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BANK PROFITABILITY AND MACROECONOMIC CONDITIONS: ARE BUSINESS MODELS DIFFERENT?

by Emilia Bonaccorsi di Patti* and Francesco Palazzo*

Abstract

The paper investigates the impact of macroeconomic conditions on the profitability of EU banks, by testing for differential effects according to the business model. We group banks into three business models using a hierarchical cluster analysis, and find that using clusters based on the share of assets invested in loans reveals heterogeneity in the sensitivity of bank profitability to economic growth across business models. Our main result is that GDP growth, credit growth and the risk-free yield curve influence profitability as expected, but we also find that the effect of GDP growth is only significant for banks that have a high and medium share of assets invested in loans, and not for banks that hold large portfolios of securities. This difference depends on the impact of growth on asset write downs, especially those on loans and, to a lesser extent, on revenues. The results suggest that studies relating bank profitability to macroeconomic conditions should take the heterogeneity of business models into account.

JEL Classification: G21.
Keywords: bank profitability, bank business model, income statement, revenues, net interest income.

Contents

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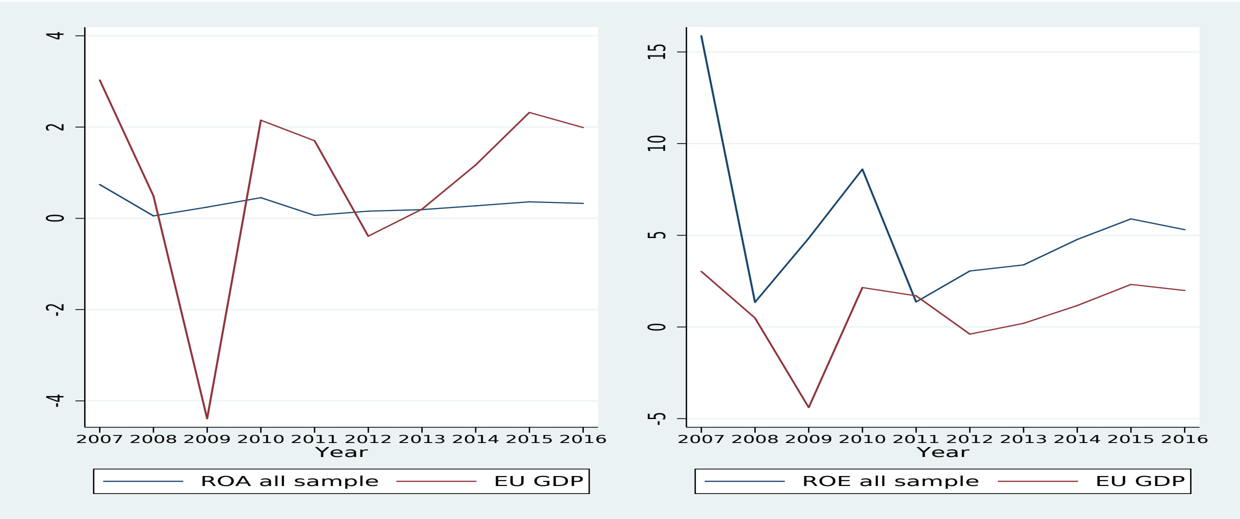
1 Introduction*

Weak profitability is one of the key challenges currently faced by many banks in the European Union (ECB (2016)). Since the outbreak of the global financial crisis the profitability of European banks declined substantially, and has not recovered to its pre-crisis level yet (Figure 1).

Macroeconomic conditions are one critical driver of bank profitability dynamics. In particular, recent analyses on single (e.g. Albertazzi et al. (2016)) or multiple countries (Kok, Móré and Pancaro (2015)) show that cyclical factors explain a significant portion of the heterogeneity in the intensity and the timing of the drop in profitability observed across banks. In countries facing the sovereign debt crisis banks were hit harder after 2011, as their economies deteriorated, while losses peaked in 2008 in countries where banks were more exposed to the subprime crisis and to toxic assets. In recent years, the low interest rate environment has been compressing net interest margins, but the empirical relationship between overall profitability and the level of nominal interest rates is not statistically robust once growth is included in the regressions (Genay and Podjasek (2014); Claessens et al. (2017); ESRB (2016)). In countries where the recession was particularly severe, banks are still paying a high cost of risk in terms of provisioning, and profitability remains weak though improving (EBA (2017)).

Figure 1: Profitability of EU banks 2007-2016



Note: ROA and ROE are averages weighted by banks' total assets or equity. GDP is annual real GDP growth in the EU. Data are from SNL Financial and the sample is an unbalanced panel including 221 banks from 25 countries.

Another strand of literature investigates to what extent the business models of European banks are the underlying cause of their weak profitability, but the results are mixed. Cross-country studies show that some business models appear to be more profitable than others, but the results are dependent on the period studied, and the countries analyzed. For example, Roengpitya et al. (2017) distinguish between retail banks (high share of retail deposits and customer loans), trading banks (high share of securities and significant reliance on wholesale funding), wholesale banks

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(highest reliance on wholesale funding). They find that retail banks have the highest profitability and the lowest variability in performance over time; on the contrary, trading banks have the most volatile performance and the highest operating costs. Similarly, Mergaerts and Vennet (2016) show that retail-oriented banks have both a higher and less volatile dynamics for profits, and they argue that income diversification improves profitability, although it also increases susceptibility to distress. Instead, Ayadi et al. (2016) find that retail banks were more resilient than wholesale banks during the 2008-09 crisis, but their profitability declined significantly in 2010-12 as the quality of credit worsened. Using data up to 2014 Farnè and Vouldis (2017) find instead that securities-holding and wholesale-funded banks seem to have the best performing business models relative to commercial banks.

One important limitation of these analyses is that they overlook macroeconomic conditions when comparing banks with different business models. Since the distribution of business models across countries is uneven, it is not possible to distinguish between the contribution of business model weakness *vis-á-vis* the effect of adverse macroeconomic conditions, unless the two factors are analyzed jointly. In this study we provide evidence on how the profitability of banks adopting distinct business models was differentially affected by macroeconomic conditions using a panel of more than 221 European banks. We first apply cluster analysis to divide banks into three business models—based on endogenous thresholds of the share of assets invested in loans—then we employ regression analysis to test for heterogeneity in the coefficients of variables measuring macroeconomic conditions faced by banks.

Our main findings are the following. First, consistently with the previous evidence, the profitability of banks is influenced by macroeconomic conditions: it is positively correlated with credit growth, and the level and slope of risk-free interest rates. Second, there are significant differences in the sensitivity of profitability to GDP growth between bank business models, but no statistically significant difference for other macroeconomic variables. In particular, banks with a stronger orientation towards lending (a high share of loans) exhibit a higher sensitivity to GDP growth than other banks. Third, GDP growth affects the profitability of lending-oriented banks through operating revenues and asset write downs; for these banks impairments on loans were more responsive to the business cycle than those on securities. The results are robust to the choice of different samples, and different estimation approaches and specifications. In particular, we consider the potential endogeneity of explanatory variables and estimate the fixed effect model not only by OLS but also by GMM.

A caveat of our analysis is that our estimated effects capture correlations, but cannot be interpreted as causal relationships. Nevertheless, we can conclude that the business model is a relevant dimension that should be taken into account when studying the relationship between macroeconomic conditions and profitability, not only when analyzing the determinants of observed dynamics but also for forecasting purposes.

The paper is structured as follows. Section 2 describes the data set. Section 3 derives different business models with hierarchical cluster analysis. Section 4 presents the main results of our regression analysis. Section 5 provides some robustness exercises. Section 6 concludes.

2 Data

We collect data on banks in the 28 EU countries for the period 2006-16 from SNL Financials. We also include banks from countries that entered the EU after 2006.[1] We select all European parent banking groups in SNL Financial still in existence as of December 2016 and for which data are available. The set includes 262 banks from 25 EU countries. Due to the use of lagged variables both for macro and bank level variables, our estimation sample includes the 10 years between 2007 and 2016. We then exclude two categories of banks: i) banks that provide financial services and act as hubs for liquidity to affiliated institutions ("network" banks), and banks controlled by local or central government ("public banks"). The former group includes five banks.[2] The latter group comprises five entities whose mandate is to serve economic development goals or to support specific industries.[3]

Bank profitability is measured as net income before taxes scaled by end of year total assets (pre-tax ROA). We also consider the main components of net income to investigate the channels through which the macroeconomic variables affect profitability, specifically: net interest margin, commission and fee net revenues, trading income, operating expenses and asset write downs. To control for bank heterogeneity we construct the following bank-level variables: the logarithm of total assets to measure bank size, loans excluding interbank loans (henceforth loans), retail deposits, cash holdings,[4] the Tier 1 capital ratio. Loans, deposits and cash holdings are divided by total assets.

We drop for each year observations in the top and bottom 1 percent of the distribution of net income—our main outcome variable—to remove outliers.[5] The final sample is an unbalanced panel of 221 banks and 1,818 bank-year observations. Table 1 provides an overview of the cross-country distribution of banks in the sample. In 2016 their total assets amounts to 28.9 trillion, equivalent to 87 percent of consolidated assets of EU credit institutions.[6]

The relevant macroeconomic variables are collected from the ECB Data Warehouse and Bloomberg. We include the short-term nominal level of the interest rate, the slope of the risk-free yield curve, annual real GDP growth, annual credit growth. We also include the sovereign spread in some of the specifications. GDP and credit growth are measured at the country level. Credit growth refers

[1] Bulgaria and Romania entered in 2007 and Croatia in 2013.

[2] DZ BANK AG Deutsche Zentral-Genossenschaftsbank, Istituto Centrale delle Banche Popolari, Münchener Hypothekenbank, OP Financial Group, Volksbanken-Verbund.

[3] Belfius Banque SA, Cassa depositi e prestiti SpA, Instituto de Crédito Oficial, La Banque Postale, SA, Patria Bank SA.

[4] The item includes cash, central bank balance and net loans to banks.

[5] We consider outliers only based on pre-tax ROA because they would depend on either an extreme observation for one of the main income statement components (revenues, costs, asset write downs)—so they would be excluded also by taking into account outliers for other main income statement variables—or an idiosyncratic one-off item that would only add noise to our estimates.

[6] EU consolidated assets of credit institutions were 33 trillion at the end of 2016 (ECB (2017)).

Table 1: Distribution of banks by country

Country	Bank-year obs.	%	Banks	%
Austria (AT)	147	8.09	17	7.69
Belgium (BE)	43	2.37	5	2.26
Bulgaria (BG)	23	1.27	3	1.36
Cyprus (CY)	24	1.32	4	1.81
Germany (DE)	394	21.67	53	23.98
Denmark (DK)	213	11.72	22	9.95
Spain (ES)	93	5.12	13	5.88
Finland (FI)	29	1.60	3	1.36
France (FR)	45	2.48	5	2.26
United Kingdom (GB)	179	9.85	22	9.95
Greece (GR)	46	2.53	5	2.26
Croatia (HR)	38	2.09	7	3.17
Hungary (HU)	29	1.60	3	1.36
Ireland (IE)	29	1.60	3	1.36
Italy (IT)	200	11.00	21	9.50
Lithuania (LT)	2	0.11	1	0.45
Latvia (LV)	4	0.22	1	0.45
Malta (MT)	17	0.94	2	0.90
Netherlands (NL)	66	3.63	8	3.62
Poland (PL)	49	2.70	6	2.71
Portugal (PT)	41	2.26	5	2.26
Romania (RO)	5	0.28	1	0.45
Sweden (SE)	66	3.63	7	3.17
Slovenia (SI)	28	1.54	3	1.36
Slovakia (SK)	8	0.44	1	0.45
Total	1,818	100	221	100

to total bank credit to the domestic private sector. We instead consider a common risk-free yield curve for all banks. The short-term interest rate is the yearly average of the daily Euribor rate with one-year maturity, and the slope is measured by the difference between the yearly average of the 10-year Interest Rate Swap (IRS) yield and the one-year Euribor rate. We apply these interest rates variables also to countries outside the euro area because they are important benchmarks for the whole European Union, and they provide a readily available risk-free measure that excludes spreads due to country-specific sovereign risk.[7] We measure sovereign risk premium as the domestic spread between the 10-year government bond for each banks and the 10-year euro Interest Rate Swap yield. As a control for the financial markets performance we construct the yearly percentage change in the Euro Stoxx 50 Index.[8] Statistics for the macroeconomic variables are shown in Table 2 below.

Table 2: Descriptive statistics - Macroeconomic variables.

	Mean	St. Dev.	25^{th} perc.	50^{th} perc.	75^{th} perc.
Euribor 1 Year	1.376	1.457	0.469	1.059	1.550
Spread IRS 10Y - Euribor 1Y	0.934	0.593	0.536	0.918	1.366
Domestic Credit Growth	1.368	5.996	-1.270	1.155	2.995
Real GDP Growth	0.696	2.489	-0.073	1.262	1.972
Real GDP Growth lag 1	0.759	2.627	-0.244	1.248	2.336
Euro Stoxx 50 Growth	1.615	17.818	-3.570	0.543	14.669
Sovereign Spread on 10Y Bond	0.814	2.064	-0.260	0.069	1.026

[7] As described below, for robustness purposes we estimate the regressions replacing the euro area interest rate slope with a country specific one for banks in the United Kingdom, Sweden and Denmark—the countries with more observations in the sample outside the euro area—computed as the difference between the yearly averages of the 1 year and 10 year rates on government bonds.

[8] National indices could have been more influenced by the behavior of the stocks of domestic banks, especially in some countries, and indices excluding banks were not always available. For the purpose of having a control variable for equity market conditions we believe the overall index is adequate.

3 Definition of bank business models

The first step of our empirical analysis is to identify the business models of the banks in the sample. The literature generally follows either of the following two approaches. The first approach is based on judgment, starting from descriptive statistics on one or more key balance sheet or income statement variables. For example, Bonaccorsi di Patti, Felici, Signoretti (2016) divide banks referring to the degree of specialization, size, share of cross border exposure and share of assets invested in loans (whether below or above 50 per cent). The second approach is data-driven and is usually based on clustering algorithms run on one or more bank characteristics, typically the composition of income, assets and/or liabilities.

The latter approach is becoming more popular. ECB (2016) identifies seven business models for the 113 significant institutions supervised by the Single Supervisory Mechanism, referring to combinations of size, composition of operating income, composition of funding, trading assets and domestic exposure as a share of total assets. Farnè and Vouldis (2017) divide a similar set of banks into four clusters, essentially based on a combination of the share of assets invested in loans and the share of funding through deposits; the outcome is four categories: wholesale funded banks, securities holding banks, traditional commercial banks and complex commercial banks. Specialized institutions such as state owned entities aimed at refinancing loans to semi-public and public entities are considered outliers by the clustering method. Similarly, Roengpitya et al. (2017) use cluster analysis on a dataset covering 178 banks from 34 countries over the period 2005-15, and identify four business models.[9] Importantly, this analysis shows that banks transition away from wholesale funding into retail funding after 2008, following the freeze of the interbank market. Bank performance is correlated to the funding model because banks that switched from wholesale to retail funding performed better, although this result could be specific to the post-Lehman default period. Irrespective of the observed performance, the fact that banks shift more rapidly the composition of their funding sources relative to their asset holdings suggests that clustering based on asset characteristics could be less influenced by temporary factors, hence better suited for regression analysis.

In this paper we follow the data-driven approach and employ a hierarchical clustering algorithm to categorize banks. The approach is based on building a hierarchy of clusters; the algorithm starts with all data points assigned to a cluster of their ow, and at each subsequent step the algorithm merges into the same cluster the two nearest clusters until there is only a single cluster left. The decision of merging two clusters is taken on the basis of a metric measuring the 'closeness' of two clusters. We follow the method proposed by Ward (1963), according to which the criterion for choosing the pair of clusters to be merged at each step is based on the optimal value of an objective function. In our case we follow Ward's minimum variance method, in which the objective

[9] The first two are commercial banks with large loan portfolios that differ in their funding base: one is mainly deposit-funded while the other wholesale-funded, through bonds and interbank markets; the third includes banks with a significant share of trading activities, and holding securities portfolios funded in the interbank and wholesale markets; the fourth, the universal banking model, is a mixture of the other three.

Table 3: Distribution of banks by loans and deposits

Year	Loans			Deposits		
	p10	p50	p90	p10	p50	p90
2007	41.08	63.15	78.29	22.38	46.84	72.47
2008	36.19	66.42	79.46	22.69	49.43	74.53
2009	39.29	63.79	79.12	21.67	53.63	78.28
2010	37.43	62.86	79.62	23.48	53.98	81.03
2011	37.92	63.83	78.80	24.79	56.60	82.03
2012	41.24	63.80	78.23	26.59	57.99	81.92
2013	41.94	63.23	78.05	29.87	59.35	82.54
2014	40.28	62.24	79.10	27.98	61.62	83.79
2015	40.16	63.81	78.54	28.49	63.92	83.71
2016	39.81	63.32	78.96	30.46	66.56	83.95

function is the standard error sum of squares.

The clustering is performed using the share of loans to the non-financial sector (henceforth just loans) on bank-year observations, following Roengpitya et al. (2017). Our data show that the share of deposit funding steadily increased after the outburst of the Global Financial Crisis, as banks adjusted to tighter conditions on wholesale markets. Table 3 reports the 10, 50 and 90-th percentile of the distribution of loans and deposits to households and firms, as shares of total assets. The share of loans might be capturing more closely than other indicators the business focus of a bank, the skills that have been developed over time, and its corporate culture. In principle, the share of income from interest might be an alternative, but we note that it is strongly influenced by cyclical factors, especially in the period examined, and by the way banks price their services. For example, in recent years banks have been increasing commission and fee income; this does not necessarily mean that commercial banks have stopped providing loans and collecting deposits, but only that they might have priced services differently since they cannot pass negative rates to depositors.

The cluster analysis yields the dendrogram reported in Figure 5 of the Appendix.[10] The plot suggests that a parsimonious choice is to have three different clusters, since it would capture the variability across banks without incurring in a too high penalization from aggregating dissimilar observations. Since the analysis is performed on one variable—the share of loans—each cluster is identified by two endogenous thresholds. We obtain three groups of banks depending on the share of assets invested in loans: "low", "medium" or "high". In particular, the "low" cluster includes all banks with a share of loans between 0 and 38.6 percent, the "medium" cluster all banks with values between 38.6 and 62 percent, while all banks above the latter threshold belong to the "high" cluster. Table 4 reports the mean and standard deviation of key bank variables, by cluster, and for the whole sample of banks.

The "low" banks are 19 entities displaying significant differences relative to the other two clusters both in terms of balance sheet and income statement composition. "Low" banks are larger,

[10]The dendrogram is a graphical tool to decide the most suitable number of clusters. See the Appendix for more details.

hold a higher share of securities, are funded to a lesser extent with retail deposits, have a a lower incidence of asset write downs and a higher share of income from fees and commissions than from net interest. The other two clusters share similar features, except for the clustering variable and, more importantly, for their size. Banks in the "high" cluster are on average significantly smaller than the others.

Table 4: Descriptive statistics by business model

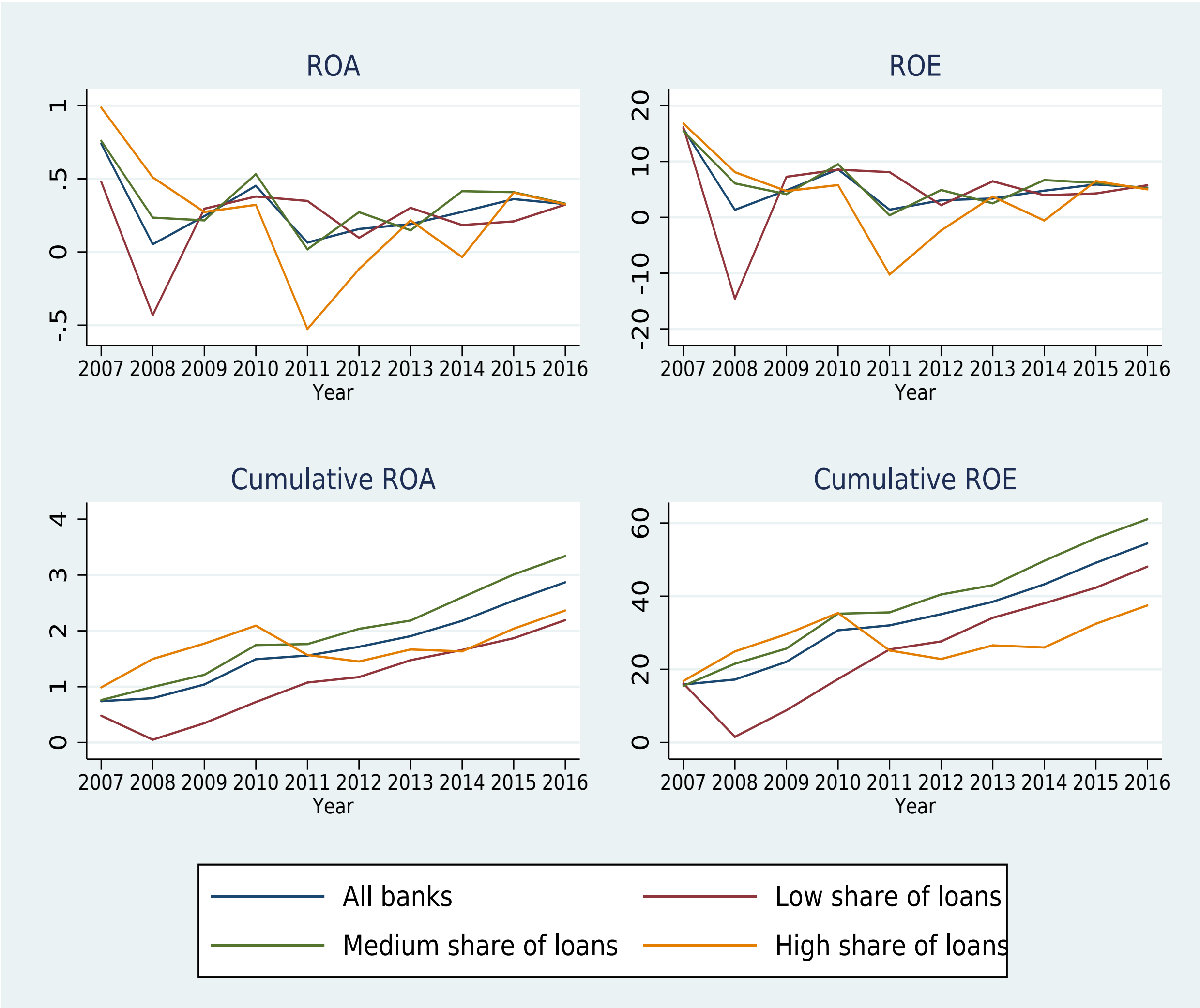
	Low	Medium	High	Total
Net Income pre-taxes	0.362	0.302	0.242	0.275
	(0.958)	(1.093)	(1.285)	(1.189)
Operating Income	2.122	2.929	2.927	2.854
	(1.611)	(1.794)	(1.627)	(1.705)
Net Interest Income	0.918	1.810	1.986	1.823
	(0.715)	(0.935)	(1.168)	(1.092)
Fee Income	1.363	0.885	0.812	0.890
	(1.888)	(0.958)	(0.580)	(0.933)
Trading Income	0.186	0.234	0.131	0.174
	(0.473)	(0.587)	(0.271)	(0.435)
Operating Expenses	1.500	1.888	1.867	1.841
	(1.288)	(1.342)	(1.067)	(1.201)
Asset write downs	0.271	0.750	0.783	0.724
	(0.378)	(1.034)	(1.027)	(0.998)
Loans and Credits Impairments	0.179	0.613	0.653	0.594
	(0.235)	(0.962)	(0.986)	(0.942)
Securities Impairments	0.0343	0.0376	0.0346	0.0357
	(0.0845)	(0.110)	(0.0856)	(0.0955)
Cash Holdings	23.12	13.62	8.459	11.72
	(16.55)	(8.812)	(4.911)	(9.254)
Loans to customers	27.31	52.68	72.39	60.92
	(9.024)	(6.384)	(6.897)	(15.74)
Securities	45.72	27.47	15.02	22.48
	(15.05)	(8.965)	(6.392)	(12.70)
Retail Deposits	41.48	54.29	58.76	55.51
	(23.57)	(21.53)	(19.45)	(21.21)
Bank debt liabilities	14.56	15.32	18.68	17.06
	(13.44)	(14.59)	(19.28)	(17.27)
Tier 1 capital	14.91	13.51	12.49	13.09
	(7.760)	(4.758)	(5.188)	(5.373)
Assets (mld euro)	451.7	216.7	49.86	148.8
	(727.4)	(402.8)	(109.3)	(361.1)
Banks in 2016	19	84	118	221
Bank-Year Obs.	167	676	975	1818

Means; standard deviation in parentheses.
Note: all variables are scaled by total assets except for Tier 1 capital, which is scaled by risk weighted assets.

Profitability declined for all the three groups (Figure 2), but starting from different levels. Before the crisis the ROA of "high" was higher than the one of "low" banks. The ROE of the two groups of banks was instead similar because banks in the former cluster generally had lower leverage than those in the latter. In the last couple of years the performance of all three groups roughly converged both in terms of ROA and ROE.

Some sharp differences exist in the responsiveness of clusters during the two major crisis episodes, i.e. the Global Financial Crisis in 2007-08 and the Sovereign Debt Crisis in 2011. Banks in the "low" group suffered exceptional losses in 2008, immediately recovered in 2009-11 with a ROE of around 8 percent but later declined to levels of around 5 percent. On the contrary, banks in the "high" group experienced a modest decline in ROE and ROA in 2008, a much sharper drop in 2011, and a gradual recovery only in the last two years. The banks in the "medium" group display an intermediate pattern: they suffered from both shocks but not as much as the "low" and "high" group, respectively.

Figure 2: Profitability dynamics by business models 2007-16



Note: Weighted averages by bank total assets or bank equity for each cluster. The cumulative ROA and ROE in year t is the sum of the yearly ROA and ROE, respectively, for all years $s \leq t$. Vertical axes in percentage points.

Cumulating ROA over the entire period we observe that the banks that performed better over the entire period were those in the "medium" category, in terms of both ROA and ROE. A more complete assessment would require a full business and credit cycle but the data are not available for the full sample before 2006. Nonetheless, the data exhibit sufficient variability at the bank level since they refer to countries that experienced shocks of different magnitude and at different times.

4 Results

4.1 Macroeconomic conditions and business model profitability

We first regress bank profitability on the macroeconomic variables, time varying bank-level controls, and bank fixed effects to account for unobserved heterogeneity. Since we are primarily interested in the coefficients of the interaction terms between categorical variables identifying the bank business models and the macroeconomic variables, we prefer this approach as opposed to dynamic models. Dynamic panel data models require estimation methods such as system GMM (Arellano and Bover (1995); Blundell and Bond (1998)), which are asymptotically consistent, but yield unstable coefficient estimates when different sets of instruments are used.[11] The interaction terms increase the number of endogenous variables that need to be instrumented and the model is even more likely to be affected by the issue of weak instruments. However, for robustness purposes, in section 5.6 we show that our main results hold if we specify a dynamic model and estimate it either with GMM or an alternative method suggested by Bruno (2005) to correct for the lagged dependent variable bias.

Our first regression does not consider the distinction between business models (Table 5).

Table 5: Estimation results - without business model distinction

	Net Income pre-taxes	Operating Income	Operating Expenses	Asset write downs
Euribor 1 Year	0.038	0.054	0.016	-0.032
	(0.036)	(0.047)	(0.042)	(0.030)
Spread IRS 10Y - Euribor 1Y	0.146*	0.109**	-0.009	-0.035
	(0.083)	(0.051)	(0.042)	(0.050)
Euro Stoxx 50 Growth	0.005***	0.002	-0.000	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Domestic Credit Growth	0.038***	-0.004	-0.009*	-0.033***
	(0.007)	(0.005)	(0.005)	(0.007)
GDP Growth	0.059***	0.008	0.001	-0.029***
	(0.020)	(0.008)	(0.007)	(0.010)
GDP Growth lag 1	0.061***	0.012	-0.003	-0.037***
	(0.020)	(0.010)	(0.008)	(0.010)
Log Total Assets lag 1	-0.356**	-0.697***	-0.568***	0.088
	(0.141)	(0.187)	(0.193)	(0.135)
Tier 1 capital lag 1	0.002	0.001	0.002	-0.013
	(0.011)	(0.011)	(0.010)	(0.009)
Deposits lag 1	0.005	0.002	0.005	-0.013*
	(0.006)	(0.008)	(0.004)	(0.008)
Cash Holdings lag 1	-0.011	-0.012	0.003	-0.002
	(0.010)	(0.009)	(0.012)	(0.005)
Constant	0.859	4.796***	3.232***	1.538*
	(0.737)	(0.890)	(0.781)	(0.824)
Adjusted R2	0.125	0.081	0.091	0.128
N	1818	1818	1817	1816

Bank fixed effects are included; robust standard error (in parentheses) clustered at the bank level.
All variables scaled by bank total assets except for Tier 1 capital, which is scaled by risk weighted assets.
* p<.1, ** p<.05, *** p<.01.

[11] Monte Carlo simulations show that the GMM estimators have a relatively large standard deviation compared to the fixed effects estimator (Arellano and Bond (1991); Kiviet (1995)). They also may suffer from a substantial finite sample bias due to weak instrument problems (Ziliak (1997); Bun and Kiviet (2006); Bun and Windmeijer (2010)). Finally, even when many valid instruments are available, instrument proliferation may render the GMM estimator invalid (Roodman (2009)).

The coefficients are consistent with those of other studies. Real GDP growth, its lag, and credit growth have a positive and significant coefficient in the overall profitability regression. The main channel through which these variables affect profitability is through asset write downs; unit revenues and unit costs are not significantly affected by the business and financial cycle fluctuations. The level of the short term interest rate is statistically insignificant, but the slope of the yield curve has a positive and statistically significant coefficient, consistently with the expectation that banks benefit when long term yields are higher than short term ones because they perform maturity transformation. The slope of the curve affects primarily bank revenues.

In a second set of regressions we test for the presence of heterogeneous effects of macroeconomic variables on the profitability of the three business models (Table 6).

Table 6: Estimation results - Effects by business model for all macroeconomic variables

	Net Income pre-taxes	Operating Income	Operating Expenses	Asset Writedowns
Euribor 1 Year	0.076	0.040	-0.003	-0.072*
	(0.047)	(0.039)	(0.027)	(0.038)
Δ Euribor 1 Year effect medium	-0.067	0.056	0.057	0.088*
	(0.052)	(0.073)	(0.076)	(0.046)
Δ Euribor 1 Year effect low	-0.095*	-0.065	-0.039	0.048
	(0.053)	(0.062)	(0.083)	(0.040)
Spread IRS 10Y - Euribor 1Y	0.173*	0.149**	-0.029	-0.011
	(0.094)	(0.065)	(0.041)	(0.061)
Δ Spread IRS 10Y - Euribor 1Y effect medium	-0.059	-0.107	0.024	-0.061
	(0.081)	(0.093)	(0.058)	(0.059)
Δ Spread IRS 10Y - Euribor 1Y effect low	-0.098	-0.055	0.093	-0.056
	(0.136)	(0.140)	(0.090)	(0.075)
Euro Stoxx 50 Growth	0.007***	0.001	-0.001	-0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Δ Euro Stoxx 50 effect medium	-0.004	0.005	0.003	0.003
	(0.003)	(0.003)	(0.002)	(0.003)
Δ Euro Stoxx 50 effect low	-0.003	-0.003	-0.003	-0.002
	(0.003)	(0.002)	(0.003)	(0.002)
Domestic Credit Growth	0.038***	-0.007	-0.005*	-0.037***
	(0.007)	(0.005)	(0.003)	(0.005)
Δ Credit Growth effect medium	-0.005	0.004	-0.010	0.010
	(0.016)	(0.008)	(0.010)	(0.014)
Δ Credit Growth effect low	-0.018	0.022	0.006	0.033**
	(0.014)	(0.019)	(0.022)	(0.013)
GDP Growth high	0.074***	0.020**	-0.001	-0.017
	(0.027)	(0.009)	(0.008)	(0.011)
Δ GDP effect medium	-0.020	-0.025**	0.002	-0.034**
	(0.028)	(0.011)	(0.009)	(0.015)
Δ GDP effect low	-0.071**	-0.051**	-0.001	-0.014
	(0.028)	(0.022)	(0.019)	(0.017)
GDP Growth lag 1 high	0.073***	0.027*	-0.004	-0.027**
	(0.025)	(0.014)	(0.008)	(0.011)
Δ GDP lag 1 effect medium	-0.019	-0.037**	0.001	-0.035*
	(0.027)	(0.016)	(0.009)	(0.019)
Δ GDP lag 1 effect low	-0.082***	-0.032*	0.011	0.032
	(0.028)	(0.019)	(0.019)	(0.021)
Log Total Assets lag 1	-0.335**	-0.697***	-0.581***	0.069
	(0.148)	(0.195)	(0.204)	(0.139)
Tier 1 capital lag 1	0.002	0.002	0.002	-0.012
	(0.011)	(0.011)	(0.010)	(0.009)
Deposits lag 1	0.005	0.002	0.005	-0.014*
	(0.006)	(0.008)	(0.004)	(0.008)
Cash Holdings lag 1	-0.008	-0.011	0.003	-0.004
	(0.009)	(0.010)	(0.012)	(0.005)
Constant	0.765	4.797***	3.271***	1.654*
	(0.770)	(0.909)	(0.804)	(0.845)
r2	0.138	0.093	0.100	0.145
N	1818	1818	1817	1816

Bank level fixed effect estimation with robust standard error (in parentheses) at bank level.
All variables scaled by bank total assets except for Tier 1 capital, which is scaled by risk weighted assets.
* p<.1, ** p<.05, *** p<.01.

Since we include bank fixed effects we cannot estimate the average difference in profitability across business models, but only the different sensitivity to the relevant variables. The reference group is made of banks with a "high" share of loans, so the estimated coefficients measure the change in the marginal effect between the "high" group and the other two groups.

Most macroeconomic variables do not have statistically different effects across business models (at least at the 5% significance level). The notable exception is GDP growth. In the net income before taxes regression both the simultaneous and the lagged GDP coefficients are statistically significant at the 1% level for banks with a "high" and "medium" share of loans. Although the two groups are not statistically different because the interaction term is not significant, the data suggest that the effect for the "medium" banks is smaller. The marginal effect for this category is statistically significant, as shown by the F test at the bottom of the table. The marginal differential effect for the group of banks with "low" share is instead negative (at the 1% level) implying that the total effect for these banks is not statistically different from zero, as confirmed by the F test. The interpretation is that GDP growth is strongly correlated with the profitability of banks with a strong focus on lending, while it exhibits no correlation for those that invest relatively more in securities. The relationship is also persistent as shown by the significance of lagged GDP growth.

In the rest of the analysis we include only the interaction terms between the business model dummy variables and GDP growth, both contemporaneous and lagged. Our main specification is shown in Table 7 below. Relative to the results in Table 5 the coefficients for GDP growth (both simultaneous and lagged) in column (1) for the "high" group are 0.070 and 0.077, slightly larger than those in the regression in Table 5. As shown by the F-tests at the bottom of the table, the effect for banks in the "low" group is not statistically different from zero. For all the other macroeconomic variables the magnitudes of the coefficients in Tables 7 and 5 are very close.

Using the estimated coefficients in Table 7 for the effect of GDP growth on profitability, we can perform a simple back-of-the-envelope exercise to estimate the change in banks' profitability in 2018 that could occur as a direct result of the improvement in EU growth in 2017, assuming that growth for 2018 will be as forecasted. The European Commission latest forecast for GDP growth in the EU is 2.4 percent in 2017 and 2.3 in 2018, against an observed value of 2.0 in 2016, but there is significant heterogeneity across countries. Therefore, we compute the predicted ROA in 2018 for each bank based on the country specific growth, holding constant all other exogenous variables.[12] The change in ROE is computed multiplying the change in ROA by the leverage of each bank observed in 2016, the last year in the sample.

[12] European Commission, Ecofin Winter 2018 forecast.

Table 7: Estimation results - Differential effects of GDP growth by business model

	Net Income pre-taxes	Operating Income	Operating Expenses	Asset Write downs
Euribor 1 Year	0.037	0.054	0.016	-0.032
	(0.036)	(0.047)	(0.042)	(0.030)
Spread IRS 10Y - Euribor 1Y	0.139*	0.105**	-0.009	-0.037
	(0.080)	(0.049)	(0.041)	(0.051)
Euro Stoxx 50 Growth	0.005***	0.002	-0.000	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Domestic Credit Growth	0.037***	-0.005	-0.009*	-0.033***
	(0.007)	(0.005)	(0.005)	(0.007)
GDP Growth high (1)	0.070***	0.018**	0.003	-0.020*
	(0.027)	(0.009)	(0.006)	(0.012)
Δ GDP effect medium (2)	-0.016	-0.021*	-0.006	-0.025*
	(0.024)	(0.011)	(0.008)	(0.015)
Δ GDP effect low (3)	-0.071***	-0.037*	-0.004	0.010
	(0.023)	(0.020)	(0.016)	(0.012)
GDP Growth lag 1 high (4)	0.077***	0.020	-0.005	-0.040***
	(0.023)	(0.015)	(0.012)	(0.010)
Δ GDP lag 1 effect medium (5)	-0.026	-0.018	0.005	-0.010
	(0.021)	(0.018)	(0.015)	(0.015)
Δ GDP lag 1 effect low (6)	-0.092***	-0.032*	-0.003	0.059***
	(0.020)	(0.018)	(0.012)	(0.016)
Log Total Assets lag 1	-0.364***	-0.700***	-0.571***	0.091
	(0.140)	(0.187)	(0.195)	(0.136)
Tier 1 capital lag 1	0.003	0.001	0.002	-0.013
	(0.011)	(0.011)	(0.010)	(0.009)
Deposits lag 1	0.004	0.002	0.005	-0.013
	(0.006)	(0.008)	(0.004)	(0.008)
Cash Holdings lag 1	-0.010	-0.012	0.003	-0.002
	(0.010)	(0.009)	(0.012)	(0.005)
Constant	0.910	4.821***	3.240***	1.531*
	(0.736)	(0.887)	(0.786)	(0.830)
r2	0.133	0.086	0.091	0.134
N	1818	1818	1817	1816
Test H_0 :		P-value F-test H_0		
(1) + (2) = 0	0.004	0.730	0.753	0.000
(1) + (3) = 0	0.979	0.350	0.946	0.264
(2) = (3)	0.003	0.455	0.904	0.010
(4) + (5) = 0	0.010	0.829	0.960	0.003
(4) + (6) = 0	0.402	0.568	0.628	0.212
(5) = (6)	0.000	0.555	0.668	0.000

Bank level fixed effect estimation with robust standard error (in parentheses) clustered at the bank level.
All variables scaled by bank total assets except for Tier 1 capital, which is scaled by risk weighted assets.
* p<.1, ** p<.05, *** p<.01.

The "high" banks would experience an increase of 0.08 percentage points in ROA, and an increase in ROE of 1.2 percentage points. For the "medium" banks the impact would be slightly larger for ROA (0.09) and smaller for ROE (1.1) because these banks are less levered than the previous category. For the "low" banks ROA would decrease by 0.01 but the effect is not statistically different from zero. If we perform the same calculation using the common coefficients estimated with the regression that excludes the interaction terms for each business model (Table 5), we could gauge the role of business model heterogeneity, as distinct from the one of the different macro economic conditions faced by banks in different countries. The common model yields an improvement in ROA of 0.06 for the "high" banks, 0.10 for the "medium" ones, and 0.08 for the "low".

The results suggest that the common coefficient model overestimates the benefits of growth on ROA for the "low" banks and underestimates it for the "high". In the specific dataset employed in this paper the effects attributable to business model differences are not economically very large for the "high" and "medium" banks because the average effect is much more influenced by these observations, than by the smaller number of "low" banks. However, "low" banks are on average significantly larger, so a prediction based on an average weighted by total assets would further increase the economic relevance of business model differences.

The estimated changes are based on the assumption that all other variables remain unchanged. To have a sense of the economic size of the estimated coefficients of the slope of the yield curve and domestic credit growth, we provide some calculations based on hypothetic scenarios applied to the sample average and not to individual countries.

An increase in the slope of the yield curve by 10 basis points would increase ROA by 0.014 percentage points. Available projections for the euro area can be employed to perform the calculations. According to the OECD forecast, in the next two years the short term interest rates would remain essentially unchanged with respect to 2017. The long term interest rate would instead increase by around 20 basis points in 2018 and another 20 basis points in 2019.[13] The technical assumptions employed by the ECB in its projections are very similar to the above forecasts (as of December 2017, an increase in the 3 month Euribor by 20 basis points only between 2018 and 2019, and an increase in the 10-year government bond yield by 30 basis points between 2018 and 2019).[14] The effect from interest rate changes on profitability would therefore be negligible in 2018.

A moderate acceleration of credit growth would have a material effect. In our static framework, a hypothetical one percentage point increase in the annual expansion of domestic credit would on average raise ROA by an extra 0.04 percentage points. A more complex model would need to take into account the interaction between credit growth, profitability and equity to estimate the effect on ROE.

For Italian banks the hypothetical improvement from the increase in GDP growth, holding constant the other variables, is as follows: for "high" banks 0.06 percentage points in ROA and 0.9 in ROE; for "medium" banks 0.04 in ROA and 0.7 in ROE, respectively. These figures for ROE are based on 2016 data for bank leverage, and could differ to some extent if the most recent information were used. These increases are smaller than those obtained for the entire sample, because the forecasts for GDP growth are less benign than the ones for the EU average. Even though these calculations are based on a static model that does not take into account any feedback between real and financial variables, the conclusions are similar to Albertazzi et al. (2016). In their study, a sizable increase in profitability would occur only assuming higher growth than recorded over a ten-year horizon, faster credit expansion and more favorable operating costs dynamics.

[13] OECD forecast are available on the OECD website; the short term rate is from OECD (2018). Short-term interest rates forecast (indicator); the long term rate is proxied by the 10 year government bond yield.

[14] ECB staff macroeconomic projections for the euro area, September 2017.

4.2 Components of operating income

Operating income and its three main components are regressed on the same set of variables as our main regression. The results show that the net interest margin is positively affected by the level and the slope of the yield curve, as expected.

Table 8: Estimation results - Revenues

	Operating Income	Net Interest Income	Fee Income	Trading Income
Euribor 1 Year	0.054	0.054**	-0.002	-0.031**
	(0.047)	(0.024)	(0.042)	(0.013)
Spread IRS 10Y - Euribor 1Y	0.105**	0.117***	-0.043	0.038
	(0.049)	(0.031)	(0.039)	(0.025)
Euro Stoxx 50 Growth	0.002	-0.002***	0.001	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
Domestic Credit Growth	-0.005	-0.003	-0.005	-0.002
	(0.005)	(0.002)	(0.004)	(0.003)
GDP Growth high (1)	0.018**	0.006	0.009*	0.010*
	(0.009)	(0.007)	(0.006)	(0.006)
Δ GDP effect medium (2)	-0.021*	-0.023***	-0.006	0.002
	(0.011)	(0.007)	(0.005)	(0.006)
Δ GDP effect low (3)	-0.037*	-0.031**	-0.005	-0.002
	(0.020)	(0.012)	(0.021)	(0.007)
GDP Growth lag 1 high (4)	0.020	0.025**	-0.008	0.006
	(0.015)	(0.010)	(0.011)	(0.006)
Δ GDP lag 1 effect medium (5)	-0.018	-0.040***	0.020	-0.016
	(0.018)	(0.009)	(0.015)	(0.018)
Δ GDP lag 1 effect low (6)	-0.032*	-0.023**	-0.019	0.012
	(0.018)	(0.010)	(0.019)	(0.008)
Log Total Assets lag 1	-0.700***	-0.132**	-0.566***	-0.139
	(0.187)	(0.064)	(0.188)	(0.085)
Tier 1 capital lag 1	0.001	0.003	-0.003	-0.004
	(0.011)	(0.005)	(0.010)	(0.004)
Deposits lag 1	0.002	0.003	0.003	-0.000
	(0.008)	(0.007)	(0.003)	(0.002)
Cash Holdings lag 1	-0.012	-0.004	-0.003	-0.002
	(0.009)	(0.006)	(0.011)	(0.003)
Constant	4.821***	1.891***	2.558***	0.681**
	(0.887)	(0.596)	(0.721)	(0.309)
r2	0.086	0.073	0.093	0.087
N	1818	1817	1790	1735
Test H_0 :		P-value F-test H_0		
(1) + (2) = 0	0.730	0.000	0.553	0.091
(1) + (3) = 0	0.350	0.032	0.852	0.331
(2) = (3)	0.455	0.486	0.983	0.615
(4) + (5) = 0	0.829	0.035	0.024	0.479
(4) + (6) = 0	0.568	0.867	0.194	0.021
(5) = (6)	0.555	0.109	0.100	0.119

Bank level fixed effect estimation with robust standard error (in parentheses) clustered at the bank level.
All variables scaled by bank total assets except for Tier 1 capital, which is scaled by risk weighted assets.
* p<.1, ** p<.05, *** p<.01.

The slope has a larger effect than the short term rate. Fee income is unaffected by interest rates variables, while trading income has a negative coefficient of the short term rate, possible reflecting the inverse relationship between market interest rates and asset values. Trading income, instead, benefits from rising stock markets, as shown by the Euro Stoxx 50 coefficient.

Our key variable of interest, GDP growth, has a moderately significant positive effect on fee and trading income for "high" lending banks, but no specific effect for other banks. We note that lagged GDP growth does not correlate with fee and trading income. The effects of GDP growth on net interest margin across the three business models are inconsistent with our main results because simultaneous GDP growth is not statistically significant for "high" banks, while it is negative for "medium" and "low" banks. Lagged GDP growth has instead a positive statistically significant effect for "high" banks, no effect on "low" banks and a negative effect on "medium" banks. The results could be driven by the fact that the interest margin was declining even before the crisis, because banks were diversifying their revenues. During the sovereign debt crisis, both negative GDP growth and low interest rates compressed the net interest margin, but most of the effect would be captured by the low rates rather than by GDP growth, given the endogeneity of monetary policy with respect to the latter variable, which is something we cannot fully account for. A similar problem is faced by other studies, for example Claessens et al. (2017).

4.3 Components of asset write downs

We now consider the effect of macroeconomic variables on impairment of loans and securities.[15] We regress total asset write downs and the two categories of impairments on the same set of regressors as in our main specification, including interaction terms between bank clusters and GDP growth. Based on the results, shown in Table 9, we can infer that banks exhibit a different sensitivity to macroeconomic conditions according to their business model, as expected. Credit growth has a negative and significant coefficient that captures the fact that asset write downs are lower in the upturn of the credit cycle. This finding holds for both categories of impairments.

GDP growth has a strong negative effect on loans impairments for banks in the "high" and "medium" groups, but it has no effect on impairments of banks in the "low" group, as shown in the results of the F-test at the bottom of the table. Also securities impairments are higher when GDP growth is lower for both "high" and "medium" banks, but there is no correlation with GDP growth for the "low" banks, notwithstanding the fact that for the latter group they represent 45 percent of total assets. The effect of GDP growth is stronger for the lagged variable, but only for "high" and "medium" banks. These results might partially reflect the different weight of loans and securities in the assets of each category of banks (everything is scaled by total assets). Therefore, we repeat the estimation scaling impairments on loans and on securities by their respective stock. The results, available from the authors, are as follows. First, the coefficient of GDP growth is on average higher in the regression of impairments on loans than in the one of impairments on securities; impairments on loans also respond to lagged GDP growth, except for "low" banks, confirming our previous finding.

[15] According to IAS 36, impairments do *not* refer to temporary changes in market values, but permanent reductions recognized to the extent the carrying amount of the asset exceeds its recoverable amount.

Table 9: Estimation results - Asset write downs

	Asset Write Downs	Loans and Credits Impairments	Securities Impairments
Euribor 1 Year	-0.032	-0.037	0.007**
	(0.030)	(0.029)	(0.003)
Spread IRS 10Y - Euribor 1Y	-0.037	-0.061	-0.000
	(0.051)	(0.048)	(0.006)
Euro Stoxx 50 Growth	-0.001	0.001	-0.001***
	(0.001)	(0.001)	(0.000)
Domestic Credit Growth	-0.033***	-0.028***	-0.001***
	(0.007)	(0.007)	(0.001)
GDP Growth high (1)	-0.020*	-0.020*	-0.004***
	(0.012)	(0.012)	(0.001)
Δ GDP effect medium (2)	-0.025*	-0.020	-0.005*
	(0.015)	(0.014)	(0.003)
Δ GDP effect low (3)	0.010	0.010	0.001
	(0.012)	(0.011)	(0.003)
GDP Growth lag 1 high (4)	-0.040***	-0.045***	-0.002
	(0.010)	(0.009)	(0.001)
Δ GDP lag 1 effect medium (5)	-0.010	-0.010	0.003*
	(0.015)	(0.015)	(0.002)
Δ GDP lag 1 effect low (6)	0.059***	0.051***	-0.000
	(0.016)	(0.012)	(0.002)
Log Total Assets lag 1	0.091	0.019	0.028**
	(0.136)	(0.126)	(0.013)
Tier 1 capital lag 1	-0.013	-0.012	-0.001
	(0.009)	(0.008)	(0.001)
Deposits lag 1	-0.013	-0.013	0.000
	(0.008)	(0.008)	(0.000)
Cash Holdings lag 1	-0.002	-0.002	0.001
	(0.005)	(0.005)	(0.001)
Constant	1.531*	1.585*	-0.053
	(0.830)	(0.806)	(0.068)
r2	0.134	0.134	0.100
N	1816	1805	1468
Test H_0 :		P-value F-test H_0	
(1) + (2) = 0	0.000	0.001	0.001
(1) + (3) = 0	0.264	0.243	0.250
(2) = (3)	0.010	0.017	0.096
(4) + (5) = 0	0.003	0.000	0.262
(4) + (6) = 0	0.212	0.623	0.468
(5) = (6)	0.000	0.000	0.190

Bank level fixed effect estimation with robust standard error (in parentheses) at bank level.
All variables scaled by bank total assets except for Tier 1 capital, which is scaled by risk weighted assets.
* p<.1, ** p<.05, *** p<.01.

Second, impairments on securities tend to be responsive only to contemporaneous GDP growth, and the result holds for all banks. However, the results have to be interpreted with caution because we cannot assess the influence of accounting rules with the available data.

In economic terms, a drop in lagged GDP real growth by 1 percentage point is associated with an increase in asset write downs (on total assets) of 0.04 percentage points, i.e. an increment of 5 percent with respect to the sample mean of total impairments as a percentage of total assets (0.72). A variation of 1 per cent of GDP is a relatively modest change relative to the standard deviation of GDP growth in the sample (around 2.6 per cent).

5 Robustness analysis

We now consider several robustness exercises to check whether our main result on the differential effect of GDP growth across business models continues to hold.

5.1 Alternatives samples

The first set of tests is based on choosing subsets of observations (Table 10). First, we consider the balanced panel of banks that are present in the entire 10-year period. Second, we slightly relax the condition, keeping only banks that are present for at least 8 years. Table 10 shows that both the magnitude and significance of our main coefficients of interest are very similar to those described before. We note that the effects of the short term rate and the slope of the yield curve are larger; the short term rates also turn significant.

Table 10: Estimation results - Balanced panel

	Balanced panel 10 years	Panel $\geq$ 8 years	Banks never changing BM category	Excluding "unstable" banks
	Net Income pre-taxes	Net Income pre-taxes	Net Income pre-taxes	Net Income pre-taxes
Euribor 1 Year	0.093**	0.083**	0.073*	0.030
	(0.046)	(0.034)	(0.041)	(0.044)
Spread IRS 10Y - Euribor 1Y	0.201*	0.185**	0.089	0.111
	(0.107)	(0.087)	(0.105)	(0.079)
Euro Stoxx 50 Growth	0.005***	0.006***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Domestic Credit Growth	0.041***	0.040***	0.023***	0.023***
	(0.010)	(0.008)	(0.007)	(0.005)
GDP Growth high	0.059*	0.071**	0.066**	0.071***
	(0.031)	(0.028)	(0.027)	(0.022)
Δ GDP effect medium	-0.039	-0.035	-0.043	-0.018
	(0.027)	(0.025)	(0.031)	(0.022)
Δ GDP effect low	-0.066**	-0.074***	-0.081***	-0.060***
	(0.025)	(0.023)	(0.024)	(0.021)
GDP Growth lag 1 high	0.076***	0.080***	0.055*	0.062***
	(0.028)	(0.025)	(0.032)	(0.024)
Δ GDP lag 1 effect medium	-0.031	-0.038*	-0.051*	-0.021
	(0.027)	(0.022)	(0.027)	(0.019)
Δ GDP lag 1 effect low	-0.097***	-0.089***	-0.123***	-0.085***
	(0.023)	(0.019)	(0.029)	(0.021)
Log Total Assets lag 1	-0.350**	-0.318**	-0.411**	-0.621***
	(0.166)	(0.153)	(0.173)	(0.176)
Tier 1 capital lag 1	0.038*	0.019	0.019**	0.006
	(0.020)	(0.014)	(0.009)	(0.016)
Deposits lag 1	0.011	0.009	0.001	-0.000
	(0.008)	(0.006)	(0.008)	(0.008)
Cash Holdings lag 1	0.010	-0.011	0.009	0.002
	(0.010)	(0.012)	(0.011)	(0.008)
Constant	-0.033	0.306	1.080	1.956**
	(0.923)	(0.709)	(0.836)	(0.912)
r2	0.203	0.165	0.166	0.125
N	1064	1530	924	1548
Test H_0 :		P-value F-test H_0		
(1) + (2) = 0	0.373	0.065	0.426	0.002
(1) + (3) = 0	0.686	0.859	0.505	0.499
(2) = (3)	0.182	0.025	0.200	0.016
(4) + (5) = 0	0.108	0.063	0.869	0.024
(4) + (6) = 0	0.252	0.585	0.013	0.223
(5) = (6)	0.008	0.008	0.017	0.001

Bank level fixed effect estimation with robust standard error (in parentheses) clustered at the bank level.
All variables scaled by bank total assets except for Tier 1 capital, which is scaled by risk weighted assets.
* p<.1, ** p<.05, *** p<.01.
Note: A bank classification is considered "unstable" if the bank changed category during the sample period at least once and either: i) the difference between the maximum and the minimum share of loans over the period is higher than 20 percentage points; (ii) the standard deviation of the share of loans is higher than 7.4 percentage points. Both thresholds are set equal to two standard deviations of the corresponding measure for the whole sample.

Third, we drop from our initial sample banks that change business model category at least once in the sample period; this conditions halves the sample size. Despite this, the results are robust. Last, we drop only banks that exhibit substantial changes in their balance sheet structure (see note below Table 10).

5.2 Inclusion of sovereign debt spread

In our main analysis we proxy the slope of the yield curve by the difference between the 10-year interest rate swap yield and the 1-year Euribor rate. It could be the case that we are mis-specifying the regression because banks in each country face funding costs that depend on their domestic yield curve, which differed substantially in countries affected by the sovereign debt crisis. We include in our regression the domestic spread, defined as the difference between the 10-year domestic sovereign bond and the yield on the 10-year interest rate swap, to capture the country-specific sovereign risk. The results in Table 11 show that including the domestic spread makes the GDP growth coefficient insignificant. The reason is that variation in the sovereign spread over time is highly correlated with recessions in some countries; the two variables are essentially capturing the same common factor. Nevertheless, "low" banks continue to be less sensitive to GDP growth than the other two groups (the marginal effect is negative and statistically significant).

The estimation is repeated distinguishing between the countries with high sovereign spread levels and the other ones.[16] GDP growth affects the ROA of banks more specialized in lending even in countries with low spread levels, but it has no effect on the other banks. For countries with high average spread levels, GDP growth is no longer significant for banks in the "high" and "medium" groups, but it still continues to have a negative marginal effect for the "low" group. The spread variable is statistically significant for "high " and "medium" groups, while it is not significant for the "low" group, even in countries with average high spread (see F-tests). We conclude that the spread is capturing the underlying negative macroeconomic conditions, conditional on differences in mean spreads across countries, which are adequately captured by GDP growth.

We prefer to include GDP growth in our main specification rather than the sovereign spread because it is more readily interpretable for all countries. Moreover, in the specification including the spread variable the coefficient of the slope of the yield curve is either not significant or negative, a result in contrast with what we expect based on the literature.

[16] Bulgaria, Croatia, Cyprus, Greece, Hungary, Ireland, Italy, Malta, Spain, Portugal, Romania, Slovakia.

Table 11: Estimation results - Effects of Sovereign Spread

	All banks	All banks	Banks in countries with high spread	Banks in countries with high spread	Banks in countries with low spread	Banks in countries with low spread
	Net Income pre-taxes	Net Income pre-taxes	Net Income pre-taxes	Net Income pre-taxes	Net Income pre-taxes	Net Income pre-taxes
Euribor 1 Year	0.037	-0.012	0.089	-0.012	0.027	0.031
	(0.036)	(0.040)	(0.075)	(0.083)	(0.031)	(0.032)
Spread IRS 10Y - Euribor 1Y	0.139*	-0.047	0.434***	0.014	-0.132***	-0.137***
	(0.080)	(0.061)	(0.149)	(0.144)	(0.047)	(0.048)
Euro Stoxx 50 Growth	0.005***	0.005***	0.003	0.003	0.008***	0.008***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
Domestic Credit Growth	0.037***	0.026***	0.042***	0.031**	0.009*	0.008*
	(0.007)	(0.007)	(0.014)	(0.014)	(0.005)	(0.004)
GDP Growth high (1)	0.070***	0.020	0.095*	-0.014	0.041***	0.043***
	(0.027)	(0.016)	(0.051)	(0.035)	(0.013)	(0.013)
Δ GDP effect medium (2)	-0.016	0.005	0.003	0.049	-0.023	-0.026*
	(0.024)	(0.021)	(0.053)	(0.050)	(0.015)	(0.015)
Δ GDP effect low (3)	-0.071***	-0.043**	-0.045	-0.001	-0.054***	-0.056***
	(0.023)	(0.021)	(0.046)	(0.056)	(0.019)	(0.019)
GDP Growth lag 1 high (4)	0.077***	0.022	0.140***	0.035	0.004	0.007
	(0.023)	(0.015)	(0.039)	(0.034)	(0.010)	(0.010)
Δ GDP lag 1 effect medium (5)	-0.026	-0.004	-0.019	0.025	-0.013	-0.017
	(0.021)	(0.019)	(0.045)	(0.047)	(0.014)	(0.014)
Δ GDP lag 1 effect low (6)	-0.092***	-0.059***	-0.150***	-0.109***	-0.045**	-0.049***
	(0.020)	(0.019)	(0.036)	(0.034)	(0.018)	(0.018)
Log Total Assets lag 1	-0.364***	-0.385**	-0.338	-0.554**	-0.302**	-0.334***
	(0.140)	(0.151)	(0.244)	(0.273)	(0.129)	(0.126)
Tier 1 capital lag 1	0.003	-0.001	-0.001	-0.009	0.007	0.007
	(0.011)	(0.012)	(0.028)	(0.034)	(0.006)	(0.006)
Deposits lag 1	0.004	-0.004	-0.008	-0.021*	0.010*	0.010**
	(0.006)	(0.006)	(0.011)	(0.010)	(0.005)	(0.005)
Cash Holdings lag 1	-0.010	-0.013	0.000	-0.008	-0.017	-0.017
	(0.010)	(0.010)	(0.015)	(0.014)	(0.012)	(0.012)
Sovereign Spread on 10Y Bond high (7)		-0.233***		-0.247***		0.215
		(0.034)		(0.038)		(0.153)
Δ Spread effect medium (8)		-0.056		-0.032		-0.214
		(0.059)		(0.069)		(0.168)
Δ Spread effect low (9)		0.237***		0.279***		-0.143
		(0.079)		(0.104)		(0.242)
Constant	0.910	2.009**	0.956	3.672**	0.962	1.055*
	(0.736)	(0.846)	(1.391)	(1.691)	(0.582)	(0.586)
r2	0.133	0.214	0.191	0.272	0.126	0.131
N	1818	1818	622	622	1196	1196
Test H_0 :				P-value F-test H_0		
(1) + (2) = 0	0.004	0.135	0.018	0.404	0.080	0.099
(1) + (3) = 0	0.979	0.152	0.184	0.763	0.445	0.462
(2) = (3)	0.003	0.017	0.244	0.381	0.069	0.462
(4) + (5) = 0	0.010	0.257	0.004	0.103	0.370	0.311
(4) + (6) = 0	0.402	0.0175	0.753	0.007	0.025	0.022
(5) = (6)	0.000	0.003	0.004	0.001	0.086	0.088
(7) + (8) = 0		0.000		0.000		0.989
(7) + (9) = 0		0.952		0.723		0.676
(8) = (9)		0.001		0.001		0.712

Bank fixed effect included; robust standard errors (in parentheses) clustered at the bank level.
All variables scaled by bank total assets except for Tier 1 capital, which is scaled by risk weighted assets.
* p<.1, ** p<.05, *** p<.01.

5.3 Do banks investing in securities respond to EU GDP?

One of our main results is that the profitability of banks in the "low" group is not sensitive to domestic GDP growth; this may be the consequence of a misspecification. These intermediaries might have operations in multiple countries and their profitability may still depend on economic growth, but in a broader economic area rather than in the country of incorporation of the parent. For robustness purposes we repeat the estimation only with the subset of "low" banks replacing domestic GDP growth with EU GDP growth. Ideally, we should include an index of GDP growth that takes into account the countries towards which each bank is exposed, but such information is not available over the full sample period.[17]

The main results of our regression replacing EU GPD do not change. The coefficient of EU GDP is not statistically significant for these banks. This result is unchanged if we replace bank fixed effects with country dummies. We can therefore conclude that the "low" banks are generally not responsive to GDP growth, controlling for financial market performance, most likely because their assets and activities are more diversified than those of banks that lend to the real economy. We also note that banks in the low spread economies were significantly affected by financial market performance, as opposed to those in the high spread economies (Table 11). This finding could be reflecting to some extent the lack of a sufficient number of "low" banks in these countries.

Table 12: Estimation results - European GDP

	Firm level fixed effects	Country level dummies
	Net Income pre-taxes	Net Income pre-taxes
Euribor 1 Year	-0.053	-0.048**
	(0.051)	(0.021)
Spread IRS 10Y - Euribor 1Y	-0.126	-0.121
	(0.212)	(0.215)
Euro Stoxx 50 Growth	0.003	0.004
	(0.003)	(0.003)
Domestic Credit Growth	0.009	0.014**
	(0.013)	(0.005)
EU GDP	-0.012	-0.020
	(0.033)	(0.038)
EU GDP lag 1	-0.045	-0.039
	(0.035)	(0.044)
Log Total Assets lag 1	-0.242	0.097**
	(0.182)	(0.042)
Tier 1 capital lag 1	-0.014	-0.040***
	(0.015)	(0.008)
Deposits lag 1	0.000	0.004
	(0.010)	(0.003)
Cash Holdings lag 1	-0.007	-0.016
	(0.006)	(0.010)
Constant	1.886*	1.188***
	(0.997)	(0.316)
Adjusted R2	0.124	0.681
N	167	167

Bank fixed effects included; robust standard errors (in parentheses) clustered at the bank level.
All variables scaled by bank total assets except for Tier 1 capital, which is scaled by risk weighted assets.
* p<.1, ** p<.05, *** p<.01.

[17] The same problem occurs for banks that lend through subsidiaries to borrowers outside the EU, e.g. some Spanish banks lending to Latin America, or other intermediaries that have a significant share of business in Asia. Nevertheless, this kind of problem would reduce rather than increase the significance of the coefficients.

5.4 Country specific yield curves for non-euro area countries

In our main estimation we use a common yield curve for all EU countries, assuming that it is a reference curve also for banks that are located in countries that do not belong to the euro area. In an alternative set of regressions we replace the euro area yield curve with a country specific one for three main countries (United Kingdom, Sweden, Denmark).

Our main results on GDP growth are robust, and the magnitude of the coefficients in the first column is virtually unchanged.

Table 13: Estimation results - Main variables - Country specific interest rates

	Net Income pre-taxes	Operating Income	Net Interest Income	Asset Write Downs
Interest rate 1Y	0.035	0.040	0.061***	-0.032
	(0.035)	(0.038)	(0.022)	(0.030)
Slope yield curve 10Y-1Y	0.142*	0.029	0.077***	-0.087*
	(0.079)	(0.038)	(0.025)	(0.046)
Euro Stoxx 50 Growth	0.005***	0.002**	-0.001***	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Domestic Credit Growth	0.037***	-0.005	-0.004	-0.033***
	(0.008)	(0.005)	(0.003)	(0.007)
GDP Growth high (1)	0.074***	0.012	0.004	-0.026**
	(0.028)	(0.009)	(0.007)	(0.012)
Δ GDP effect medium (2)	-0.017	-0.022**	-0.023***	-0.025*
	(0.024)	(0.011)	(0.007)	(0.015)
Δ GDP effect low (3)	-0.071***	-0.037*	-0.032***	0.010
	(0.023)	(0.020)	(0.012)	(0.012)
GDP Growth lag 1 high (4)	0.080***	0.014	0.021**	-0.047***
	(0.024)	(0.013)	(0.009)	(0.009)
Δ GDP lag 1 effect medium (5)	-0.026	-0.019	-0.040***	-0.011
	(0.021)	(0.018)	(0.009)	(0.015)
Δ GDP lag 1 effect low (6)	-0.092***	-0.033*	-0.024**	0.059***
	(0.020)	(0.019)	(0.010)	(0.016)
Log Total Assets lag 1	-0.364***	-0.731***	-0.131**	0.093
	(0.133)	(0.203)	(0.061)	(0.126)
Tier 1 capital lag 1	0.003	-0.001	0.004	-0.013
	(0.010)	(0.009)	(0.005)	(0.008)
Deposits lag 1	0.004	0.001	0.003	-0.013*
	(0.006)	(0.008)	(0.007)	(0.008)
Cash Holdings lag 1	-0.010	-0.011	-0.004	-0.002
	(0.010)	(0.009)	(0.006)	(0.005)
Constant	0.897	5.093***	1.916***	1.588**
	(0.676)	(0.940)	(0.568)	(0.774)
r2	0.134	0.082	0.071	0.135
N	1818	1818	1817	1816
Test H_0 :		P-value F-test H_0		
(1) + (2) = 0	0.005	0.343	0.773	0.000
(1) + (3) = 0	0.860	0.218	0.968	0.090
(2) = (3)	0.003	0.464	0.907	0.009
(4) + (5) = 0	0.010	0.644	0.728	0.000
(4) + (6) = 0	0.496	0.328	0.756	0.428
(5) = (6)	0.001	0.556	0.678	0.000

Bank level fixed effect estimation with robust standard error (in parentheses) clustered at bank level.
All variables scaled by bank total assets except for Tier 1 capital, which is scaled by risk weighted assets.
* p<.1, ** p<.05, *** p<.01.

5.5 Different clustering

For robustness purposes we consider an alternative business model classification based on a broader set of balance sheet variables: loans to non-financial sector, loans to banks, deposits, securities, debt, cash, derivative assets and liabilities, fixed assets, equity. All the variables are expressed as ratios to total assets, as before.

We first perform a factor analysis to reduce the number of components that explain the data variability. The plot in Figure 3 suggests that it is a reasonable choice to consider only two components, as additional components would explain a significantly lower portion of data variability. For these two components the loadings on the individual variables in Figure 4 point out that it is sufficient to restrict attention to four main balance sheet variables: loans, securities holdings, deposits and debt securities issued.

Figure 3: Scree plot from factor analysis of main balance sheet variables.

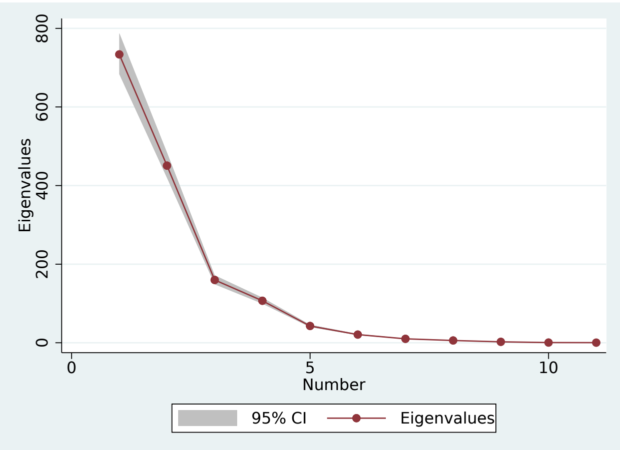
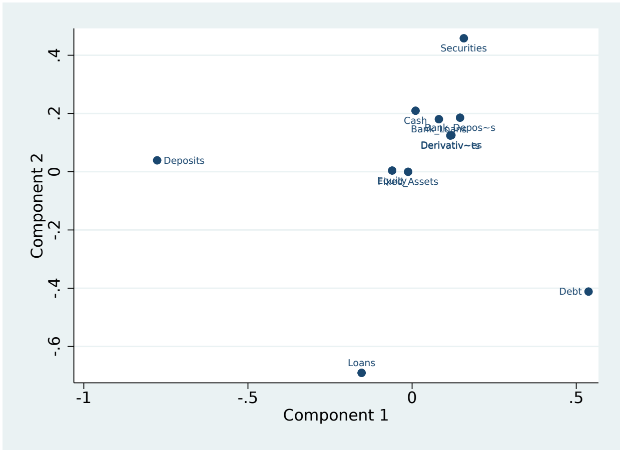


Figure 4: Component loadings of the main balance sheet variables.



Using these four variables we perform a cluster analysis with the Ward distance method. The resulting dendrogram, showed in Figure 6, suggests to divide banks into four clusters. Table 15 provides a set of summary statistics for the four clusters. We show in Table 14 the joint distribution of bank-year observations between the two clusterings.

Table 14: Comparison between two clustering methods

	Main balance sheet items				
Share of loans to customers	1	2	3	4	Total
1	146	0	21	0	167
2	182	41	236	215	674
3	27	116	426	402	971
Total	355	157	683	617	1812

The first group in the new clustering includes almost all of the observations in our "low" group and some from the second group ("medium" banks). These banks feature a low share of loans and

Table 15: Descriptive statistics - four business models.

	1	2	3	4	Total
Net Income pre-taxes	0.262	0.351	0.355	0.171	0.274
	(0.799)	(0.629)	(1.287)	(1.359)	(1.191)
Operating Income	1.885	1.371	3.404	3.176	2.853
	(1.305)	(1.062)	(1.793)	(1.485)	(1.707)
Net Interest Income	0.975	1.013	2.248	2.042	1.821
	(0.571)	(0.848)	(1.011)	(1.088)	(1.093)
Fee Income	0.876	0.289	0.989	0.940	0.889
	(1.280)	(0.262)	(1.031)	(0.562)	(0.934)
Trading Income	0.140	0.0863	0.186	0.204	0.174
	(0.692)	(0.217)	(0.310)	(0.396)	(0.435)
Operating Expenses	1.232	0.734	2.275	1.989	1.840
	(0.956)	(0.521)	(1.336)	(0.963)	(1.203)
Asset write downs	0.394	0.308	0.749	0.993	0.725
	(0.581)	(0.661)	(0.945)	(1.209)	(0.999)
Loans and Credits Impairments	0.285	0.255	0.598	0.861	0.596
	(0.399)	(0.606)	(0.953)	(1.128)	(0.943)
Securities Impairments	0.0412	0.0256	0.0233	0.0459	0.0357
	(0.0956)	(0.0790)	(0.0858)	(0.105)	(0.0955)
Cash Holdings	15.95	8.681	12.47	9.234	11.72
	(12.36)	(7.833)	(9.499)	(5.470)	(9.266)
Retail Loans	41.35	70.22	64.63	65.59	60.88
	(15.08)	(12.61)	(13.13)	(9.298)	(15.74)
Securities	37.44	18.16	18.74	19.10	22.48
	(14.03)	(9.482)	(10.29)	(7.805)	(12.71)
Retail Deposits	34.58	20.10	76.07	53.70	55.48
	(14.58)	(12.25)	(7.560)	(7.462)	(21.22)
Bank debt liabilities	21.76	58.33	4.638	17.68	17.08
	(11.30)	(16.86)	(4.519)	(9.542)	(17.27)
Tier 1 capital	13.73	15.22	13.77	11.47	13.10
	(6.457)	(7.038)	(5.133)	(3.828)	(5.373)
Log Total Assets	4.761	3.550	1.739	3.393	3.051
	(1.996)	(1.442)	(1.697)	(1.793)	(2.102)
Assets	466.2	84.28	18.31	126.7	148.7
	(639.4)	(105.9)	(48.90)	(253.0)	(360.9)
Observations	355	157	683	617	1812

Means; standard deviation in parentheses.

deposits and a high share of securities. The second group is a small group that includes banks that are active in traditional lending, but have a low share of retail deposits and a high share of bank debt. Most of these banks are small cooperative banks in Northern countries that are likely to place debt to their retail clients. The third and fourth group have a similar average share of loans, but the banks in the third group are significantly smaller, have more deposits and less bank debt than those in the fourth group.

We repeat our main regressions replacing the three-cluster groups with the new four-cluster ones. Results no longer have a clear interpretation as in the case of the three-cluster groups, for which the share of loans is monotonically increasing. We still find that profitability is less sensitive to GDP growth for banks with a lower share of loans, while the effect of the funding structure is not clear. Therefore, we prefer to focus on our main classification because there are no significant benefits from considering the new clusters.

Table 16: Estimation with four-cluster business models

	Net Income pre-taxes	Operating Income	Operating Expenses	Asset Write Downs
Euribor 1 Year	0.124***	0.049	-0.003	-0.100***
	(0.042)	(0.041)	(0.035)	(0.033)
Spread IRS 10Y - Euribor 1Y	0.141*	0.105**	-0.014	-0.032
	(0.085)	(0.051)	(0.045)	(0.054)
Euro Stoxx 50 Growth	0.008***	0.002	-0.001	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
GDP Growth cluster 4	0.077***	0.013	0.003	-0.034**
	(0.028)	(0.011)	(0.008)	(0.015)
Δ GDP cluster 3	0.052	-0.001	-0.025**	-0.030
	(0.041)	(0.013)	(0.012)	(0.018)
Δ GDP cluster 2	-0.035	-0.023	0.001	-0.013
	(0.035)	(0.029)	(0.009)	(0.025)
Δ GDP cluster 1	-0.034	-0.026**	-0.006	-0.012
	(0.026)	(0.013)	(0.010)	(0.016)
GDP growth lag 1	0.074***	0.001	-0.006	-0.057***
	(0.023)	(0.014)	(0.012)	(0.016)
Δ GDP lag 1 cluster 3	0.020	0.024	0.012	-0.008
	(0.029)	(0.017)	(0.013)	(0.017)
Δ GDP lag 1 cluster 2	-0.021	0.048	-0.000	0.058***
	(0.029)	(0.034)	(0.008)	(0.020)
Δ GDP lag 1 cluster 1	-0.080***	-0.014	-0.007	0.067***
	(0.022)	(0.015)	(0.008)	(0.018)
Log Total Assets lag 1	-0.406***	-0.704***	-0.561***	0.135
	(0.145)	(0.186)	(0.189)	(0.151)
Tier 1 capital lag 1	0.002	0.001	0.002	-0.012
	(0.011)	(0.011)	(0.010)	(0.009)
Deposits lag 1	0.003	0.002	0.005	-0.012
	(0.006)	(0.008)	(0.004)	(0.008)
Cash Holdings lag 1	-0.011	-0.012	0.003	-0.002
	(0.010)	(0.009)	(0.012)	(0.005)
Constant	1.023	4.828***	3.227***	1.393
	(0.738)	(0.881)	(0.774)	(0.857)
r2	0.107	0.087	0.087	0.096
N	1818	1818	1817	1816

Bank level fixed effect estimation with robust standard error (in parentheses) clustered at bank level.
All variables scaled by bank total assets except for Tier 1 capital, which is scaled by risk weighted assets.
* p<.1, ** p<.05, *** p<.01.

5.6 Alternative estimation methods

Many recent studies employ dynamic panel data techniques to estimate the relationship between bank profitability and macroeconomic variables. The choice is usually motivated by the observation that bank profits exhibit persistence over time, possibly because of impediments to competition and serial correlation in regional or macroeconomic shocks (Berger et al. (2000)). For robustness purpose we check whether our results are robust to including a lagged dependent variable.

Adding the lagged dependent variable to the specification requires a different estimation method because the fixed effects estimation yields a biased coefficient for the lagged dependent variable, especially if the number of periods is small and the number of observations is large (Nickell (1981)).

One possible solution adopted in the recent literature is to correct the estimate according to the method proposed by Bruno (2005). We focus on net income before tax and asset write downs, the key variables for which we find business model heterogeneity. The results of the dynamic model with the bias correction (LSDVC estimation) are shown in Table 17, column 1 and 3, and are very similar to our main ones. We do find evidence of persistence in profitability (first row) since the coefficient of the lagged dependent variable is positive and statistically significant, but the coefficient is not high. The size of the effect is similar to the ones found in country-level studies (Albertazzi and Gambacorta (2009)) and bank-level analyses (Borio, Gambacorta and Hofmann (2015)). While the coefficient of GDP growth and the interaction terms with the business model dummies are very similar to our main results and remain statistically significant, we note that the coefficient of lagged GDP growth becomes smaller for the "high" banks. For "medium" banks we still find no significant difference with respect to the "high" banks, and for "low" banks the marginal effect is not statistically different from zero as in our main findings. The reduction in the effect of lagged GDP growth is explained by the fact that part of the impact of this variable is mediated through lagged profitability. In this specification we are capturing the direct effect that past GDP growth has on today's profits.

An alternative estimation approach for a dynamic model is the Generalized Method of Moments (GMM), which can handle also potential endogeneity issues related to some regressors. Endogeneity could occur if bank profitability affects contemporaneous variables, especially credit growth. In principle, bank profitability could also indirectly affect GDP growth, and euro area money market rates. As noted by Borio, Gambacorta and Hofmann (2015), while aggregate banking conditions could influence the monetary policy stance, the profitability of any given bank is less likely to affect central bank decisions. Furthermore, many of the banks in our sample operate in more than one jurisdiction, which reduces the potential for endogeneity. We estimate the model with the System Generalized Method of Moments (SYS-GMM) which reduces endogeneity bias whilst taking into account time invariant unobserved sources of heterogeneity across banks (Blundell and Bond (1998)). We consider endogenous all simultaneous variables (level and slope of interest rates, Euro Stoxx 50, domestic credit and GDP growth) and exogenous all the lagged ones (lagged GDP and all bank level variables). We use as instruments 2 to 5 lags of first differences and lagged levels of the endogenous variables.

The results are shown in Table 17, columns 2 and 4. The differential effect of GDP growth across business models is robust. The magnitude is larger than in our main specification.

Table 17: Estimation results - Lagged dependent variable

	Net Income pre-taxes		Asset Writedowns	
	LSDVC Bruno (2005)	System GMM	LSDVC Bruno (2005)	System GMM
Lagged dependent	0.354***	0.394***	0.446***	0.595***
	(0.031)	(0.103)	(0.031)	(0.052)
Euribor 1 Year	0.028	0.042	0.016	0.048
	(0.046)	(0.056)	(0.039)	(0.032)
Spread IRS 10Y - Euribor 1Y	0.092	0.112*	-0.083	-0.082*
	(0.073)	(0.064)	(0.061)	(0.047)
Euro Stoxx 50 Growth	0.009***	0.011***	-0.001	-0.003
	(0.003)	(0.004)	(0.003)	(0.002)
Domestic Credit Growth	0.031***	0.034***	-0.021***	-0.027***
	(0.006)	(0.010)	(0.005)	(0.008)
GDP Growth high (1)	0.076***	0.107**	-0.033**	-0.059***
	(0.019)	(0.049)	(0.015)	(0.015)
Δ GDP effect medium (2)	-0.025	-0.024	-0.032*	-0.028
	(0.024)	(0.048)	(0.019)	(0.024)
Δ GDP effect low (3)	-0.071*	-0.094**	0.018	0.033*
	(0.036)	(0.042)	(0.030)	(0.020)
GDP Growth lag 1 high (4)	0.038**	0.055**	-0.016	-0.040***
	(0.016)	(0.022)	(0.013)	(0.013)
Δ GDP lag 1 effect medium (5)	0.002	-0.007	-0.028	0.001
	(0.022)	(0.020)	(0.017)	(0.015)
Δ GDP lag 1 effect low (6)	-0.045	-0.030	0.019	0.016
	(0.035)	(0.023)	(0.029)	(0.016)
Log Total Assets lag 1	-0.437***	0.019	0.298**	-0.075**
	(0.150)	(0.040)	(0.121)	(0.030)
Tier 1 capital lag 1	-0.011	-0.005	-0.005	-0.004
	(0.010)	(0.018)	(0.008)	(0.013)
Deposits lag 1	0.009*	0.003	-0.010**	-0.001
	(0.005)	(0.004)	(0.004)	(0.003)
Cash Holdings lag 1	-0.005	0.012*	-0.005	-0.012**
	(0.007)	(0.006)	(0.006)	(0.005)
Constant		-0.422		0.863**
		(0.467)		(0.397)
N	1564	1564	1561	1561
Test for AR(2) in first difference (p-value)		0.509		0.212
Hansen test (p-value)		0.162		0.226
Test H_0 :	P-value F-test H_0			
(1) + (2) = 0	0.019	0.002	0.773	0.000
(1) + (3) = 0	0.883	0.590	0.968	0.615
(2) = (3)	0.210	0.035	0.907	0.123
(4) + (5) = 0	0.035	0.018	0.728	0.004
(4) + (6) = 0	0.842	0.165	0.756	0.931
(5) = (6)	0.196	0.289	0.678	0.129

Notes: Standard errors in parentheses. For LSDVC estimator standard errors are computed with bootstrap method with 1000 iterations. For system GMM robust standard errors are clustered at bank level and all contemporaneous variables are considered endogenous. We use as instruments 2 to 5 lags of first differences and levels for a total of 200 instruments. All variables scaled by bank total assets except for Tier 1 capital, which is scaled by risk weighted assets.
 * p<.1, ** p<.05, *** p<.01.

6 Conclusions

The estimation of a fixed effects panel data model of banks' profitability allowing coefficients of macroeconomic variables to be different across business models shows that banks that are more oriented towards traditional lending exhibit greater sensitivity to GDP growth than banks that mostly invest in securities. Clustering banks based on the combination of their funding model and the composition of assets masks this difference. The results suggests to take into account such difference in future analyses of the evolution of bank profitability. The results are robust to other estimation approaches, specifically bias corrected LSDV and System GMM.

Using the estimated coefficients, simple calculations indicate that the forecasted improvement in economic growth for EU countries in the near future would increase the return on assets of banks engaging in lending by almost 10 basis points on average, i.e. a little more than one percentage points of ROE holding constant banks' leverage to 2016 level. The increase is a conservative estimate because it is based on the assumption that interest rates and credit growth remain constant; a rise in long term interest rates and an acceleration of credit growth would increase ROA as well. Nevertheless, the findings suggest that, given the outlook, profitability would improve moderately as the sole result of the macroeconomic scenario, and that banks would need to be proactive to strengthen their profitability.

7 Appendix: Dendrograms

Hierarchical clustering is an algorithm that builds a hierarchy of clusters. The algorithm begins with each data point in a separate cluster and, at each step, the two clusters that are more similar—according to a pre-specified similarity measure—are joined into a single new cluster. The algorithm terminates when there is only a single cluster left. The results of hierarchical clustering are graphically depicted using a dendrogram.

In the dendrograms reported below the vertical axis represents the distance or dissimilarity between clusters, while the horizontal axis represents the clusters in the data space. If two clusters are joined the graph reports an horizontal line joining two clusters, at the corresponding dissimilarity measure on the vertical axis. The higher the dissimilarity measure the less convenient is to join two clusters. The decision over the total number of clusters to consider has to trade-off a parsimonious choice of clusters to guarantee sufficient sample size and the corresponding loss from aggregating in the same cluster too dissimilar observations.

The dendrogram in Figure 5 shows the clustering obtained using the share of assets invested in loans. A reasonable choice is to have three clusters. A more parsimonious choice of two clusters, by joining the first two clusters on the left side of the graph, would imply a substantial increase in the dissimilarity measure. In the second dendrogram in Figure 6 the clusters are obtained by comparing four balance sheet variables: loans, securities, deposits and debt over total assets. The dendrogram obtained suggests that four clusters should be the best choice.

Figure 5: Dendrogram from cluster analysis on the share of loans based on Ward linkage method.

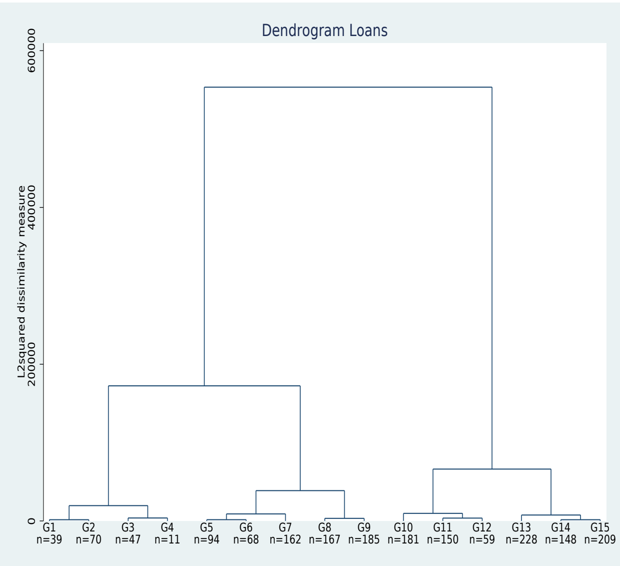
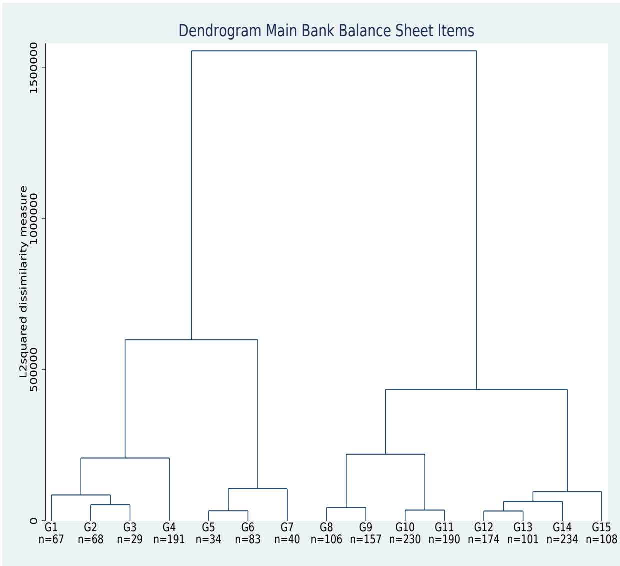


Figure 6: Dendrogram from cluster analysis on multiple balance sheet variables based on Ward linkage method.



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