	(2.447)	(3.077)	(3.240)
CET1 (t–1)	–1.015*	–1.586***	–2.609***	–3.375***	–2.361***	–3.048***	0.159	–0.799**	–1.069*	–1.456***
	(0.547)	(0.552)	(0.706)	(0.673)	(0.709)	(0.648)	(0.331)	(0.386)	(0.551)	(0.526)
High NPL dummy	–0.154**	–0.235***								
	(0.061)	(0.058)								
Low Deposits Dummy	0.086*	–0.023								
	(0.047)	(0.050)								
Low CET1 Dummy	0.015	–0.006								
	(0.032)	(0.038)								
Euro Area Crisis Dummy			0.049	0.105**						
			(0.045)	(0.041)						
SSM Bank Dummy					0.19	0.563***				
					(0.143)	(0.122)				
Post SSM (1)					–0.107***	–0.156***				
					(0.039)	(0.033)				
*SSM Bank Dummy * Post SSM (2)*					0.032	0.017				
					(0.082)	(0.082)				
Below Country Avg. Dummy (t–1)							–0.001	–0.049**		
							(0.020)	(0.022)		
Absolute Deviation from Country Avg. (t–1)							–0.377***	0.467***		
							(0.109)	(0.128)		
*Abs. Deviation * Below Country Avg. Dummy (t–1)*							1.086***	–0.734***		
							(0.270)	(0.256)		
Real GDP growth									0.017**	0.009*
									(0.008)	(0.005)
Secondary market transactions over country TA									32.304***	19.947***
									(4.677)	(4.114)
Constant	2.281	0.81	–3.390***	–3.266***	–2.767***	–1.551**	2.827**	3.119**	4.152**	3.064*
	(2.214)	(2.089)	(0.703)	(0.605)	(0.798)	(0.648)	(1.409)	(1.582)	(2.095)	(1.843)
Observations	1471	1471	1570	1570	1570	1570	1460	1460	1494	1494
No. of banks	409	409	487	487	487	487	406	406	411	411
Within R–squared	0.097	0.175	0.738	0.804	0.74	0.814	0.064	0.107	0.419	0.417
FE Bank	yes	yes	no	no	no	no	yes	yes	yes	yes
FE Country	no	no	yes	yes	yes	yes	no	no	no	no
FE Country * Year	yes	yes	no	no	no	no	yes	yes	no	no
FE Year	yes	yes	no	no	no	no	yes	yes	yes	yes

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