Asset-Quality-at-Risk

This paper introduces a novel approach to predicting future asset quality deterioration in euro area banks: "asset-quality-at-risk".

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Abstract

Non-performing loans (NPLs) have been at the core of financial sector policy discussions since the Great Financial Crisis. In this study, we first investigate the drivers of asset quality deterioration for a sample of euro area banks and document the existing non-linear relationships between NPLs and their macro-financial determinants. By employing dynamic fixed effects panel quantile regression, we find that different macroeconomic and bank-specific variables have different explanatory power at different quantiles of the distribution of NPLs. In the second part of the paper, we leverage on the Growth-at-Risk framework to link current macro-financial conditions to the probability distribution of future NPL ratios and construct a new measure, "asset-quality-at-risk", which could serve as a forward-looking indicator of possible future asset quality deterioration in banks' balance sheets.

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1. Introduction

Over the last decade, non-performing loans (hereafter NPLs) have been at the centre of prudential authorities' discussions and policy priorities. While their current level remains rather low, in the aftermath of the global financial crisis (2007-2009) and the European sovereign debt crisis (2010-2012), gross NPLs in the euro area banking system reached a historical high of €1 trillion in 2014 (8.1% of total gross loans).

High levels of impaired loans in banks' balance sheets have micro- and macroprudential implications for banks and policymakers (European Systemic Risk Board, ESRB, 2017). From a microprudential perspective, a high volume of NPLs creates a vicious circle between profitability, capital, and lending. Non-performing loans depress profitability since they require banks to book provisions for credit losses and to dedicate resources for their management, restructuring, and disposal (Berger and DeYoung, 1997; Badunenko et al., 2021). The weakened earnings profile ultimately hinders the capacity of banks to strengthen their capital positions, limiting their ability and willingness to support new lending to the real economy (Baldini and Causi, 2020; Huljak et al., 2022). Banks' capital is also affected by NPLs via increased risk-weighted assets (RWA) due to the higher risk weights applied to impaired loans. As such, banks must raise more capital to keep operating above their minimum regulatory capital requirements, thus depressing their return on equity (RoE). However, since tapping the markets with weak fundamentals could be particularly difficult and costly due to investors' perception of banks' riskiness, banks could decide to shrink their balance sheet by reducing their credit supply (Accornero et al., 2017).

From a macroprudential perspective, a large stock of NPLs could represent a threat to financial stability as they weaken banks' balance sheets, rendering the banking sector more vulnerable to shocks. A large stock of NPLs also requires banks to use additional resources for their management, thus impairing the core role of banks as financial intermediaries. Banks could also become unable (and/or unwilling) to adequately support the recovery of the economy by extending the necessary credit (Tölö and Virén, 2021). In bank-centred economies, such as the euro area, where small and medium enterprises are mostly bank-dependent for their financing needs, credit supply constraints represent a major obstacle to economic growth and recovery.[2] Nonetheless, subdued credit growth could also be the result of weak demand, as NPLs tend to rise in countries with stagnating economic activity. High NPLs could signal a debt overhang problem, whereby the excessive leverage of the corporate

[2] Small and medium enterprises represent the backbone of the euro area economy.

and household sectors hinders economic growth via lower investments (Vanlaer et al., 2021). An additional dimension to consider relates to the conditions under which households and corporates can access credit in a banking sector characterised by high NPLs. Banks might try to compensate their higher funding costs and depressed profits by tightening credit standards and applying higher interest rates to borrowers. In such a context, high-risk customers could be the only ones willing to take loans at higher rates (i.e., adverse selection).[3] Ultimately, this will result in another vicious circle, whereby the higher cost of debt for borrowers translates into higher probability of financial distress and in a new wave of defaults (Accornero et al., 2017).

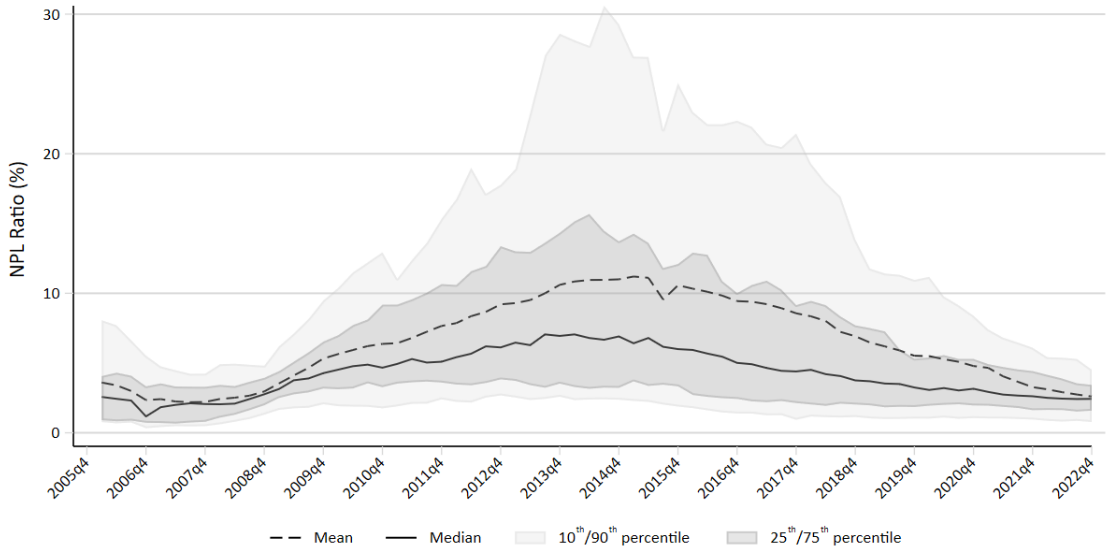
Given the significant micro- and macroprudential implications of non-performing loans, investigating the drivers of their evolution continues to be of utmost importance. In this context, it is crucial to account for possible non-linearities in the relationship between NPLs and macro-financial factors. The drivers behind the build-up of NPLs could in fact be different during crisis periods and “normal” times. Additionally, having a forward-looking view on the potential evolution of credit risk, particularly so in a non-linear setting, is crucial to ensure the preparedness of banks and supervisors. Therefore, in this paper, we present a credit risk framework aimed at i) detecting non-linearities between NPLs and macro-financial variables and ii) estimating the distribution of future NPLs in line with the Growth-at-Risk (GaR) approach (Adrian et al., 2018).

We start the analysis by studying the non-linear relations existing between a sample of euro area banks’ NPLs and their main macro-financial risk factors. In doing so, we contribute to the existing literature on the drivers of NPLs by employing state-of-the-art dynamic fixed effects panel quantile regressions (Machado and Santos Silva, 2019) and investigating whether and how different explanatory variables affect different percentiles of the distribution of non-performing loans. The choice of quantile models is explained in Figure 1, which illustrates the distribution of the NPLs over total gross loans (NPL ratio) for a sample of euro are banks between 2005 and 2022. At the beginning of the sample, the NPL ratios at different percentiles of the distribution are remarkably close, suggesting the presence of a normal distribution. The distribution shows instead significantly fatter tails starting from 2011, when credit risk began to materialise in the aftermath of the sovereign debt crisis. The presence of a left-skewed distribution with a fat right tail could point to different relationships between NPLs and their determinants, which might vary across the business cycle and

[3] Banks being attracted by higher interest income could become even more exposed to riskier borrowers.

especially during crisis periods. These considerations support the use of quantile regressions over other estimators focusing on the conditional mean. Quantile regressions have in fact a major advantage over alternative methods because they allow to cater for different dynamics on the tails of NPL distribution and to make an inference on the drivers behind higher-than-average NPL levels.

Figure 1. Evolution of NPL ratios in the euro area



Source: Authors' calculation based on data from Fitch Connect and a sample of 101 banks.

Our results show that macroeconomic variables have different explanatory powers at different quantiles of the distribution of NPLs. GDP growth and house price growth display statistical significance across the entire distribution, with the magnitude increasing when moving towards the right tail, while the yield on government bonds shows a stronger explanatory power on the left tail of the distribution of NPLs (i.e., banks with low NPLs). Contrarily, balance sheet characteristics do not seem to drive NPLs, exception made for the growth of the loan book.

The results from the quantile models are more informative compared to the findings obtained when running an ordinary least squares (OLS) regression. For example, in the case of inflation and credit growth, while the OLS regression provides a statistically significant coefficient, the quantile regression shows that the significance of these variables actually depends on the specific levels (i.e. quantile) of the NPL ratio. As such, these findings represent novel evidence of the presence of heterogenous effects produced by the drivers of asset quality in euro area banks, a fact that was overlooked by past approaches focusing on the conditional mean.[4]

In the second step of the analysis, we leverage on the Growth-at-Risk (GaR) framework (Adrian et al., 2018) to link current macro-financial conditions to the probability distribution of future NPL ratios. Such a framework has been extensively employed to enhance macro-financial surveillance when looking at tail risks to the global economic outlook based on the prevailing global financial conditions (Prasad et al., 2019). For this paper, we estimate the probability density of the NPL distribution of each bank, effectively calculating the probability that a bank will report NPL ratios above a predefined threshold of its conditional distribution e.g., above the 95th percentile of its distribution ("asset-quality-at-risk"). By looking at this information over time, we infer the evolution of the asset quality of a bank, effectively serving as a forward-looking assessment of its riskiness.[5]

This study could be of particular interest for micro- and macroprudential authorities. First, the findings from the quantile regressions show that failing to account for non-linearities might result in a misrepresentation of the interlinkages between credit risk and macro-financial conditions. Second, we show how quantile regressions can be used for the construction of forward-looking measures of asset quality deterioration, the "asset-quality-at-risk". As such, the proposed framework could help inform prudential authorities on bank-specific risks that may arise during specific adverse macroeconomic developments, while also providing a measure of the likelihood of certain NPL ratios materialising.

The rest of the paper is organised as follows: section 2 reviews the empirical literature studying banks' drivers of NPLs as well as forecasts of banks' asset quality in the context of stress test exercises. Section 3 presents the methodological framework employed to model NPLs, the data, and the explanatory variables included in the model. Section 4 describes the estimation results. Section 5 estimates the conditional non-performing loan distribution and Section 6 concludes.

[4] Among others papers, see Espinoza and Prasad, 2010; Bofondi and Ropele, 2011; Castro, 2013; Klein, 2013; Makri, Tsagkanos and Bellas, 2014; Ghosh, 2015; Chaibi and Ftiti, 2015; Staehr and Uuskula, 2017; Cerulli et al., 2020.

[5] The probability of NPL ratios materialising above a specific threshold can also be translated in the actual volumes of bad loans that could materialise in banks' balance sheets with a certain probability.

2. Literature Review

Given the significant micro- and macroprudential implications for banks and policymakers of high levels of non-performing loans, it is not surprising that the analysis of their drivers has been the subject of a considerable number of studies. Among the earliest studies, Rinaldi and Sanchis-Arellano (2006) focus on the macroeconomic determinants of households’ problem loans in seven European countries between 1989Q3 and 2004Q2. Their results show that an increase in unemployment, inflation, and the real lending rate worsen the financial conditions of debtors. Interestingly, they also observe that house prices are negatively related to NPLs, suggesting that either private wealth can act as a buffer against unexpected losses, or that housing wealth can be used as collateral to facilitate access to credit. Similarly, but with a focus on Nordic banks between 1993 and 2005, Berge and Boye (2007) observe that asset quality is negatively associated to developments in real interest rates and unemployment. Studying the difference between households and corporate sector, they also find that while reductions in households’ bad loans are driven by falling real interest rates and increasing house prices, problem loans in the corporate sector are reduced via higher domestic demand, lower real interest rates, and high oil prices. Quagliariello (2007) shows that NPLs in Italian banks follow a cyclical pattern between 1985 and 2002 with the impact of recessionary conditions being strong and long-lasting in term of asset quality deterioration. Similarly, Bofondi and Ropele (2011) investigate the macroeconomic drivers of Italian banks' bad loans over the period 1990-2010. They find that the new bad loans ratio for households is negatively related to real GDP growth and house prices, while it is positively related to the level of the unemployment rate and short-term interest rate. With respect to the bad loans ratio for firms, it increases with the unemployment rate and the level of firms’ debt, while it diminishes as the consumption of durables increases. Adopting a broader scope, Beck et al. (2015) study the macroeconomic determinants of NPLs in 75 countries over the period 2000-2010. After identifying real GDP growth as the main driver of impaired loans, they show that exchange rate depreciations could also result in higher NPLs in countries with a high degree of lending in foreign currencies to unhedged borrowers. Furthermore, they find that a drop in stock prices can negatively affect banks’ asset quality in countries with large stock markets relative to the size of the economy.

A strand of literature also focuses on the bi-directional relationship between NPLs and macro-financial conditions. Marcucci and Quagliariello (2008) assess the effects of business cycle conditions on the default rate of banks’ customers in Italy for the period 1990-

2004. They observe that default rates follow a cyclical pattern and that there is a feedback effect to the economy in place, which operates via bank capital. Focusing on 26 advanced economies for the period 1998-2009, Nkusu (2011) shows that an increase in the level of NPLs significantly affects the macroeconomic performance of a country via slower growth, higher unemployment rate, and a fall in the asset prices (such as real estate properties). At the same time, a rise in inflation and house prices, and a decrease in the credit to-GDP ratio, could produce a worsening in the loan quality. Similar results were obtained by Castro (2013), who investigates the link between macroeconomic environment and credit risk in a group of five European countries (Greece, Ireland, Portugal, Spain and Italy). The results show that NPLs increase when GDP growth slows down, and share, and housing prices decrease, and NPLs also rise when the unemployment rate, interest rate, and credit growth increase.

Despite the relatively broad and developed body of research on credit risk, existing non-linear relationships between NPLs (or other credit risk parameters) and macro-financial factors have been overlooked by the literature, with a very limited number of exceptions (Covas, et al., 2014; Kanas and Molyneux, 2018; Schechtman and Gaglianone, 2012). This represents an important limitation of the current modelling framework, particularly so for euro area countries. Given that the distribution of credit risk variables is often skewed, linear models would fail to capture the sensitivity of the explanatory variables at the tails of the distribution. Schechtman and Gaglianone (2012) use a quantile regression model to focus on credit risk coming from the Brazilian household sector between 1995Q1 and 2009Q3. They find significant negative effects on credit risk of real GDP growth and credit volume growth, and significant positive effects of the unemployment and inflation rate, with the relative importance of macro variables varying along the conditional credit risk distribution. To estimate capital shortfalls of US bank holding companies, Covas, et al. (2014) use a fixed effects quantile autoregressive model with exogenous macroeconomic factors. Their results point to a superior out-of-sample forecasting performance relative to the standard linear framework, which is instead found to underestimate loan losses. Kanas and Molyneux (2018) propose an additive semi-parametric quantile approach to model the dynamics of NPLs in the US banking system between 1984 and 2013. Focusing on the 90% and 95% percentiles, they show that NPLs are determined non-linearly by real GDP growth, the effective federal funds rate, and the federal debt to GDP ratio, and claim that these relationships would have not been uncovered by linear models.

By focusing on the estimation of conditional probability forecasts of non-performing loans, our paper also contributes to the strand of literature studying credit risk in the context of stress-test exercises and scenario analyses. These studies, often developed within central banks, aim at assessing in a forward-looking manner the resilience of banks' loan books to severe but plausible adverse macro-financial and economic shocks. Among these studies, the IMF approach is noteworthy. Using a Generalized Method of Moments (GMM) approach, Wezel, Canta and Luy (2014) model the logistic transformation of the NPL ratio as a function of real GDP growth, changes in unemployment, changes in external sector variables, and interest rates, and project their evolution under three different macroeconomic scenarios. Bonaccorsi Di Patti and Cascarino (2020) provide forecasts of households and corporate NPLs of Italian banks conditional to macroeconomic and financial variables, by employing a Bayesian Model Averaging approach. Finally, the Organisation for Economic Co-operation and Development (OECD, 2021) conducted a simulation analysis on 37 countries to assess the extent of the potential rise in NPLs depending on the severity of the COVID-19 crisis, using linear fixed effect models. While explicit scenario analyses are beyond the scope of our paper, to a certain extent we contribute to this strand of literature as the GaR approach supports a forward-looking view on how NPL ratios are expected to evolve under different economic conditions.

3. Empirical Approach and Data

3.1 Quantile Regressions

To estimate the drivers of non-performing loans, we implement a dynamic fixed effect quantile regression, estimated via the approach proposed by Machado and Santos Silva (2019). Specifically, we estimate the following equation (1):

$$y_{i,t+1}^{q} = \beta^{q} y_{i,t} + \gamma^{q} Z_{i,t} + \theta^{q} X_{i,t} + v_{i}^{q} + \varepsilon_{i,t}^{q} \qquad (1)$$

where $y_{i,t+1}^{q}$ represents the variable of interest for bank *i* at time *t+1* for quantile *q* where $q \in [0.5; 0.95]$, $y_{i,t}$ is its first lag, $Z_{i,t}$ includes the macro-financial variables, and $X_{i,t}$ are bank-specific controls Bank-specific fixed effects (FE) v_{i}^{q} are capturing , time-invariant unobserved heterogeneity across banks and $\varepsilon_{i,t}^{q}$ is the error term for each bank *i*.

In line with the literature, the dependent variable is the logistic transformation of the NPL ratio (Espinoza and Prasad, 2010; Ghosh, 2015; Wezel, Canta and Luy, 2014). The logit is constructed as $Npl\ logit_{i,t} = ln\left(\frac{NPL\ ratio_{i,t}}{1-NPL\ ratio_{i,t}}\right)$ to ensure that the dependent variable spans over the interval [-∞; +∞] as opposed to the [0;100] interval and is distributed symmetrically.[6] To consider the persistency of non-performing loans, we augment the model with an autoregressive component, captured in Eq. (1) by the coefficient β^q.[7]

All the control variables are lagged to ease endogeneity concerns and to account for the lagged materialisation of credit risk in banks' balance sheets. The set of macro-financial risk factors is chosen to be in line with the one commonly used in EU-wide stress testing exercises, such as the year-on-year growth rate of real GDP, the unemployment rate, the inflation rate, the year-on-year change in residential property prices, and the 10-year government bond yield.[8] The year-on-year growth rate of real GDP (*Real GDP growth*) is included to take into account the effects of the business cycle on banks' credit risk. The unemployment rate (*Unemployment*) is included to account for the impact of households' ability to repay their loans. Regarding the inflation rate (*Inflation*), calculated as a year-on-year change in the Consumer Price Index (CPI), we do not have an a priori belief on the direction of the relationship with credit risk. On the one hand, inflation helps borrowers to reduce the real value of its debt. On the other hand, high inflation passes through to higher nominal interest rates, making debt servicing more onerous, thus increasing the risks of borrowers defaulting (Rinaldi and Sanchis-Arellano, 2006; Nkusu, 2011).The year-on-year change in residential property prices (*Hpi*) is included to cater for borrowers' wealth effects linked to real estate assets. The 10-year government bond yield (*10-year gov. bond yield*) is included to capture how the interest rate on public debt might influence credit risk in the banking sector (Cerulli et al., 2020). In the Eurozone case, the high yields observed in our sample are the reflection of the sovereign debt crisis. Concerns about the current and future general economic condition of countries, and especially of the ability of sovereigns to repay the outstanding debt resulted in rising yields, increasing risk aversion, and tightening of credit standards. As such, we expect a positive relationship between yield and NPLs. Finally, we introduce a linear trend (*Trend*) to capture the reduction in the NPL ratio observed over the last years due to the intensification of large transactions for NPLs disposal, also in response to new supervisory targets.

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[6] An exponential transformation applied to the NPL logit allows to recompute the variable of interest, i.e. NPL ratio.

[7] The inclusion of the autoregressive component introduces a correlation between the regressors and the error term. However, as showed in the literature, we expect the bias on the estimated coefficient of the autoregressive components to be small given our large time dimension (T>30) (Nickell, 1981; Machado and Santos Silva, 2019). The bias is sizable for small T, while it tends to be reduced for reasonable large values of T (Nickell, 1981; Roodman, 2009).

[8] The macro-financial variables included in the scenarios of the EU-wide stress test exercises would also allow to extend the forecast horizon of the analysis up to 3 years ahead.

To limit the omitted variable bias, we also include bank-specific controls into the model. We consider the natural logarithm of total assets (*Size*) to account for the size of banks. While small banks may have access to soft information about their customers, large banks enjoy economies of scale in terms of information collection and processing (Louzis et al. 2012) Large banks can devote more resources to the selection of borrowers, thus reducing the risk of future defaults. However, large banks may have an incentive to have riskier balance sheets because of their "too-big-to-fail" status (Stern and Feldman, 2009). Furthermore, we include the equity-to-asset ratio (*Equity/assets*) to control for moral hazard behaviour. Poorly capitalised banks may engage in riskier activities as they have less "skin in the game", resulting in higher levels of distressed debt on their balance sheets. However, banks could also increase the riskiness of their investments due to their strong capital position, ultimately suffering from more bad loans (Tan and Floros, 2013). In addition, we control for the difference in banks' profitability via the return on equity (*ROE*). More profitable banks can generate and retain earnings, and use them to boost capital, which would give them the ability to absorb the losses arising from the selling/disposing of bad loans, thus fuelling again a type of moral hazard behaviour (Chaibi and Ftiti, 2015; Ghosh, 2015). We further include in our model the year-on-year growth rate of the loan portfolio (*Loan growth*) to capture the condition of credit markets, as excessive credit growth might be symptomatic of banks lowering their credit standards (Castro, 2013; Garrido et al., 2016, Cerulli et al., 2020). Finally, the model includes a measure of coverage ratio (*Coverage ratio*), computed as loan reserves over total loans to control for the extent to which bad loans are provisioned by banks. Higher coverage ratios influence the pace of NPLs resolution and write-offs (Aiyar et al., 2015).[9]

The choice to adopt the dynamic fixed effect quantile regression approach is driven by several considerations. First, the main advantage of quantile regressions is the informational gains they provide in comparison to linear models (Machado and Santos Silva, 2019). Although the literature on credit risk is dominated by linear models, these models are ill-equipped to approximate relationships that may materialise during severe shocks (Ongena et al., 2014, Covas et al., 2014). By using quantile regressions, one can in fact differentiate between factors driving high and low levels of non-performing loans, as the coefficients of bank-specific and macroeconomic variables ($X_{i,t} and\ Z_{i,t}$) are permitted to vary across the different quantiles. This technique thus allows to focus on the tails of the distributions of NPLs and to make an inference on what drives high levels of NPLs, which is of key importance for

[9] An increase in coverage ratios might also signal worsening banks' expectations on the evolution of credit risk.

crisis prevention and financial stability functions. This is in sharp contrast to ordinary least squared (OLS) estimators that focus on the conditional mean and do not allow inference at different points of the distribution of the dependent variable. While OLS provides information about a single slope parameter, quantile regressions allow inference about the slope at different points of the dependent variable (NPL ratio) given the set of explanatory variables (Schaeck, 2008). Additionally, interpreting the estimated coefficients as conditional mean can lead to misleading results when the dependent variable is skewed. In these cases, the mean effect might be more a reflection of what is happening in the upper tails of the distributions than a reflection of what is happening in the middle (Hao and Naiman, 2007).

In the context of scenario analyses, and especially of stress test exercises, quantile regressions allow accounting for potential non-linearities arising during adverse or crisis scenarios when high credit risk materialises (Chavleishvili and Manganelli, 2023). This is a major advantage as the relative importance of the macro variables might vary according to the quantile of credit risk distribution. One could in fact observe macro-variables that have a negligible effect at the mean of the distribution, whereas they gain relevance at higher (or lower) quantiles of the distribution of the NPL ratios. Likewise, the effect of the various control variables could be different in the lower and upper tail of the distribution of NPLs (Chuliá et al., 2017). As such, quantile regressions are particularly useful when the objective is to assess the relationship between variables in periods of macroeconomic stress when non-linear relationships might materialise. By offering a more complete picture of the effects of the explanatory variables across the distribution of NPLs, quantile models are therefore particularly relevant from a policymaker's perspective (Mydland et al., 2018).

The second advantage is that the approach proposed by Machado and Santos Silva (2019) permits the inclusion of bank fixed-effects (FE) that are quantile-specific, allowing us to introduce a level difference in the intercept among banks and to capture any remaining time-invariant bank-specific heterogeneity.[10]

3.2 Data

The sample considered in this paper consists of 101 euro area banks, featuring quarterly data spanning from the first quarter of 2005 to the fourth quarter of 2022. The banks included in our datasets are significant credit institutions under the remit of the Single Supervisory Mechanism. We source bank-specific balance sheet and income statement data

[10] The inclusion of FE represents a major improvement over past studies applying quantile regressions where the FE were instead quantile invariant (Schechtman and Piazza Gaglianone, 2012; Kanas and Molyneux, 2018).

from Fitch Connect, while the macro-financial variables are collected from Haver. Table A1 in the Appendix shows the number of banks in each of the countries considered. Table A2 in the Appendix provides the summary statistics of the dependent and explanatory variables at different percentiles of the distribution.

4. Determinants of NPL ratios using quantile regressions

Table 1 exhibits the estimated coefficients of the model presented in Eq. (1).[11] Column (1) reports the results from running a linear fixed effect model, while columns (2) to (8) refer to quantile regressions (QR) at the 5th, 10th, 25th, 50th, 75th, 90th and 95th percentiles.

As expected, and in line with previous studies, the dependent variable shows a high and statistically significant degree of persistency across the distribution of NPLs, being between 0.94 and 0.97 for the QR models. Not surprisingly, high NPL ratios in the previous quarters tend to be followed by high ratios as NPLs are traditionally slow moving. Once credit risk materialises in banks' loan books, the resolution of these bad loans tends to be a lengthy and burdensome process that can take several years, as evidence from some countries shows (e.g., Greece, Cyprus, Italy).

Moving to the macroeconomic factors driving a build-up of NPLs, we show evidence of a negative and statistically significant relationship between *Real GDP growth* and bad loans across the entire distribution of NPLs in line with previous studies (Castro, 2013; Chaibi and Ftiti, 2015; Cerulli et al., 2020). Albeit to a limited extent, the magnitude of the elasticities and significance of *Real GDP growth* changes across quantiles. As expected a priori, a positive macroeconomic performance is generally associated with lower NPLs as borrowers' repayment capacity is maintained, and NPL portfolio sales might pick up, as investors are optimistic about the recovery opportunities.

On the contrary, the relationship of NPLs with *Inflation* is changing across quantiles, with the coefficient being significant only on the right tail of the distribution. Inflation dynamics do not seem to play a role for banks with low credit risk, as it might help borrowers to reduce the value of their debt (Rinaldi and Sanchis-Arellano, 2006; Nkusu, 2011).

As expected, we find a negative relationship between residential house price dynamics (*Hpi*) and NPLs, which is in line with Bofondi and Ropele (2011) and Ghosh (2015, 2017). While it remains statistically significant along the entire distribution of NPLs, the magnitude is stronger for the higher quantiles of the distribution. Higher real estate prices tend to be

[11] We use a 1000 sample replications bootstrap procedure to estimate the quantile pseudo standard errors and p-values, and to account for heteroskedasticity.

associated with lower default rates of borrowers, especially for banks on the right tail of the distribution as "housing wealth" increases borrowers' opportunities to refinance their debt. At the same time, when the real estate market is booming, banks may dispose of their bad loans more easily, without incurring losses on the collateral value of the loans.

Furthermore, we document a positive relationship between the *10-year gov. bond yield* and NPLs as in Cerulli et al. (2020). Higher sovereign yields can in fact translate into higher borrowing costs for the private sector and potential repayment difficulties. The coefficient is positive throughout the distribution of NPLs but loses statistical significance for banks with elevated NPLs levels (above the 95^{th} percentile).

Finally, the time *Trend* displays a negative but significant coefficient only for values of NPLs equal or above the median. This finding is consistent with the developments in NPL resolution in Europe over time, particularly from the start of the SSM in 2014, leading to more deleveraging by banks with higher credit risk over time, either via organic solutions or portfolio sales. As in the linear case, we do not find evidence of a statistically significant relationship between *Unemployment* rate and NPLs, probably due to other macroeconomic variables present in the regression capturing a similar effect.

Moving to the bank-specific controls, we find an overall limited contribution of banks' individual features in explaining non-performing loans dynamics across our sample period. The only control that displays a significant relationship with NPLs is $gross\ loans\ growth$ on the right tail, pointing to more risky loans being approved by riskier banks.

Overall, comparing in Table 1 the results from columns (2) to (8) with those from column (1), it appears clear how the OLS estimator provides a rather limited view of the drivers of NPLs. For instance, in the case of *Coverage ratio, Loan growth*, *10-year gov. bond yield* and *Trend,* the OLS regression provides a statistically significant coefficient. From the quantile regressions instead, we can learn how these variables play a different role depending on the NPL ratios of the banks. The OLS regression also fails to shed light on how the *sign* of covariates affect differently NPLs depending on their levels. This is particularly evident for certain explanatory variables such as *Inflation*, *Coverage ratio*, *ROE* and *Equity/assets*. Overall, this reinforces our choice to model NPLs via quantile regressions, as they paint a more informative picture compared to the linear models and thus are valuable from a policymaker perspective, particularly in distressed situations.

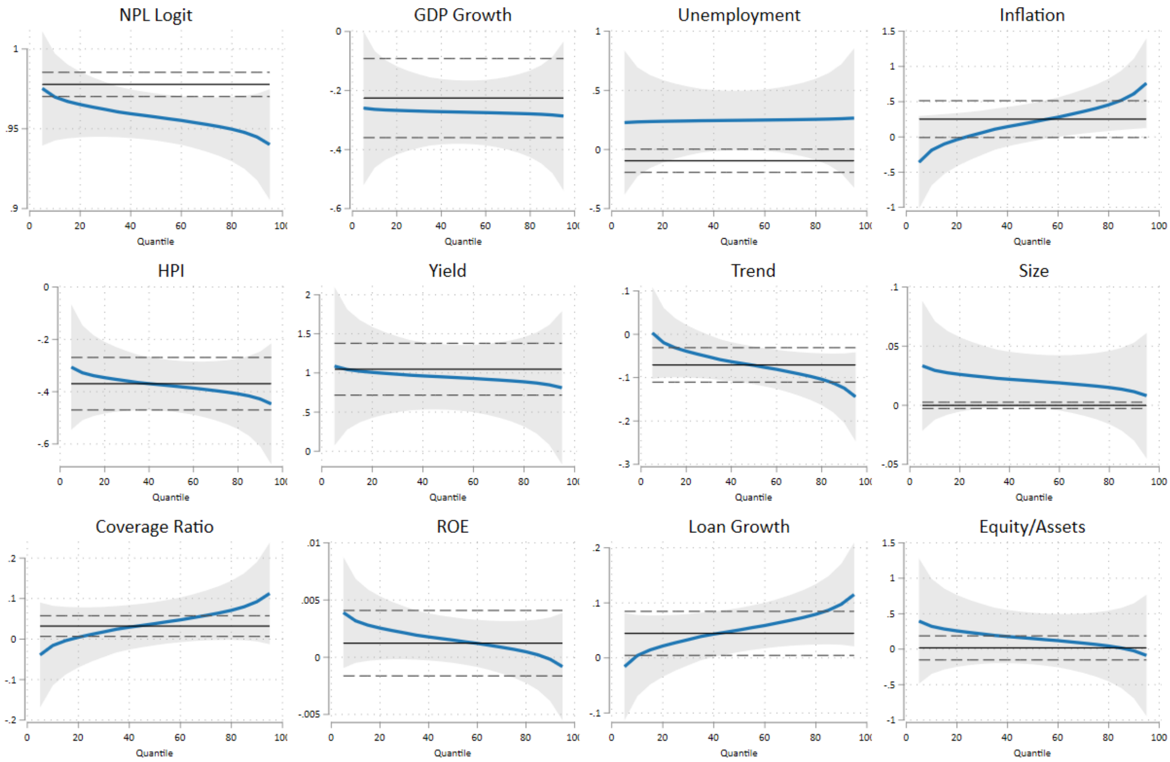
Figure 2 depicts the results discussed above. The y-axis reports the estimated coefficient for each explanatory variable, while the x-axis reports the quantiles of the NPL distribution. The solid blue line represents the estimated coefficients across the entire distribution of NPLs with the light blue area indicating the 95% confidence bands. The black horizontal line represents the coefficient estimated in the OLS regression (column 1 of Table 1), with the dashed lines representing the related confidence bands.

Table 1. OLS and Quantile Regression estimates

	(1) OLS	(2) 0.05	(3) 0.10	(4) 0.25	(5) 0.50	(6) 0.75	(7) 0.90	(8) 0.95
NPLs Logit	**0.9577*****	**0.9753*****	**0.9699*****	**0.9636*****	**0.9574*****	**0.9514*****	**0.9449*****	**0.9401*****
	(0.0078)	**(0.0188)**	**(0.0147)**	**(0.0106)**	**(0.0084)**	**(0.0091)**	**(0.0126)**	**(0.0165)**
Real GDP growth	**-0.2729*****	**-0.2596***	**-0.2637****	**-0.2685*****	**-0.2732*****	**-0.2778*****	**-0.2827*****	**-0.2863****
	(0.0701)	**(0.1503)**	**(0.1192)**	**(0.0878)**	**(0.0714)**	**(0.0764)**	**(0.1013)**	**(0.1292)**
Unemployment	0.2467	0.2277	0.2335	0.2403	0.2470	0.2536	0.2606	0.2657
	(0.1866)	(0.4913)	(0.3797)	(0.2630)	(0.1981)	(0.2132)	(0.3044)	(0.4034)
Inflation	0.2001	-0.3609	-0.1886	0.0130	0.2110	0.4042	**0.6119***	**0.7632***
	(0.2085)	(0.3041)	(0.2437)	(0.2042)	(0.2137)	(0.2664)	**(0.3472)**	**(0.4203)**
Hpi	**-0.3762*****	**-0.3060*****	**-0.3276*****	**-0.3528*****	**-0.3776*****	**-0.4017*****	**-0.4277*****	**-0.4466*****
	(0.0630)	**(0.0877)**	**(0.0716)**	**(0.0613)**	**(0.0642)**	**(0.0779)**	**(0.0996)**	**(0.1199)**
$10-year\ gov.bond\ yield$	**0.9490*****	**1.0866****	**1.0444*****	**0.9949*****	**0.9463*****	**0.8989****	**0.8479***	0.8108
	(0.2235)	**(0.4227)**	**(0.3044)**	**(0.2183)**	**(0.2483)**	**(0.3564)**	**(0.5085)**	(0.6393)
Trend	**-0.0703****	0.0032	-0.0194	-0.0458	**-0.0718****	**-0.0971*****	**-0.1243*****	**-0.1441****
	(0.0286)	(0.0704)	(0.0554)	(0.0398)	**(0.0312)**	**(0.0333)**	**(0.0453)**	**(0.0588)**
Size	0.0207	0.0333	0.0295	0.0249	0.0205	0.0161	0.0115	0.0081
	(0.0158)	(0.0397)	(0.0311)	(0.0221)	(0.0168)	(0.0174)	(0.0241)	(0.0315)
Coverage ratio	**0.0366***	-0.0391	-0.0158	0.0114	0.0381	0.0642	0.0922	0.1127
	(0.0211)	(0.0277)	(0.0197)	(0.0208)	(0.0307)	(0.0431)	(0.0588)	(0.0714)
ROE	0.0015	0.0039	0.0032	0.0023	0.0015	0.0007	-0.0002	-0.0008
	(0.0012)	(0.0056)	(0.0045)	(0.0035)	(0.0031)	(0.0036)	(0.0047)	(0.0059)
Loan growth	**0.0496***	-0.0158	0.0043	0.0278	0.0508	**0.0734***	**0.0976****	**0.1152****
	(0.0289)	(0.0448)	(0.0364)	(0.0305)	(0.0313)	**(0.0379)**	**(0.0488)**	**(0.0587)**
Equity/assets	0.1546	0.3964	0.3221	0.2352	0.1499	0.0666	-0.0229	-0.0881
	(0.3039)	(0.6036)	(0.4851)	(0.3674)	(0.3080)	(0.3257)	(0.4159)	(0.5172)
Constant	**-0.4087****							
	(0.1896)							
N	5319	5319	5319	5319	5319	5319	5319	5319

Note: standard errors estimated using 1000 sample replication bootstrap procedure are in parentheses and $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 2. Estimated coeffiecients across quantiles



Note: The Figure displays the estimated coefficients also reported in Table 1. The y-axis indicates the estimated coefficient for each explanatory variable while the x-axis represents the quantiles of the NPL distribution. The solid blue line represents the quantile regression estimates and the light blue area the related 95% confidence bands. The black horizontal line represents the coefficient of the OLS regression and the dashed lines the related 95% confidence bands.

5. Asset-Quality-at-Risk

In this section, applying the Growth-at-Risk framework, we show how quantile regression models can be used in the assessment of credit risk building up in individual banks. From Eq. (1) above, we can estimate the fitted conditional quantiles of the NPL ratio for each bank *i* for a given *t*, conditional on the macro-financial dependent variables, based on the point estimates of the coefficients:

$$Q[y_{i,t+1}^{q}] = \hat{\beta}^{q} y_{i,t} + \hat{\gamma}^{q} Z_{i,t} + \hat{\theta}^{q} X_{i,t} + \hat{v}_{i}^{q} + \hat{\varepsilon}_{i,t}^{q} \qquad (2)$$

The estimated conditional quantiles are a sufficient statistic for describing the conditional cumulative distribution function (CDF). However, mapping these estimates into a probability distribution function is more challenging due to approximation error and estimation noise. Thus, following Adrian et al. (2019), we use the *t*-skew distribution of Azzalini and

Capitanio (2003) to fit and smooth the predicted values of the estimated conditional quantiles to derive the probability density function (PDF) parametrically:[12]

$$f(y;\mu,\sigma,\alpha,v) = \frac{2}{\sigma}t\left(\frac{y-\mu}{\sigma};v\right)T\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{v+1}{v+\left(\frac{y-\mu}{\sigma}\right)^2}};v+1\right) \qquad (3)$$

where $t(.)$ and $T(.)$ denote respectively the PDF and CDF of the Student *t*-distribution, and μ, σ, α, v are respectively the location, the scale, the fatness, and the shape parameters of the distribution. With respect to the *t*-distribution, the skewed *t*-distribution adds the shape parameter to regulate the skewing effect of the CDF over the PDF. The four parameters are estimated by minimising the quadratic distance between the estimated quantiles and the quantiles of a *t*-skew distribution to match the 5th to the 95th quantiles.[13]

Estimating the entire distribution of future NPL ratios conditional to the state of the macro-financial environment allows to quantify the likelihood of future asset quality deterioration ("asset-quality-at-risk") via conditional quantile for any percentile of the distribution.[14] Such an approach could be used to monitor the evolution of asset quality deterioration over time by keeping track of the probabilities of adverse outcomes. Specifically, one could – at any given point in time – estimate the probability that one quarter ahead, a bank will report NPL ratios above a pre-defined "risky" percentile of the conditional distribution, e.g. above the 90th percentile. Likewise, authorities can estimate the probability that NPL ratios will materialise above a specific threshold of interest, for instance 5%.

Figure 3 below reports the estimated one-quarter ahead conditional distributions of NPL ratios for a selected number of periods (specifically 2010Q4, 2015Q4, 2019Q4, and 2022Q4) for two banks in our sample, one depicted in Panel A and one Panel B. Together with the conditional distribution, the vertical lines in the figure indicate the previous quarter realisation of the NPL ratio for the institution. By focusing on the position of the bank's reported NPL ratio with respect to the estimated distribution, we can assess whether the realised ratio is close to the centrality measures of the distribution or rather to a "riskier" percentile. If

[12] The *t*-skew distributions have proven useful to model tail events in finance due to the skewness of many distributions in this field (Azzalini and Capitanio, 2003).

[13] The four parameters of a *t*-skew distribution fully characterise the distribution and summarise the whole information about variance, skewness, and kurtosis in a relatively parsimonious and comprehensive way.

[14] Quantile regressions have many advantages when used to estimate the conditional distribution: they provide the best unbiased linear estimator for the conditional quantile, they are robust to outliers, and their asymptotic properties are easy to derive.

we look over different forecast horizons (1,…, h-quarters ahead), the comparison will also shed light on likely dynamics of asset quality deterioration at for each bank in the sample.

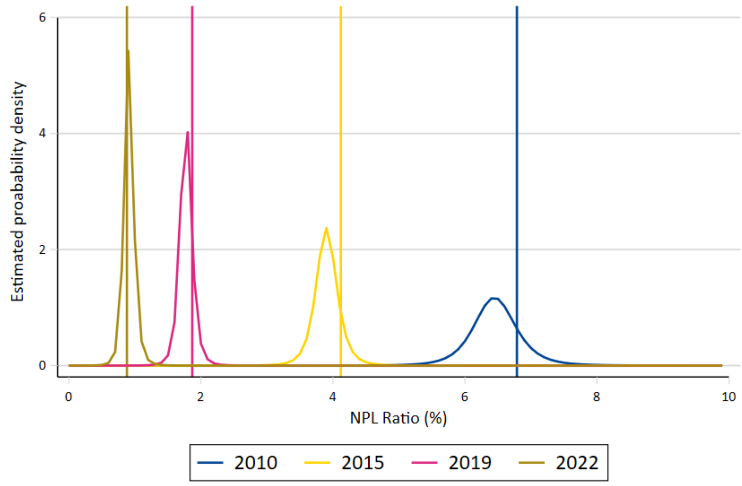
Panel A of Figure 3 demonstrates the usefulness of the "asset-quality-at-risk" approach. The graph illustrates how the conditional distributions of NPL ratios shift towards the left as years pass, signalling a general improvement in the asset quality of this banks over time. In 2010, the realised NPL ratio, represented by the blue vertical line, are located on the right tail of the NPL distribution. This positioning implies that the larger probability mass lies on the left of the reported NPL ratio, indicating a greater "upside" risk, compared to "downside" risk to asset quality for the selected bank (Panel A). By examining the probability density curve for 2015, one can observe that the predicted positive outlook for this bank materialised, as the NPL ratio improved. Also in this instance, the probability mass remains on the left, revealing that the likelihood of further improvements in asset quality, given the current macro-financial conditions, is higher than the likelihood of a deterioration. The curves estimated for 2019 and 2022 further corroborate these predictions. Overall, the shape of the estimated probability densities in 2010 and 2015 reveals greater uncertainty around the estimates compared to those for 2019 and 2022, as the estimated probability density curves display higher dispersion.

Panel B shows a slightly different pattern compared to panel A, with the asset quality of the selected bank deteriorating between 2010 and 2015 before showing improvements. In panel B, the distributions generally exhibit a fatter right tail compared to those in panel A, which could be indicative of a more likely materialisation of risk in adverse scenarios for this bank. At the end of 2010, the realised NPL ratio (blue vertical line) is positioned in the central part of the conditional distribution, suggesting that if adverse macro-financial developments were to occur, there would be equal probabilities of higher or lower NPL ratios in the next quarter. This information suggests that a closer monitoring of this bank might have been warranted at the time by the supervisory authorities. In 2015, the deterioration of the NPL ratio had occurred, but at that point in time, "upside" risks were prevailing as the probability mass was larger to the left of the realised NPLs value. Overall, the "asset-quality-at-risk" framework highlights how, as the realised values move on the tails of the NPL ratio distribution, relying on mean or median estimates could lead to a severe underestimation of the risks of future asset quality deterioration for banks.

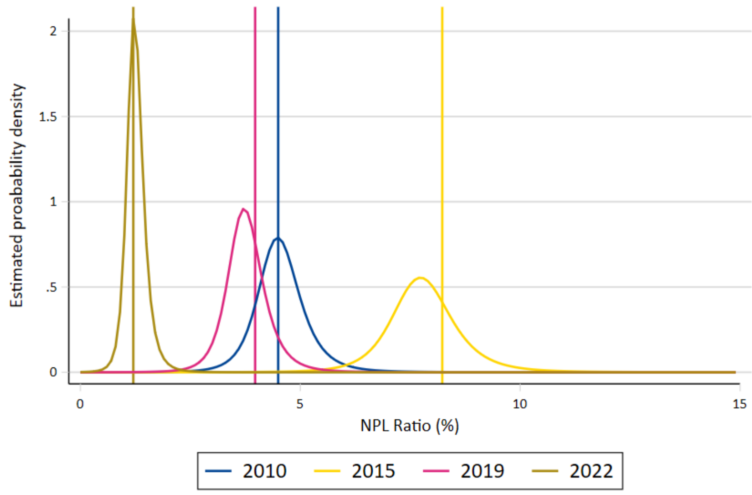
A comparison between the main percentiles of the NPL ratio distributions of the two banks and their realised values is displayed in the boxplot of Figure 5 in the Appendix. Looking at Panel A, we can notice how the realised values are close or above the 75th percentiles in three out of the four years. In panel B, on the other hand, the realised values appear close or above the 75th percentile only in the first two years.

Figure 3. One-quarter ahead conditional distributions of NPL ratios

Panel A.



Panel B.



Note: the two panels report the one-quarter ahead conditional distributions of NPL ratios in 2010Q4, 2015Q4, 2019Q4, and 2022Q4 for a specific bank in our sample. The vertical lines represent the observed data of NPL ratio in the previous quarter.

From a system-wide perspective, this approach could also be used to identify whether risk is building up at the aggregate level. Supervisors could in fact set a specific threshold of risk tolerance in term asset quality deterioration and assess whether banks' asset quality is moving in line with their expectations or not. Assessing the number of banks above that specific threshold and/or the related stock of impaired loans (or NPL ratio) and repeating the exercise over different forecast horizons would allow to grasp the evolution of asset quality over time at a system level.

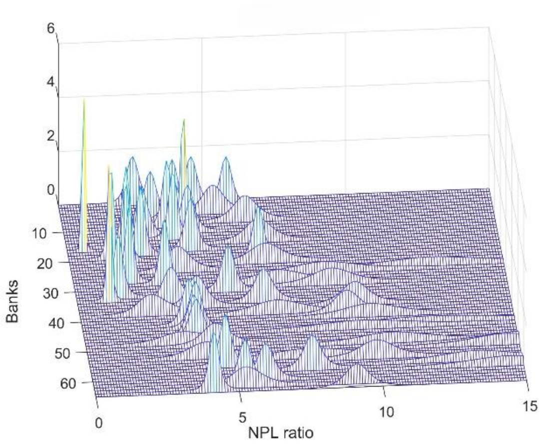
Figure 4 below shows the conditional distribution functions for all the banks in our sample in four selected periods. For each period, the graph of the conditional quantiles is divided into two segments to appreciate the long tails of the NPL ratio distributions of certain banks in our sample. Thus, in Column (1) the conditional distributions are reported for NPL ratios up to 15%, while in Column (2) refer to NPL ratios ranging from 15% to 40%. In 2010, following the global financial crisis, credit risk was on the rise but still at moderate levels, as shown in Panel A. By contrast, in 2015, NPLs were at historical high levels. Moving from 2010 to 2015, we can notice how the mass of the distributions moves to the right, signalling a worsening in asset quality. In Column (2) of Panel B, more banks appear to have distributions displaying large dispersion and long right tails compared to 2010. These movements of the conditional distributions of NPLs signal that the probability of high NPL ratios materialising one-quarter ahead has increased. Conversely, comparing 2015 with 2019, Panel C shows that the mass of the distributions has shifted back toward the left. Additionally, the tails of the distributions become much slimmer, implying a lower probability of banks experiencing high NPLs in the next quarter. Unsurprisingly, the pattern remains the same when looking at the chart displaying the distributions of NPL ratios in 2022Q4. Despite the initial concerns, credit risk did not materialise during (and following) the pandemic, and banks further progressed in cleaning their balance sheet by offloading large portfolios of legacy NPLs. This is particularly evident when looking at Column (2) of Panel D, where the long right tails have disappeared.

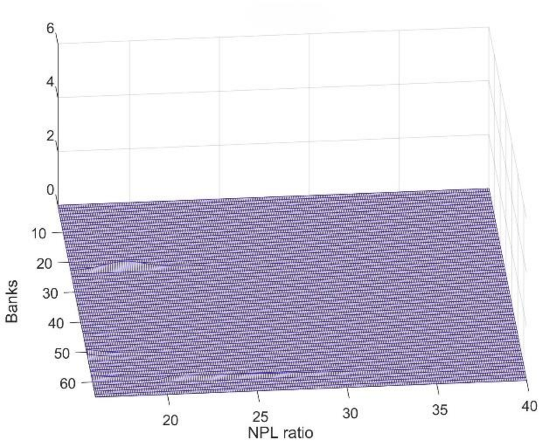
The analysis developed in this Section can help enhance the toolkit of micro- and macroprudential authorities in several dimensions. First, estimating the conditional distribution of NPL ratios for each bank in each time period and the related predictive densities enable the quantification risks of future asset quality deterioration conditional on a set of macro-financial indicators and to monitor their evolution over time. This is because we can assign a probability that a certain NPL ratio threshold will be crossed one quarter ahead for a given bank of interest. Additionally, by looking at the positioning of the bank in terms of NPL ratio with respect to its conditional distribution, one can assess whether the bank is moving toward the right tails, thus suggesting increased risk. This bank-specific view on the forward-looking evolution of risk can add to the micro- and macroprudential toolkit by establishing a closer and more forward-looking link with the evolution of the macro environment. Second, such analysis allows for an assessment of the severity of bank-specific risks by studying the right tail of the conditional distributions and the associated probabilities. Finally, by studying the entire distribution of probabilities, this framework provides not only a point estimate of future NPLs, but more importantly it provides insights about the system-wide distribution of future realisations of NPL ratios.

Figure 4. Conditional distribution of NPL ratios

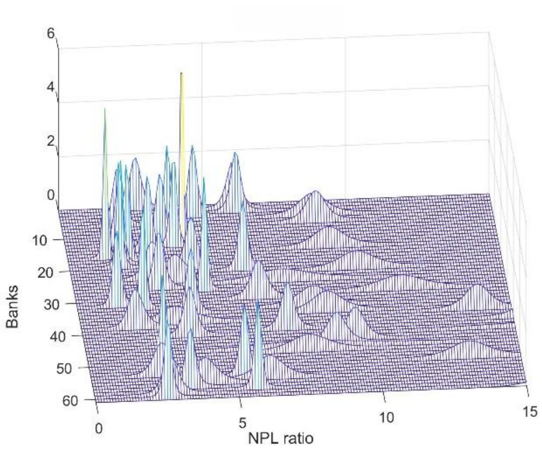
(1) **(2)**

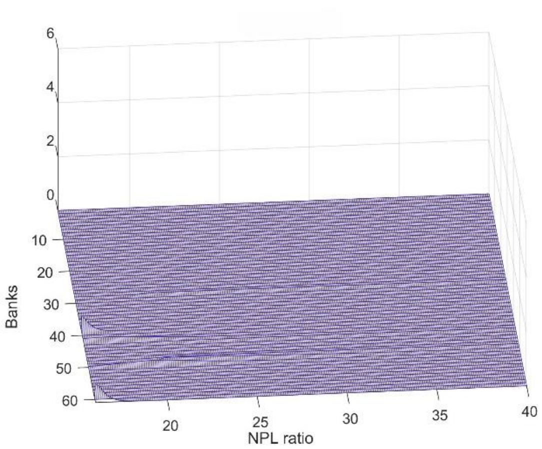
Panel A. One quarter ahead: 2010Q4



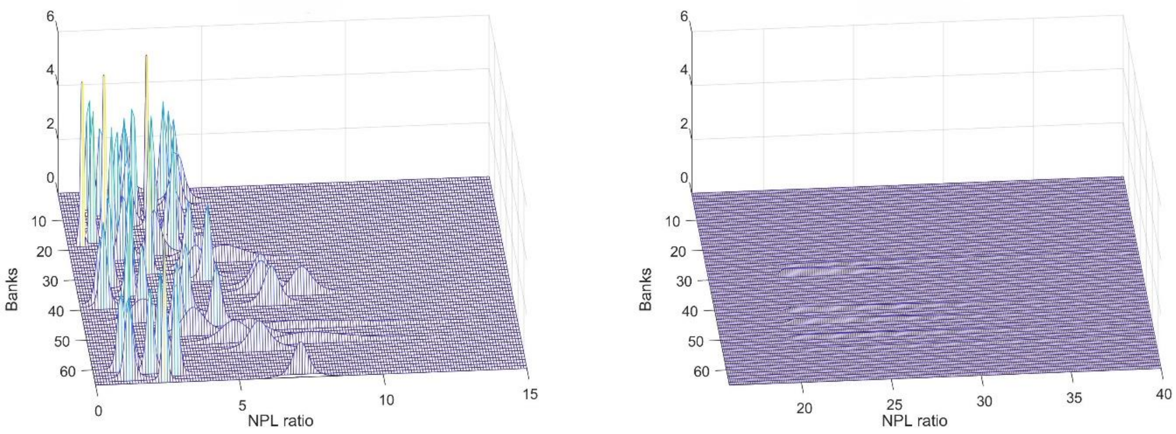


Panel B. One quarter ahead: 2015Q4

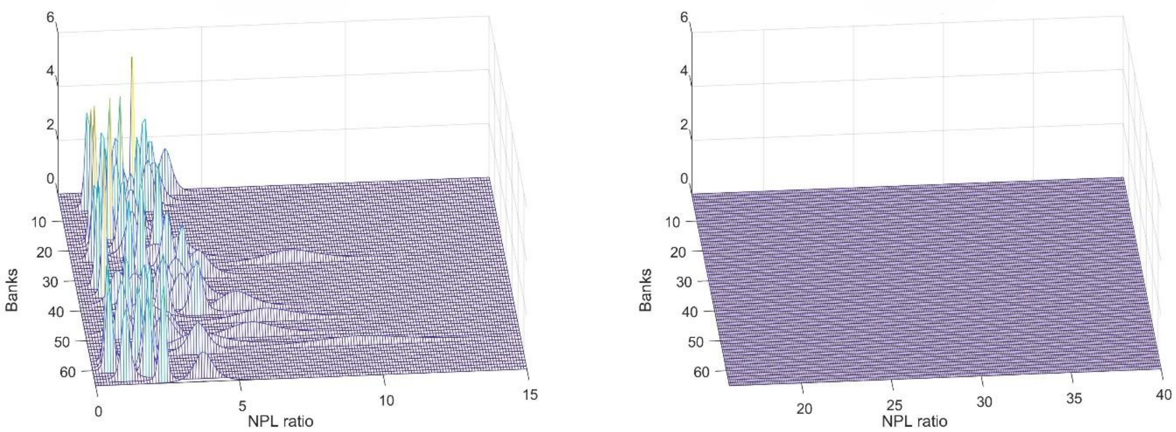




Panel C. One quarter ahead: 2019Q4



Panel D. One quarter ahead: 2022Q4



Notes: The panels show the estimated conditional smoothed distribution of NPL ratio one quarter ahead for each bank in our sample. For visualisation purposes, the panels are split in two for each year given the presence of few banks with large amounts of NPLs in our sample. For the ease of comparison among the differnet panels, we only report the banks displaying data in all four selected time periods. Each bank is represented along the z-axis. NPL ratios are presented in percentage points along the x-axis. The y-axis displays the predictive densities.

6. Conclusions

Non-performing loans represent a long-standing policy concern in the euro area. Over the last decade, they have been under the scrutiny of both banks and policymakers because of their micro- and macroprudential implications. A high volume of NPLs has in fact the potential to create a vicious circle between bank profitability and capital. Additionally, high levels of NPLs may contribute to financial stability problems by weakening the banking sector's resilience to shocks and affecting banks' ability and willingness to provide credit to the economy. Ultimately, the lack of bank credit could impair economic recovery, particularly so in European countries, distinguished by bank-centred financial systems.

Following the COVID-19 pandemic, coupled with the global economic slowdown triggered by rising geopolitical tensions and monetary policy tightening, non-performing loans are poised to re-emerge as a significant challenge. In light of these pressing concerns, the development of forward-looking models designed to assess bank performance has become increasingly crucial.

Therefore, this paper proposes a credit risk framework that enables the study of non-linear dynamics between NPLs and macro-financial variables and to estimate the probability distribution of future NPL ratios. First, we use novel non-linear techniques to gain a deeper and more nuanced understanding of the drivers behind the build-up of NPLs in euro area banks. By using dynamic fixed effects quantile models, we provide evidence that our selected macroeconomic variables have heterogenous explanatory powers at different quantiles of the distribution of NPLs. As non-linearities (and NPLs) tend to arise in particular during periods of macroeconomic distress, our approach represents a valuable source of information for prudential and supervisory authorities.

Second, we leverage on the GaR framework to estimate the probability distribution of future NPL ratios conditional on current macro-financial conditions. This innovative approach allows us to observe how banks' realised values of NPLs move with respect to the entire probability distribution of future NPL ratios and to effectively compute the probability of "asset-quality-at-risk", that is identifying banks with NPL ratios (or a volumes of bad loans) above a predefined threshold of the conditional distribution. By looking at this information over time, we can also infer how and whether risks are building up, thus providing a forward-looking assessment of the riskiness of a bank or at system-wide level.

Overall, the proposed approach could enhance micro- and macroprudential supervisory authorities' toolkits. Compared to previous studies, our approach bypasses the limitations of linear models by shedding light on the dynamics at the tail of the distributions of NPLs, thus avoiding severe underestimation of the NPLs under stressed conditions. In addition, by utilising a macro approach (GaR), we can estimate the entire probability distribution conditional to the macro-financial environment in which banks operate. This flexible approach can easily be applied to other profit and loss or balance sheet variables typically forecasted in the context of stress testing exercises.

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Appendix

Table A1. Sample Composition

Country	N Banks	Country	N Banks
Austria	7	Italy	12
Belgium	5	Latvia	3
Bulgaria	1	Lithuania	3
Cyprus	2	Luxembourg	3
Croatia	4	Malta	3
Germany	16	Netherland	4
Finland	3	Portugal	4
France	8	Slovenia	3
Greece	4	Slovakia	2
Ireland	4	Spain	10
		TOTAL	101

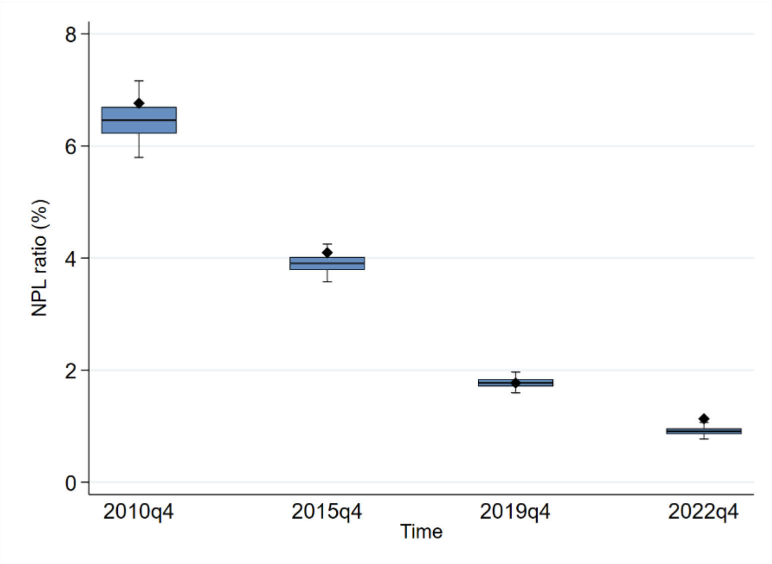
Note: The sample includes Bulgaria, which is not officially part of the euro area yet, but for which the SSM has started supervising one institution. The sample also exclude Estonia, for which we miss some key data.

Table A2. Summary Statistics

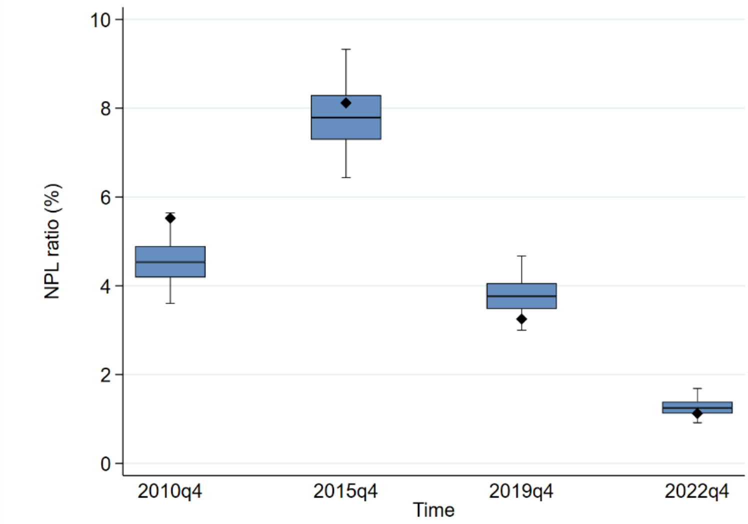
	Obs	p5	p10	p25	Mean	Median	p75	p90	p95
$Npl\ ratio$ (%)	5319	0.0077	0.0119	0.0227	0.0687	0.0400	0.0754	0.1540	0.2414
$Size$ (log)	5319	8.4786	8.8294	9.9197	11.1699	11.0950	12.3505	13.6218	14.0927
$Equity/assets$ (%)	5319	0.0255	0.0326	0.0474	0.0694	0.0629	0.0846	0.1178	0.1386
ROE (%)	5319	-0.1901	-0.0528	0.0280	0.0613	0.0675	0.1138	0.1687	0.2181
$Coverage\ ratio$ (%)	5319	0.2717	0.3517	0.4667	0.6486	0.5901	0.7471	0.9549	1.1270
$Gros\ loans\ growth$ (%)	5319	-0.1159	-0.0735	-0.0216	0.0460	0.0277	0.0800	0.1677	0.2636
$Real\ growth$ (%)	5319	-0.0630	-0.0350	0.0010	0.0145	0.0170	0.0330	0.0590	0.0830
$Unemployment$ (%)	5319	0.0357	0.0427	0.0573	0.0939	0.0807	0.1160	0.1673	0.2077
$Inflation$ (%)	5319	-0.0061	-0.0021	0.0051	0.0193	0.0151	0.0256	0.0406	0.0652
Hpi (%)	5319	-0.0766	-0.0494	-0.0036	0.0315	0.0374	0.0669	0.1031	0.1295
$10\ year\ gov.bond\ yield$ (%)	5319	-0.0024	0.0004	0.0055	0.0244	0.0175	0.0393	0.0507	0.0643

Figure 5. Comparison between fitted quantile distribution and realised NPLs

Panel A



Panel B



Note: the two panels report the comparison between estimated fitted quantiles and realized values of NPL ratios for two banks in our sample. The boxplot goes from the 25th to the 75th percentile of the NPL ratio of a specific bank, the whiskers represent the 95th and 5th, and the horizontal line the median value. The black diamond dot represents instead the realized value of the NPL ratio in each time by the institution.

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