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Bank competition, concentration and non-performing loans in the euro area: An intricate relationship

by

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Bank competition, concentration and non-performing loans in the euro area: An intricate relationship

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Abstract

In this study we investigate the impact of bank market power as evidenced by concentration (CR5 and HHI) and (lack of) competition (Lerner indices), on the change in NPL ratios in the euro area over the period 2005-2017 by employing a penalized quantile regression model for dynamic panel data. The results suggest that post-crisis consolidation facilitates the faster reduction of NPLs, while competition discourages the growth of new NPLs. The effect of concentration is stronger in periphery euro area countries, while the effect of competition is enhanced in countries with higher foreign bank presence. In addition, competition is more beneficial for commercial banks in reducing NPLs than for savings and mortgage banks.

Keywords: Non-performing loans, Competition, Concentration, Quantile regression, PIVQRFE estimator

JEL Classification: C23, C51, G21

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1. INTRODUCTION

Although several years have passed since the onset of the financial crisis of 2008, many euro area banks still have high levels of non-performing loans (NPLs) on their balance sheets[3]. According to the latest ECB data (2019), the non-performing loans to total gross loans ratio (NPL ratio) of the euro area reached 3.6% in June 2019, following a downward trend after 2012, when it reached an all-time high of 8.1%. But despite this positive evolution for the euro area in total, large dispersions remain across euro area countries (ratios between 1% and 39%). Such a large stock of NPLs puts serious constraints on the lending capacity of many banks and their ability to build further capital buffers, thus exerting a strong negative influence on economic growth through the reduction of credit supply (Vithessonthi, 2016).

Bank competition is one of the factors that have been extensively investigated in the past as one of the major determinants of bank risk in general. So far, two completely opposing views have emerged about the relationship between bank competition and the overall bank risk: the “competition-fragility” view which predicts a negative relationship between bank competition and financial stability, arguing that lower competition mitigates risk taking incentives, and the “competition-stability” view which indicates a positive relationship between bank competition and financial stability, arguing that higher competition tends to reduce bank risk. The debate is still ongoing supported by conflicting theoretical predictions and empirical results. As bank consolidation in the euro area has taken on large proportions post-2008 leading to higher concentration and possibly less competition, while at the same time the

[3] A widely used approach to determine whether a loan is non-performing is the ’90-day criterion’ which classifies a loan as NPL when payments of principal and interest are past due by 90 days or more.

increase in NPLs has become the major problem of European banks, the analysis of their relationship has received renewed attention recently.

The investigation of the possible impact of bank competition on NPLs has so far been based on linear regression methods, describing the impact of bank competition on the mean of the NPL distribution. This approach does not take into account the possibility that bank competition may have a different impact at various points of the NPL distribution, especially if this distribution is not normal. To fill this gap in the literature, we follow a Quantile Regression (QR) approach which allows assessment of the impact of bank competition, as expressed by (the inverse of) profit margins or Lerner indices, and of concentration (CR5 and HHI concentration indices) at any point of the NPL distribution. More specifically, we follow a penalized quantile regression for dynamic panel data with fixed effects approach, using both the Penalized Instrumental Variables Quantile Regression with Fixed Effects (PIVQRFE) estimator, developed by Galvao and Montes-Rojas (2010), and the Penalized Quantile Regression with Fixed Effects (PQRFE) estimator introduced by Koenker (2004).

To our knowledge, this is the first attempt to use QR in order to estimate the impact of competition and concentration on changes in NPL ratios in the euro area using a new data sample covering the 2005-2017 period. Three different Lerner indices have been used in order to test the robustness of our results. This is also the first attempt to examine the interaction of competition and concentration with (a) fragmentation between core and periphery countries, (b) foreign bank presence, and (c) type of bank (commercial banks vs savings and mortgage banks).

The rest of the paper is organized as follows: Section 2 reviews the theoretical and empirical literature of the impact of competition on loan portfolio and general bank risk. Section 3 describes the data and the econometric model, while Section 4 explains the econometric methodology. Section 5 specifies the measurement of market power. Section 6 presents the empirical results, while Section 7 concludes.

2. LITERATURE REVIEW

2.1 Theoretical Literature

There are two main opposing views in the theoretical literature on the relationship between competition and risk in banking: the competition-fragility view and the competition-stability view.

The competition-fragility view, also known as franchise value paradigm, has long been dominant in the literature. This view was developed in the midst of the US banking system deregulation during the decades of the 1980s and 1990s which witnessed a large amount of consolidation through both mergers and failures. During the preceding years, the US banking system had experienced stability which was challenged seriously by the new reforms. The competition-fragility view suggests that higher competition erodes banks' profits and reduces their franchise value. Hence, banks may take excessive risks to enhance their profitability. Allen and Gale (2000) develop a model of contagion through the interbank market in the case of a perfectly competitive banking sector. They show that a small aggregate shock in liquidity demand can lead to systemic risk, as banks act as price takers and have no incentive to provide liquidity to troubled banks with negative consequences for the entire banking sector. The analysis is complemented by Allen and Gale (2004) who show that under imperfect competition the banking sector is not so susceptible to contagion as in the case of perfect competition.

The competition-stability view predicts that more competition will lead to more stable banking systems. In their influential work, which challenged seriously the competition-fragility view, Boyd and De Nicoló (2005) disagree with the view that banks rationally choose riskier portfolios when confronted with increased competition. In contrast, they show that when competition decreases, banks charge higher loan rates leading borrowers to choose higher risk projects. Martinez-Miera and Repullo (2010) extend the model of Boyd and De Nicoló by introducing imperfect correlation among borrowing firms. They use a static model of Cournot competition in a market for entrepreneurial loans. They show that more competition in monopolistic markets leads to lower loan rates which subsequently lead to lower default probability. But as competition leads to lower loan rates and lower revenues from non-defaulting loans that provide a buffer against loan losses, bank risk increases suggesting a U-shaped relationship between competition and the risk of bank failure.

2.2 Empirical Literature

Despite the large number of empirical studies investigating the relationship between bank competition and risk, no clear answers are provided so far. The relationship has proven to be extremely complex as a set of different factors have been identified to affect the results.

First, regression results are greatly influenced by the selection of the competition measure. Davis and Karim (2013) study the dynamics of the relationship between bank competition and risk, measured by the Z-score, using a dataset on 6,008 banks from the EU-27 countries for the years 1998-2012. The usage of two different competition measures, the H-statistic of Panzar and Rosse and the Lerner index, led to contradicting results. Using the H-statistic, they find a negative effect of the level of competition on risk. When competition is measured by the Lerner index, it is found to have a positive effect on risk. The differences in the effects of the H-statistic and the Lerner index are attributed by the authors to the different impact of the above measures on the volatility of profits, a key input for the calculation of the Z-score risk indicator. Using a dataset provided by the Deutsche Bundesbank which comprises bank-level balance-sheet data and risk taking information for all German banks over the period 1994-2010, Kick and Prieto (2015) investigate the links between competition and bank risk taking behavior. Their study shows that market power proxied by the Lerner index reduces the default probability. In contrast, when the Boone Indicator or the regional branch share is used as a measure of competition, the results suggest that increased competition lowers the riskiness of banks.

In other cases, different results may be obtained despite the use of the same competition measure depending on its estimation procedure. A typical example is that of the Lerner index, which may be correlated with the Z-score measured bank stability. To address the potential endogeneity bias, some studies use the efficiency-adjusted Lerner index suggested by Koetter et al. (2012). In addition to the efficiency-adjusted Lerner index, Turk-Ariss (2010) employs a funding-adjusted Lerner index in order to account for market power which arises from the deposit market.

Differences in regression results may also be attributed to the employed measure or type of risk (individual-bank vs. systemic risk). Some empirical studies use banking system-wide measures of risk which are focused on the stability of the banking system as a whole. Beck et al. (2006) employ a dummy variable which equals one when a country is going through a systemic crisis. Using data on 69 countries worldwide and 47 crisis episodes in the period 1980-1997, they find that banking crises are less likely in countries with more concentrated banking systems. On the other hand, they find that fewer regulatory restrictions on banks, such as lower barriers to entry and fewer restrictions from engaging in non-loan making activities, reduce the banking system fragility. Moreover, the results of the study indicate that institutions which foster competition are associated with a lower likelihood of a systemic banking crisis. In the same vein, Schaeck et al. (2009) employ a dummy variable which equals one when a systemic crisis is observed in a particular year. Using a dataset with 31 systemic crises in 45 countries for the period 1980-2005, they find that competition reduces the likelihood of a crisis and increases time to crisis.

The empirical studies which are focused on individual bank risk typically employ the Z-score as the dependent variable in their regression models. A Z-score measures the number of standard deviations by which a bank's ROA has to fall for the bank to become insolvent. A higher value of Z-score indicates a lower probability of insolvency. Using the Z-score for data from EU-25 banks over the period 1997-2005, Uhde and Heimeshoff (2009) find that bank concentration has a negative impact on financial soundness. Some other types of bank risk have also been used in the empirical literature, such as the market-value capital to assets ratio, a dummy variable denoting revocation or not of a bank's license (Fungacova and Weill, 2013), the probability of bankruptcy (Fu et al., 2014), the distance to default (Anginer et al., 2014; Kabir and Worthington, 2017; Leroy and Lucotte, 2017), and outright bank defaults or milder forms of bank distress (Kick and Prieto, 2015). The NPL ratio is widely used in the empirical literature as a measure of credit risk or, less frequently, as an alternative measure of overall bank risk (Amidu and Wolfe, 2013; Berger et al., 2009; Brei et al., 2018; Jimenez et al., 2013; Kabir and Worthington, 2017; Kick and Prieto, 2015; Schaeck and Cihak, 2014; Vardar, 2015).

The differences in the obtained results due to the employed measure or type of risk, are more perceptible in studies which examine the impact of competition on both the individual banks' risk and systemic risk. Leroy and Lucotte (2017) examine the relationship between bank competition and risk, using a sample of the largest 97

European listed banks for the period 2004-2013. Their results indicate that competition increases individual bank risk, thus supporting the competition-fragility view. In contrast, competition reduces systemic risk, a result which is attributed to the fact that correlation in the risk-taking behavior of banks tends to increase under weak competition conditions. De-Ramon et al. (2018) examine the impact of competition on bank stability in the United Kingdom over the period 1994-2013. They find that competition decreases individual banks' risk, thus lending support to the competition-stability view. On the other hand, competition is found to lower the overall banking market stability, providing support to the competition-fragility view. Using quantile regression they find that the effect of competition on the overall stability depends on the financial health of each bank.

Mixed results have also emerged due to the use of concentration measures (CR3, CR5 and HHI) as inverted proxies of competition. Based on results indicating that both bank concentration and competition are positively related with banking stability, Beck et al. (2006) suggest that bank concentration is an insufficient measure of bank competition.

Moreover, differences in the obtained results may arise from the use of different regression models or methods. The fixed effect within-group estimator is the most used regression method for static panel data models (Davis and Karim, 2013; Turk-Ariss, 2010), while GMM is the method typically used for dynamic panel data models (Berger et al., 2009; Fu et al., 2014). A couple of other regression methods have also been used, such as the 2SLS/3SLS methods (Amidu and Wolfe, 2013; Uhde and Heimeshoff, 2009) and the logistic regression method (Beck et al., 2006; Fungacova and Weill, 2013). Furthermore, there are studies which employ quantile regression methods to examine the impact of competition at different quantiles of the distribution of risk. Using a sample of 3,325 banks from 10 European countries over the period 1995-2005, Schaeck and Cihak (2014) find that efficiency is the channel through which bank competition has an enhancing effect on stability. In addition, two-stage quantile regression estimates of the Boone indicator on Z-score suggest that the stability enhancement effect of competition is increased in accordance with the health level of a bank (higher Z-scores indicating stronger banks). Kabir and Worthington (2017) investigate the relationship between competition and risk, using data from 16 countries which have both conventional and Islamic banks for the period 2000–2012. The results from the use of the PVAR and the two-stage quantile regression methods are in support of the competition-fragility hypothesis in both banking systems. In addition, the quantile regression results suggest that the impact of the Lerner index of market power is larger at the median quantile of credit risk.

Some studies examine the case of one country only, such as Fungacova and Weill (2013) who find that an increase in bank competition in Russia over the period 2001-2007 has been associated with more bank failures, thus supporting the competition-fragility view. Tabak et al. (2015) using data from Brazilian banks for the period 2001-2011 find that market power is negatively related to risk-taking behavior, and more so for private and foreign banks. On the other hand, Vardar (2015) finds that competition has a negative impact on the financial fragility of 28 Turkish banks over the period 2002-2011, a result supporting the competition-stability view. In contrast, concentration is found to be negatively related to bank risk.

Mixed results are also received from cross-country empirical studies which provide more generic results by estimating the average effect of competition on stability for a group of countries, while controlling for country-specific effects. Except for other differences across groups in terms of geographical coverage and number of countries, some country groups may actually be less homogeneous than expected. Zigraiova and Havranek (2016) show that studies which use samples including both developed and developing countries tend to obtain lower estimates. Turk-Ariss (2010) investigates how different levels of market power affect cost and profit efficiency levels and overall bank stability in 60 developing countries worldwide over the period 1999-2005. Higher market power leads to greater bank stability and profit efficiency, while there is a significant negative impact of bank market power on cost efficiency. These results are different to those reported by Amidu and Wolfe (2013) who use a sample of 978 banks from 55 emerging and developing countries over the period 2000–2007. Their results reveal the significance of the revenue diversification as a channel through which competition increases stability in emerging countries. Using data on 14 Asia Pacific economies over the period 2003-2010, Fu et al. (2014) find a negative association between market power and individual bank risk, supporting the competition-fragility view. This result is opposite to that presented by Liu et al. (2012) who investigate the effects of competition on bank risk in four South East Asian countries over the period 1998-2008. They find that increased competition reduces bank risk-taking. Anginer et al. (2014) investigate the relationship between bank competition and systemic risk using a sample of 1,872 publicly traded banks in 63 countries over the period 1997-2009. Instead of focusing on the absolute level of risk of individual banks, they examine the correlation in the risk-taking behavior of banks. They find that greater competition encourages banks to take on more diversified risks, making the banking system less fragile to shocks. Another finding is that banking systems are more fragile in countries with public policies that restrict competition.

2.3 Reconciling ambivalent results

Even if some of the differences in employed measures, estimation methods, and time or geographical coverage could be lessened, it would still be too risky to give a clear vote in favor of the competition-fragility or the competition-stability hypothesis.

First, under certain conditions the two hypotheses may to some extent be reconciled. By examining a sample of 8,235 banks in 23 industrialized countries over the period 1999-2005, Berger et al. (2009) find that banks with a greater degree of market power have less overall risk exposure, measured by the Z-score. Their results also show that market power increases loan portfolio risk proxied by the NPL ratio which however may be offset in part by higher equity capital ratios.

Second, there may be a non-linear relationship between competition and risk, thus supporting both hypotheses in different parts of the distribution. Using data from 10 Latin American countries over the period 2003-2008, Tabak et al. (2012) find that competition affects the risk-taking behavior of banks in a non-linear way. While both high and low competition levels enhance financial stability, the opposite effect is observed for average competition levels. The relationship is affected by bank size and capitalization.

Using information on loan data for the period 1988-2003, Jimenez et al. (2013) find that the relationship between competition (measured by HHI and CR5) and risk taking is convex in the loan market, but concave in the deposit market. Brei et al. (2018) use data from 33 countries in Sub-Saharan Africa over the period 2000-2015 to investigate the influence of bank competition on credit risk which is estimated to be U-shaped. Increased competition can lower credit risk via efficiency gains, while excessive competition can cause adverse effects (lower profit margins and increased risk incentives).

In the present study, we have tried to eliminate some potential sources of bias in the estimation of the trade-off between competition and risk. First, we use a dataset which contains data from euro area countries only. The euro area has a common currency and a single bank supervisory mechanism. From this point of view, our data should be considered adequately homogeneous, thus reducing the bias that could result from the use of data coming from a heterogeneous group of countries. In addition, our data have been obtained from the unconsolidated financial statements of banks, thus eliminating any potential bias stemming from double counting of assets or liabilities. Second, we use three different specifications of the Lerner index, as well as two measures of concentration (HHI and CR5) so as to mitigate a possible bias stemming from the use of only one competition or concentration specification. And third, we employ quantile regression to investigate the possibility that bank competition may have a different impact at various points of the NPL distribution. Linear regression methods describe the impact of competition on the mean of the NPL distribution, so they may mask substantial heterogeneity across other parts of the distribution.

3. DATA AND ECONOMETRIC MODEL

3.1 Data description

We use macroeconomic, sectoral and bank-specific annual data for the period 2005-2017 from the 19 member countries of the euro area (namely, Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia, and Spain).

We employ two datasets. First, an unbalanced panel dataset containing 13,890 observations from 1,442 banks from all euro area countries. The full dataset was used to calculate the three different versions of the Lerner index. Second, a subset of the above dataset, containing only the observations which include a non-missing value of the NPL ratio. This second dataset, which is used as the basis of our econometric estimations, contains 3,747 observations from 646 banks from all euro area countries.

Bank-specific data have been collected from the Orbis BankFocus (BankScope) Database provided by Bureau van Dijk and obtained from the unconsolidated financial statements of commercial banks, savings banks and mortgage banks. Macroeconomic and sectoral data have been collected from Eurostat, the World Bank, and the ECB.

3.2 Econometric model

Our empirical analysis is based on the following dynamic panel data model with individual fixed effects:

$$y_{it} = \alpha y_{it-1} + x'_{1,it}\beta_1 + x'_{2,it-1}\beta_2 + \eta_i + \delta Crisis + u_{it} \quad (1)$$

where

y_{it} is the dependent variable (the first difference of the NPL ratio) for bank i and year t, $x_{1,it}$ is a vector of macroeconomic variables, $x_{2,it-1}$ is a vector of sectoral and bank-specific variables, η_i represent the unobserved individual (bank specific) effects, Crisis is a dummy variable used to assess the impact of the global financial crisis of 2008 on NPLs, and u_{it} is the error term.

3.3 Regression variables

The first difference of the NPL ratio (ΔNPL) is used as a proxy for the loan portfolio risk. The NPL ratio is defined as the ratio of impaired loans to total gross loans of a bank.

The real GDP annual growth rate (GDP) is used as a proxy for the fluctuations in economic activity. A negative effect of GDP growth on NPLs has been thoroughly documented in the literature (Beck et al., 2015; De Bock and Demyanets, 2012; Jimenez and Saurina, 2006; Louzis et al., 2012).

The inflation rate (Inflation) is measured by the annual rate of change of the Harmonized Index of Consumer Prices (HICP). According to Klein (2013), the impact of inflation on NPLs may be ambiguous, since higher inflation reduces both the real value of outstanding loans and the borrowers' real income.

The ratio of total net loans to total assets (LAR) is used as a proxy for the portfolio mix of a bank. It can also be useful as a measure of the specialization of a bank in providing loans. Brei et al. (2018) find that banks that are more involved in lending report relatively more NPLs.

The natural logarithm of the total assets of a bank is used as a measure of the size of the bank (SIZE). It should be noted that there is not a general agreement in the literature about the impact of bank size on NPLs. Reddy (2015) suggests a negative relationship between size and NPLs, while Garcia-Marco and Robles-Fernandez (2008) find that small banks in Spain appear to assume lower loan risks. However, when size interacts with ownership, the results reveal that Spanish commercial banks of medium size seem to be the riskiest entities, while there are no differences related to size in the case of Spanish savings banks.

The annual growth rate of total gross loans (Loans_growth) is used to measure the degree of the credit expansion of a bank. Jimenez and Saurina (2006) find a positive, although quite lagged, relationship between rapid credit growth and future NPLs.

The ratio of total net loans to total customer deposits (LDR**)** is used as a proxy for the liquidity risk of a bank. An increase in the loans to deposits ratio is expected to increase NPLs (Anastasiou et al., 2019).

The return on assets (ROA) is used as a proxy for the quality management of the bank. Based on prior evidence in the literature (Anastasiou et al., 2016; Charalambakis et al., 2017), we expect a negative sign for ROA.

Three different Lerner indices (variables Lerner_KBL, Lerner_adjusted and Lerner_FE, respectivelty) are used to measure the market power of a bank (in this study, market power is used as an inverse proxy for competition). They are described in more detail in Section 5.

The Herfindahl-Hirschman Index (HHI) and the CR5 concentration index are used to measure bank concentration.

A crisis dummy variable (Crisis) is used to assess the impact of the global financial crisis of 2008 on NPLs in the euro are taking the value 1 for the years 2008-2014 and 0 for the rest.

A dummy variable (Periphery), which takes the value 1 for periphery euro countries (namely, Cyprus, Greece, Ireland, Italy, Malta, Portugal, Slovenia and Spain) and 0 otherwise, is used to investigate the possible influence of fragmentation in the euro area on the impact of competition and concentration on ΔNPL (Anastasiou et al., 2019). This possibility is tested by interacting the competition and concentration indices with the Periphery dummy.

The share of foreign banks (in terms of total assets) in a banking system (Foreign) is used to investigate the possible influence of foreign banks on the impact of competition and concentration on the dependent variable ΔNPL. This issue is examined through the interaction of the competition and concentration indices with the Foreign variable. To facilitate the interpretation of the results, the terms participating in the interaction have been centered. In addition, the Foreign variable is expressed in first-difference form in order to achieve its stationarity, since a Fischer-type Augmented Dickey-Fuller (ADF) test showed the presence of unit root at levels. Due to data limitations the above interaction is tested only for the period 2008-2017.

The possibility that the impact of competition and concentration on the dependent variable ΔNPL is differentiated according to the type of bank pursuing a different business model, is examined by interacting the competition and concentration indices with the Commercial dummy variable, which takes the value 1 for commercial banks and 0 otherwise (i.e. for savings banks and mortgage banks).

3.4 Data cleaning

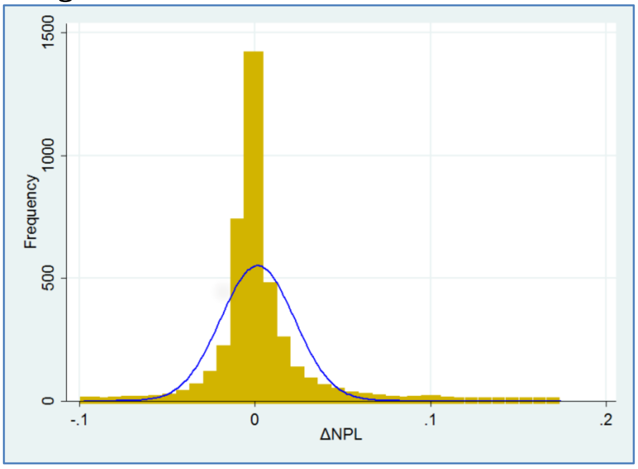
The data cleaning procedure of both datasets comprised the following steps. First, observations with missing values for one or more variables were excluded from the sample. Second, a set of basic plausibility checks were performed on the sample (e.g. total assets should exceed total loans). The incorrect observations were deleted from the sample. Third, each variable was checked for possible outliers using the Median Absolute Deviation method (MAD). This method is generally more effective than the traditional mean and standard deviation method, which may fail to detect outliers because outliers increase the standard deviation. Fourth, the MAD method was also used to check for large fluctuations within each bank. The detected outliers were removed from the sample. Fifth, the remaining data were checked to ensure that each bank had at least four consecutive observations, otherwise the bank was deleted from the sample.

4. ECONOMETRIC METHODOLOGY

4.1 The non-normality of the ΔNPL distribution

Both Figure 1 and Table 2 indicate that the distribution of the dependent variable ΔNPL is positively skewed (skewness=1.83) and leptokurtic (kurtosis=14.45).

Figure 1: ΔNPL distribution



Faced with the above distributional characteristics, a reliable solution for the estimation of our regression model would be the use of Quantile Regression (QR), which models quantiles of the dependent variable's distribution as functions of explanatory variables. As Buchinsky (1998) notes, quantile regression estimators are not only robust to outlier observations, but also more efficient than least-square estimators when the regression errors are not normal.

Furthermore, since any quantile of the dependent variable's distribution can be used, QR provides the great capability to assess the impact of explanatory variables at any point of the distribution of the regression's dependent variable. This important feature of QR offers the unique opportunity to investigate the possibility that bank competition may have a different impact at various points of the NPL distribution, thus extending the usual approach in the literature which is focused only on the mean.

For all the above reasons, we decided to employ QR as the approach that fits better to the distributional characteristics of our dataset and the goals of our study. Regarding the selection of the most appropriate quantile regression method, QR methods can be divided into two broad categories: unconditional and conditional.

(1) Unconditional quantile regression methods assess the impact of changing the distribution of explanatory variables on the marginal quantiles of the dependent variable.

(2) Conditional quantile regression methods assess the impact of an explanatory variable on a quantile of interest of the dependent variable, conditional on specific values of the other explanatory variables.

In the case of our model, which is a dynamic panel data model with fixed effects, the value of the dependent variable will be treated as conditional on its one year lagged value, following the conditional quantile regression approach (Koenker and Basset, 1978).

4.2 Penalized quantile regression for dynamic panel data model with fixed effects

For a specific quantile τ, of interest, the τ-th conditional quantile function of y_{it} is:

$$Q_{y_{it}}(\tau | y_{it-1}, x_{1,it}, x_{2,it-1}) = \alpha(\tau) y_{it-1} + x'_{1,it}\beta_1(\tau) + x'_{2,it-1}\beta_2(\tau) + \eta_i + \delta_t \quad (2)$$

Koenker (2004) points out that if the number of observations for each individual (bank) is too small (in our case there are 13 observations per individual bank, at most), then it would be quite unrealistic to estimate a τ-dependent distribution effect for η_i's. For this reason, in (2) only the effects of variables x_1 and x_2 are permitted to depend upon the quantile τ. In contrast, the η_i's have a pure location shift effect.

We estimate (2) following the method introduced by Koenker (2004) for estimating quantile regressions for panel data with fixed effects. By applying this method, we have to solve the following equation:

$$(\hat{\alpha}, \widehat{\beta_1}, \widehat{\beta_2}, \hat{\eta}, \hat{\delta}) = \min_{\alpha,\beta_1,\beta_2,\eta,\delta} \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{t=1}^{T} w_k \, \rho_{\tau_k}(y_{it} - \alpha(\tau_k) y_{it-1} - x'_{1,it}\beta_1(\tau_k)$$

$$- x'_{2,it-1}\beta_2(\tau_k) - \eta_i - \delta_t) \quad (3)$$

where $\rho_\tau(u)=u(1-I(u<0))$ denotes the piecewise linear quantile loss function of Koenker and Bassett (1978). The weights w_k control the relative influence of the K quantiles on the estimation of the η_i parameters. Koenker (2005) notes that the above approach pools sample information over several quantiles in order to improve the estimation of the individual specific estimates of the η_i's.

When the number of individuals is large relating to the number of observations per individual (which fits to our case), it may be advantageous in controlling the variability introduced by the large number of estimated η_i's. In this case, Koenker (2004, 2005) proposes the introduction of the $\ell 1$ penalty

$$P(\eta)=\sum_{i=1}^{N}|\eta_i|$$

Equation (3) now becomes:

$$(\widehat{\alpha},\widehat{\beta_1},\widehat{\beta_2},\widehat{\eta},\widehat{\delta})=\min_{\alpha,\beta_1,\beta_2,\eta,\delta}\sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{t=1}^{T}w_k\,\rho_{\tau_k}(y_{it}-\alpha(\tau_k)y_{it-1}-x'_{1,it}\beta_1(\tau_k)$$

$$-x'_{2,it-1}\beta_2(\tau_k)-\eta_i-\delta_t)+\lambda\sum_{i=1}^{N}|\eta_i| \quad (4)$$

For $\lambda \to 0$ we obtain the fixed effects estimator described in (3), while as $\lambda\to\infty$ then $\widehat{\eta_i} \to 0$ for all i = 1, 2, ..., N and we obtain an estimate of the regression model purged of the fixed effects.

If our model were not dynamic, we would estimate regression coefficients using the Koenker's (2004) Penalized Quantile Regression with Fixed Effects (PQRFE) estimator. However, by applying a Monte Carlo simulation approach, Galvao (2011) showed that Koenker's estimator is downward biased in the presence of lagged dependent variables as regressors when T is moderate. This problem can be ameliorated through the use of instrumental variables (IV), as proposed by Chernozhukov and Hansen (2006, 2008) who introduced the Instrumental Variables Quantile Regression (IVQR) estimator. Galvao and Montes-Rojas (2010) introduced the Penalized Instrumental Variables Quantile Regression with Fixed Effects (PIVQRFE) estimator as a penalized panel data version of the IVQR method, using lagged values (or lagged differences) of the regressors as instruments.

The PIVQRFE estimator is defined as

$$\widehat{\alpha}\,(\lambda) = \min_{\alpha} || \,\hat{\gamma}\,(\alpha, \lambda)||_A \qquad (5)$$

where

$$(\widehat{\beta_1}\,(\alpha,\lambda), \widehat{\beta_2}\,(\alpha,\lambda), \hat{\eta}\,(\alpha,\lambda), \widehat{\delta}\,(\alpha,\lambda), \hat{\gamma}\,(\alpha,\lambda)) =$$

$$\min_{\beta_1,\beta_2,\eta,\delta,\gamma} \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{t=1}^{T} w_k\, \rho_{\tau_k}(y_{it} - \alpha(\tau_k) y_{it-1} -$$

$$x'_{1,it}\beta_1(\tau_k) - x'_{2,it-1}\beta_2(\tau_k) - \eta_i - \delta_t - w'_{it}\gamma(\tau_k)) + \lambda \sum_{i=1}^{N} |\,\eta_i| \qquad (6)$$

and

$||x||_A = \sqrt{x'Ax}$, where A is a positive definite matrix.

The intuition underlying this estimator is that the coefficient γ of w should be zero, since w is a valid instrument and independent of u. Based on this, the estimator finds a value for α through the inverse step (5) such that the coefficient of γ in (6) is as close to zero as possible. According to Galvao (2011), values of y lagged (or differences) two periods or more and/or lags of the exogenous variables can be potentially used as instruments.

To implement the PIVQRFE procedure, for a specific quantile of interest τ and a specific value for λ, we follow the steps below:

(1) We define a grid of values {aj, j = -0.99, -0.98, …, 0.98, 0.99}.

(2) For each a_j, we run the ordinary τ-quantile panel regression of $(y_{it} - a_j y_{it-1})$ on $(x_{1,it}, x_{2,it-1}, w_{it}, \eta_i, \delta_t)$ to obtain coefficients $\widehat{\beta_1}(a_j,\tau)$, $\widehat{\beta_2}(a_j,\tau), \hat{\gamma}(a_j,\tau)$, $\hat{\eta}(a_j,\tau)$, and $\hat{\delta}(a_j,\tau)$. In our case, we are using as an instrument (w_{it}) the second lag of the dependent variable y. Regressions are performed using the program rqpd, developed in R software.

(3) We choose $\hat{\alpha}(\tau)$ as that value of the grid that makes $||\hat{\gamma}(a_j,\tau)||$ closest to zero.

In our case, $\hat{\alpha}(\tau)$ is the value of the coefficient of the autoregressive term (ΔNPL lagged one year). Standard errors are calculated following the bootstrap approach, introduced by Efron (1979), based on 200 resamples of our actual observed dataset.

(4) The estimates $\widehat{\beta_1}(\tau)$ and $\widehat{\beta_2}(\tau)$ are given by $\widehat{\beta_1}(\hat{\alpha}(\tau),\tau)$ and $\widehat{\beta_2}(\hat{\alpha}(\tau),\tau)$ respectively.

The value of the parameter λ was set to 1, which is a value that was found to set about the one third of the FE terms to zero.

Except for the implementation of the PIVQRFE method, we have also estimated (4) using the PQRFE method with equally weighted quantiles, in order not only to facilitate the comparison of its results with those produced by the PIVQRFE estimator, but also to provide a lower bound for the value of the autoregressive term (similar to the Within-Group Fixed Effect estimator, which gives a lower bound for the GMM estimation of the autoregressive term).

In addition, we have performed Wald tests for the equality of coefficients across different quantiles in order to find out whether the differences between coefficients corresponding to the same independent variable but across different quantiles, are statistically significant. The hypothesis test is the following:

$$H_0: \beta_j^{(p)} = \beta_j^{(q)} \text{ versus } H_1: \beta_j^{(p)} \neq \beta_j^{(q)} \quad (7)$$

where $\beta_j^{(p)}$ and $\beta_j^{(q)}$ are the coefficients corresponding to the j-th independent variable at quantiles p and q respectively.

The test is based on the following Wald statistic:

$$\text{Wald statistic} = \frac{(\hat{\beta}_j^{(p)} - \hat{\beta}_j^{(q)})^2}{\hat{\sigma}^2_{\hat{\beta}_j^{(p)} - \hat{\beta}_j^{(q)}}} \qquad (8)$$

The term $\hat{\sigma}^2_{\hat{\beta}_j^{(p)} - \hat{\beta}_j^{(q)}}$, which is the variance of the difference $\hat{\beta}_j^{(p)} - \hat{\beta}_j^{(q)}$, can be obtained from the following equation:

$$\mathrm{Var}(\hat{\beta}_j^{(p)} - \hat{\beta}_j^{(q)}) = \mathrm{Var}(\hat{\beta}_j^{(p)}) + \mathrm{Var}(\hat{\beta}_j^{(q)}) - 2\mathrm{Cov}(\hat{\beta}_j^{(p)}, \hat{\beta}_j^{(q)}) \quad (9)$$

Under the null hypothesis, the Wald statistic has an approximate χ^2 distribution with one degree of freedom.

5. MEASURING MARKET POWER

5.1 The Lerner index and market power

In this study, market power is used as an inverse proxy for competition. The most widely used measure of market power is the Lerner index of monopoly power, which identifies the degree of monopoly power as the difference between the price (P) of a firm and its marginal cost (MC) at the profit-maximizing rate of output:

$$L = \frac{P - MC}{P} \qquad (10)$$

A zero value of the Lerner index indicates competitive behavior, while a bigger distance between price and marginal cost is generally considered to be associated with higher market power.

We consider the following translog cost function:

$$lnTC_{it}=\alpha_0+\alpha_Q lnQ_{it}+0.5\alpha_{QQ}(lnQ_{it})^2+\sum_{k=1}^{3}\alpha_k lnW_{k,it}+\sum_{k=1}^{3}\alpha_{Qk}lnQ_{it}lnW_{k,it}+$$

$$+0.5\sum_{j=1}^{3}\sum_{k=1}^{3}\alpha_{jk}lnW_{j,it}lnW_{k,it}+\alpha_E lnE_{it}+0.5\alpha_{EE}(lnE_{it})^2+\sum_{k=1}^{3}\alpha_{Ek}lnE_{it}lnW_{k,it}+$$

$$+\alpha_{EQ}lnE_{it}lnQ_{it}+\alpha_T T+0.5\alpha_{TT}T^2+\alpha_{TQ}T\,lnQ_{it}+\sum_{k=1}^{3}\alpha_{Tk}T\,lnW_{k,it} \quad (11)$$

where TC is total cost (sum of total interest and non-interest expenses), Q is total assets (proxy for bank output), W1 is the ratio of other operating expenses to total assets (proxy for input price of capital), W2 is the ratio of personnel expenses to total assets (proxy for input price of labor), W3 is the ratio of total interest expenses to total funding (proxy for input price of funds), T is a time trend and E is total equity. The subscripts i and t denote bank i and year t, respectively.

The time trend (T) has been included in (11) to account for advances in banking technology. The level of Total Equity (E) has also been included in (11), since it can be used in loan funding as a substitute for deposits or other borrowed funds.

Symmetry conditions and linear homogeneity in input prices can be imposed by dividing in (11) both total cost and input prices by one of the input prices.

$$ln(TC_{it}/W_{3,it})=\alpha_0+\alpha_Q lnQ_{it}+0.5\alpha_{QQ}(lnQ_{it})^2+\sum_{k=1}^{2}\alpha_k ln(W_{k,it}/W_{3,it})+$$

$$+\sum_{k=1}^{2}\alpha_{Qk}lnQ_{it}ln(W_{k,it}/W_{3,it})+0.5\sum_{j=1}^{2}\sum_{k=1}^{2}\alpha_{jk}ln(W_{j,it}/W_{3,it})\,ln(W_{k,it}/W_{3,it})+$$

$$+\alpha_E lnE_{it}+0.5\alpha_{EE}(lnE_{it})^2+\sum_{k=1}^{2}\alpha_{Ek}lnE_{it}ln(W_{k,it}/W_{3,it})+\alpha_{EQ}lnE_{it}lnQ_{it}+$$

$$+\alpha_T T+0.5\alpha_{TT}T^2+\alpha_{TQ}T\,lnQ_{it}+\sum_{k=1}^{2}\alpha_{Tk}T\,ln(W_{k,it}/W_{3,it}) \quad (12)$$

5.2 Calculation of Lerner index

We calculate the Lerner index from Equation (12) following three different approaches:

a. Using the Kumbhakar et al. (2012) method drawing on a stochastic frontier methodology from the efficiency literature to estimate the mark-up for each observation. Unlike the traditional calculation of mark-ups, this method is not based on the assumption of either a profit maximization behavior from firms or the presence of only constant returns to scale.

b. Using the Koetter et al. (2012) method to produce an “efficiency-adjusted” Lerner index which, unlike the conventional Lerner index, takes into account inefficiencies that may arise when firms do not fully exploit their pricing opportunities due to market power.

c. Using the traditional and widely used fixed effect within-group estimator.

6. EMPIRICAL RESULTS

The results of our econometric estimations describe the impact of the explanatory variables, presented in Section 3.3, on the dependent variable ΔNPL (annual change in NPL ratios). As shown in Table 2, the quantiles up to the median of the ΔNPL distribution correspond to decreases in NPL ratios, while the quantiles above the median correspond to increases in NPL ratios. The results showed robustness when alternative variables and methods were used.

The Wald tests, described in the last part of Section 4.2, are performed in order to find out whether the differences between coefficients corresponding to the same independent variable but across different quantiles are statistically significant. To preserve space, the results of the Wald tests are not presented in the tables, but can be provided upon request.

Tables 4-11 present the results obtained with the PIVQRFE method. To preserve space, the tables with the results from the application of the PQRFE method are not presented here but can be provided upon request. It is worth however noting that in general the two methods produced similar results, as well as that the coefficient of the autoregressive term with the PQRFE method, which provides a lower bound for the corresponding coefficient of the autoregressive term with the PIVQRFE method, is presented in the "Diagnostics" part of Tables 4-11.

As shown in Tables 4-6, the three different specifications of the Lerner index exert a statistically significant and positive impact on ΔNPL at quantiles 0.40-0.90, across all models. Since the Lerner index is used as an inverse proxy for competition, the results show that competition has a negative impact on ΔNPL at its middle and upper quantiles, thus supporting the "competition-stability" hypothesis. The Wald tests show that only the coefficients of the Lerner index at quantiles 0.70-0.90 are statistically different.

As shown in Tables 7-8, the Herfindahl-Hirschman Index (HHI) and the CR5 concentration index have a statistically significant and negative impact on ΔNPL at quantiles 0.10-0.30, as well as a statistically significant and positive impact at quantiles 0.60-0.90. The negative impact at quantiles 0.10-0.30 is possibly due to the ability of concentration to help banks create more homogeneous loan portfolios, which in turn can facilitate the resolution of problem loans. The positive impact at quantiles 0.60-0.90 suggests that greater concentration worsens the NPL problem, perhaps due to a delay in the pooling of loan portfolios, a process which may require additional time for proper analysis and monitoring. The coefficients of HHI as those for CR5 are statistically different from each other at all quantiles.

The real GDP growth rate (GDP) has a statistically significant, negative (as expected) and homogeneous impact on NPLs across all models and quantiles, while the inflation rate (Inflation) has a positive impact on NPLs but not statistically significant across all quantiles.

The impact of total net loans to total assets ratio (LAR) is statistically significant and positive at all quantiles up to the median across all models. This suggests that the bigger the loan portfolio, the greater is the difficulty to reduce NPLs. The coefficients of LAR in the above quantiles are statistically different from each other.

The size of a bank (SIZE), proxied by the natural logarithm of the total assets of the bank, has a statistically significant influence on NPLs, which is positive at the lower quantiles (0.10-0.30) and negative at the upper quantiles (0.70-0.90). The coefficients of SIZE are statistically different from each other. The positive impact of SIZE at the lower quantiles of the ΔNPL distribution (high decreases in NPL volumes) suggests that larger banks are possibly not so fast in making arrangements that decrease NPLs (write-offs, sales, restructurings of loan agreements, etc.). The negative impact of SIZE at the upper quantiles of the ΔNPL distribution can be attributed to a possibly better loan diversification and managerial ability at larger banks.

The growth rate of gross loans (Loans_growth) is not found to play a significant role.

The net loans to customer deposits ratio (LDR) has a statistically significant, positive (as expected) and homogeneous impact on ΔNPL at quantiles 0.25-0.80. An increase of LDR implies that the bank may be taking on higher liquidity risk by increasing loans faster than it could fund them through customer deposits.

The Return on Assets (ROA) has a statistically significant, negative (as expected) and homogeneous impact on ΔNPL, however not across all models and quantiles. In general it provides support to the “bad management” hypothesis, according to which reduced cost efficiency fosters an increase in NPLs.

The crisis dummy variable (Crisis) was found to exert a statistically significant and positive impact on ΔNPL, suggesting that the global financial crisis of 2008 shifted NPLs upwards over the years 2008-2014, its effect being homogeneous.

The interaction between the Periphery dummy variable and the bank competition and concentration indices was found to be statistically significant only in the case of concentration (Table 9 presents, indicatively, the regression results for the HHI). The sign of the interaction is negative, suggesting that concentration is more favorable to periphery euro area countries, facilitating them to obtain lower increases or bigger decreases in NPL ratios than countries belonging to the core of the euro area. The Periphery variable *per se* is statistically significant and positive, indicating that the periphery euro area countries have a flat disadvantage against the core countries with respect to problem loans.

The interaction between the Foreign variable and the bank competition /concentration indices was found to be statistically significant only in the case of competition, although in a non-systematic way across all quantiles and Lerner indices (Table 10 presents, indicatively, the regression results for the Lerner_KBL index). The negative sign of the interaction implies that the effect of competition is enhanced when the share of foreign banks in a banking sector is higher. The negative sign of the Foreign variable *per se* indicates that higher foreign presence is associated with lower NPL ratios.

The interaction between the Commercial dummy variable and the bank competition and concentration indices was found to be statistically significant only in the case of competition, although in a non-systematic way across all quantiles and Lerner indices

(Table 11 presents, indicatively, the regression results for the Lerner_KBL index). The negative sign of the interaction implies that competition is more beneficial for the commercial banks in reducing NPLs. On the other hand, the positive sign of the Commercial dummy variable *per se* suggests that commercial banks are more prone to creating NPLs than the more conservative savings banks and mortgage banks.

7. CONCLUSIONS

The relationship between market power and stability/fragility in the banking sector has been researched extensively in the literature with ambivalent results. As consolidation in the banking sector has increased impressively in the wake of the global financial crisis, the question of the impact of competition and concentration on bank risk, and more specifically on non-performing loans (NPLs), remains pertinent.

In this study we investigated empirically the impact of both bank competition as expressed by a variety of Lerner indices and bank concentration as expressed by the structural CR5 and HHI indices on ΔNPL. We used an unbalanced panel dataset of 646 banks from the 19 member countries of the euro area over the period 2005-2017. By adopting a penalized quantile regression for dynamic panel data approach, we found that profit margins exert a positive impact on ΔNPL at the middle and upper quantiles of its distribution, supporting the "competition-stability" view. On the contrary, the impact of profit margins on ΔNPL at the lower quantiles of its distribution is not statistically significant. The regression results for concentration suggest another complex relationship. Concentration is found to exert a positive impact on ΔNPL at the upper quantiles of its distribution, supporting the "competition-stability" view, and a negative impact at the lower quantiles, supporting the "competition-fragility view". The conflicting results of the impacts of competition and concentration on ΔNPL, which are in line with the argument that more concentration does not always imply less competition, suggest that competition seems to support stability when it comes to increases in NPLs but that concentration enhances the faster reduction of NPLs. From this point of view, our study can be classified into the strand of the empirical literature that suggests a complex relationship between competition and risk. In some of the works reviewed in Section 2, the complex relationship between competition and risk is related to the different impact of different levels of competition (low/average/high) on the mean of the distribution of NPLs. In our study, the complex relationship is related to the different impact of competition at different quantiles of the ΔNPL distribution.

In addition, the results obtained from the interaction of competition and concentration indices with other regression variables lead to the following findings. First, bank concentration is more favorable to periphery euro area countries, contributing to lower increases or bigger decreases in NPL ratios than countries belonging to the core of the euro area. On the other hand, the periphery euro area countries have a flat disadvantage against the core countries with respect to NPLs. Second, bank competition is enhanced by the presence of foreign banks in reducing NPLs. A higher share of foreign banks in a banking sector is also associated with lower NPL ratios. Third, bank competition is more beneficial for commercial banks in reducing NPLs than for the savings banks and the mortgage banks. On the other hand, commercial banks are more prone to creating NPLs than other more conservative types of banks. Our results showed remarkable robustness to alternative variables and methods.

A tentative conclusion of our study could be that post-crisis consolidation facilitates the faster reduction of NPLs, while as the situation normalizes competition discourages the growth of new NPLs. Policy makers should take such findings into account by encouraging consolidation as concentration has been found to exert a stronger effect, but also by inserting competition in the banking sector through either regulating anti-competitive behavior or possibly inviting entry by new and/or foreign banks.

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Tables

Table 1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ΔNPL	3,747	0.0015	0.0210	-0.0976	0.1738
GDP	3,747	0.0101	0.0217	-0.1481	0.2556
Inflation	3,747	0.0117	0.0122	-0.0170	0.1530
LAR	3,747	0.5980	0.1771	0.0147	0.9687
SIZE	3,747	14.4342	1.8714	10.0397	21.0080
Loans_Growth	3,747	0.0514	0.1600	-0.8402	3.7657
LDR	3,747	1.0704	0.9316	0.0351	13.9043
ROA	3,747	0.0032	0.0079	-0.1679	0.0763
Lerner_KBL	3,747	0.1637	0.0872	0.0000	0.6731
Lerner_adjusted	3,747	0.3060	0.1127	-0.3962	0.6533
Lerner_FE	3,747	0.2001	0.1162	-0.1767	0.6414
HHI	3,747	0.0570	0.0399	0.0206	0.2613
CR5	3,747	0.4400	0.1550	0.2501	0.9728
Foreign	3,014	0.0040	0.0190	-0.1684	0.1210

Table 2: ΔNPL additional statistics and quantiles

Additional statistics	Quantiles		
Variance 0.000442	1%	-0.0507	Biggest decrease
Skewness 1.831018	5%	-0.0243	
Kurtosis 14.44932	10%	-0.0153	
	20%	-0.0079	NPLs decrease
	25%	-0.0063	
	30%	-0.0050	
	40%	-0.0029	
	50%	-0.0010	Smallest decrease
	60%	0.0006	Smallest increase
	70%	0.0033	
	75%	0.0057	NPLs increase
	80%	0.0089	
	90%	0.0210	
	95%	0.0364	
	99%	0.0853	Biggest increase

Table 3: Evolution of ΔNPL per year

Year	Average ΔNPL
2006	-0.0054
2007	-0.0026
2008	0.0063
2009	0.0164
2010	0.0068
2011	0.0086
2012	0.0069
2013	0.0026
2014	0.0011
2015	-0.0012
2016	-0.0039
2017	-0.0059

Table 4	Regression results with the PIVQRFE method (Competition index: Lerner_KBL)									Dependent Variable: ΔNPL
	Quantile										
Variable	0.10	0.20	0.25	0.30	0.40	0.50	0.60	0.70	0.75	0.80	0.90
Intercept	-0.0455*** (0.0032)	-0.0260*** (0.0025)	-0.0205*** (0.0025)	-0.0169*** (0.0019)	-0.0098*** (0.0017)	-0.0064*** (0.0015)	-0.0002 (0.0019)	0.0074*** (0.0021)	0.0101*** (0.0023)	0.0148*** (0.0026)	0.0320*** (0.0033)
ΔNPL (-1)	-0.0600** (0.0473)	0.0200* (0.0397)	0.0200 (0.0395)	0.0200** (0.0407)	0.0500** (0.0424)	0.1100** (0.0420)	0.1900** (0.0514)	0.2300*** (0.0538)	0.2600*** (0.0588)	0.2800*** (0.0626)	0.2900** (0.0595)
GDP	-0.1975*** (0.0224)	-0.1474*** (0.0231)	-0.1572*** (0.0252)	-0.1622*** (0.0230)	-0.1583*** (0.0182)	-0.1569*** (0.0171)	-0.1714*** (0.0235)	-0.1985*** (0.0332)	-0.2385*** (0.0434)	-0.2492*** (0.0418)	-0.3026*** (0.0590)
Inflation	0.1139*** (0.0384)	0.0429 (0.0314)	0.0520* (0.0287)	0.0536* (0.0299)	0.0578** (0.0254)	0.0508* (0.0269)	0.0507 (0.0315)	0.0453 (0.0316)	0.0530 (0.0334)	0.0559 (0.0414)	0.1241** (0.0542)
LAR (-1)	0.0190*** (0.0018)	0.0118*** (0.0015)	0.0098*** (0.0014)	0.0086*** (0.0013)	0.0064*** (0.0011)	0.0048*** (0.0011)	0.0017 (0.0013)	-0.0011 (0.0014)	-0.0011 (0.0014)	-0.0027 (0.0017)	-0.0052** (0.0026)
SIZE (-1)	0.0018*** (0.0002)	0.0009*** (0.0001)	0.0007*** (0.0001)	0.0006*** (0.0001)	0.0002* (0.0001)	0.0001 (0.0001)	0.0000 (0.0001)	-0.0003*** (0.0001)	-0.0005*** (0.0001)	-0.0007*** (0.0001)	-0.0016*** (0.0002)
Loans_growth (-1)	0.0014 (0.0016)	0.0025 (0.0016)	0.0025 (0.0016)	0.0018 (0.0013)	0.0008 (0.0014)	0.0007 (0.0014)	0.0003 (0.0018)	-0.0003 (0.0020)	0.0000 (0.0025)	-0.0004 (0.0025)	-0.0038 (0.0032)
LDR (-1)	0.0000 (0.0006)	0.0007** (0.0003)	0.0007** (0.0003)	0.0008*** (0.0003)	0.0010*** (0.0003)	0.0011*** (0.0002)	0.0011*** (0.0003)	0.0009*** (0.0003)	0.0008** (0.0004)	0.0008* (0.0004)	0.0008 (0.0008)
ROA (-1)	0.0647 (0.1058)	-0.0893 (0.0830)	-0.1692* (0.0864)	-0.2053*** (0.0715)	-0.2108** (0.0910)	-0.1740** (0.0761)	-0.1565** (0.0656)	-0.1118 (0.0924)	-0.0838 (0.1044)	-0.1417 (0.1302)	-0.3212** (0.1526)
Lerner_KBL (-1)	-0.0076 (0.0048)	-0.0021 (0.0046)	0.0024 (0.0042)	0.0031 (0.0032)	0.0067** (0.0034)	0.0066** (0.0030)	0.0061* (0.0032)	0.0107*** (0.0040)	0.0147*** (0.0044)	0.0182*** (0.0055)	0.0385*** (0.0069)
Crisis	0.0004 (0.0008)	0.0015** (0.0007)	0.0015** (0.0007)	0.0016*** (0.0006)	0.0013*** (0.0005)	0.0012*** (0.0005)	0.0008 (0.0005)	0.0012* (0.0007)	0.0015** (0.0008)	0.0024*** (0.0008)	0.0043*** (0.0013)
Diagnostics											
Nb. of observations	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055
ΔNPL (-1) coeff. with the PQRFE method	-0.0945	-0.0529	-0.0165	-0.0028	0.0481	0.0936	0.1383	0.1680	0.1798	0.1906)	0.2102
Goodness of Fit	0.4559	0.3512	0.3251	0.3192	0.3246	0.3270	0.3444	0.3685	0.3894	0.4253	0.5366

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Standard errors are reported in parentheses. (-1) denotes previous year's values. Goodness of Fit for a particular quantile is calculated as in Koenker and Machado (1999).

Table 5	**Regression results with the PIVQRFE method (Competition index: Lerner_adjusted)**								Dependent Variable: ΔNPL		
	Quantile										
Variable	0.10	0.20	0.25	0.30	0.40	0.50	0.60	0.70	0.75	0.80	0.90
Intercept	-0.0450***	-0.0250***	-0.0179***	-0.0156***	-0.0080***	-0.0037**	-0.0001	0.0101***	0.0138***	0.0187***	0.0384***
	(0.0028)	(0.0025)	(0.0023)	(0.0019)	(0.0016)	(0.0017)	(0.0017)	(0.0021)	(0.0021)	(0.0023)	(0.0033)
ΔNPL (-1)	-0.0800**	0.0200**	0.0200**	0.0300	0.0600**	0.1200**	0.1500**	0.2300**	0.2800***	0.3000***	0.3300**
	(0.0494)	(0.0414)	(0.0384)	(0.0387)	(0.0429)	(0.0426)	(0.0504)	(0.0506)	(0.0560)	(0.0586)	(0.0579)
GDP	-0.1895***	-0.1503***	-0.1620***	-0.1706***	-0.1609***	-0.1619***	-0.1783***	-0.1941***	-0.2263***	-0.2496***	-0.3041***
	(0.0236)	(0.0261)	(0.0266)	(0.0243)	(0.0196)	(0.0155)	(0.0225)	(0.0344)	(0.0394)	(0.0389)	(0.0512)
Inflation	0.1041***	0.0413	0.0518*	0.0528**	0.0583*	0.0604**	0.0488*	0.0454	0.0545	0.0617*	0.0609
	(0.0367)	(0.0311)	(0.0300)	(0.0252)	(0.0316)	(0.0281)	(0.0264)	(0.0315)	(0.0340)	(0.0353)	(0.0508)
LAR (-1)	0.0191***	0.0113***	0.0082***	0.0072***	0.0041***	0.0033***	0.0015	-0.0030*	-0.0032**	-0.0042***	-0.0106***
	(0.0017)	(0.0016)	(0.0015)	(0.0012)	(0.0014)	(0.0012)	(0.0011)	(0.0016)	(0.0016)	(0.0016)	(0.0026)
SIZE (-1)	0.0016***	0.0008***	0.0005***	0.0004***	0.0001	-0.0001	-0.0002	-0.0005***	-0.0007***	-0.0009***	-0.0019***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Loans_growth (-1)	0.0018	0.0027*	0.0019	0.0019	0.0008	0.0007	0.0002	-0.0001	0.0001	0.0023	-0.0031
	(0.0016)	(0.0014)	(0.0015)	(0.0014)	(0.0014)	(0.0017)	(0.0019)	(0.0023)	(0.0028)	(0.0031)	(0.0034)
LDR (-1)	-0.0001	0.0005*	0.0008***	0.0011***	0.0012***	0.0012***	0.0012***	0.0011***	0.0010**	0.0011**	0.0019
	(0.0005)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0005)	(0.0005)	(0.0012)
ROA (-1)	-0.0005	-0.1227	-0.1852**	-0.1937***	-0.1928***	-0.1396**	-0.1315*	-0.0689	-0.0254	-0.0283	-0.0531
	(0.0944)	(0.0806)	(0.0757)	(0.0718)	(0.0720)	(0.0686)	(0.0677)	(0.0709)	(0.0872)	(0.0966)	(0.1446)
Lerner_adjusted (-1)	0.0045	0.0040	0.0051*	0.0064***	0.0069***	0.0068***	0.0083***	0.0079***	0.0074***	0.0087***	0.0194***
	(0.0028)	(0.0026)	(0.0029)	(0.0023)	(0.0026)	(0.0022)	(0.0023)	(0.0026)	(0.0024)	(0.0027)	(0.0035)
Crisis	0.0008	0.0016**	0.0019**	0.0019***	0.0017***	0.0013**	0.0013**	0.0016**	0.0022***	0.0000	0.0050***
	(0.0008)	(0.0008)	(0.0008)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0000)	(0.0011)
Diagnostics											
Nb. of observations	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055
ΔNPL (-1) coeff. with the PQRFE method	-0.1001	-0.0528	-0.0166	0.0030	0.0544	0.1020	0.1429	0.1759	0.1954	0.2108	0.2351
Goodness of Fit	0.4578	0.3516	0.3262	0.3179	0.3236	0.3257	0.3516	0.3681	0.3836	0.4198	0.5322

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Standard errors are reported in parentheses. (-1) denotes previous year's values. Goodness of Fit for a particular quantile is calculated as in Koenker and Machado (1999).

Table 6	Regression results with the PIVQRFE method (Competition index: Lerner_FE)								Dependent Variable: ΔNPL	
	Quantile										
Variable	0.10	0.20	0.25	0.30	0.40	0.50	0.60	0.70	0.75	0.80	0.90
Intercept	-0.0451*** (0.0031)	-0.0269*** (0.0022)	-0.0209*** (0.0023)	-0.0170*** (0.0018)	-0.0100*** (0.0018)	-0.0060*** (0.0015)	-0.0019 (0.0020)	0.0077*** (0.0020)	0.0098*** (0.0021)	0.0142*** (0.0028)	0.0324*** (0.0035)
ΔNPL (-1)	-0.0600** (0.0474)	-0.0200** (0.0408)	0.0100** (0.0401)	0.0100** (0.0404)	0.0800** (0.0425)	0.1000** (0.0421)	0.1700*** (0.0511)	0.2600*** (0.0548)	0.2700*** (0.0587)	0.3000*** (0.0617)	0.3200** (0.0626)
GDP	-0.1926*** (0.0236)	-0.1537*** (0.0244)	-0.1589*** (0.0243)	-0.1634*** (0.0249)	-0.1600*** (0.0198)	-0.1618*** (0.0171)	-0.1785*** (0.0265)	-0.1979*** (0.0372)	-0.2384*** (0.0388)	-0.2678*** (0.0406)	-0.2809*** (0.0470)
Inflation	0.1008*** (0.0362)	0.0439 (0.0316)	0.0487* (0.0295)	0.0520** (0.0253)	0.0607** (0.0308)	0.0513* (0.0262)	0.0613** (0.0308)	0.0555* (0.0303)	0.0611** (0.0300)	0.0758** (0.0383)	0.1030* (0.0569)
LAR (-1)	0.0202*** (0.0019)	0.0127*** (0.0014)	0.0098*** (0.0014)	0.0092*** (0.0014)	0.0063*** (0.0012)	0.0042*** (0.0010)	0.0027* (0.0014)	-0.0016 (0.0012)	-0.0008 (0.0013)	-0.0019 (0.0018)	-0.0052** (0.0025)
SIZE (-1)	0.0017*** (0.0002)	0.0009*** (0.0001)	0.0007*** (0.0001)	0.0005*** (0.0001)	0.0002* (0.0001)	0.0001 (0.0001)	0.0000 (0.0001)	-0.0004*** (0.0001)	-0.0005*** (0.0001)	-0.0007*** (0.0002)	-0.0016*** (0.0002)
Loans_growth (-1)	0.0018 (0.0016)	0.0023* (0.0014)	0.0016 (0.0016)	0.0013 (0.0014)	0.0011 (0.0017)	0.0008 (0.0013)	-0.0001 (0.0019)	0.0001 (0.0022)	0.0000 (0.0022)	-0.0003 (0.0026)	-0.0040 (0.0035)
LDR (-1)	-0.0003 (0.0006)	0.0005* (0.0003)	0.0007** (0.0003)	0.0008** (0.0003)	0.0011*** (0.0003)	0.0012*** (0.0002)	0.0011*** (0.0003)	0.0011*** (0.0003)	0.0009*** (0.0003)	0.0010** (0.0004)	0.0010 (0.0008)
ROA (-1)	0.0383 (0.1044)	-0.1383 (0.0904)	-0.2040** (0.0864)	-0.2420*** (0.0752)	-0.2179** (0.0900)	-0.2194*** (0.0796)	-0.1843** (0.0816)	-0.1234 (0.0871)	-0.1091 (0.1088)	-0.1937 (0.1315)	-0.3253** (0.1508)
Lerner FE (-1)	-0.0024 (0.0033)	0.0049 (0.0031)	0.0053* (0.0031)	0.0056** (0.0026)	0.0065** (0.0027)	0.0067*** (0.0020)	0.0079*** (0.0026)	0.0100*** (0.0026)	0.0117*** (0.0034)	0.0163*** (0.0039)	0.0277*** (0.0045)
Crisis	0.0007 (0.0007)	0.0016** (0.0007)	0.0017** (0.0007)	0.0018*** (0.0006)	0.0012** (0.0005)	0.0014*** (0.0005)	0.0011* (0.0006)	0.0013* (0.0007)	0.0020*** (0.0007)	0.0024*** (0.0007)	0.0046*** (0.0013)
Diagnostics											
Nb. of observations	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055
ΔNPL (-1) coeff. with the PQRFE method	-0.0999	-0.0498	-0.0153	0.0025	0.0507	0.0909	0.1369	0.1689	0.1831	0.2050)	0.2258
Goodness of Fit	0.4599	0.3560	0.3277	0.3209	0.3209	0.3292	0.3487	0.3626	0.3869	0.4205	0.5290

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Standard errors are reported in parentheses. (-1) denotes previous year's values. Goodness of Fit for a particular quantile is calculated as in Koenker and Machado (1999).

Table 7	**Regression results with the PIVQRFE method (Concentration index: HHI)**								Dependent Variable: ΔNPL		
	Quantile										
Variable	0.10	0.20	0.25	0.30	0.40	0.50	0.60	0.70	0.75	0.80	0.90
Intercept	-0.0358*** (0.0026)	-0.0211*** (0.0019)	-0.0177*** (0.0018)	-0.0133*** (0.0017)	-0.0077*** (0.0017)	-0.0063*** (0.0019)	-0.0018 (0.0022)	0.0056** (0.0022)	0.0084*** (0.0022)	0.0108*** (0.0021)	0.0194*** (0.0032)
ΔNPL (-1)	-0.0300** (0.0514)	0.0200 (0.0376)	0.0300 (0.0415)	0.0800** (0.0432)	0.0600 (0.0411)	0.1500** (0.0422)	0.1500** (0.0495)	0.2100*** (0.0502)	0.2100** (0.0534)	0.2500*** (0.0578)	0.2900** (0.0652)
GDP	-0.1803*** (0.0271)	-0.1713*** (0.0278)	-0.1644*** (0.0250)	-0.1651*** (0.0224)	-0.1576*** (0.0199)	-0.1624*** (0.0179)	-0.1718*** (0.0253)	-0.2094*** (0.0356)	-0.2482*** (0.0382)	-0.2522*** (0.0387)	-0.3606*** (0.0647)
Inflation	0.1577*** (0.0363)	0.0880*** (0.0332)	0.0653** (0.0269)	0.0614** (0.0264)	0.0577** (0.0263)	0.0543** (0.0264)	0.0409 (0.0283)	0.0242 (0.0263)	0.0379 (0.0307)	0.0456 (0.0408)	0.0027 (0.0424)
LAR (-1)	0.0138*** (0.0017)	0.0086*** (0.0013)	0.0080*** (0.0011)	0.0063*** (0.0013)	0.0051*** (0.0011)	0.0055*** (0.0012)	0.0027** (0.0012)	0.0001 (0.0015)	-0.0002 (0.0017)	-0.0013 (0.0015)	0.0016 (0.0021)
SIZE (-1)	0.0016*** (0.0001)	0.0010*** (0.0001)	0.0008*** (0.0001)	0.0006*** (0.0001)	0.0002** (0.0001)	0.0002* (0.0001)	0.0000 (0.0001)	-0.0003** (0.0001)	-0.0004*** (0.0001)	-0.0005*** (0.0001)	-0.0009*** (0.0002)
Loans_growth (-1)	0.0018 (0.0012)	0.0020 (0.0016)	0.0022 (0.0014)	0.0015 (0.0016)	0.0007 (0.0016)	0.0012 (0.0018)	-0.0001 (0.0019)	-0.0003 (0.0022)	-0.0007 (0.0021)	-0.0005 (0.0024)	-0.0027 (0.0025)
LDR (-1)	-0.0006 (0.0005)	0.0004 (0.0003)	0.0008** (0.0003)	0.0009*** (0.0003)	0.0009*** (0.0003)	0.0008*** (0.0003)	0.0011*** (0.0003)	0.0010*** (0.0004)	0.0009** (0.0004)	0.0009*** (0.0003)	0.0006 (0.0007)
ROA (-1)	0.0832 (0.0780)	-0.0282 (0.0788)	-0.0886 (0.0673)	-0.1100 (0.0689)	-0.1618** (0.0703)	-0.1304* (0.0692)	-0.1563** (0.0647)	-0.1020 (0.0952)	-0.1386 (0.1022)	-0.2205** (0.1107)	-0.2872* (0.1711)
HHI (-1)	-0.1199*** (0.0116)	-0.0854*** (0.0123)	-0.0624*** (0.0098)	-0.0493*** (0.0091)	-0.0099 (0.0078)	0.0071 (0.0072)	0.0245*** (0.0066)	0.0419*** (0.0085)	0.0596*** (0.0119)	0.0866*** (0.0113)	0.1187*** (0.0153)
Crisis	0.0007 (0.0009)	0.0014* (0.0008)	0.0016** (0.0007)	0.0015*** (0.0006)	0.0014*** (0.0005)	0.0009** (0.0005)	0.0009* (0.0005)	0.0012* (0.0007)	0.0015** (0.0006)	0.0019** (0.0007)	0.0041*** (0.0012)
Diagnostics											
Nb. of observations	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055
ΔNPL (-1) coeff. with the PQRFE method	-0.0683	-0.0304	-0.0137	-0.0053	0.0518	0.0915	0.1356	0.1718	0.1813	0.2202	0.2452
Goodness of Fit	0.4579	0.3553	0.3263	0.3127	0.3228	0.3205	0.3512	0.3737	0.4067	0.4301	0.5360

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Standard errors are reported in parentheses. (-1) denotes previous year's values. Goodness of Fit for a particular quantile is calculated as in Koenker and Machado (1999).

Table 8	**Regression results with the PIVQRFE method (Concentration index: CR5)**								Dependent Variable: ΔNPL		
	Quantile										
Variable	0.10	0.20	0.25	0.30	0.40	0.50	0.60	0.70	0.75	0.80	0.90
Intercept	-0.0260*** (0.0030)	-0.0182*** (0.0026)	-0.0150*** (0.0017)	-0.0114*** (0.0017)	-0.0089*** (0.0018)	-0.0068*** (0.0017)	-0.0038* (0.0022)	0.0025 (0.0023)	0.0050** (0.0023)	0.0066*** (0.0023)	0.0134*** (0.0034)
ΔNPL (-1)	-0.0700** (0.0515)	0.0300** (0.0407)	0.0300 (0.0402)	0.0800** (0.0397)	0.0800** (0.0420)	0.1300** (0.0430)	0.1500** (0.0503)	0.2200*** (0.0503)	0.2200*** (0.0548)	0.2400** (0.0553)	0.2700** (0.0649)
GDP	-0.1885*** (0.0239)	-0.1600*** (0.0275)	-0.1555*** (0.0244)	-0.1675*** (0.0243)	-0.1559*** (0.0194)	-0.1591*** (0.0160)	-0.1698*** (0.0253)	-0.2028*** (0.0361)	-0.2428*** (0.0360)	-0.2589*** (0.0359)	-0.3406*** (0.0684)
Inflation	0.1896*** (0.0393)	0.0832*** (0.0302)	0.0628** (0.0257)	0.0564** (0.0256)	0.0556* (0.0302)	0.0471* (0.0252)	0.0349 (0.0282)	0.0180 (0.0315)	0.0421 (0.0330)	0.0593 (0.0366)	0.0227 (0.0491)
LAR (-1)	0.0121*** (0.0016)	0.0095*** (0.0014)	0.0085*** (0.0012)	0.0062*** (0.0014)	0.0061*** (0.0011)	0.0049*** (0.0012)	0.0027** (0.0013)	0.0010 (0.0014)	0.0002 (0.0018)	-0.0010 (0.0015)	0.0000 (0.0020)
SIZE (-1)	0.0015*** (0.0001)	0.0010*** (0.0001)	0.0008*** (0.0001)	0.0006*** (0.0001)	0.0003** (0.0001)	0.0002** (0.0001)	0.0001 (0.0001)	-0.0003*** (0.0001)	-0.0005*** (0.0001)	-0.0005*** (0.0001)	-0.0009*** (0.0002)
Loans_growth (-1)	0.0015 (0.0012)	0.0017 (0.0015)	0.0019 (0.0016)	0.0013 (0.0016)	0.0007 (0.0015)	0.0009 (0.0015)	0.0003 (0.0019)	0.0001 (0.0019)	-0.0007 (0.0022)	0.0007 (0.0018)	-0.0022 (0.0025)
LDR (-1)	-0.0004 (0.0005)	0.0003 (0.0003)	0.0007** (0.0003)	0.0009*** (0.0003)	0.0008*** (0.0003)	0.0010*** (0.0002)	0.0011*** (0.0003)	0.0010*** (0.0003)	0.0009** (0.0004)	0.0009** (0.0003)	0.0012* (0.0006)
ROA (-1)	0.0849 (0.0888)	-0.0318 (0.0808)	-0.0783 (0.0741)	-0.1063 (0.0744)	-0.1410** (0.0669)	-0.1237* (0.0680)	-0.1607** (0.0647)	-0.1075 (0.0914)	-0.1621* (0.0972)	-0.2540** (0.1111)	-0.3115* (0.1668)
CR5 (-1)	-0.0304*** (0.0030)	-0.0205*** (0.0028)	-0.0148*** (0.0024)	-0.0111*** (0.0027)	-0.0009 (0.0017)	0.0019 (0.0016)	0.0063*** (0.0017)	0.0127*** (0.0020)	0.0171*** (0.0024)	0.0221*** (0.0027)	0.0295*** (0.0033)
Crisis	0.0003 (0.0008)	0.0017** (0.0007)	0.0018*** (0.0007)	0.0016** (0.0006)	0.0013*** (0.0005)	0.0010** (0.0004)	0.0010* (0.0005)	0.0011* (0.0006)	0.0014** (0.0007)	0.0018** (0.0008)	0.0042*** (0.0012)
Diagnostics											
Nb. of observations	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055
ΔNPL (-1) coeff. with the PQRFE method	-0.0833	-0.0321	-0.0136	0.0005	0.0479)	0.0917	0.1356	0.1740	0.1864	0.2220	0.2354
Goodness of Fit	0.4593	0.3539	0.3259	0.3123	0.3200	0.3236	0.3515	0.3716	0.3983	0.4317	0.5376

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Standard errors are reported in parentheses. (-1) denotes previous year's values. Goodness of Fit for a particular quantile is calculated as in Koenker and Machado (1999).

Table 9	**Interaction between the Periphery dummy and HHI (PIVQRFE method)**							Dependent Variable: ΔNPL			
	Quantile										
Variable	0.10	0.20	0.25	0.30	0.40	0.50	0.60	0.70	0.75	0.80	0.90
Intercept	-0.0339*** (0.0028)	-0.0215*** (0.0020)	-0.0180*** (0.0018)	-0.0156*** (0.0017)	-0.0099*** (0.0019)	-0.0069*** (0.0018)	-0.0033 (0.0021)	0.0039* (0.0022)	0.0071*** (0.0023)	0.0080*** (0.0025)	0.0181*** (0.0030)
ΔNPL (-1)	-0.0200** (0.0503)	0.0000** (0.0375)	0.0100** (0.0368)	0.0300** (0.0405)	0.0600 (0.0419)	0.0700 (0.0443)	0.1100 (0.0527)	0.1700** (0.0481)	0.2000** (0.0492)	0.2000** (0.0548)	0.2500** (0.0714)
GDP	-0.1785*** (0.0299)	-0.1502*** (0.0262)	-0.1488*** (0.0269)	-0.1383*** (0.0218)	-0.1405*** (0.0189)	-0.1410*** (0.0179)	-0.1323*** (0.0242)	-0.1459*** (0.0381)	-0.1622*** (0.0476)	-0.1820*** (0.0501)	-0.2435*** (0.0635)
Inflation	0.1751*** (0.0384)	0.0788*** (0.0286)	0.0655** (0.0271)	0.0543* (0.0294)	0.0527** (0.0223)	0.0370 (0.0273)	0.0175 (0.0294)	0.0040 (0.0334)	0.0142 (0.0315)	0.0221 (0.0348)	0.0289 (0.0488)
LAR (-1)	0.0121*** (0.0018)	0.0087*** (0.0013)	0.0083*** (0.0012)	0.0069*** (0.0011)	0.0069*** (0.0013)	0.0060*** (0.0014)	0.0043*** (0.0013)	0.0013 (0.0013)	0.0013 (0.0015)	0.0002 (0.0016)	0.0011 (0.0017)
SIZE (-1)	0.0016*** (0.0001)	0.0009*** (0.0001)	0.0007*** (0.0001)	0.0006*** (0.0001)	0.0002** (0.0001)	0.0001 (0.0001)	0.0000 (0.0001)	-0.0003** (0.0001)	-0.0005*** (0.0001)	-0.0004*** (0.0001)	-0.0010*** (0.0002)
Loans_growth (-1)	0.0024** (0.0011)	0.0017 (0.0015)	0.0019 (0.0019)	0.0011 (0.0015)	0.0006 (0.0017)	0.0003 (0.0018)	0.0001 (0.0021)	0.0002 (0.0020)	-0.0006 (0.0024)	0.0014 (0.0025)	0.0001 (0.0030)
LDR (-1)	-0.0002 (0.0006)	0.0003 (0.0003)	0.0005 (0.0003)	0.0008*** (0.0003)	0.0009*** (0.0003)	0.0007** (0.0003)	0.0009*** (0.0003)	0.0006** (0.0003)	0.0006** (0.0003)	0.0005* (0.0003)	0.0006* (0.0003)
ROA (-1)	0.0913 (0.0855)	-0.0651 (0.0780)	-0.1220 (0.0813)	-0.1933** (0.0766)	-0.2169*** (0.0820)	-0.1842** (0.0776)	-0.2015*** (0.0749)	-0.1270 (0.0906)	-0.1532 (0.1107)	-0.2234* (0.1192)	-0.2673* (0.1589)
HHI (-1)	-0.1349*** (0.0242)	-0.0640*** (0.0129)	-0.0423*** (0.0136)	-0.0334** (0.0141)	0.0044 (0.0113)	0.0188* (0.0112)	0.0430*** (0.0109)	0.0418*** (0.0124)	0.0521*** (0.0133)	0.0666*** (0.0171)	0.0974*** (0.0256)
Periphery	-0.0019 (0.0021)	0.0056*** (0.0016)	0.0069*** (0.0017)	0.0070*** (0.0017)	0.0097*** (0.0015)	0.0117*** (0.0014)	0.0134*** (0.0020)	0.0161*** (0.0020)	0.0179*** (0.0027)	0.0199*** (0.0028)	0.0260*** (0.0033)
Periphery **x** HHI (-1)	0.0198 (0.0319)	-0.0773*** (0.0257)	-0.0898*** (0.0279)	-0.0676** (0.0278)	-0.0876*** (0.0211)	-0.1026*** (0.0205)	-0.1215*** (0.0242)	-0.1250*** (0.0258)	-0.1265*** (0.0322)	-0.1340*** (0.0313)	-0.1849*** (0.0447)
Crisis	0.0007 (0.0008)	0.0014* (0.0008)	0.0012* (0.0007)	0.0015** (0.0007)	0.0012** (0.0005)	0.0011** (0.0004)	0.0010* (0.0005)	0.0013* (0.0007)	0.0016** (0.0007)	0.0017** (0.0008)	0.0030*** (0.0009)
Diagnostics											
Nb. of observations	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055
ΔNPL (-1) coeff. with the PQRFE method	-0.0410	-0.0182	-0.0172	-0.0070	0.0140	0.0509)	0.0862)	0.1011	0.1039	0.1243	0.1696
Goodness of Fit	0.4573	0.3565	0.3299	0.3209	0.3275	0.3370	0.3619	0.3854	0.4070	0.4408	0.5455

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Standard errors are reported in parentheses. (-1) denotes previous year's values and **x** denotes interaction. Goodness of Fit for a particular quantile is calculated as in Koenker and Machado (1999).

Table 10	**Interaction between Foreign share and Lerner_KBL (PIVQRFE method)**								Dependent Variable: ΔNPL		
	Quantile										
Variable	0.10	0.20	0.25	0.30	0.40	0.50	0.60	0.70	0.75	0.80	0.90
Intercept	-0.0457*** (0.0031)	-0.0260*** (0.0025)	-0.0201*** (0.0022)	-0.0156*** (0.0018)	-0.0083*** (0.0018)	-0.0054*** (0.0015)	-0.0014 (0.0021)	0.0071*** (0.0018)	0.0094*** (0.0020)	0.0162*** (0.0026)	0.0345*** (0.0035)
ΔNPL (-1)	-0.0400*** (0.0552)	0.0100*** (0.0440)	0.0200** (0.0437)	0.0500*** (0.0438)	0.0600*** (0.0446)	0.0800*** (0.0475)	0.0800*** (0.0463)	0.0900*** (0.0528)	0.1200*** (0.0606)	0.1500*** (0.0656)	0.2400*** (0.0607)
GDP	-0.1986*** (0.0244)	-0.1513*** (0.0239)	-0.1628*** (0.0243)	-0.1683*** (0.0215)	-0.1640*** (0.0191)	-0.1668*** (0.0197)	-0.1976*** (0.0261)	-0.2330*** (0.0336)	-0.2582*** (0.0406)	-0.2942*** (0.0449)	-0.3410*** (0.0580)
Inflation	0.1421*** (0.0457)	0.0518 (0.0394)	0.0498 (0.0357)	0.0522 (0.0344)	0.0651* (0.0365)	0.0571* (0.0347)	0.0263 (0.0317)	0.0228 (0.0445)	0.0364 (0.0445)	0.0476 (0.0510)	0.1119* (0.0587)
LAR (-1)	0.0179*** (0.0017)	0.0125*** (0.0016)	0.0100*** (0.0013)	0.0078*** (0.0012)	0.0057*** (0.0012)	0.0046*** (0.0011)	0.0030** (0.0014)	0.0022 (0.0014)	0.0022 (0.0013)	-0.0001 (0.0018)	-0.0033 (0.0028)
SIZE (-1)	0.0017*** (0.0002)	0.0009*** (0.0001)	0.0007*** (0.0001)	0.0005*** (0.0001)	0.0002* (0.0001)	0.0002 (0.0001)	0.0001 (0.0001)	-0.0003*** (0.0001)	-0.0003*** (0.0001)	-0.0006*** (0.0001)	-0.0014*** (0.0002)
Loans_growth (-1)	0.0040* (0.0024)	0.0028 (0.0021)	0.0027 (0.0020)	0.0020 (0.0018)	0.0013 (0.0020)	0.0010 (0.0018)	0.0001 (0.0019)	-0.0014 (0.0020)	-0.0018 (0.0021)	-0.0020 (0.0024)	-0.0025 (0.0032)
LDR (-1)	0.0002 (0.0006)	0.0005* (0.0003)	0.0007* (0.0003)	0.0008** (0.0003)	0.0010*** (0.0003)	0.0011*** (0.0003)	0.0009*** (0.0003)	0.0007* (0.0004)	0.0005 (0.0004)	0.0006 (0.0004)	0.0008 (0.0009)
ROA (-1)	0.0608 (0.0983)	-0.1441 (0.0940)	-0.1648* (0.0952)	-0.1610* (0.0948)	-0.1920** (0.0949)	-0.2150** (0.0848)	-0.2128** (0.0885)	-0.2670*** (0.0937)	-0.2645*** (0.0979)	-0.2725*** (0.1010)	-0.2384* (0.1243)
Lerner_KBL (-1)	-0.0108** (0.0055)	-0.0005 (0.0047)	-0.0008 (0.0045)	0.0008 (0.0038)	0.0059* (0.0035)	0.0070** (0.0029)	0.0087** (0.0035)	0.0167*** (0.0045)	0.0197*** (0.0041)	0.0202*** (0.0052)	0.0368*** (0.0059)
Foreign (-1)	-0.0085 (0.0292)	-0.0079 (0.0249)	-0.0124 (0.0235)	-0.0103 (0.0219)	-0.0120 (0.0191)	-0.0234 (0.0158)	-0.0315* (0.0180)	-0.0305* (0.0179)	-0.0345* (0.0187)	-0.0364* (0.0218)	-0.0958*** (0.0327)
Foreign (-1) **x** Lerner_KBL (-1)	-0.0521 (0.2438)	-0.3935* (0.2161)	-0.4250* (0.2226)	-0.3779* (0.2266)	-0.3069 (0.2098)	-0.2043 (0.2212)	-0.3783 (0.2858)	-0.4657* (0.2672)	-0.6750** (0.2883)	-0.7680*** (0.2797)	-1.2944*** (0.3720)
Crisis	0.0002 (0.0008)	0.0014* (0.0007)	0.0015** (0.0007)	0.0015** (0.0006)	0.0012** (0.0005)	0.0010** (0.0005)	0.0010 (0.0006)	0.0016** (0.0008)	0.0018** (0.0008)	0.0022** (0.0010)	0.0027** (0.0013)
Diagnostics											
Nb. of observations	2,352	2,352	2,352	2,352	2,352	2,352	2,352	2,352	2,352	2,352	2,352
ΔNPL (-1) coeff. with the PQRFE method	-0.0544	-0.0133	-0.0029	0.0131	0.0228	0.0647	0.0540	0.0634	0.0755	0.1020	0.1937
Goodness of fit	0.4646	0.3638	0.3363	0.3272	0.3358	0.3457	0.3792	0.4146	0.4367	0.4684	0.5577

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Standard errors are reported in parentheses. (-1) denotes previous year's values and **x** denotes interaction. Goodness of Fit for a particular quantile is calculated as in Koenker and Machado (1999).

Table 11	**Interaction between the Commercial dummy and Lerner_KBL (PIVQRFE method)**								Dependent Variable: ΔNPL		
Variable	Quantile										
	0.10	0.20	0.25	0.30	0.40	0.50	0.60	0.70	0.75	0.80	0.90
Intercept	-0.0491*** (0.0032)	-0.0303*** (0.0025)	-0.0234*** (0.0024)	-0.0177*** (0.0022)	-0.0124*** (0.0017)	-0.0072*** (0.0015)	-0.0042** (0.0018)	0.0044** (0.0021)	0.0089*** (0.0021)	0.0141*** (0.0027)	0.0336*** (0.0036)
ΔNPL (-1)	-0.0600*** (0.0517)	-0.0100*** (0.0414)	0.0100*** (0.0385)	0.0100*** (0.0375)	0.0300*** (0.0407)	0.0600*** (0.0423)	0.0800*** (0.0526)	0.1300*** (0.0537)	0.1700*** (0.0601)	0.1900*** (0.0593)	0.2600*** (0.0664)
GDP	-0.1962*** (0.0230)	-0.1450*** (0.0248)	-0.1618*** (0.0239)	-0.1622*** (0.0234)	-0.1555*** (0.0210)	-0.1582*** (0.0199)	-0.1656*** (0.0251)	-0.2007*** (0.0332)	-0.2082*** (0.0382)	-0.2304*** (0.0379)	-0.2757*** (0.0637)
Inflation	0.1243*** (0.0333)	0.0457 (0.0315)	0.0607** (0.0280)	0.0560** (0.0269)	0.0565* (0.0290)	0.0562** (0.0283)	0.0626** (0.0288)	0.0559 (0.0366)	0.0686* (0.0363)	0.0745** (0.0330)	0.0585 (0.0435)
LAR (-1)	0.0179*** (0.0022)	0.0116*** (0.0014)	0.0096*** (0.0013)	0.0082*** (0.0015)	0.0074*** (0.0012)	0.0045*** (0.0012)	0.0039*** (0.0012)	0.0025 (0.0015)	0.0013 (0.0014)	0.0000 (0.0015)	0.0002 (0.0026)
SIZE (-1)	0.0020*** (0.0002)	0.0011*** (0.0001)	0.0008*** (0.0001)	0.0005*** (0.0001)	0.0003*** (0.0001)	0.0002** (0.0001)	0.0000 (0.0001)	-0.0003*** (0.0001)	-0.0006*** (0.0001)	-0.0008*** (0.0001)	-0.0021*** (0.0002)
Loans_growth (-1)	-0.0002 (0.0017)	0.0021 (0.0016)	0.0018 (0.0016)	0.0018 (0.0017)	0.0008 (0.0015)	-0.0001 (0.0013)	-0.0009 (0.0017)	-0.0013 (0.0018)	-0.0021 (0.0017)	-0.0027 (0.0021)	-0.0045 (0.0028)
LDR (-1)	0.0001 (0.0006)	0.0009*** (0.0003)	0.0009*** (0.0003)	0.0009*** (0.0003)	0.0008*** (0.0003)	0.0012*** (0.0003)	0.0011*** (0.0003)	0.0004 (0.0004)	0.0005* (0.0003)	0.0006** (0.0003)	0.0007 (0.0005)
ROA (-1)	0.0186 (0.1060)	-0.0456 (0.0908)	-0.1309 (0.0883)	-0.2103** (0.0828)	-0.2323*** (0.0876)	-0.2269*** (0.0758)	-0.2524*** (0.0864)	-0.1515 (0.0959)	-0.2217** (0.1121)	-0.2338** (0.1119)	-0.4351*** (0.1451)
Lerner_KBL (-1)	0.0073 (0.0065)	0.0101** (0.0048)	0.0132** (0.0052)	0.0120** (0.0052)	0.0137*** (0.0040)	0.0098** (0.0042)	0.0174*** (0.0059)	0.0146** (0.0057)	0.0186*** (0.0054)	0.0234*** (0.0063)	0.0499*** (0.0117)
Commercial	-0.0039** (0.0016)	-0.0008 (0.0016)	0.0006 (0.0015)	0.0013 (0.0014)	0.0029** (0.0012)	0.0022* (0.0013)	0.0056*** (0.0016)	0.0077*** (0.0020)	0.0093*** (0.0018)	0.0096*** (0.0021)	0.0163*** (0.0028)
Commercial **x** Lerner_KBL (-1)	-0.0073 (0.0083)	-0.0109 (0.0080)	-0.0141* (0.0084)	-0.0110 (0.0080)	-0.0139** (0.0059)	-0.0068 (0.0059)	-0.0195** (0.0076)	-0.0210** (0.0095)	-0.0214** (0.0091)	-0.0246** (0.0100)	-0.0401*** (0.0146)
Crisis	0.0014* (0.0008)	0.0016** (0.0007)	0.0015** (0.0006)	0.0016*** (0.0005)	0.0013** (0.0005)	0.0011** (0.0005)	0.0009* (0.0005)	0.0009 (0.0007)	0.0014* (0.0008)	0.0020*** (0.0007)	0.0033*** (0.0010)
Diagnostics											
Nb. of observations	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055	3,055
ΔNPL (-1) coeff. with the PQRFE method	-0.0730	-0.0277	-0.0076)	-0.0006	0.0182	0.0562	0.0784	0.1209	0.1375	0.1553	0.2338
Goodness of fit	0.4613	0.3549	0.3338	0.3206	0.3280	0.3353	0.3648	0.3905	0.4068	0.4421	0.5345

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Standard errors are reported in parentheses. (-1) denotes previous year's values and **x** denotes interaction. Goodness of Fit for a particular quantile is calculated as in Koenker and Machado (1999).