Detecting Financial Stability Vulnerabilities in Due Time: Can Simple Indicators Identify a Complex Issue?

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This paper analyzes the resilience of credit institutions to instances of financial instability based on simple publicly available balance sheet and income statement figures. In the course of the recent financial crisis and the related credit turmoil, the loss absorption capacity of the global financial system has been stretched to its limit. Globally active financial institutions, many of them systemically relevant, needed government support to keep their capital ratios above regulatory and/or market required minima. Central banks had to step in to provide liquidity when large parts of the financial markets ceased to function. From an ex-post perspective, the crisis provided a real stress scenario which we use to explain bank performance by examining simple indicators such as capitalization, liquidity, funding structure and asset-side exposure. To cover systemically important European banks we choose a subset from the bank sample used by the European Banking Association for the EU-wide stress-testing exercise in 2011. We add three Austrian banks to arrive at a sample of 90 European banks in total (including altogether six Austrian banks). To measure bank performance, we use return on average assets, return on average equity, operating profits, required government support and equity prices. We show that these performance measures can be explained adequately by our simple indicators. We are able to identify the strong, respectively weak, banks that did not, respectively did, need government support in 2009. Regarding the other performance measures we give a forecast for 2011 about which banks are expected to perform well, ordinarily and poorly.

1 Motivation

The recent global financial crisis turned public, political and academic attention to the development of early warning indicators for banks' resilience to instances of financial instability. This is a growing policy concern also in Europe, as highlighted by the EU-wide stress-testing exercise coordinated by the newly established European Banking Authority (EBA) in 2011. Academic interest typically focusses on early warning indicators in the aftermath of banking crises.

Any study on bank resilience must address a number of complex issues: How can bank performance and resilience be measured in a meaningful way and what kind of variables do influence them? Which indicators deliver robust results that can be used as early warning signals? And how to deal with the creative tension between complex models that account for the limited availability of timely data and simpler models applying lower data standards?

1.1 Defining Bank Performance

In the literature, it is an established practice to use bank performance as a general indicator for bank resilience.[2] Measuring bank performance, however, is not a straightforward exercise as banks may differ substantially in their

risk-taking profile. As long as markets work properly, bank performance needs to be risk-adjusted to serve as a meaningful indicator since risk and return are correlated. Otherwise, there is the danger that excessive risk-taking might go unnoticed in good times, since potential flaws in flat risk-weighted assets for certain sectors as well as toxic assets, misleading ratings, lenient provisioning policies and looser lending standards cannot be detected easily.

As Poghosyan and Cihak (2009) point out, up to the recent crisis Europe has seen only a small number of outright bank failures, which makes it very difficult from a statistical point of view to estimate and calibrate early warning models to be used in banking supervision. Although the deep current crisis has put many European banks on the brink of insolvency, government intervention has saved many institutions from failure. To solve the econometrical problem of having too few actual bank failures to draw from, Ratnovski and Huang (2009) suggest to measure bank performance by a dummy variable which indicates government support in response to extreme stress.

In our study we measure bank performance by different performance indicators such as equity price changes, government support and return on average assets.

1.2 Explaining Bank Performance

After defining bank performance, we must find variables that explain bank performance. With respect to the trade-off between model complexity and data availability, we follow Rat-

novski and Huang (2009) and Sun (2011) and test the hypothesis that simple publicly available balance sheet data serve as good explanatory variables to identify weak banks.[3]

Moreover, Poghosyan and Cihak (2001) report that well established complex indicators such as capital, asset quality, management quality as well as equity and liquidity grades are somewhat limited when it comes to predicting bank failures and therefore need to be complemented by other indicators.

To control for the robustness of our results, we test our set of indicators based on a sample of international banks without regard to institution-specific data. After all, any bank resilience analysis boils down to classifying a sample of banks into weak and sound institutions. Only a few papers have addressed the topic of resilience indicators based on the recent global financial crisis, i.a. Poghosyan and Cihak (2009) and Beltratti (2009). We hope the approach we suggest proves useful in enhancing supervisors' abilities to take a more forward-looking view on banks.

2 Data

To test our hypothesis, we analyze annual balance sheet and income statement data obtained from Bankscope and some additional market data obtained from Bloomberg. Our sample covers 90 banks from 21 European countries[4]. The sample largely mimics the EBA sample used for the EU-wide stress-testing exercise conducted in July 2011. The banks in the EBA sample account for over 65% of the EU banking system's total assets and for at least 50% of total consolidated assets

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[3] Our dataset consists of annual balance and income statement data derived from the financial statements of banks made available through the Bankscope database of Bureau van Dijk.

[4] Austria, Belgium, Cyprus, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Hungary, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Sweden and Slovenia.

of the national banking sectors in each EU Member State at the end of 2010. In our subset of this sample, we had to exclude some smaller Spanish banks (cajas) as for these, some data relevant to our methodology are not available.[5]

In addition, to improve the robustness and check the plausibility of our results we apply our estimation methodology to an enlarged bank sample of 957 consolidated banks from various OECD countries, with each bank's total assets coming to over EUR 5 billion as of end-2010.

We selected our endogenous (performance) and exogenous (explanatory) variables based on related literature and with respect to the following criteria: comparability of results, data availability.

2.1 Variables to Measure Bank Performance

Following the standard literature on bank performance, we look at the return on average assets (ROAA = net income divided by average total assets) and the return on average equity (ROAE = net income divided by average total equity). The ROAA shows a bank's profitability before leverage, while the ROAE is an easily comparable profitability measure of shareholder value. In the literature, the ROAA is widely perceived to be valuable as a profitability and performance indicator since it is adjusted for the leverage effect. For this reason, focusing on the ROAE alone might sometimes render misleading results (Sun, 2011).

The second pair of performance measures are two variables derived from the income statement, namely operating profits (after impairments), adjusted both for risk-weighted assets (RWA) and total assets, (operating profits divided by RWA; operating profits divided by total assets) to differentiate between risk weight-adjusted and non-risk weight-adjusted profitability ratios.[6]

Next, we include the relative year-on-year equity price change using year-end data.[7] According to Ratnovski and Huang (2009), the decline in equity prices serves as a credible performance measure since it includes credit losses, securities write-downs and dilution from new equity issuances including government capital injections.

The last performance measure we include is a dummy variable that captures government intervention during crisis periods. Here, we include banks that have received capital injections (excluding temporary central bank liquidity injections), loans or similar support vehicles or have been nationalized or merged during the crisis to avoid bankruptcy.

2.2 Variables Used to Explain Bank Performance

As explanatory variables we use a set of balance sheet and income statement variables. Three of our 13 explanatory variables mimic the ratios used by Ratnovski and Huang (2009). We include additional publically available variables to capture different areas of balance sheet fundamentals to improve the predictive power of the model.

To assess asset quality, we first proxy the flows in loan loss provisions (LLP) and use Bankscope stock data on impairment flows divided by total as-

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[5] *In 2009 and 2010, the Spanish banking sector was significantly restructured.*

[6] *Operating profits and net income are both risk adjusted with respect to impairments.*

[7] *In our performance variable selection we also compare year-end data with average December stock prices. Both measures provide very similar results.*

sets as a proxy for nonperforming loans (NPLs). To measure the unexpected loss potential of banks' total portfolio we divide RWA by total assets. For capitalization we use a simple ratio of total balance sheet equity to total assets. To account for different bank business models (e.g. investment and universal banks), we assess the effects of banks' income structure on their resilience. Therefore, we include the ratio of net interest income to total assets and the ratio of non-interest operating income to total assets as explanatory variables. Concerning funding and liquidity, we look at the ratios of liquid assets[8] to total assets and customer deposits to total assets as used by Ratnovski and Huang (2009) in their analysis. We enhance these variables by the loan-to-customer deposit ratio (LDR) and long-term funding divided by total assets. To capture the portfolio structure of the observed banks, we use the ratios of relative trading book size to total assets and loan growth.

3 Empirical Analysis

In this section, we outline the econometric theory and estimation procedures behind our models to explain the different bank performance measures outlined in the data section. As stated in the introduction, we intend to answer the question of what kind of variables influence the status of the bank performance measure as a proxy for bank resilience. In line with a number of related papers on bank performance such as Sun (2011), we choose a panel model approach to link our perfor-

mance measures to balance sheet and income statement positions.[9]

We start from a model in which all coefficients are the same across individual banks and time, except the intercept term.

$$y_{i,t} = \alpha_i + x'_{i,t-1}\beta + u_{i,t} \qquad (1)$$

It is assumed that $u_{i,t} \sim N(0, \sigma_u^2)$ is independent of all $x_{i,t}$. Aside from these standard technical details, two further important remarks are necessary. First, we regress the current bank performance measure $y_{i,t}$ on past balance sheet and income statement variables. This approach avoids endogeneity problems, helps identify problem banks based on their past balance and income statement structure and serves as a prerequisite for early warning indicators. Second, we fix $\beta_i = \beta$ for all banks within our sample. This implies that the slope coefficients are supposed to be identical for all institutions and time periods. The most important advantage of panel models relates to the model intercept α_i. As pointed out by Verbeek (2008), the availability of panel data will ease the problem of distinguishing between true and spurious state dependence, because individual histories are observed and can be included in the analysis. An individual specific intercept term allows controlling for unobserved variables such as management quality, bank business models and other bank-specific characteristics that are time invariant at least for the time span observed. For this paper we analyze in detail the influence of our explanatory

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[8] The Bankscope position of liquid assets is harmonized for different jurisdictions and includes trading securities at fair value, cash, reverse repos and collateral and short-term claims on other banks.

[9] Referring to Verbeek (2008), panel models have two major advantages over models using only time series or cross sections, namely the efficiency of parameter estimation and the improved identification of parameters. We do not consider lags of higher order as we assume that the history of all past management decisions is reflected in the previous year's balance sheet and the resulting income statement structure.

variables on the return on average assets, on government support and equity prices.[10]

3.1 Return on Average Assets

First, we look at the ROAA as a performance measure.[11] In a series of tests, we come to the conclusion to reject the poolability hypothesis of our data sample. Following the standard literature on static panel econometrics, we are left with two options concerning: considering fixed effects or random effects. A Hausmann test implies that only the fixed-effect model provides consistent results.[12]

Table 1 in the annex reveals interesting empirical results. After controlling for several variables, three of the chosen variables show economic and statistical significance. The loan impairment charge ratio as a proxy for the LLP flow ratio lagged by one period has a significant negative influence on the current ROAA. The same holds true for net interest income ratio and the noninterest income ratio.

To test for the robustness of the insignificant RWA ratio, we estimated two further panel models with the same exogenous variables as listed in table 1, but using operating profits divided by total assets and operating profits divided by RWA as performance measures. The operating profits-di-

vided-by-total assets model gives a much better fit, indicating that RWA might not mirror economic risk in a meaningful way.[13] The fact that the influence of the leverage ratio (equity divided by total assets) on the ROAA is insignificant seems to be a surprising result at first glance. Since the balance sheet position "equity" does not distinguish between types of capital, "equity" does not include any information on capital quality (e.g. risk-bearing capacity). If the value for equity in the balance sheet equity is high, this does not necessarily signal that the respective institution is particularly crisis resilient, as pointed out by Sun (2011).

In contrast to Ratnovski and Huang (2009), neither the ratio of long-term funding to total assets, the ratio of depository funding to total assets nor the loan-to-deposit ratio have a significant influence on the ROAA in the subset of the EBA bank sample we use here. These surprising findings – no influence of long-term funding and depository funding on ROAA – could be explained by the fact that banks had access to ECB tenders during the crisis years, which means that banks with a riskier (short-term) funding structure, which relied mostly on the interbank market, were able to easily gain access to (unlimited) ECB tenders.[14] Finally, we could not provide empirical evi-

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[10] The additional performance measures ROAE, operating income divided by total assets and operating income divided by RWA are used to check for the plausibility and robustness of the results obtained for the other three performance measures. On the one hand, ROAE is similar to ROAA except for the leverage effect and on the other hand, the operating income-related variables are used to analyze the importance of RWAs. The results of the additional performance measures are provided in tables 4, 5 and 6 in the annex.

[11] All estimations are carried out by the statistical software R and Stata.

[12] The same test procedure, ranging from poolability test to Hausmann test, is applied to all other performance measure estimations.

[13] Our result is in line with Sun (2011), who claims the RWA ratio is not always a useful indicator since there are difficulties in determining the unexpected loss potential of assets, accounting for deficiencies in mark-to-market accounting practices and locating assets and contingent claims (e.g. derivatives) in off-balance sheet vehicles where they can receive lower risk weights.

[14] In an additional panel model, we extended our bank sample to 957 OECD banks and find significant positive influence of the long-term funding and customer deposits-to-total asset ratio on the ROAA.

dence that the liquid asset ratio is a prominent factor in explaining the ROAA.[15]

3.2 Government Support

Table 2 in the annex shows our estimation outcome for the government support dummy in a linear panel probability model.[16] The positive coefficient for our loan loss provision ratio (LLPR) flow for the last period observed implies that the probability of government support increases. In contrast to the ROAA results, the total equity ratio is found to have a significant negative influence on government support, which implies that better capitalized banks were less likely to receive government support. The same holds true for the total noninterest operating income ratio and the liquid asset ratio. Surprisingly, the trading book ratio initially included into the estimation to control for banks' portfolio structure has a significantly negative sign, which ceteris paribus reduces the influence of the total noninterest operating income ratio on the probability of government support.

3.3 Equity Price Change

In contrast to the previous tables, table 3 in the annex shows hardly any significant explanatory variables that predict the relative year-on-year equity price change.[17] Only the total equity ratio is found to have a significantly positive influence on the equity price change. Moreover, the overall explanatory power of the model is relatively low.[18] We think a couple of arguments might support our findings. First, the equity price change might not be the best market-based indicator for bank performance.[19] Second, we apply a different methodology than Ratnovski and Huang (2009) to classify banks according to their equity price performance. Third, equity prices are expected to be forward looking, which implies that balance sheet and income statement developments are priced in instantaneously to avoid arbitrage opportunities. Finally, the highly significant year dummies[20] point toward herding behavior, especially in periods of crisis and euphoria.

4 Early Warning Results

In this section we provide some evidence for the predictive power of our models to indicate whether they may serve as macroprudential early warning tools. First, we use the government support model to predict – for each

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[15] Again, Ratnovski and Huang (2009) come up with a significant result. We think that their results are dominated by a special characteristic of the Canadian banking system, namely the liquidity guidelines stating that banks have to maintain a stock of highly liquid assets appropriate for their cash flow and funding profile.

[16] As we model government support as a binary variable, a correctly specified probability model would require a logit or probit transformation to ensure that the estimated probability of government support lies within the interval (0,1). However, especially in fixed-effect models, a couple of statistical problems with logit or probit transformations arise. E.g. for a fixed number of time periods and $N \rightarrow \infty$, the problem of incidental parameters makes an (unconditional) maximum likelihood estimation inconsistent because the number of unknown parameters grows with the sample size. As a consequence, we stick to the linear panel probability model and compare our results with probit-transformed random effect models to ensure robustness.

[17] Similar results are observed when using both year-end stock prices and average December prices.

[18] For the enlarged OECD bank sample we obtain slightly different results. Here, only the LLPR flow is significant at the 1% level with a somehow surprisingly positive coefficient. The overall fit is even worse than in the sample of European banks.

[19] See also Sun (2011), who uses the price-to-earnings ratio and the earnings and book values per share in his model.

[20] Year dummies refer to the level of each year's specific intercept, which means that by using these variables we account for developments that took place in the European market in the specific year.

bank – the probability of receiving government support (for the 90 European sample banks) in 2009 by applying lagged balance sheet and income statement variables from 2008. We rank the sample according to the probability distribution of the model output, where the first quartile is supposed to represent the most resilient banks and the last quartile the banks most likely to receive government support in the following year. The results of our model are in line with banks' actual performance during the crisis. In the first quartile, 16 of a total of 17 banks did not receive government support while in the fourth quartile, 14 of a total of 17 banks received government support in 2009.[21]

In the sample forecast of the ROAA, our model performed slightly less successfully, which can be attributed to the fact that, unlike government support, the ROAA is a continuous variable. Nevertheless, the model succeeds in identifying more than 60% of both the strongest and weakest banks. The out-of-sample ROAA forecast for end-2011 shows reasonable results. On the one hand, banks with a relatively low predicted ROAA broadly correspond with banks that showed negative results in their interim statements 2011. On the other hand, banks with low predicted returns are mostly located in countries that are perceived to experience adverse macroeconomic developments in 2011. This shows that the proposed models qualify as effective early warning tools.

5 Conclusions

In this paper we establish potential early warning tools for analyzing bank performance and contribute to the pre-

vious literature on bank performance by explaining different performance measures with the help of simple and publically available balance sheet and income-based variables and by comparing these measures.

Among the standard bank performance measures, our fixed explanatory variable set yields better results in explaining the ROAA than both the ROAE and equity price changes. The financial crisis provided a real adverse scenario that created an additional bank performance variable, namely the injection of government support capital.

Our explanatory variables capture different areas of balance sheet and income statement fundamentals. To a certain extent our method makes it possible to predict future banking performance using only a limited number of selected explanatory variables. The part of the model that is based on government support figures provides an accurate in-sample forecast for receiving government support in 2009.

Concerning the significance of the explanatory variables, we find differences among the performance measures. The probability of receiving government support and the ROAA are significantly influenced by the LLP flow ratio, by net interest income and the total noninterest income ratio. The balance sheet equity ratio and liquid asset ratio are found to only influence the probability of government support.

The funding-related variables (long-term funding and depository funding) appear not to be significant for government support and the ROAA in the sample of European banks. One explanation of this counter-intuitive result might be that mitigating actions by central banks, i.e. ample provision of

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[21] *According to the model, Austrian banks belong in the second and third quartiles with government support probabilities ranging between 27% and 54%.*

liquidity, prevented the differences in bank performance between the banks in the sample to fully play out.

We also looked beyond mere structural ratios into banks' asset side. Interestingly, we found that in our bank sample the RWA ratio does not significantly influence any of the performance measures. This raises the question of whether RWA capture economic risk appropriately.

When explaining equity price changes, only a few exogenous variables apart from the year dummies seem to be significant. The year dummies are found to be highly significant for European banks and for the enlarged OECD control sample. This leads us to the conclusion that equity prices are dominated mostly by the overall market environment and do not reflect idiosyncratic bank characteristics very accurately.

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Annex

Table 1

Return on Average Assets

	Estimate	Standard error	t-value	p-value
Sample of European banks (90 banks)				
Lag(LoanImpairmentCharge/TotalAssets,1)	−118.5035	15.4221	−7.68	0.0000 ***
Lag(ProxyNPLStock/TotalAssets,1)	8.5323	5.6812	1.50	0.1351
Lag(TotalEquity/TotalAssets,1)	1.5883	6.1111	0.26	0.7953
Lag(RWAs/TotalAssets,1)	−1.0430	0.7350	−1.42	0.1578
Lag(NetInterestIncome/TotalAssets,1)	71.0205	17.4660	4.07	0.0001 ***
Lag(TotalNonInterestOpIncome/TotalAssets,1)	29.0752	13.4458	2.16	0.0321 *
Lag(LiquidAssets/TotalAssets,1)	1.1193	1.0301	1.09	0.2788
Lag(TotalCustomerDeposits/TotalAssets,1)	−0.6100	1.3829	−0.44	0.6598
Lag(Longtermfunding/TotalAssets,1)	1.5505	0.9892	1.57	0.1190
Lag(Loan.CustomerDeposit,1)	0.1315	0.0751	1.75	0.0819 •
Lag(ProxyTradingBook/TotalAssets,1)	1.0851	1.0147	1.07	0.2865
Lag(GrossLoanGrowth,1)	0.0855	0.2094	0.41	0.6837
Year dummy for 2007	−0.7547	1.0464	−0.72	0.4720
Year dummy for 2008	−1.2317	0.0901	−5.29	0.0000 ***
Year dummy for 2009	−1.7087	0.1308	−2.60	0.0100 *
Year dummy for 2010	−2.1857	0.1557	−0.33	0.7440
Root-squared: within, between and overall	0.5266	0.1366	0.3469	
Number of groups and observations	70	247		
From 2007 to 2010	4			

Source: Authors' calculations.

*Note: Significance codes: 0.001 = ***, 0.01 = **, 0.05 = *, 0.1 = •.*

Table 2

Government Support

	Estimate	Standard error	t-value	p-value
Sample of European banks (90 banks)				
Lag(LoanImpairmentCharge/TotalAssets,1)	24.8513	7.6571	3.25	0.0014 **
Lag(ProxyNPLStock/TotalAssets,1)	3.6956	2.8886	1.28	0.2025
Lag(TotalEquity/TotalAssets,1)	−8.2203	3.1832	−2.58	0.0107 *
Lag(RWAs/TotalAssets,1)	−0.0245	0.3932	−0.06	0.9504
Lag(NetInterestIncome/TotalAssets,1)	−8.0598	9.6317	−0.84	0.4039
Lag(TotalNonInterestOpIncome/TotalAssets,1)	−18.2033	6.9452	−2.62	0.0096 **
Lag(LiquidAssets/TotalAssets,1)	−1.5832	0.5126	−3.09	0.0024 **
Lag(TotalCustomerDeposits/TotalAssets,1)	0.3265	0.7796	0.42	0.6759
Lag(Longtermfunding/TotalAssets,1)	−1.0287	0.5444	−1.89	0.0605 •
Lag(Loan.CustomerDeposit,1)	0.0333	0.0422	0.79	0.4316
Lag(ProxyTradingBook/TotalAssets,1)	−1.7152	0.5637	−3.04	0.0027 **
Lag(GrossLoanGrowth,1)	−0.2374	0.1134	−2.09	0.0379 *
Year dummy for 2007	−	−	−	−
Year dummy for 2008	−	−	−	−
Year dummy for 2009	−	−	−	−
Year dummy for 2010	−	−	−	−
Root-squared: within, between and overall	0.4794	0.2031	0.2492	
Number of groups and observations	71	252		
From 2007 to 2010	4			

Source: Authors' calculations.

*Note: Significance codes: 0.001 = ***, 0.01 = **, 0.05 = *, 0.1 = •.*

Table 3

Equity Price Change

	Estimate	Standard error	t-value	p-value
Sample of European banks (90 banks)				
Lag(LoanImpairmentCharge/TotalAssets,1)	−4.8091	10.4480	−0.46	0.6463
Lag(ProxyNPLStock/TotalAssets,1)	0.5525	4.3886	0.13	0.9001
Lag(TotalEquity/TotalAssets,1)	10.2260	4.5980	2.22	0.0283 *
Lag(RWAs/TotalAssets,1)	−0.0514	0.5635	−0.09	0.9275
Lag(NetInterestIncome/TotalAssets,1)	−3.3542	12.1735	−0.28	0.7834
Lag(TotalNonInterestOpIncome/TotalAssets,1)	14.3501	12.5364	1.14	0.2549
Lag(LiquidAssets/TotalAssets,1)	0.4465	0.7776	0.57	0.5670
Lag(TotalCustomerDeposits/TotalAssets,1)	−1.2442	1.0460	−1.19	0.2369
Lag(Longtermfunding/TotalAssets,1)	−0.1519	0.7169	−0.21	0.8326
Lag(Loan.CustomerDeposit,1)	0.0197	0.0494	0.40	0.6909
Lag(ProxyTradingBook/TotalAssets,1)	0.2808	0.7298	0.38	0.7012
Lag(GrossLoanGrowth,1)	0.2019	0.1435	1.41	0.1623
Year dummy for 2007	−0.4089	0.7486	−0.55	0.5860
Year dummy for 2008	−0.9372	0.0689	−7.67	0.0000 ***
Year dummy for 2009	0.2305	0.0983	6.51	0.0000 ***
Year dummy for 2010	−0.3685	0.1153	0.35	0.7270
Root-squared: within, between and overall	0.7228	0.0698	0.5422	
Number of groups and observations	46	167		
From 2007 to 2010	4			

Source: Authors' calculations.

*Note: Significance codes: 0.001 = ***, 0.01 = **, 0.05 = *, 0.1 = •.*

Table 4

Return on Average Equity

	Estimate	Standard error	t-value	p-value
Sample of European banks (90 banks)				
Lag(LoanImpairmentCharge/TotalAssets,1)	−2,362.5527	609.2942	−3.88	0.0002 ***
Lag(ProxyNPLStock/TotalAssets,1)	428.7573	224.4500	1.91	0.0579 •
Lag(TotalEquity/TotalAssets,1)	57.9417	241.4367	0.24	0.8106
Lag(RWAs/TotalAssets,1)	13.5442	29.0388	0.47	0.6415
Lag(NetInterestIncome/TotalAssets,1)	1,322.0367	690.0451	1.92	0.0571 •
Lag(TotalNonInterestOpIncome/TotalAssets,1)	679.3825	531.2135	1.28	0.2028
Lag(LiquidAssets/TotalAssets,1)	19.4388	40.6963	0.48	0.6335
Lag(TotalCustomerDeposits/TotalAssets,1)	−48.1181	54.6359	−0.88	0.3798
Lag(Longtermfunding/TotalAssets,1)	30.5188	39.0819	0.78	0.4360
Lag(Loan.CustomerDeposit,1)	3.7719	2.9667	1.27	0.2054
Lag(ProxyTradingBook/TotalAssets,1)	−20.4427	40.0873	−0.51	0.6108
Lag(GrossLoanGrowth,1)	−29.4994	8.2746	−3.57	0.0005 ***
Year dummy for 2007	−10.9185	41.3429	−0.26	0.7920
Year dummy for 2008	−25.2006	3.5604	−4.01	0.0000 ***
Year dummy for 2009	−22.5234	5.1692	−2.25	0.0260 *
Year dummy for 2010	−19.5475	6.1504	−1.40	0.1630
Root-squared: within, between and overall	0.312	0.0014	0.0698	
Number of groups and observations	70	247		
From 2007 to 2010	4			

Source: Authors' calculations.

*Note: Significance codes: 0.001 = ***, 0.01 = **, 0.05 = *, 0.1 = •.*

Table 5

Ratio of Operating Profit to Total Assets

	Estimate	Standard error	t-value	p-value
Sample of European banks (90 banks)				
Lag(LoanImpairmentCharge/TotalAssets,1)	−0.8651	0.1422	−6.08	0.0000***
Lag(ProxyNPLStock/TotalAssets,1)	0.0001	0.0533	0.00	0.9978
Lag(TotalEquity/TotalAssets,1)	0.0933	0.0568	1.64	0.1023
Lag(RWAs/TotalAssets,1)	−	−	−	−
Lag(NetInterestIncome/TotalAssets,1)	0.5777	0.1705	3.39	0.0009***
Lag(TotalNonInterestOpIncome/TotalAssets,1)	−0.0061	0.1207	−0.05	0.9596
Lag(LiquidAssets/TotalAssets,1)	0.0083	0.0092	0.90	0.3676
Lag(TotalCustomerDeposits/TotalAssets,1)	0.0120	0.0129	0.93	0.3526
Lag(Longtermfunding/TotalAssets,1)	0.0132	0.0097	1.37	0.1720
Lag(Loan.CustomerDeposit,1)	0.0014	0.0007	1.97	0.0509 •
Lag(ProxyTradingBook/TotalAssets,1)	0.0146	0.0090	1.62	0.1077
Lag(GrossLoanGrowth,1)	0.0038	0.0019	2.02	0.0452 *
Year dummy for 2007	−0.0190	0.0085	−2.22	0.0280 *
Year dummy for 2008	−0.0246	0.0009	−6.49	0.0000***
Year dummy for 2009	−0.0232	0.0012	−3.46	0.0010 **
Year dummy for 2010	−0.0194	0.0014	−0.29	0.7720
Root-squared: within, between and overall	0.4742	0.4829	0.4999	
Number of groups and observations	70	249		
From 2007 to 2010	4			

Source: Authors' calculations.

*Note: Significance codes: 0.001 = ***, 0.01 = **, 0.05 = *, 0.1 = •.*

Table 6

Ratio of Operating Profit to Risk-Weighted Assets

	Estimate	Standard error	t-value	p-value
Sample of European banks (90 banks)				
Lag(LoanImpairmentCharge/TotalAssets,1)	15.5571	10.1909	1.53	0.1288
Lag(ProxyNPLStock/TotalAssets,1)	−4.3718	3.7577	−1.16	0.2463
Lag(TotalEquity/TotalAssets,1)	3.6111	3.8726	0.93	0.3525
Lag(RWAs/TotalAssets,1)	−	−	−	−
Lag(NetInterestIncome/TotalAssets,1)	9.4413	11.5288	0.82	0.4140
Lag(TotalNonInterestOpIncome/TotalAssets,1)	−14.5574	8.7791	−1.66	0.0992 •
Lag(LiquidAssets/TotalAssets,1)	0.3312	0.6485	0.51	0.6102
Lag(TotalCustomerDeposits/TotalAssets,1)	2.8747	0.9086	3.16	0.0019 **
Lag(Longtermfunding/TotalAssets,1)	0.4440	0.6697	0.66	0.5082
Lag(Loan.CustomerDeposit,1)	0.0747	0.0491	1.52	0.1301
Lag(ProxyTradingBook/TotalAssets,1)	0.6973	0.6938	1.01	0.3164
Lag(GrossLoanGrowth,1)	0.1228	0.1312	0.94	0.3505
Year dummy for 2007	−1.7446	0.5996	−2.91	0.0040**
Year dummy for 2008	−1.7297	0.0599	0.25	0.8040
Year dummy for 2009	−1.8392	0.0838	−1.13	0.2610
Year dummy for 2010	−1.8511	0.0994	−1.07	0.2850
Root-squared: within, between and overall	0.1193	0.1131	0.0596	
Number of groups and observations	70	249		
From 2007 to 2010	4			

Source: Authors' calculations.

*Note: Significance codes: 0.001 = ***, 0.01 = **, 0.05 = *, 0.1 = •.*

Table 7

Return on Average Assets

	Estimate	Standard error	t-value	p-value
Sample of OECD banks (957 banks)				
Lag(LoanImpairmentCharge/TotalAssets,1)	−83.1925	5.3625	−15.51	0.0000***
Lag(ProxyNPLStock/TotalAssets,1)	12.9437	2.6189	4.94	0.0000***
Lag(TotalEquity/TotalAssets,1)	−5.7711	2.6482	−2.18	0.0296*
Lag(RWAs/TotalAssets,1)	−0.7030	0.4937	−1.42	0.1548
Lag(NetInterestIncome/TotalAssets,1)	35.6976	10.8601	3.29	0.0011**
Lag(TotalNonInterestOpIncome/TotalAssets,1)	5.3246	5.8989	0.90	0.3670
Lag(LiquidAssets/TotalAssets,1)	1.3127	0.6502	2.02	0.0438*
Lag(TotalCustomerDeposits/TotalAssets,1)	2.6332	0.7192	3.66	0.0003***
Lag(Longtermfunding/TotalAssets,1)	2.5088	0.7652	3.28	0.0011**
Lag(Loan.CustomerDeposit,1)	0.0000	0.0001	0.01	0.9906
Lag(GrossLoanGrowth,1)	0.0198	0.0964	0.21	0.8374
Year dummy for 2007	−0.9392	0.4998	−1.88	0.0610•
Year dummy for 2008	−1.3841	0.0796	−5.59	0.0000***
Year dummy for 2009	−1.3984	0.0902	−5.09	0.0000***
Year dummy for 2010	−1.1468	0.0964	−2.15	0.0320*
Root-squared: within, between and overall	0.3314	0.0476	0.159	
Number of groups and observations From 2007 to 2010	444 4	1,267		

Source: Authors' calculations.
*Note: Significance codes: 0.001 = ***, 0.01 = **, 0.05 = *, 0.1 = •.*

Table 8

Return on Average Equity

	Estimate	Standard error	t-value	p-value
Sample of OECD banks (957 banks)				
Lag(LoanImpairmentCharge/TotalAssets,1)	−1,754.7538	123.4648	−14.21	0.0000***
Lag(ProxyNPLStock/TotalAssets,1)	395.0031	60.2978	6.55	0.0000***
Lag(TotalEquity/TotalAssets,1)	−168.0256	60.9728	−2.76	0.0060**
Lag(RWAs/TotalAssets,1)	−4.6233	11.3664	−0.41	0.6843
Lag(NetInterestIncome/TotalAssets,1)	795.5429	250.0419	3.18	0.0015**
Lag(TotalNonInterestOpIncome/TotalAssets,1)	93.5276	135.8151	0.69	0.4912
Lag(LiquidAssets/TotalAssets,1)	28.2402	14.9701	1.89	0.0596•
Lag(TotalCustomerDeposits/TotalAssets,1)	51.2948	16.5584	3.10	0.0020**
Lag(Longtermfunding/TotalAssets,1)	72.0967	17.6182	4.09	0.0000***
Lag(Loan.CustomerDeposit,1)	−0.0003	0.0023	−0.15	0.8845
Lag(GrossLoanGrowth,1)	−0.5005	2.2192	−0.23	0.8216
Year dummy for 2007	−16.2603	7.6940	−2.11	0.0350*
Year dummy for 2008	−25.4831	1.8081	−5.10	0.0000***
Year dummy for 2009	−23.6577	1.9121	−3.87	0.0000***
Year dummy for 2010	−18.5681	2.0673	−1.12	0.2640
Root-squared: within, between and overall	0.2665	0.0813	0.177	
Number of groups and observations From 2007 to 2010	444 4	1,276		

Source: Authors' calculations.
*Note: Significance codes: 0.001 = ***, 0.01 = **, 0.05 = *, 0.1 = •.*

Table 9

Equity Price

	Estimate	Standard error	t-value	p-value
Sample of OECD banks (957 banks)				
Lag(LoanImpairmentCharge/TotalAssets,1)	21.1577	5.9573	3.55	0.0004 ***
Lag(ProxyNPLStock/TotalAssets,1)	−2.3263	2.2681	−1.03	0.3058
Lag(TotalEquity/TotalAssets,1)	3.5615	2.3079	1.54	0.1237
Lag(RWAs/TotalAssets,1)	0.0800	0.3810	0.21	0.8339
Lag(NetInterestIncome/TotalAssets,1)	−8.7091	7.5249	−1.16	0.2479
Lag(TotalNonInterestOpIncome/TotalAssets,1)	4.9954	4.0292	1.24	0.2159
Lag(LiquidAssets/TotalAssets,1)	−0.8662	0.4894	−1.77	0.0776 •
Lag(TotalCustomerDeposits/TotalAssets,1)	0.6185	0.5839	1.06	0.2902
Lag(Longtermfunding/TotalAssets,1)	−0.8976	0.5704	−1.57	0.1165
Lag(Loan.CustomerDeposit,1)	0.0721	0.0362	1.99	0.0469 *
Lag(GrossLoanGrowth,1)	−0.1916	0.0772	−2.48	0.0135
Year dummy for 2007	−0.3342	0.4292	−0.78	0.4370
Year dummy for 2008	−0.8146	0.0549	−8.75	0.0000 ***
Year dummy for 2009	−0.0518	0.0656	4.30	0.0000 ***
Year dummy for 2010	−0.4029	0.0782	−0.88	0.3810
Root-squared: within, between and overall	0.4843	0.1227	0.2555	
Number of groups and observations	209	568		
From 2007 to 2010	4			

Source: Authors' calculations.

*Note: Significance codes: 0.001 = ***, 0.01 = **, 0.05 = *, 0.1 = •.*