Business models and bank performance: A long-term perspective*

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Abstract

This paper examines the effects of bank business models on performance and risk for a sample of more than 500 banks from 30 European countries over the period from 1998 to 2013. We document that business models in the European banking sector are characterized by a continuum, rather than a discrete set, of possible strategies. Using factor analysis to identify business models, we can account for this continuity. To estimate the impact of business models on performance, we use a methodology that is able to separate short-run effects from the impact of business model choices. Our findings show that retail-oriented banks perform better in terms of both profitability and stability and that diversification improves profitability, but also increases susceptibility to distress. We report substantial variation of business model effects over different bank types. Our results lend support to the new regulations proposed in the Basel III framework, but we also argue that business model considerations should be more fundamentally integrated in the post-crisis regulatory and supervisory practice.
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1 Introduction

This paper examines the impact of bank business model choices on their profitability, net interest margin and default risk for a panel of over 500 banks from 30 European countries over the period from 1998 to 2013. The motivation for this research originates in the financial crisis and the subsequent initiatives to strengthen the resilience of banks. Various studies (Altunbas et al., 2011; Beltratti and Stulz, 2012) show that some types of banks proved to be particularly vulnerable. Reforms in banking regulations, including Basel III as well as

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several initiatives to limit the scope of bank activities, will further induce banks to reconsider their business models. The assessment of these initiatives requires a deeper understanding of the performance outcomes associated with different bank business models.

Our investigation is related to a growing literature that focuses on the concept of bank business models to explain bank performance. Altunbas et al. (2011), who use a broad set of pre-crisis bank characteristics to capture business models, report that low capital, large balance sheets, reliance on short-term market funding and aggressive credit growth can cause distress while a strong deposit ratio and greater income diversification improve resilience. Ayadi et al. (2012) use cluster analysis to identify business models of which they then compare the performance during and after the banking crisis. They document that retail-oriented banks are less likely to default, but also that a diversified funding structure can support profitability during a downturn. Wholesale banks are shown to be more risky due to an apparent failure to build adequate liquidity buffers. Demirgüç-Kunt and Huizinga (2010) and Köhler (2015) examine the effect of income and funding diversification on bank profitability and stability. The former find that a more diverse activity mix and a larger share of wholesale funding materially increase bank risk, while diversification benefits are only observed at low levels. Köhler (2015), on the other hand, using a sample of listed and unlisted banks over a period that includes the crisis, provides evidence that income diversification improves performance for retail banks, but hurts the stability of investment banks. A larger share of wholesale funding improves the stability of investment banks, while the reverse is true for retail banks.

We attempt to contribute to this literature in several ways. First, we evaluate the accuracy of different classification techniques, i.e. the allocation of banks to specific business model groups, taking into account the very diverse landscape of business models in the European banking sector. We find that the European banking sector is characterized by a continuum of possible business models, rendering classification difficult. Second, as an alternative to classification we propose a new approach to identify banks' business models that is based on factor analysis. In line with cluster analysis it uses a combination of observed variables to identify business models, but since it produces continuous variables, rather than discrete groups, this procedure also accounts for the existence of mixed business models. Third, the econometric approach, based on Mundlak (1978), differentiates in a clear way the within and between dimension of the panel data. This is important for two reasons. Statistically, we find that the differences across banks, i.e. the between dimension, are quite large compared with the observed changes within individual banks over time. Economically, the estimation enables an interpretation that disentangles short- and long-term effects (Baltagi and Griffin, 1984). In previous studies long-term effects were left largely unexplored, whereas we deem them crucial to understand the impact of business models on bank performance. Fourth, we exclude domestic subsidiaries of banking groups from our dataset. This is important since the strategic choices and performance of these subsidiaries are not independent from their parent firms, so that their inclusion might bias the results. These considerations are to a lesser extent valid for foreign subsidiaries since these enjoy more autonomy and fall under the jurisdiction of different supervisory agencies.

The factor analysis suggests that there are two important business model strategies, which we label *RETAIL* and *DIVERSIFICATION* based on their relation with the individual business model variables. In the investigation of the impact of business models on bank performance, we use four indicators: return on equity (ROE), return on assets (ROA), the net interest margin (NIM) and stability as measured by the Z-score[1]. We perform two sets of regressions. The first set uses the individual business model variables as regressors, while the second examines the impact of the principal factors. Finally, we also examine the impact of the individual variables for different levels of the *RETAIL* factor to assess the heterogeneity of these effects.

Our results provide evidence for the importance of business model characteristics as determinants of bank performance. We find that a strong reliance on retail activities is associated with higher profitability and stability. Functional diversification also improves profitability, but at the cost of increasing a bank's susceptibility to distress. The results for the individual business model variables reveal that the improved performance of retail banks can mainly be attributed to their reliance on customer deposits and larger capital ratio, while their typically low level of income diversification may undermine their profitability. The impact of the loan ratio appears to be negative, but the heterogeneity analysis demonstrates that this is not the case for more retail-oriented banks. These banks are also better able to convert additional credit risk into a higher NIM, suggesting that retail banks are better able to effectively screen and monitor loans. The results furthermore support the new regulations of the Basel III framework. Business models characterized by higher capital ratios are, ceteris paribus, associated with an improved trade-off between risk and profitability. The impact on bank stability is moreover found to be more positive for banks with a low degree of retail activities, that are typically larger and more highly leveraged. With respect to funding risk, we do not find evidence that a higher net stable funding ratio (NSFR) affects ROA or the Z-score, but there appears to be a positive effect on both profitability and stability for more retail-oriented banks. Finally, we also find that balance sheet size can improve stability. However, the increased stability of an individual bank due to its size is not necessarily consistent with the macroprudential aim of bank sector stability.

This paper is organized in the following way. In the next section, we discuss the methodology to identify bank business models and how they can be related to bank performance . In section 3 we discuss the data. Section 4 presents the results of our analysis. In section 5 we explore the robustness of our findings. In the final section, we state our conclusions and consider some implications.

2 Methodology

2.1 Identification of bank business models

The concept of business models originates from the literature concerning strategic groups (Porter, 1979), i.e. sets of firms that are active in a single sector and use similar strategies. The space of possible strategies in banking, and therefore of possible business models, is spanned by a number of strategic variables that reflect the long-term choices of bank man-

[1]The Z-score is most often used as a direct measure of bank risk. Delis et al. (2014), however, document the failure of the Z-score to measure the build-up of risk prior to the crisis in the US. For our purposes, however, the Z-score is still preferable as it measures the ex-post realization of default risk and, as such, the distress experienced by banks.

agement with respect to assets, funding, capitalization and diversification. Given that a strategy is necessarily a long-term notion, we consider business models to be very stable, implying that the differences between banks are empirically more important than changes over time within banks to identify the performance impact of business model choices. The identification of bank business models requires a set of variables that determine the space of possible strategies. In this respect, the use of balance sheet and income statement data has a long history in the banking literature (Amel and Rhoades, 1988; Passmore, 1985). Although other non-financial variables, such as distribution channels and types of clients and products, may also provide information regarding a bank's strategy, we believe that this information should ultimately be reflected in the observed financial ratios. In order to be constitutive of a business model, these variables should not be independent from each other, i.e. some combinations of strategic variables should be more common than others. Concretely, we use a set of variables that capture a bank's strategic choices related to asset, liability, capital and income structure, including financial ratios linked to a bank's risk profile (see also, for instance, Altunbas et al., 2011). The specific variables are presented in section 3.3. We now discuss several procedures to use the information contained in these variables to identify business models.

The first approach is based on the allocation of banks to specific groups through direct or indirect classification. Direct classification uses qualitative variables, e.g. the bank type according to Bankscope (Köhler, 2015), that are equated to the business model. Indirect classification, usually achieved through cluster analysis[2], combines the information from a set of continuous variables to construct distinct groups of observations, that are as homogeneous as possible (Ayadi et al., 2011, 2012; Martín-Oliver et al., 2015; Roengpitya et al., 2014). An important drawback of classification that has remained underappreciated, however, is the validity of its assumption that there exist clearly separable business models, i.e. the unavailability of intermediate strategies. Compared to the US, the European banking sector is historically characterized by very limited regulations regarding the scope of bank activities. As a result, e.g. through mergers and acquisitions, a banking sector has developed that is characterized by a broad and continuous spectrum of available intermediate strategies, ranging from small savings and cooperative banks to big financial conglomerates in which non-retail activities dominate. We empirically document this issue in section 4.1.

As an alternative to classification, the banking literature (Altunbas et al., 2011; Demirgüç-Kunt and Huizinga, 2010) suggests an approach that directly relates individual business model characteristics to performance. We also apply this strategy, because it allows us to identify the specific features of a business model that improve bank performance. However, this approach is unable to directly identify the impact of the business model, because it does not clearly define how the individual characteristics are interrelated to constitute a business model. This model also does not account for the bank-specific variation of the business model variables that is not related to a business model strategy, e.g. a high capital ratio may reflect a bank's business model as it is related to the funding strategy, but it may also reflect the risk preferences of the individual bank. In this respect Fahlenbrach et al. (2012)

[2] Cluster analysis is a statistical technique to identify groups of observations in a dataset based on a dissimilarity measure of observations and a specific clustering method, e.g. hierarchical clustering (Everitt et al., 2011).

demonstrate that banks are also characterized by a persistent ‘risk culture’ that may also affect the long-run levels of the individual bank characteristics.

We therefore propose a method that considers a business model to be an underlying, latent, strategy. The observed strategic variables are the outcome of this strategy, but also of bank-specific variation. Our identification strategy is based on factor analysis. It uses the common variation of the business model variables to capture latent strategies, which are assumed to be of lower dimension. In the spirit of cluster analysis, it combines the information from all variables and observations, but instead of resulting in binary group membership, it generates continuous common factors. Critically, common factors load more heavily on variables that have more variation in common, i.e. that more clearly define the business model. Accordingly, the factor analysis recognizes the degree to which variables are part of the underlying strategy and to what extent their variation is unique, i.e. bank-specific.

2.2 Measuring the impact of business models on performance

The empirical literature suggests several approaches to investigate the impact of bank business models on bank performance. In general, these methods can be divided into two categories. First, Altunbas et al. (2011) and Beltratti and Stulz (2012) use cross-section analysis to relate pre-crisis bank characteristics to crisis performance. Although such an approach avoids endogeneity-related issues, it does not fully exploit the information that is available in a panel dataset and might be sensitive to unobserved heterogeneity. The second approach uses panel data analysis, ranging from pooled OLS (Demirgüç-Kunt and Huizinga, 2010; Van Oordt and Zhou, 2014) to fixed effects and dynamic panel GMM methods (Dietrich et al., 2014; Köhler, 2015). Stiroh and Rumble (2006) furthermore investigate the relationship between income diversification and bank performance using both the between and the within dimension of the data. They argue that long-term strategic choices are best captured by the between dimension, as it averages out noisy short-term fluctuations.

Given our emphasis on business models as long-term concepts, the differences across banks are crucial to identify the impact of business models on performance. The interpretation that the between dimension captures long-run effects, and therefore business model effects, is also supported by the econometric literature on panel analysis. Baltagi and Griffin (1984) find that a difference between the temporal and cross-sectional dimension is caused by dynamic misspecification. Pirotte (1999) argues that the between estimator provides a solution, because it allows one to obtain long-run effects directly from a static model. We therefore use the approach proposed by Mundlak (1978), which simultaneously explores both the within and the between dimension. This method extends the random effects model with the individual means of the independent variables as regressors, thereby avoiding the bias that is introduced by the correlation between explanatory variables and unobserved effects. However, Köhler (2015) specifically advocates the use of the within estimator, and thus of bank fixed effects, to control for persistent differences between banks that are not directly related to the business model, but also influence the observed bank characteristics, e.g. risk culture (Fahlenbrach et al., 2012). The model based on individual bank characteristics is indeed unable to decompose the individual variables into one part that is related to the business model and another that reflects other persistent differences. Instead, in line with Altunbas et al. (2011), it assumes that all differences, e.g. risk preferences, are part of the business model. The factor approach, on the other hand, is able to distinguish the part of the variable that is related to the business model, while the residual variation is associated with the persistent bank-specific differences that also influence bank characteristics. In other words, the common factors allow us to decompose the bank fixed effect into a business model component and a residual component.

As a result of these considerations, we conduct two sets of estimations. The first set explains performance using the individual bank characteristics directly, while the second set uses the common factors. In practice, we estimate the following model using the random effects estimator:

$$y_{ict} = x'_{ict}\beta + \bar{x}'_{ic}\gamma + \delta_{ct} + \alpha_{ic} + \varepsilon_{ict}$$

where y_{ict} represents the performance indicator of bank i based in country c in year t. The matrix x contains the levels of all independent variables, i.e. business model and bank-specific control variables, and $\bar{x}$ the bank-specific averages of those variables over the whole sample period. To control for endogeneity we use the first lag of the bank-specific variables x_{ict}. We furthermore include country-year fixed effectsδ_{ct} to capture differences in macroeconomic environment since these may also drive variation in performance outcomes for otherwise similar banks. The within and between parameters, given by $\hat{\beta}$ and $(\hat{\beta} + \hat{\gamma})$ respectively, are directly reported in the results section. This model accounts for unobserved heterogeneity and correlation between unobserved effects α_{ic} and explanatory variables x_{ict}, while also exploiting the cross-sectional dispersion of the data. This setup allows an intuitively clear interpretation, i.e. while the within effects reflect the impact of changes over time within banks, the between effects can be interpreted as business model effects.

3 Data

3.1 Sample selection

We construct a dataset containing both bank-specific and macroeconomic variables with annual frequency. Balance sheet and income statement data of banks from 30 European countries are retrieved from the Bankscope database, which is maintained by Bureau Van Dijk. Macroeconomic time series data are obtained from Eurostat, the IMF International Financial Statistics database and national central banks. Long-term credit ratings for all included countries' sovereign debt are gathered from Fitch Ratings. The sample period runs from 1998 to 2013. In order to fully exploit the Bankscope database we use balance sheet data based on IFRS as well as GAAP accounting standards. A large share of the banks in our sample converted to IFRS during the sample period. In those cases we merge GAAP and IFRS observations that refer to the same bank to the same bank identifier[3]. We select the banks that satisfy all three of the following criteria:

1. The bank is active in a country of the EU (28), Norway or Switzerland. We exclude domestic subsidiary banks, but include foreign subsidiaries that satisfy the remaining criteria.

[3]We perform a robustness analysis to assess the validity of this procedure by not using the GAAP-based data for banks that switch to IFRS in section 5.

	Condition	If condition is not satisfied, removal of:
1.	Customer **deposits** exceed 5% of liabilities.	Bank-year observation.
2.	**Loans** exceed 5% of assets.	Bank-year observation.
3.	Income data are fully **available**.	Bank-year observation.
4.	Bank data are continuously **available** (no gaps).	All bank observations prior to gap.

Table 1: Additional criteria for sample selection.

2. The bank satisfies at least once, over the period from 2005 to 2013, one or both of two size criteria: absolute size (total assets) larger than 5 billion euro or systemic size (total assets to domestic GDP) exceeding 5%. Assessing this criterion for the period 2005-2013 instead of the full sample period 1998-2013 assures that the selected banks were active in the period covering the financial crisis.

3. The institution is engaged in financial intermediation activity. We therefore include a bank if it is, according to the Bankscope classification, a commercial bank, a savings bank, a cooperative bank, a mortgage bank, a governmental credit institution or a bank holding company[4]. Institutions that do not focus on financial intermediation, such as investment banks and Luxembourg-based foreign subsidiaries, which are mainly responsible for the wholesale activities of their parent groups, are excluded. We furthermore apply criteria, outlined in table 1, based on the importance of customer deposits in funding, loans in earning assets and data availability.

The application of the three criteria results in a dataset of 513 banks for a total of 6378 bank-year observations. These banks represent a large share of their domestic banking sector. In table 2 and figure 1 we present the distribution of the banks and observations over different countries and years, respectively. The size criteria restrict the sample to the most important European banking groups. These criteria are also found to be important to ensure the geographical balance of our sample, since a further loosening would give more weight to countries with extensive networks of local savings and cooperative banks, such as Germany. More importantly, we exclude domestic subsidiaries from our sample, because decisions with respect to fundamental business model choices are taken at the level of the parent firm, which will consider the performance of the whole banking group. A foreign subsidiary, on the other hand, is more independent and its performance is less likely to be influenced by the state of its parent. For bank supervisors interest lies with either the performance of a domestic banking group or a local subsidiary of a foreign banking group[5]. The coexistence of a strongly interconnected banking market and a network of separate national supervisory agencies was typical for Europe before the Banking Union. The activation of the Single Supervisory Mechanism in November 2014, under which the ECB has taken over euro area bank supervision, is outside the scope of our sample.

[4] In line with Köhler (2015) our sample includes both listed and unlisted banks to allow for a wider variety of bank specializations, as for instance the majority of savings banks are unlisted.

[5] Taking these considerations into account, we believe that foreign subsidiaries can act independently, while also being a part of their parent group's strategy. We therefore use observations of the highest available level of consolidation for parent banks as well as foreign subsidiaries.

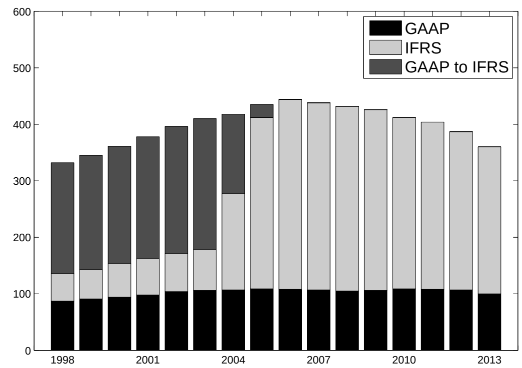


Figure 1: Distribution of bank observations according to accounting standards and years. '*GAAP to IFRS*' indicates GAAP-based observations for banks that switch to IFRS during the sample period.

	Banks	**Obs.**	**Freq.**	**> EUR 30 bln. (obs.)**	**Listed (obs.)**
Austria	26	368	5.8%	23%	24%
Belgium	11	129	2.0%	57%	28%
Bulgaria	9	85	1.3%	-	13%
Croatia	7	87	1.4%	-	57%
Cyprus	9	104	1.6%	7%	29%
Czech Republic	5	73	1.1%	22%	27%
Denmark	5	80	1.3%	48%	80%
Estonia	2	26	0.4%	-	27%
Finland	5	66	1.0%	50%	15%
France	12	132	2.1%	92%	28%
Germany	100	1381	21.7%	26%	7%
Greece	10	138	2.2%	36%	86%
Hungary	7	106	1.7%	7%	15%
Ireland	13	141	2.2%	43%	43%
Italy	41	495	7.8%	37%	52%
Latvia	9	99	1.6%	-	14%
Lithuania	5	68	1.1%	-	59%
Luxembourg	2	23	0.4%	30%	-
Malta	4	44	0.7%	-	50%
Netherlands	15	158	2.5%	46%	30%
Norway	14	190	3.0%	13%	56%
Poland	18	206	3.2%	7%	75%
Portugal	13	152	2.4%	41%	42%
Romania	8	102	1.6%	-	25%
Slovak Republic	6	71	1.1%	-	46%
Slovenia	9	141	2.2%	-	13%
Spain	76	776	12.2%	23%	18%
Sweden	6	88	1.4%	74%	72%
Switzerland	27	388	6.1%	18%	49%
United Kingdom	39	461	7.2%	41%	26%
Total	513	6378	100%	27%	31%

Table 2: Distribution of banks and observations over countries.

3.2 Performance indicators

Bank profitability is captured by three indicators: return on equity, return on assets and the net interest margin. Profits are calculated as the sum of net interest income and non-interest income minus operating expenses and loan loss provisions, i.e. we focus on the recurring part of profits on a pre-tax basis. The NIM should reflect the ability of a bank to tap into various funding sources and transform those funds into assets with attractive yields. In the absence of public sources of granular and reliable interest income and expense data on different types of assets and liabilities, we use the ratio of net interest income to earning assets. We measure individual bank distress using the Z-score, or rather its natural logarithm as the variable itself is strongly positively skewed. This variable is defined in the following way:

$$Z - score_{it} = \frac{\frac{Total\ \ Equity_{it}}{Total\ \ Assets_{it}} + E_{it}(ROA)}{\sigma_{it}(ROA)} = \frac{CAP_{it} + E_{it}(ROA)}{\sigma_{it}(ROA)}$$

Following Beck et al. (2013) we construct $E_{it}(ROA)$ and $\sigma_{it}(ROA)$ over a rolling window with three observations of ROA over the period $t-2$ to t[6]. This procedure reduces the number of available observations slightly and removes banks with less than three consecutive observations. The Z-score should be interpreted as a distance-to-default measure, i.e. as the number of standard deviations ROA can diverge from its mean before the bank defaults. A higher Z-score indicates a safer bank. Figure 2 demonstrates the negative evolution of European bank performance during the sample period. We note that the observed evolution of the Z-score underlines its usefulness as a distress indicator, rather than as a direct measure of bank risk-taking: it decreases during, instead of before, the financial crisis.

3.3 Business model variables

Our set of business model variables reflects bank's strategic choices related to asset, liability, capital and income structure.

Asset structure The **ratio of net loans to earning assets** captures the extent to which a bank is engaged in traditional intermediary activities, i.e. the transformation of liquid deposits into illiquid loans reflecting the role of a delegated monitor (Diamond, 1984). The **ratio of loan loss provisions to loans** is a forward-looking measure of loan quality and a reflection of a bank's own opinion of the quality of its loans. Loan loss provisions (LLP) can, however, be used to smooth income (Laeven and Majnoni, 2003) and may be

[6] The calculation of the expected value and the standard deviation of ROA is problematic for at least four reasons. First, we only have a limited number of observations available for each bank as we have annual data for a maximum of 16 years. Any estimation of $E_{it}(ROA)$ or $\sigma_{it}(ROA)$ could therefore be quite noisy. Second, the moments of ROA are probably time-varying, decreasing the relevance of observations that are further away in the past. Third, not all banks are observed over the same period, decreasing the comparability of the estimated moments across banks if we would use the entire sample to calculate them. Finally, the use of lagged values of ROA to construct its mean and standard deviation consumes observations. Apart from the first argument, these considerations support a reduction in the number of observations used to calculate the mean and standard deviation of ROA.

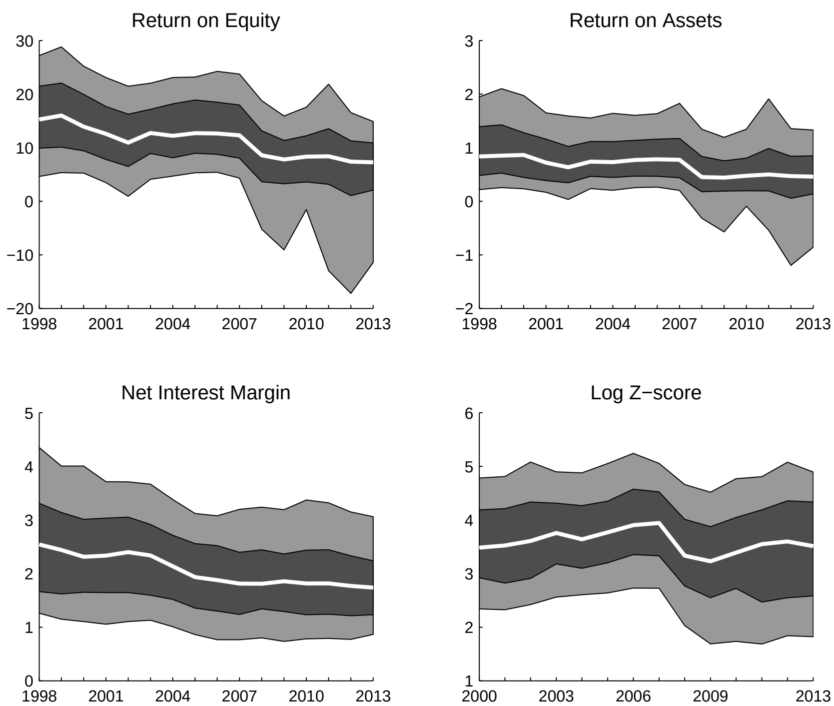


Figure 2: Evolution of the distribution of the performance indicators for European banks. The white line indicates the median. The dark area represents the second and third quartiles, whereas the lighter area spans the values between the tenth and ninetieth percentile.

Available Stable Funding	*Weight*	Required Stable Funding	*Weight*
Loans to customers	100%	Customer Deposits	90%
Loans to banks	50%	Deposits from banks	25%
Securities	50%	Long-term funding	100%
Derivatives	50%	Loan loss and other reserves	100%
Cash	0%	Other Liabilities	0%
Other assets	100%	Total Equity	100%

Table 3: Weights for the calculation of the net stable funding ratio (NSFR), which is calculated as the ratio of available stable funding to required stable funding. These weights are based on those given by BCBS (2014) and adapted to the granularity of our data.

distorted by forbearance, especially during a financial crisis. **Size** (log of total assets) is an important feature of a bank's business model as it determines its possibilities to exploit economies of scale and scope.

Liability structure The **ratio of deposits to liabilities** represents the reliance on traditional customer deposits. Gatev et al. (2009) furthermore show that banks with access to deposits may benefit from synergies with their lending activities, especially in periods of financial market stress. The **net stable funding ratio** captures the risk related to the funding strategy that originates in the mismatch between the liquidity of a bank's assets and liabilities. This measure is based on the NSFR that is part of the Basel III regulatory framework[7]. Table 3 presents our weighting scheme, which is based on the weights set out by the Basel Committee for Banking Supervision BCBS (2014)[8]. A higher NSFR indicates a lower level of funding risk.

Income structure The **income diversification ratio** measures the importance of non-interest income with respect to net interest income. Although preceding research has shown that not every type of non-interest income is equally volatile or conducive to bank stress (DeYoung and Torna, 2013; Stiroh, 2007), the data concerning non-interest income subcategories are not sufficiently granular for European banks to implement such subdivisions in our analysis. The calculation of the share of non-interest income is rendered problematic by its evolution during the financial crisis, when its level dropped substantially for most banks and in some cases even became negative. We mitigate this problem by setting negative values of non-interest income to zero since a negative income diversification ratio lacks a clear economic interpretation.

Capital structure The **capital ratio** is the ratio of equity to total assets, rather than a regulatory risk-weighted ratio. As a consequence of declining risk weights, unweighted and regulatory ratios have diverged in the preceding decade (BCBS, 2013; EBA, 2013; Le

[7]It should be noted that during our sample period the NSFR ratio was not compulsory for the banks. Still, it is a natural proxy for funding risk.

[8]We cannot exactly replicate the NSFR, due to the granularity of data required by the BCBS rules. In line with the existing literature on the NSFR (Dietrich et al., 2014), we propose an approximation taking into account both the BCBS classification and data availability.

	Unit	Obs.	Mean	Standard Deviation			
				Within	*Between*	*Overall*	*Between/Within*
Return on Equity	%	6356	10.09	11.47	9.84	13.56	0.86
Return on Assets	%	6378	0.69	0.72	0.65	0.90	0.90
Net Interest Margin	%	6378	2.16	0.56	1.01	1.14	1.82
Log Z-score		5506	3.56	0.89	0.82	1.12	0.92
Cost to Income	%	6378	63.93	12.09	14.21	16.84	1.18
Loans to Earning Assets	%	6378	65.58	8.25	16.09	17.76	1.95
Loan Loss Provisions to Loans	%	6378	0.73	0.89	0.73	1.08	0.83
Log Assets		6378	9.53	0.37	1.60	1.65	4.31
Deposits to Liabilities	%	6378	59.78	8.04	20.27	21.14	2.52
Net Stable Funding Ratio	%	6378	91.56	8.74	14.82	16.85	1.69
Income Diversification	%	6378	32.39	8.95	13.30	15.75	1.49
Equity to Assets	%	6378	6.70	1.60	2.95	3.23	1.84

Table 4: Descriptive statistics. All variables are winsorized at the 0.01 and 0.99 quantiles. These variables are based on bank-specific data, obtained from Bankscope.

	LOAN	DEP	DIV	SIZE	LLP	NSFR
DEP	45.3*					
DIV	25.4*	35.2*				
SIZE	31.1*	33.3*	32.1*			
LLP	12.9*	2.5	26.3*	6.7		
NSFR	47.9*	60.2*	28.5*	64.9*	9.6*	
CAP	30.7*	49.1*	17.3*	69.9*	50.1*	41.6*

Table 5: The Pearson chi-squared statistics from bivariate frequency tables. For each variable banks are distributed over three equally-sized buckets (each containing 171 out of 513 banks), based on the average of the respective variable over the whole sample period. The statistic is used to test the null hypothesis of independence. Variable names are abbreviated in the following way: loans to earning assets (LOAN), deposits to liabilities (DEP), income diversification (DIV), log of total assets (SIZE), loan loss provisions (LLP), net stable funding ratio (NSFR), and equity to total assets (CAP). A * indicates a significance level of 5%.

Leslé and Avramova, 2012). Mariathasan and Merrouche (2014) attribute the decline in risk weights to the strategic use of internal risk models by banks.

The descriptive statistics for the strategic variables in table 4 show that for six out of seven variables the between variation exceeds the within variation. This implies that the differences across banks are larger than changes over time within banks. This is consistent with our characterization of business models as long-term concepts and underlines the importance of exploiting the cross-sectional information. We furthermore test the interrelatedness of the proposed business model variables: we distribute all banks over three equally sized buckets, based on the bank-specific average of each variable over the entire sample period. We construct bivariate frequency tables to formally test the interdependence of the strategy variables, which allows for a richer characterization than would be possible with correlation coefficients. The Pearson test-statistics, presented in table 5, indicate that independence is rejected at the 5% level of significance in all but two cases. These results establish the interrelatedness of the strategic variables and thus their relevance in the determination of bank business models.

3.4 Control variables

We introduce a number of control variables to capture differences that are not directly related to a bank's business model, but are nonetheless important to determine bank performance. At the bank level we must account for operational efficiency. We use a standard cost-income ratio, where costs include all non-interest operational expenses and income is defined as the sum of non-interest and net interest income. We do not consider efficiency to be a business model characteristic, as it can be regarded as an outcome of strategic choices. Vander Vennet (2002), for instance, finds that European financial conglomerates, i.e. larger and more diversified banks, are more efficient. We also include a dummy-variable to control for differences between listed and non-listed banks. Finally, to control for all country-specific information, we include country-year fixed effects.

4 Results

4.1 Identification of bank business models

4.1.1 Limitations of classification

In section 2.1 we express some concerns regarding the use of classification strategies to distinguish the business models of European banks. In figure 3 we graphically document the continuous nature of business models using multidimensional scaling (MDS). This technique approximates the true distances between the banks[9] by a two-dimensional representation as accurately as possible so that similar banks are grouped together (Kruskal and Wish, 1978)[10]. Figure 3a shows the results of MDS, including a contour plot of an estimated bivariate density. Inspection of the density function suggests that there is only one mode, which is a first indication that the data do not support classification in discrete groups, but rather a continuum of business models (Everitt et al., 2011). In figure 3b banks are distributed using a direct classification based on the Bankscope typology. While cooperative and savings banks appear to be grouped, commercial banks occupy the entire space, illustrating that the Bankscope typology misses important similarities and differences between banks. Finally figures 3c and 3d also show the results of a cluster analysis [11]. They demonstrate that the cluster analysis groups similar observations, but also that the distances between banks of different clusters are often relatively small.

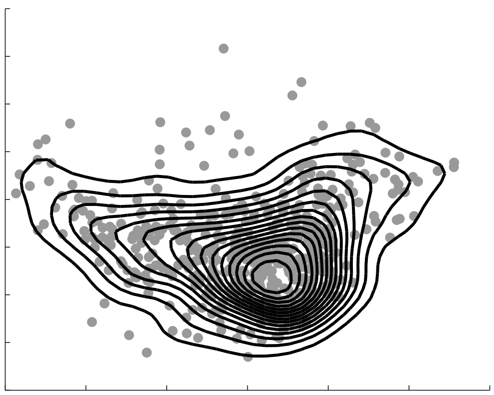
To further assess the quality of classification strategies, we calculate the silhouette width[12]

[9] These (Euclidean) distances are based on the standardized business model characteristics. Hence, they are seven-dimensional.

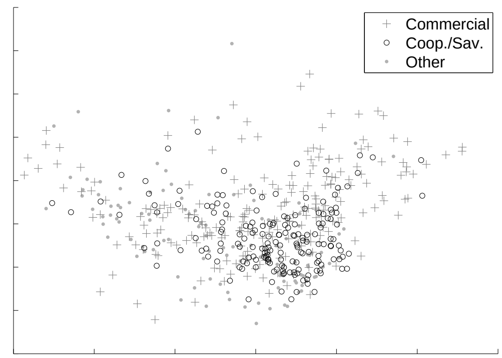
[10] In practice, MDS is equivalent to plotting the first two principal components of the seven business model variables, but the axes are effectively meaningless, as only the relative distances between observations are important.

[11] In line with Ayadi et al. (2011, 2012) we use the procedure proposed by Ward (1963) for clustering. The Calinski and Harabasz (2007) pseudo-F index, which is often used to determine the number of clusters implied by the data, suggests that the two-cluster solution is to be preferred over the three-cluster one.

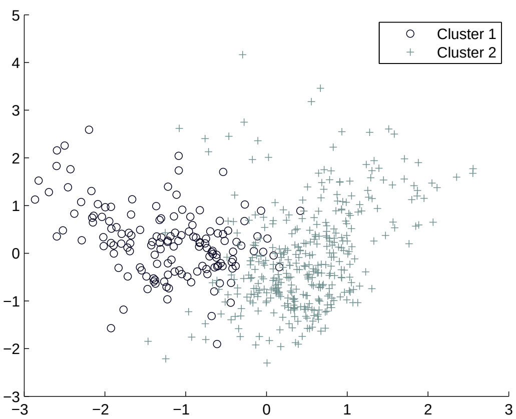
[12] The term silhouette width is derived from the silhouette plot, in which these values are represented as horizontal bars, hence width, ordered from high to low by cluster so that a *silhouette* is obtained for each cluster. This plot can then be used as a diagnostic tool to determine the number of clusters in the data (Kaufman and Rousseeuw, 1990). However, to assess the suitability of cluster analysis, summary statistics



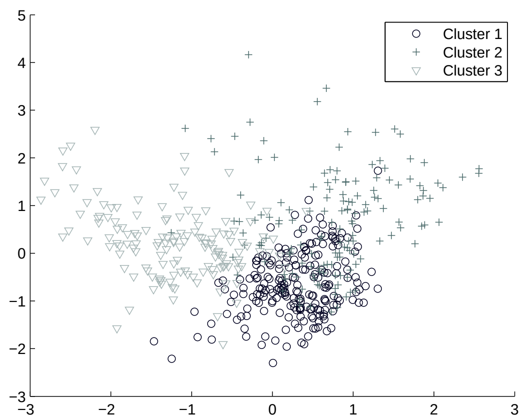
(a) Estimated bivariate density.



(b) Distribution of banks according to specialization.



(c) Distribution of banks in the two-cluster model.



(d) Distribution of banks in the three-cluster model.

Figure 3: Two-dimensional representation of the distances between banks using classical multi-dimensional scaling.

Number of groups		Avg. SW	SW > 0.5	SW < 0.2	SW < 0
Clusters:	2	0.23	0.0%	33.5%	7.6%
	3	0.17	0.2%	50.3%	21.4%
	4	0.17	0.0%	50.3%	16.8%
	5	0.19	0.0%	47.8%	12.7%
	6	0.16	0.0%	57.7%	12.9%
Bankscope classification		-0.06	0.0%	97.3%	62.8%

Table 6: Averages and distribution of silhouette width (SW) for different classifications. The Bankscope classification is based on five groups: bank holding companies, commercial banks, savings and cooperative banks, mortgage banks and governmental credit institutions.

(SW) of each bank for a number of possible classifications. This measure compares observed within- and between-group distances for each bank. SW is normalized to take values between -1 and 1 and a higher value implies better classification: the bank is more similar to the banks in the same cluster than to those in the nearest other cluster. Kaufman and Rousseeuw (1990) suggest that an average silhouette width of above 0.5 implies a reasonable classification, whereas a value below 0.2 indicates the absence of underlying clusters. The results in table 6 do not support any of the classification approaches: silhouette widths are low and in the case of the Bankscope typology even negative. These findings suggest that a large number of banks are only loosely situated within their cluster and often fall between two groups. A rigid classification will therefore separate very similar banks into different categories.

4.1.2 Factor analysis

As an alternative to classification and to a model using individual bank characteristics directly, we propose an identification strategy based on factor analysis (see section 2.1). The results of the factor analysis are reported in table 7. If there is common variance, this will be reflected by factors associated with eigenvalues above 0. To determine the number of factors the data support, we construct confidence intervals around the estimated eigenvalues using parallel analysis[13]. We find that six eigenvalues are significantly positive. However, an eigenvalue above 0 does not necessarily indicate that a factor is economically meaningful. As its eigenvalue gets lower, a factor explains less common variation. This implies that factors with low eigenvalues are less likely to reflect the broad common strategies that we relate to bank business models. We therefore focus on the two factors with the highest eigenvalues[14]. This choice is consistent with Demirgüç-Kunt and Huizinga (2010) and Köhler (2015) who also describe a bank's business model using two variables, i.e. the share of non-deposit fund-

suffice.

[13]This technique was developed by Horn (1965). It uses Monte Carlo simulation to estimate, for a given number of observations and variables, the distribution of eigenvalues associated with the factors if the data were randomly generated, i.e. in the absence of common variation. Parallel analysis is considered to be among the most precise methods to determine the number of factors (see, among others, Dinno, 2009).

[14]In the regression analysis, we still control for the variation of the bank characteristics that is not captured by the two business model factors, i.e. the four non-retained factors and a variable capturing the unique variation are included as regressors. The additional regressors are orthogonal to the business model factors and lack individual economic interpretation (jointly they capture the variation of the bank characteristics that is not related to the business model). We will therefore not discuss their effects on bank performance.

	Eigenvalue	Critical values (5%)	
Factor 1	2.03	0.093	
Factor 2	0.94	0.072	
Factor 3	0.59	0.053	
Factor 4	0.21	0.036	
Factor 5	0.07	0.023	
Factor 6	0.04	0.001	
Factor 7	-0.00	-	
	Correlation with characteristics		Communality
Loans to Earning Assets	0.23	-0.84	58.6%
Loan Loss Provisions to Loans	0.05	-0.02	0.3%
Log Assets	-0.70	0.22	47.5%
Deposits to Liabilities	0.89	0.01	69.9%
Net Stable Funding Ratio	0.79	0.60	82.7%
Income Diversification	-0.23	0.30	13.5%
Equity to Assets	0.51	-0.11	24.3%

Table 7: This table displays the results of the factor analysis, which is conducted using the iterated principal factor method (see, for instance, Kim and Mueller, 1978) . The upper panel displays the eigenvalues of the common factors. We also perform (one-sided) tests to determine whether these eigenvalues are significantly greater than zero using parallel analysis (Horn, 1965). We report critical values at the 5% significance level. The lower panel reports correlations of the predicted factors with the observed variables and the communality associated with each variable. A higher communality indicates that the variable is better explained by the common factors.

ing and income diversification. These variables are moreover closely related to the factors with respect to interpretation. The first factor is associated with a retail-based strategy. It positively relates to the loan, deposit, capital and net stable funding ratios, but is negatively related to size and income diversification. The second factor describes the negative relationship between a high loan ratio and high income diversification. Figure 4 contains a graphical representation of the relations of the common factors with the original business model variables. Based on these correlations, we label the first factor *RETAIL* and the second factor *DIVERSIFICATION*. Finally, the communalities in the lower panel of table 7 show that size and the loan, deposit and net stable funding ratios appear to be best explained by the common factors.

4.2 Impact of individual bank characteristics

The results of the model using individual business model characteristics are presented in tables 8 and 9. In table 8 we report the results for the four performance indicators and in table 9 we further examine the transmission of the strategic variables by decomposing the performance indicators into several of their components: interest income and expenses, non-interest income and operating expenses, all relative to total assets[15], and the volatility of ROA. The upper half of each table displays the within (short-term) effects, whereas the lower part presents the between effects, which in these regressions can be interpreted as business model effects and are therefore the focus of our investigation. The model fits the data reasonably well, but is more powerful in explaining the between than the within variation,

[15]We do not include a regression for the ratio of loan loss provisions to assets in our results, as the ratio of LLP to total loans is one of our explanatory variables.

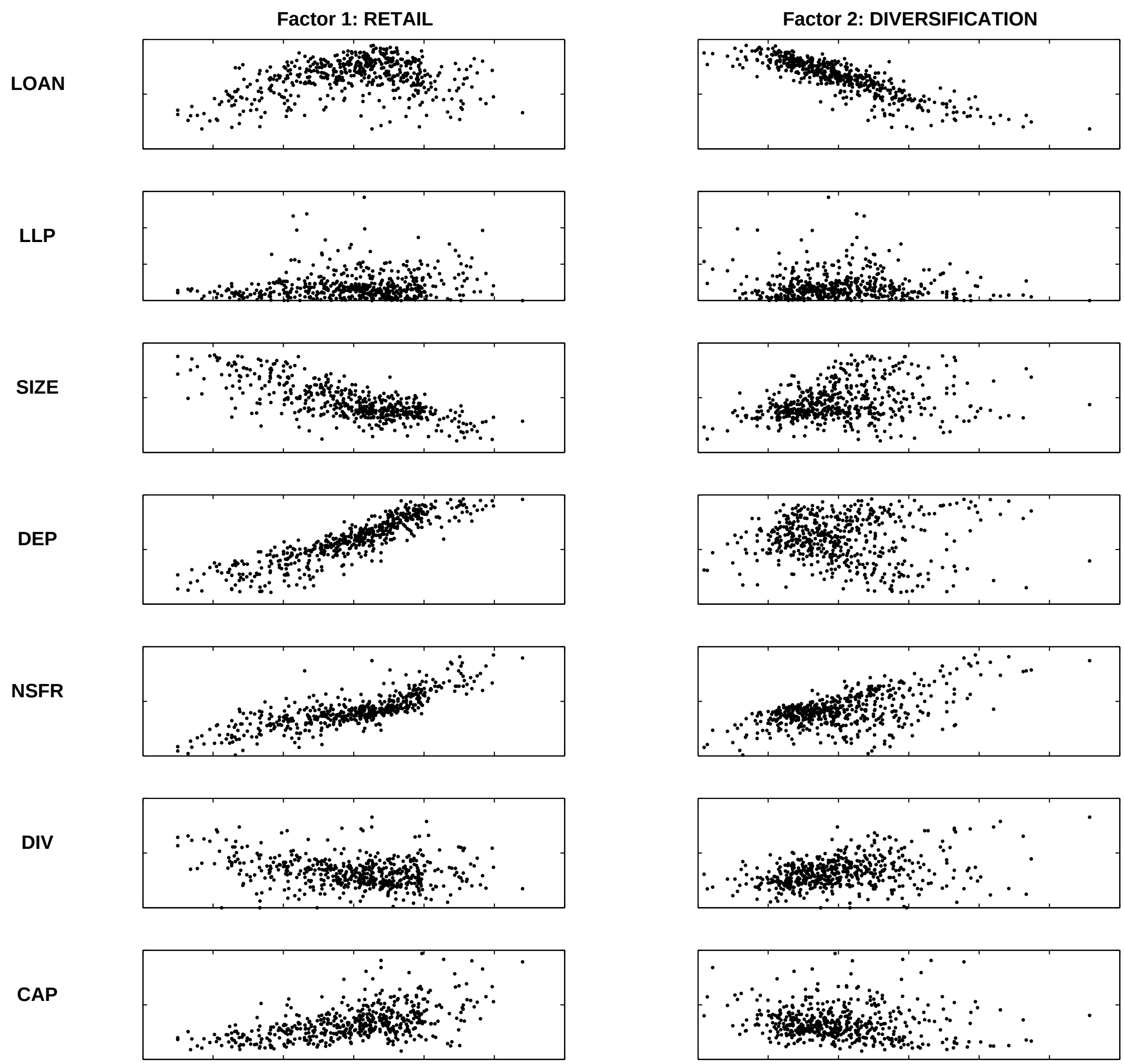


Figure 4: The relation of the common factors (horizontal axis) and the business model variables (vertical axis).

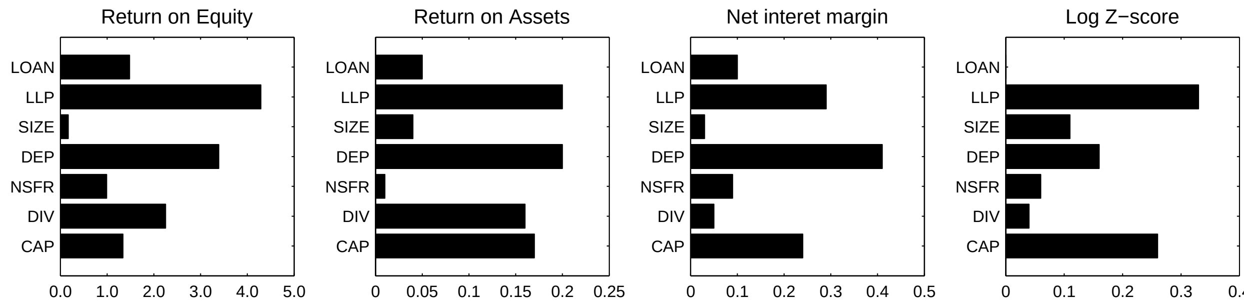


Figure 5: Absolute between effects on bank performance of a one (between) standard deviation change of the business model variables. Variable names are abbreviated in the following way: loans to earning assets (LOAN), loan loss provisions (LLP), log of total assets (SIZE), deposits to liabilities (DEP), net stable funding ratio (NSFR), income diversification (DIV), equity to total assets (CAP).

as can be observed from the R^2 statistics. We furthermore note that many of the between effects are found to be statistically significant both jointly and individually. These findings support the thesis that business models, i.e. long-term strategic choices, are important to explain bank performance. In the following sections we discuss the effects of each of the business model characteristics on bank performance. In order to judge and compare the economic importance of these effects, we also calculate the impact of a one (between) standard deviation change of the business model variables. These results are presented in figure 5.

4.2.1 Asset structure

The between panel of table 8 shows that, notwithstanding a positive impact on the net interest margin, a higher loan ratio decreases profitability in the long run. Combined with the statistically insignificant effect on the Z-score, this implies that a focus on lending activity results in a worse risk-return trade-off than alternative asset structures. Table 9 clarifies the underlying drivers of these findings. A higher loan ratio appears to enable banks to generate both more net interest and non-interest income from each euro of assets (columns 3-4), but also increases operating expenses (column 5), albeit to a lower degree: the impact on pre-impairment ROA is significantly positive (column 6). The total effect on ROA, however, is negative due to the need for extra loan loss provisions per asset. Even for constant credit risk, a higher loan ratio can increase loan impairment charges on the average asset. As a consequence, the increased revenues, induced by a higher loan ratio, are lost to the extra expenses such a strategy entails.

Table 8 demonstrates that the effects of the asset quality measure (the LLP ratio) are statistically significant for all performance indicators. A strategy based on targeting less creditworthy borrowers can generate a higher NIM, but it also causes profitability, ROE and ROA, to drop in the long term. A more detailed examination of these effects in table 9 reveals that banks following a business model reliant on riskier lending are compensated for this risk by a higher pre-impairment ROA, as as they can generate more net interest and non-interest income per asset. The negative impact on total ROA, however, implies that these improvements are more than compensated by higher exposure to loan impairments.

	ROE (1)	ROA (2)	NIM (3)	Log Z-score (4)
Within				
Loans to earning assets	-0.001	0.002	0.010***	0.002
	(0.029)	(0.002)	(0.002)	(0.003)
LLP to total loans	-2.539***	-0.163***	0.042***	-0.218***
	(0.395)	(0.024)	(0.013)	(0.023)
Log size	-3.281***	-0.192***	-0.149**	-0.159*
	(1.054)	(0.068)	(0.060)	(0.085)
Deposits to liabilities	0.073**	0.004**	0.004**	0.009***
	(0.034)	(0.002)	(0.002)	(0.003)
Net stable funding ratio	-0.014	-0.002	0.002	-0.004
	(0.026)	(0.001)	(0.001)	(0.002)
Share of non-interest income	-0.035	-0.002	-0.010***	-0.004**
	(0.023)	(0.001)	(0.001)	(0.002)
Capital ratio	-0.583***	0.016	0.033***	0.040***
	(0.156)	(0.012)	(0.009)	(0.013)
Cost-income ratio	-0.150***	-0.010***	-0.006***	-0.012***
	(0.025)	(0.002)	(0.001)	(0.002)
Listed	-1.053	0.001	0.018	-0.182*
	(1.492)	(0.092)	(0.063)	(0.105)
Between				
Loans to earning assets	-0.092***	-0.003**	0.006***	0.000
	(0.026)	(0.002)	(0.002)	(0.003)
LLP to total loans	-5.883***	-0.280***	0.404***	-0.453***
	(0.888)	(0.045)	(0.077)	(0.047)
Log size	0.106	0.025*	0.016	0.070***
	(0.223)	(0.014)	(0.021)	(0.025)
Deposits to liabilities	0.167***	0.010***	0.020***	0.008***
	(0.023)	(0.001)	(0.002)	(0.002)
Net stable funding ratio	-0.067***	-0.001	-0.006**	-0.004
	(0.026)	(0.002)	(0.002)	(0.004)
Share of non-interest income	0.169***	0.012***	-0.004*	-0.003
	(0.027)	(0.002)	(0.002)	(0.003)
Capital ratio	-0.454***	0.057***	0.080***	0.087***
	(0.168)	(0.010)	(0.015)	(0.016)
Cost-income ratio	-0.379***	-0.023***	-0.002	-0.016***
	(0.030)	(0.002)	(0.003)	(0.003)
Listed	1.295**	0.117***	0.204***	0.069
	(0.613)	(0.045)	(0.064)	(0.058)
Observations	5845	5865	5865	5436
Banks	508	508	508	498
Av. nr. of periods	11.51	11.55	11.55	10.92
R^2 (within)	0.45	0.53	0.58	0.31
R^2 (between)	0.72	0.77	0.79	0.64
R^2 (overall)	0.52	0.61	0.76	0.41
Between Effects	123.49***	145.13***	92.02***	36.37***

Table 8: This table shows the results of the regressions explaining the performance indicators using the individual bank characteristics to capture the business model. The model is estimated using the Mundlak (1978) estimator. The upper panel displays the estimated within parameters, whereas the lower panel shows the between parameters, which we relate to long-term business model effects. All estimations use country-year fixed effects to control for the macroeconomic environment. Standard errors in parentheses are clustered at the bank level. We also test for the joint significance of the between effects. Stars indicate significance levels: *, **, *** represent significance at the 10%, 5%, and 1% level respectively.

	Total int. income (1)	Total int. expenses (2)	Net int. income (3)	Non-int. income (4)	Operating expenses (5)	Pre-imp. ROA (6)	Log σ_{ROA} (7)
Within							
Loans to earning assets	0.011***	0.003	0.007***	0.004**	0.004*	0.006***	0.001
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
LLP to total loans	0.041**	0.020	0.031***	0.023*	0.065***	-0.005	0.167***
	(0.019)	(0.016)	(0.011)	(0.012)	(0.014)	(0.016)	(0.022)
Log size	0.279**	0.450***	-0.145**	-0.130**	-0.162***	-0.093	0.116
	(0.110)	(0.102)	(0.057)	(0.051)	(0.057)	(0.059)	(0.082)
Deposits to liabilities	0.005	0.000	0.004***	-0.002	0.004**	-0.002	-0.006**
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Net stable funding ratio	0.002	0.003	0.000	0.004***	0.004***	0.000	0.004*
	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Share of non-interest income	-0.010***	0.000	-0.009***	0.012***	0.008***	-0.004***	0.004**
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Capital ratio	-0.006	-0.031***	0.030***	0.021***	0.034***	0.032***	0.040***
	(0.015)	(0.012)	(0.008)	(0.008)	(0.009)	(0.009)	(0.012)
Cost-income ratio	-0.004**	0.001	-0.005***	0.002*	0.008***	-0.010***	0.009***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Listed	0.130	0.046	-0.003	-0.155**	-0.094	-0.054	0.148
	(0.114)	(0.078)	(0.058)	(0.066)	(0.070)	(0.068)	(0.098)
Between							
Loans to earning assets	0.017***	0.011***	0.006***	0.004**	0.007***	0.002*	0.001
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)
LLP to total loans	0.375***	0.008	0.359***	0.138***	0.299***	0.252***	0.459***
	(0.113)	(0.071)	(0.071)	(0.030)	(0.051)	(0.041)	(0.045)
Log size	-0.018	-0.016	0.001	-0.021	-0.037*	0.018	-0.072***
	(0.042)	(0.036)	(0.019)	(0.015)	(0.021)	(0.013)	(0.023)
Deposits to liabilities	-0.002	-0.020***	0.018***	0.006***	0.015***	0.010***	-0.004
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Net stable funding ratio	0.013**	0.020***	-0.007***	0.005**	0.000	-0.001	0.001
	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Share of non-interest income	-0.012***	-0.006	-0.005**	0.042***	0.027***	0.012***	0.007***
	(0.005)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Capital ratio	-0.009	-0.081***	0.069***	0.022***	0.035***	0.058***	0.043***
	(0.021)	(0.018)	(0.013)	(0.008)	(0.012)	(0.009)	(0.014)
Cost-income ratio	-0.004	-0.001	-0.003	-0.002	0.018***	-0.022***	0.012***
	(0.004)	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Listed	0.023	-0.132*	0.173***	0.043	0.092*	0.111**	-0.042
	(0.100)	(0.080)	(0.056)	(0.041)	(0.054)	(0.044)	(0.056)
Observations	5862	5835	5865	5865	5865	5865	5436
Banks	508	507	508	508	508	508	498
Av. nr. of periods	11.54	11.51	11.55	11.55	11.55	11.55	10.92
R^2 (within)	0.68	0.71	0.58	0.43	0.61	0.39	0.27
R^2 (between)	0.64	0.53	0.77	0.85	0.78	0.82	0.66
R^2 (overall)	0.68	0.63	0.75	0.74	0.75	0.69	0.42
Between Effects	23.69***	38.81***	88.27***	198.91***	129.48***	200.74***	51.11***

Table 9: This table shows the results of the regressions explaining the subcomponents of the performance indicators using the individual bank characteristics to capture the business model. The model is estimated using the Mundlak (1978) estimator. The upper panel displays the estimated within parameters, whereas the lower panel shows the between parameters, which we relate to long-term business model effects. All estimations use country-year fixed effects to control for the macroeconomic environment. Standard errors in parentheses are clustered at the bank level. We also test for the joint significance of the between effects. Stars indicate significance levels: *, **, *** represent significance at the 10%, 5%, and 1% level respectively.

Finally, credit risk also negatively affects the Z-score, meaning that business models characterized by riskier loan portfolios are associated with more distress. Hence, when a bank strategically concentrates on risky lending or is forced by disintermediation to target more risk loan segments, it can only pursue this option in a viable way when it succeeds in lowering impairments by developing effective screening and monitoring capabilities.

Finally, tables 8 and 9 reveal that a business model characterized by large size tends to improve long-run performance: it is associated with increased ROA and stability. Short-term changes to bank size, however, have a very negative effect on bank performance: the impact on ROE, ROA, NIM and Z-score is significantly negative. The explanation for these different short-term outcomes can be found by comparing the effects on pre- and post-impairment ROA in tables 9 and 8 respectively. In the short run, asset growth results in more loan loss provisions per asset, i.e. a higher concentration of loans or a lower quality of loans. Note, finally, that our analysis is bank-specific and that while we find that business models characterized by large size are more stable in the long run, there may be a high societal cost associated with very large banks due to systemic risk concerns (see ESRB, 2014). Increasing bank size is therefore probably not the desired channel to achieve bank stability.

4.2.2 Liability structure

With respect to the funding composition, Huang and Ratnovski (2011) show that wholesale financiers react strongly to noisy public signals and, as a consequence, these funding sources can dry up quickly during a financial crisis. Recent studies have also demonstrated that a higher reliance on customer deposits reduces bank distress (Altunbas et al., 2011; Betz et al., 2013) and inspires market confidence (Beltratti and Stulz, 2012). Consistent with these results, we show in the between panel of table 8 that banks characterized by a traditional funding structure are both more profitable and stable in the long run. Table 9 clarifies the transmission of funding composition to performance outcomes. First, a higher deposit ratio increases the net interest income gained from the average asset by decreasing interest expenses (columns 1-3). Second, a business model characterized by a high deposit ratio is also better able to generate non-interest income (column 4), which is likely due to the greater scope of cross-selling products to an expanded group of retail clients, which can raise fee income. Finally, higher operating expenses per asset (column 5) are not large enough to cancel out the income increase: the effect on pre-impairment ROA is significantly positive (column 6).

Funding stability is an essential novel feature of the Basel III regulation through the imposition of a net stable funding ratio. Although it is generally expected that banks with fragile funding structures will have to adjust their business model (King, 2013), it is uncertain whether this will affect profitability (Dietrich et al., 2014). Our findings should not be interpreted as an impact study of the NSFR regulation, since the relationship between various sources of funding and their respective costs might change when the banking industry as a whole increases its demand for stable funding. Nevertheless, a study of the long-term performance impact of funding risk may demonstrate the benefits and drawbacks of such regulation. The results in table 8 indicate that a business model's funding risk has no significant impact on either ROA or the Z-score. The effects on ROE and NIM are even significantly negative. The regression results in table 9 demonstrate that the absence of a significant impact on ROA is in fact the outcome of a combination of effects. Most notably, banks characterized by high levels of funding stability have higher funding expenses, which they compensate with increased interest income and non-interest income (columns 1-4). The higher interest income is unlikely to be caused by a higher loan ratio[16], and may therefore imply that banks that have to raise NSFR do so by partly passing the increased funding cost on to their borrowers by charging higher interest rates and fees, an effect that has been anticipated by the supervisors (BCBS, 2010).

4.2.3 Income structure

Theoretically diversification should allow banks to reach a better position on the risk-return frontier. Stiroh and Rumble (2006) and Demirgüç-Kunt and Huizinga (2010) demonstrate that income diversification is beneficial for profitability, but that it also increases bank risk. Altunbas et al. (2011) and Köhler (2015), on the other hand, find that more diversified banks are generally less susceptible to distress. With respect to market valuation, it is unclear whether diversified banks are valued higher (Baele et al., 2007) or lower (Laeven and Levine, 2007) than their specialized peers. The results in table 8 demonstrate that banks characterized by a high degree of income diversification perform better in the long run: they enjoy higher ROE and ROA without becoming more susceptible to distress. Again, table 9 provides a more detailed analysis of these effects. A business model that relies on income diversification enables banks to generate more non-interest income from the average asset, which more than compensates the lower level of net interest income and higher expenses (columns 3-5). The insignificant business model effect of income diversification on the Z-score results from the positive impacts on both ROA and ROA volatility, which appear to offset each other[17]. These results are not restricted to the already well-diversified financial conglomerates and therefore suggest that income diversification is essential to attain a viable business model in the long term.

4.2.4 Capital structure

Theory predicts that equity financing can reduce the ability of creditors to exert market discipline (Diamond and Rajan, 2001), but also that it may induce banks to screen borrowers more intensively (Mehran and Thakor, 2010). Most empirical research (e.g. Beltratti and Stulz, 2012) finds that during the financial crisis banks with higher capital ratios performed better and were less likely to experience severe distress. The results in table 8 suggest that business models that are characterized by high capital ratios lead to better performance in terms of NIM and ROA, but that this does not suffice to offset the mechanical negative impact on ROE. The positive business model effect on ROA and NIM can mainly be attributed to decreasing interest expenses (see table 9). A higher capital ratio reduces the reliance on interest-bearing funding sources, but can moreover negatively affect banks' own risk

[16]Loans are subject to a high weight in the calculation of required stable funding, i.e. the denominator of the NSFR. In our scheme customer loans uniformly receive a weight of 100%. In the Basel III framework the weight also depends on encumbrance and credit risk.

[17]Note that in the short term changes to income diversification also result in increased ROA volatility, but not in higher ROA. This means that in the short run diversification is expensive and exposes banks to more distress.

	ROE (1)	ROA (2)	NIM (3)	Log Z-score (4)
Within				
RETAIL	4.208***	0.330***	0.438***	0.391***
	(1.359)	(0.080)	(0.073)	(0.104)
DIVERSIFICATION	-1.303**	-0.140***	-0.282***	-0.163***
	(0.596)	(0.039)	(0.034)	(0.048)
Cost-income ratio	-0.150***	-0.010***	-0.006***	-0.012***
	(0.025)	(0.002)	(0.001)	(0.002)
Listed	-1.053	0.001	0.018	-0.182*
	(1.492)	(0.092)	(0.063)	(0.105)
Between				
RETAIL	-0.322	0.149***	0.487***	0.144***
	(0.354)	(0.020)	(0.032)	(0.051)
DIVERSIFICATION	2.360***	0.115***	-0.211***	-0.057*
	(0.271)	(0.021)	(0.029)	(0.033)
Cost-income ratio	-0.379***	-0.023***	-0.002	-0.016***
	(0.030)	(0.002)	(0.003)	(0.003)
Listed	1.295**	0.117***	0.204***	0.069
	(0.613)	(0.045)	(0.064)	(0.058)
Observations	5845	5865	5865	5436
Banks	508	508	508	498
Av. nr. of periods	11.51	11.55	11.55	10.92
R^2 (within)	0.45	0.53	0.58	0.31
R^2 (between)	0.72	0.77	0.79	0.64
R^2 (overall)	0.52	0.61	0.76	0.41
Between Effects	123.49***	145.13***	92.02***	36.37***

Table 10: This table shows the results of the regressions explaining the subcomponents of the performance indicators using the common factors to capture the business model. The model is estimated using the Mundlak (1978) estimator. The upper panel displays the estimated within parameters, whereas the lower panel shows the between parameters, which we relate to long-term business model effects. All estimations use country-year fixed effects to control for the macroeconomic environment. Standard errors in parentheses are clustered at the bank level. We also test for the joint significance of the between effects. Stars indicate significance levels: *, **, *** represent significance at the 10%, 5%, and 1% level respectively.

premiums and thereby lower the cost of external funding. In line with most empirical work we find that banks relying on high capital ratios exhibit significantly higher Z-scores and hence are less fragile (column 4 of table 8). However, we also confirm the findings of, among others, Delis et al. (2014), who show that a higher capital ratio increases bank risk, as the effect on ROA volatility is significantly positive (column 7 of table 9). Our findings demonstrate that the higher capital ratio and its positive impact on ROA more than offset the positive effect on ROA volatility, resulting in an unambiguous superior risk-return trade-off. These results unambiguously support the strengthening of the capital rules by Basel III and the continuous pressure of supervisors on banks to increase capital ratios.

4.3 Impact of the common factors

To complement the analysis of the individual business model characteristics, we apply an identification strategy based on factor analysis (see section 4.1.2). In this section we discuss the results of the model that uses the common factors to explain bank performance. The

	Total int. income (1)	Total int. expenses (2)	Net int. income (3)	Non-int. income (4)	Operating expenses (5)	Pre-imp. ROA (6)	Log $\sigma_{\mathbf{ROA}}$ (7)
Within							
RETAIL	-0.151	-0.581***	0.398***	0.176***	0.379***	0.185***	-0.137
	(0.133)	(0.121)	(0.066)	(0.062)	(0.070)	(0.068)	(0.098)
DIVERSIFICATION	-0.107*	0.174***	-0.243***	-0.014	-0.057	-0.173***	0.065
	(0.064)	(0.059)	(0.029)	(0.032)	(0.036)	(0.033)	(0.047)
Cost-income ratio	-0.004**	0.001	-0.005***	0.002*	0.008***	-0.010***	0.009***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Listed	0.130	0.046	-0.003	-0.155**	-0.094	-0.054	0.148
	(0.114)	(0.078)	(0.058)	(0.066)	(0.070)	(0.068)	(0.098)
Between							
RETAIL	0.294***	-0.170***	0.447***	0.092***	0.324***	0.220***	0.131***
	(0.068)	(0.060)	(0.028)	(0.021)	(0.030)	(0.018)	(0.046)
DIVERSIFICATION	-0.241***	-0.007	-0.219***	0.250***	0.038	0.005	-0.023
	(0.054)	(0.045)	(0.025)	(0.028)	(0.031)	(0.020)	(0.032)
Cost-income ratio	-0.004	-0.001	-0.003	-0.002	0.018***	-0.022***	0.012***
	(0.004)	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Listed	0.023	-0.132*	0.173***	0.043	0.092*	0.111**	-0.042
	(0.100)	(0.080)	(0.056)	(0.041)	(0.054)	(0.044)	(0.056)
Observations	5862	5835	5865	5865	5865	5865	5436
Banks	508	507	508	508	508	508	498
Av. nr. of periods	11.54	11.51	11.55	11.55	11.55	11.55	10.92
R^2 (within)	0.68	0.71	0.58	0.43	0.61	0.39	0.27
R^2 (between)	0.64	0.53	0.77	0.85	0.78	0.82	0.66
R^2 (overall)	0.68	0.63	0.75	0.74	0.75	0.69	0.42
Between Effects	23.69***	38.81***	88.27***	198.91***	129.48***	200.74***	51.11***

Table 11: This table shows the results of the regressions explaining the subcomponents of the performance indicators using the common factors to capture the business model. The model is estimated using the Mundlak (1978) estimator. The upper panel displays the estimated within parameters, whereas the lower panel shows the between parameters, which we relate to long-term business model effects. All estimations use country-year fixed effects to control for the macroeconomic environment. Standard errors in parentheses are clustered at the bank level. We also test for the joint significance of the between effects. Stars indicate significance levels: *, **, *** represent significance at the 10%, 5%, and 1% level respectively.

results are presented in tables 10 and 11 (they follow the same structure as the model based on the individual bank characteristics). In order to avoid misspecification issues, we control for all variation of the business model variables. This means that apart from the first two factors, which in our view are related to the dominant underlying bank strategies, we also include the other four factors and the variation of the variables that cannot be explained by the common factors. Since these variables lack interpretation, we do not report their impact on bank performance. Given that we control for exactly the same information as is reflected by the individual variables, there is essentially no change in the properties and goodness-of-fit of the estimation. Hence, we refer to section 4.2 for a discussion of these general results. Also note that the factors are by construction standardized.

The first factor is labeled *RETAIL* based on its positive relation with funding stability, the loan, deposit and capital ratio and its negative relation with size and income diversification (see table 7 and figure 4). A higher value of this factor indicates that the bank is more similar to a traditional retail bank. The results in table 10 suggest that business models characterized by a stronger retail orientation are more profitable: the factor positively affects the NIM and ROA. Because retail banks are typically characterized by higher capital ratios, the effect on ROA is not translated into a positive impact on ROE. Inspection of the components of ROA in table 11 indicates that business models characterized by a focus on retail activities incur higher expenses per asset, but that this is more than offset by a positive effect on net interest and non-interest income (columns 1-5). Finally, while there is a significantly positive impact on ROA volatility (column 7), retail banks' higher capital ratios and the positive effect on ROA ensure that a higher degree of retail activity also increases banks' stability (column 4 in table 6).

The second factor, *DIVERSIFICATION*, reflects the trade-off between a loan-oriented asset composition and a high degree of income diversification. A high level of this factor is associated with business models with a more diversified asset composition and income structure. The results, presented in the between panel of table 10, demonstrate that business models that are characterized by a high level of functional diversification perform better: they are more profitable, measured either as ROE or ROA, but are also more susceptible to distress (columns 1, 2 and 4). The more detailed analysis of ROA in table 11 suggests that such business models allow banks to generate more non-interest income, but that this benefit is to a great extent offset by lower net interest income (columns 3 and 4). A comparison of the effects on pre- and post-impairment ROA, however, reveal that banks with a more diversified business model are less exposed to loan impairments and are therefore more profitable. The positive impact on ROA combined with the negative, though not significant, effect on ROA variability imply that a more diversified business model improves the risk-return trade-off for banks.

However, the negative effect on the Z-score indicates that this improvement is more than offset by the lower capital ratios that characterize more diversified banks (see table 7). In other words, banks appear to overestimate the beneficial effect of diversification, leading to a reduction of capital ratios that is too deep. Finally, the within effects of this factor imply that increasing the level of functional diversification can hurt performance in the short term: it negatively affects all performance indicators (table 10). The results in table 11 show that this is due to a combination of two effects: in the short term it is harder for banks to obtain more non-interest income per asset, but there is still a sharp drop in net interest income generation.

4.4 Heterogeneity of business model effects

Finally, we explore the heterogeneity of business model effects. The concern is that the impact of business model characteristics on bank performance may depend on a bank's business model itself. Köhler (2015), for instance, finds that the impact of income diversification and reliance on wholesale funding differs across bank types. We therefore investigate how the effects of the strategic variables change conditional on the degree to which a bank resembles a retail business model, as measured by the *RETAIL* factor. We propose an estimation framework based on a rolling regression in which the subsamples are based on the average level of the *RETAIL* factor. The size of each subsample equals 171 banks, i.e. one third of all banks, so that we have sufficient observations to accurately estimate the model. We set the step size to 19 banks, which results in 19 parameter estimates per rolling regression[18]. Such an approach offers some advantages over alternative methods. First, interaction variables (as in Demirgüç-Kunt and Huizinga, 2010) impose the constraint that the effect of the variables vary linearly with the level of *RETAIL* factor. The second alternative is based on re-estimating the model for non-overlapping subsamples (Köhler, 2015). The cut-off for such samples is hard to determine and therefore often arbitrary. The limited number of subsample parameters might furthermore be quite noisy. Rolling regressions, on the other hand, yield a pattern of the parameter heterogeneity, making it easier to abstract from noise in separate parameter estimates. One must of course be careful not to overfit the data. We therefore focus on the global pattern of the parameter variability and never on individual parameters. The results of the rolling regression analysis are shown in figure 6.

With respect to asset structure, the results for the whole sample (tables 8 and 9) demonstrate that a loan-oriented asset composition decreases profitability, but does not affect stability. Banks with lower loan quality are both less profitable and more susceptible to distress. There is, however, some reason to believe that this effect varies according to the retail orientation of a bank. Salas and Saurina (2002) find that the loan quality of savings banks is less sensitive to macroeconomic circumstances than that of commercial banks due to their focus on local and smaller borrowers. This may also enable retail-oriented banks to more adequately price and monitor credit risk, for instance through a greater emphasis on relationship banking (Boot, 2000; Jiménez and Saurina, 2004). The first two rows of figure 6 indeed suggest that the effects of the loan and LLP ratio depend on the degree of a bank's retail orientation. First, a high loan ratio only decreases distress for retail-oriented banks, while such a strategy significantly increases non-retail banks' susceptibility to distress (row 1). Second, the negative effect of the LLP ratio on profitability almost disappears for business models with a strong retail orientation, as they are better able to convert the additional credit risk into a higher NIM (row 2). The results regarding asset composition and quality

[18] The volatility of the parameter estimates increases with the number of estimations in the rolling regression. Our choice for the step size is motivated by the trade-off that a low number of estimations may hide important variation, while a high number hinders interpretation of the results. The number of estimations in a rolling regression equals $1+\frac{N_{sample}-N_{window}}{N_{step}}$. We set the step to 19 for convenience, because it generates an integer if we set N_{window} to 171. We experiment with smaller and larger window and step sizes, but this does not affect our findings.

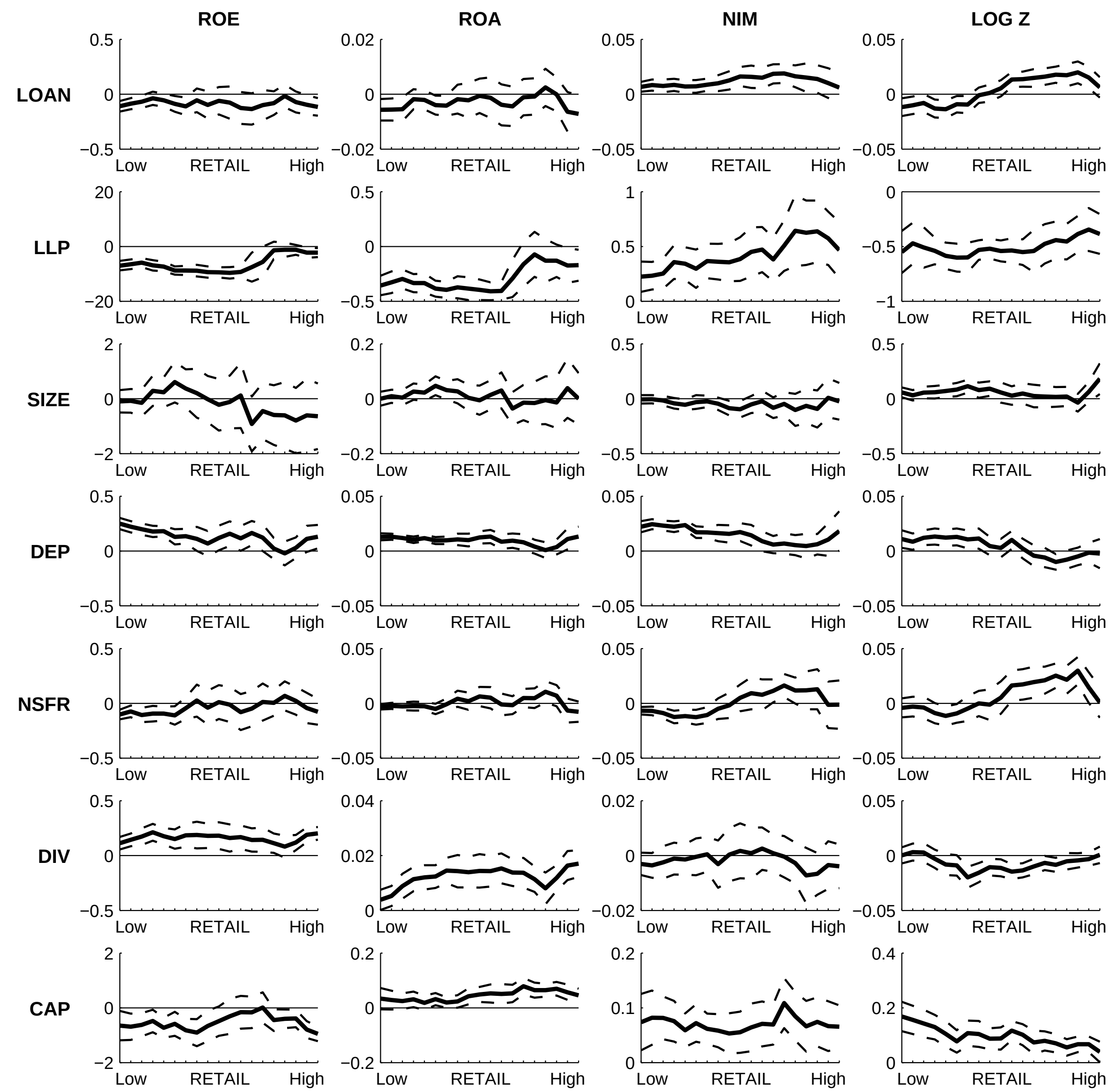


Figure 6: Heterogeneity of the impact of the business model variables.The label on the y-axis corresponds to the variable of which the effect is measured over different levels of the *RETAIL* factor. The solid line represents the point estimates of the coefficient and the dashed lines represent 90% confidence intervals based on standard errors clustered at the bank level. Variable names are abbreviated in the following way: loans to earning assets (LOAN), loan loss provisions (LLP), log of total assets (SIZE), deposits to liabilities (DEP), net stable funding ratio (NSFR), income diversification (DIV), equity to total assets (CAP).

imply that retail banks are uniquely qualified to act as delegated monitors.

The results for the whole sample show that business models characterized by a strong reliance on customer deposits are associated with higher profitability, a higher NIM and lower susceptibility to distress. Köhler (2015) finds that deposit funding is particularly important for the stability of retail-oriented banks. In contrast, Huang and Ratnovski (2011) show that wholesale financiers may be especially sensitive to public signals concerning bank soundness. Because non-retail banks are typically more leveraged and more exposed to volatile types of non-interest income, they may benefit most from a higher share of deposit funding. The results in figure 6 (row 4) indeed indicate that a high deposit ratio primarily benefits non-retail banks. This means that the post-crisis refocusing on traditional funding sources is beneficial for banks, as well as for society in general. With respect to funding risk, the results based on the full sample demonstrate that it does not affect ROA or stability, but has a negative impact on ROE and NIM. Still, attracting more stable deposits or other types of stable funding may prove to be only achievable at higher cost for non-retail banks, while the conservative risk profile of retail banks may provide a funding advantage. The rolling regression results (row 5) reveal that, if a bank's business model more closely resembles a retail model, the NSFR no longer negatively affects ROE or NIM, while the effect on the Z-score becomes significantly positive. This result also implies that more retail-oriented banks' susceptibility to distress is more sensitive to funding risk, while larger non-retail banks appear to be able to absorb funding risk in other ways so that it does not affect their general stability.

For the whole sample, income diversification supports banks' profitability, without decreasing stability. With respect to stability, De Jonghe et al. (2015) show that bank size is necessary to offset the risks incurred through more diversified income. Köhler (2014, 2015) instead demonstrates that income diversification mainly improves the stability of smaller retail-oriented banks, likely because their non-interest income is mainly generated by more stable fees and commissions. While the rolling regression (row 6) confirm the results of the baseline model regarding profitability, we indeed find that the impact on the Z-score is not stable: it becomes significantly negative for banks with a median level of the *RETAIL* factor. This result might reflect that more retail-oriented banks rely on more stable sources of non-interest income, while for less retail-oriented banks an adequate scale is necessary to avoid decreasing stability.

Finally, the examination of the full sample reveals that a business model characterized by a high capital ratio leads to a higher ROA, NIM and Z-score. These effects are unambiguously confirmed in the rolling regression analysis (row 7). However, consistent with Huang and Ratnovski (2011), a high capital ratio appears to have the largest impact on banks that are furthest away from the retail business model, which are typically larger, more leveraged and rely more on wholesale sources of funding. This result therefore provides some justification for the extra capital buffers imposed on systemically important banks in the application of the Basel III regulations.

5 Robustness

In this section we discuss the results of the robustness analysis of our findings. First, we examine whether the use of country-year fixed effects is justified, given that some countries contain only a small number of banks in our sample. Second, we check whether the Bankscope bank types contain information for which we are not able to control using only the balance sheet and income statement data. Third, we investigate how the use of different accounting standards affects our results. Finally, we explore the influence of the relative dominance of Germany-based banks in our sample. The results of this robustness analysis are reported in table 12 for the estimations using the individual business model variables and table 13 for the estimations using the factors. For brevity, we limit ourselves to the between estimations of ROA and the Z-score, which we consider to be the most important performance indicators. We also check whether the results of the factor analysis are sensitive to changes in the sample.

5.1 Macroeconomic control variables

The inclusion of country-year fixed effects ensures that we control for the macroeconomic, financial and institutional environment in which banks operate, as well as the changes thereof. However, given the limited number of banks in some countries (see table 2), we may be relating too much variation to country-specific circumstances. We therefore replace the country-year fixed effects by a combination of year fixed effects and a set of macroeconomic variables: real GDP growth, the 3-month money market rate and the sovereign probability of default. The latter is constructed by linking rating information to observed 10-year cumulative sovereign default probabilities (Fitch Ratings, 2014). While the macroeconomic control variables have statistically significant effects on long-term bank performance, the results in columns 3 and 4 of tables 12 and 13 mainly reveal that our conclusions are not sensitive to the method used to control for the country-specific environment. The effect of the *DIVERSIFICATION* factor on the Z-score is no longer statistically significant, although the size of the effect hardly changes, which reflects that this effect is borderline significant in the baseline estimations.

5.2 Bankscope classification

In line with other studies using only financial information to identify a bank's business model, we have so far assumed that our set of strategic variables suffices for identification. It is, however, an interesting question whether a direct classification of banks captures information for which balance sheet data cannot control. We therefore include the bank type according to Bankscope in our regressions (columns 5 and 6 of tables 12 and 13) using bank holding companies as the base type. Given the set of strategic variables, specialized governmental credit institutions are less profitable, cooperative banks are more stable and real estate and mortgage banks are both less profitable and more stable. These results are likely related to the focus of these bank types on a specific segment of borrowers. Nevertheless, the inclusion of bank types appears to have only a small impact and does not affect our conclusions. Only the effect of the loan ratio on ROA (table 12) and of the *DIVERSIFICATION* factor on

	Baseline		Macroeconomic controls		Bank type		No combination of GAAP and IFRS		Only IFRS		No banks from Germany	
	ROA	**Log Z**	**ROA**	**Log Z**	**ROA**	**Log Z**	**ROA**	**Log Z**	**ROA**	**Log Z**	**ROA**	**Log Z**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Loans to earning assets	-0.003**	0.000	-0.003***	0.003	-0.003	-0.001	-0.004**	0.001	-0.008***	0.001	-0.004**	0.001
	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.004)
LLP to total loans	-0.280***	-0.453***	-0.337***	-0.461***	-0.306***	-0.412***	-0.345***	-0.458***	-0.388***	-0.461***	-0.296***	-0.456***
	(0.045)	(0.047)	(0.048)	(0.048)	(0.046)	(0.048)	(0.039)	(0.048)	(0.044)	(0.049)	(0.045)	(0.049)
Log size	0.025*	0.070***	0.003	0.084***	0.025*	0.073***	0.022	0.056*	0.049**	0.050*	0.048***	0.064**
	(0.014)	(0.025)	(0.013)	(0.026)	(0.014)	(0.024)	(0.016)	(0.029)	(0.021)	(0.030)	(0.016)	(0.028)
Deposits to liabilities	0.010***	0.008***	0.007***	0.005**	0.009***	0.009***	0.010***	0.009***	0.006***	0.007**	0.008***	0.009***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Net stable funding ratio	-0.001	-0.004	0.003	0.000	0.000	-0.005	-0.002	-0.005	0.004*	-0.002	0.002	-0.007
	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.005)
Share of non-interest income	0.012***	-0.003	0.011***	-0.001	0.012***	-0.002	0.012***	0.000	0.008***	0.002	0.013***	-0.002
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Capital ratio	0.057***	0.087***	0.054***	0.094***	0.054***	0.092***	0.055***	0.104***	0.082***	0.125***	0.059***	0.081***
	(0.010)	(0.016)	(0.010)	(0.016)	(0.010)	(0.016)	(0.013)	(0.018)	(0.019)	(0.017)	(0.011)	(0.016)
Cost-income ratio	-0.023***	-0.016***	-0.023***	-0.015***	-0.024***	-0.016***	-0.022***	-0.017***	-0.017***	-0.018***	-0.023***	-0.015***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Listed	0.117***	0.069	0.088**	0.011	0.108**	0.092	0.106**	0.083	0.121**	0.140*	0.104**	0.068
	(0.045)	(0.058)	(0.042)	(0.058)	(0.045)	(0.061)	(0.048)	(0.068)	(0.059)	(0.074)	(0.048)	(0.062)
3m MMR			0.038***	0.011								
			(0.013)	(0.010)								
Sovereign PD			0.013	-0.088***								
			(0.014)	(0.017)								
Real GDP growth			0.057***	-0.052**								
			(0.020)	(0.022)								
Commercial					0.000	0.050						
					(0.043)	(0.112)						
Cooperative					-0.065	0.342**						
					(0.054)	(0.142)						
Mortgage and Real Est.					-0.174***	0.342**						
					(0.066)	(0.152)						
Savings					0.002	0.083						
					(0.056)	(0.130)						
Specialized gov. credit institution					-0.188***	0.179						
					(0.073)	(0.166)						
Fixed effects	COUNTRY-YEAR		YEAR		COUNTRY-YEAR		COUNTRY-YEAR		COUNTRY-YEAR		COUNTRY-YEAR	
Observations	5865	5436	5850	5433	5865	5436	4408	3902	2885	2496	4584	4241
Banks	508	498	508	498	508	498	506	485	389	369	408	398
Av. nr. of periods	11.55	10.92	11.52	10.91	11.55	10.92	8.71	8.05	7.42	6.76	11.24	10.66
R^2 (within)	0.53	0.31	0.33	0.18	0.53	0.31	0.53	0.34	0.56	0.47	0.55	0.37
R^2 (between)	0.77	0.64	0.69	0.54	0.78	0.66	0.79	0.63	0.81	0.72	0.79	0.69
R^2 (overall)	0.61	0.41	0.45	0.28	0.62	0.42	0.64	0.45	0.67	0.55	0.63	0.46
Between Effects	145.13***	36.37***	113.14***	52.34***	147.78***	33.90***	199.51***	38.81***	184.81***	41.03***	131.20***	21.54**

Table 12: This table shows the results of the robustness analysis of the model using the individual bank characteristics to capture the business model. The model is estimated using the Mundlak (1978) estimator. This table only displays the estimated between parameters, which we relate to long-term business model effects. All estimations, except for those in columns 3 and 4, use country-year fixed effects to control for the macroeconomic environment. Standard errors in parentheses are clustered at the bank level. We also test for the joint significance of the between effects. Stars indicate significance levels: *, **, *** represent significance at the 10%, 5%, and 1% level respectively.

	Baseline		Macroeconomic controls		Bank type		No combination of GAAP and IFRS		Only IFRS		No banks from Germany	
	ROA (1)	Log Z (2)	ROA (3)	Log Z (4)	ROA (5)	Log Z (6)	ROA (7)	Log Z (8)	ROA (9)	Log Z (10)	ROA (11)	Log Z (12)
RETAIL	0.149***	0.144***	0.161***	0.140***	0.145***	0.129**	0.165***	0.180***	0.154***	0.214***	0.137***	0.096
	(0.020)	(0.051)	(0.018)	(0.036)	(0.022)	(0.054)	(0.022)	(0.060)	(0.044)	(0.058)	(0.026)	(0.065)
DIVERSIFICATION	0.115***	-0.057*	0.135***	-0.055	0.109***	-0.044	0.109***	-0.075*	0.310***	0.063	0.222***	-0.071*
	(0.021)	(0.033)	(0.021)	(0.035)	(0.021)	(0.033)	(0.023)	(0.040)	(0.041)	(0.051)	(0.023)	(0.041)
Cost-income ratio	-0.023***	-0.016***	-0.023***	-0.015***	-0.024***	-0.016***	-0.022***	-0.017***	-0.017***	-0.018***	-0.023***	-0.015***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Listed	0.117***	0.069	0.088**	0.011	0.108**	0.092	0.106**	0.083	0.121**	0.140*	0.104**	0.068
	(0.045)	(0.058)	(0.042)	(0.058)	(0.045)	(0.061)	(0.048)	(0.068)	(0.059)	(0.074)	(0.048)	(0.062)
3m MMR			0.038***	0.011								
			(0.013)	(0.010)								
Sovereign PD			0.013	-0.088***								
			(0.014)	(0.017)								
Real GDP growth			0.057***	-0.052**								
			(0.020)	(0.022)								
Commercial					0.000	0.050						
					(0.043)	(0.112)						
Cooperative					-0.065	0.342**						
					(0.054)	(0.142)						
Mortgage and Real Est.					-0.174***	0.342**						
					(0.066)	(0.152)						
Savings					0.002	0.083						
					(0.056)	(0.130)						
Specialized gov. credit institution					-0.188***	0.179						
					(0.073)	(0.166)						
Correlation of factors												
RETAIL	-		-		-		1.00		1.00		1.00	
DIVERSIFICATION	-		-		-		0.99		0.99		0.97	
Fixed effects	COUNTRY-YEAR		YEAR		COUNTRY-YEAR		COUNTRY-YEAR		COUNTRY-YEAR		COUNTRY-YEAR	
Observations	5865	5436	5850	5433	5865	5436	4408	3902	2885	2496	4584	4241
Banks	508	498	508	498	508	498	506	485	389	369	408	398
Av. nr. of periods	11.55	10.92	11.52	10.91	11.55	10.92	8.71	8.05	7.42	6.76	11.24	10.66
R^2 (within)	0.53	0.31	0.33	0.18	0.53	0.31	0.53	0.34	0.56	0.47	0.55	0.37
R^2 (between)	0.77	0.64	0.69	0.54	0.78	0.66	0.79	0.63	0.81	0.72	0.79	0.69
R^2 (overall)	0.61	0.41	0.45	0.28	0.62	0.42	0.64	0.45	0.67	0.55	0.63	0.46
Between Effects	145.13***	36.37***	113.14***	52.34***	147.78***	33.90***	199.51***	38.81***	184.81***	41.03***	131.20***	21.54**

Table 13: This table shows the results of the robustness analysis of the model using the common factors to capture the business model. The model is estimated using the Mundlak (1978) estimator. This table only displays the estimated between parameters, which we relate to long-term business model effects. All estimations, except for those in columns 3 and 4, use country-year fixed effects to control for the macroeconomic environment. Standard errors in parentheses are clustered at the bank level. We also test for the joint significance of the between effects. In case the sample used to estimate the common factors differs from the one used in the baseline regressions (columns 7 to 12), we also report the pairwise correlation of the estimated factors with those obtained from the baseline model. Stars indicate significance levels: *, **, *** represent significance at the 10%, 5%, and 1% level respectively.

the Z-score lose their statistical significance. Again, the latter may be attributed to the borderline significance of the effect of the *DIVERSIFICATION* factor on the Z-score in the baseline estimations.

5.3 Accounting standards

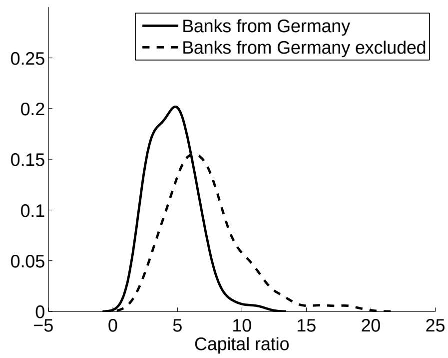
In our sample we include banks that use either IFRS or local GAAP accounting standards to report financial results. In case a bank switches to IFRS during the sample period, we combine the 'old' GAAP-based data with the 'new' IFRS-based observations. Given that IFRS-reporting banks represent only a minority of European banks prior to 2004 (see figure 1), this procedure ensures that we can observe banks over a longer time span, which in turn leads to a more balanced sample. Disregarding old GAAP-based information would put more weight on the crisis period. However, different accounting standards may affect the treatment of financial information, and can therefore result in observed differences where there are none. Hence, we check whether the combination of GAAP and IFRS data with respect to the same bank influences our conclusions. The results in columns 7 and 8 of tables 12 and 13, in which the old GAAP information of currently IFRS-reporting banks is not included, confirm our earlier findings. This suggests that combining GAAP- and IFRS-based information for a single bank does not systematically affect the results. If we only take IFRS-reporting banks into account (columns 9 and 10), thereby also ignoring data from banks that only use local standards throughout the sample period, the baseline results are again confirmed. Finally, the estimated factors also appear to be robust to changes in the sample.

5.4 Dominance of banks from Germany

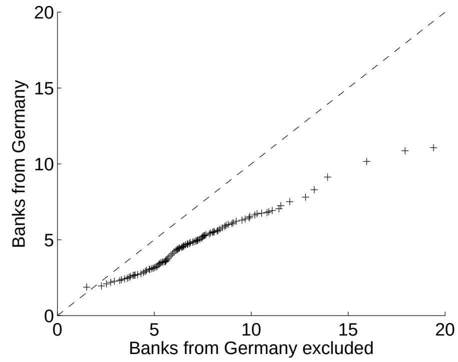
Banks based in Germany represent a relatively large part of our sample: about 20% of total banks and observations (see table 2). To examine the influence on our findings, we exclude all banks from Germany. The results in columns 11 and 12 of tables 12 and 13 are very similar to those of the baseline estimations. The factors estimated from this subsample are also almost identical. However, the impact of the *RETAIL* factor on the Z-score is no longer statistically significant as its impact has become less positive. A likely explanation is that the removal of Germany-based banks from the sample is not neutral, because they have lower capital ratios (see figure 7). The lower impact on the Z-score may thus capture that a retail orientation is more important to ensure stability for banks of which the business model is characterized by a lower capital ratio. Excluding such banks therefore leads to a lower effect of the *RETAIL* factor on stability. Nevertheless, excluding banks based in Germany from our sample appears to have only a minor impact and does not affect our conclusions.

6 Conclusion

This paper investigates the long-term performance impact of bank business models in Europe, observed from 1998 to 2013, using three profitability indicators and the Z-score as a proxy for banks' distress. This research is motivated by the observation that seemingly



(a) Estimated kernel densities of the capital ratio (average of individual banks).



(b) Quantile-quantile plot of the capital ratio (average of individual banks).

Figure 7: Comparison of the capital ratio for Germany-based banks and all other banks within the sample. The QQ-plot displays the quantiles of the capital ratios within the two subsamples: if the two subsamples share an identical distribution the plot will be linear and will follow the dashed line. The figures show that the capital ratios for banks from Germany are lower than those in other countries. The difference of the distributions is confirmed by the Kolmogorov-Smirnov test (p=0.00) and the Kruskal-Wallis test (p=0.00).

successful business models proved fragile during the financial crisis and by the regulatory responses to the crisis that will profoundly impact banks' business models. We devote particular attention to the composition of the sample. A fundamental issue is to observe banks at the level at which business model decisions are taken. In this respect, we deem the consolidated level to be the most relevant. We therefore exclude domestic subsidiaries of each parent bank, but retain the foreign subsidiaries, because we consider them more independent from the performance of the parent group. We also elaborate on the issues involved with the identification of bank business models. Apart from documenting the difficulties of a classification approach for European banks, we propose two alternative strategies that account for the continuity of the spectrum of business models. The first approach directly relates individual bank characteristics to performance. Among other issues, however, the individual variables may capture bank-specific information that is not part of the business model (e.g. risk culture). A relevant contribution is therefore the development of a new approach based on factor analysis that uses the common variance of the business model variables to capture latent strategies. We focus on two factors, of which the first captures the retail orientation of the bank and the second the degree of functional diversification , i.e. a lower loan ratio in favor of a higher share of non-interest income. To study the impact of business models on bank performance, we explicitly consider that it is a long-term concept and hence very stable over time. We therefore apply an econometric approach that distinguishes the temporal (within) and cross-sectional (between) dimensions, of which the latter identifies business model effects. This is, moreover, statistically important because we also find that the differences across banks are in general larger than the observed changes within banks.

The results based on the common factors show that retail-oriented business models lead to better long-term performance, since they appear to enhance both stability and profitability in terms of ROA and NIM. These findings provide support to the post-crisis refocusing on traditional intermediary activities. The impact of higher functional diversification is more ambiguous. While it improves profitability, it also increases banks' susceptibility to distress, because more diversified banks are typically less well capitalized. A broader approach to banking supervision should therefore be considered in which not only the liquidity and capital structure of the banks are regulated to increase their stability. Supervisors should in addition consider a bank's business model to assess the viability of the bank.

With respect to the individual bank characteristics we document substantial heterogeneity. First, we find that more retail-oriented banks are better able to correctly screen loans and price credit risk. For these banks, focusing on lending supports stability, while the impact of the LLP ratio on profitability becomes less negative. Second, a high deposit ratio appears to be particularly beneficial for non-retail banks, which typically rely more on wholesale sources of funding. In contrast, the results show that a high NSFR reduces the profitability of non-retail banks, but only increases the stability of more retail-oriented banks. However, it remains to be seen whether the enforcement of the NSFR ratio will have different effects in the future. Third, business models that are characterized by a more diversified income structure improve profitability, without lowering stability. Still, the heterogeneity of the impact on the Z-score suggests that the impact on stability depends on the type of non-interest income. The impact is only neutral for banks with either a very low or very high retail orientation. While retail-oriented banks typically rely on more stable sources of non-interest income, an adequate scale is necessary for less retail-oriented banks to avoid decreasing stability. Finally, we report that the capital ratio has a more positive impact on the performance of non-retail banks, which are typically larger, more leveraged and rely more on wholesale sources of funding. This finding supports the inclusion of additional capital buffers imposed on systemically important banks in the Basel III framework. These considerations imply that the application of prudential regulation should also reflect the heterogeneity of bank business model decisions. In this regard, supervisors are increasingly aware that business models matter for banks' risk-return profiles. In the future, the Supervisory Review and Evaluation Process (SREP) published by the European Banking Authority (EBA, 2014) will become the cornerstone of European bank supervision. Apart from capital and liquidity requirements and compulsory risk governance standards, the SREP also incorporates a business model analysis to assess the sustainability of banks' strategies.

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