# The profitability and distance to distress of European banks: do business choices matter?

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This draft: December 20th, 2020

This is a preliminary draft.

**Abstract**

In this paper we examine which business choices are more likely to increase the profitability and distance to distress of banks, and whether changing business model pays off. Our analysis is framed under the theoretical premises of the strategic groups theory and the agency theory. We find that the profitability and distance to distress increase with the use of customer deposits and equity, and decrease with size; also, relationship banks and banks with a retail focused business model tend to outperform those with other orientations and business models, respectively. Moreover, we document the heterogeneous impact of business model choices on performance by finding that income diversification only bears a positive impact on the distance to distress of banks highly focused on relationship banking, and size only bears a negative effect on the profitability of these banks as well; additionally, only banks with low relationship banking orientation significantly benefit from customer deposits. We also dedicate considerable effort to studying the effects of business model changes on profitability and find that shifts from the retail diversified funding model to either the retail focused or the large diversified model improve performance in the medium term. Finally, we find evidence that large diversified banks benefited from internal capital markets during the twin financial crisis in Europe (2008-10, 2011-13) by tapping into low-cost funding from subsidiaries. Our results are robust to changes to our baseline model that account for endogeneity and persistency issues.

**JEL classification:** G20; G21; G28; G32.
**Keywords:** banking; business models; bank orientation; profitability; distance to distress.

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## 1. Introduction

The European banking sector has been severely affected by a range of events and threats over the past decade or so, including the spillover effects from the 2007-08 US subprime crisis, the 2012-13 European sovereign debt crisis, the emergence of competition from fintech companies, the implementation of additional (and more stringent) regulatory requirements and the low-for-long interest rates environment (Goddard *et al.*, 2016; Molyneux & Wilson, 2017). Under such turbulence, banks have been impelled to re-examine their long-term business choices, such as those related with the types of activities, funding sources, level of diversification, and size. In other words, their business model. This exercise of self-appraisal, however, has left bank managers (and supervisors) confronted with a number of unanswered questions, such as: which business choices are more likely to increase bank profitability and resilience (and which ones should be avoided)? Can such choices be expected to yield similar results for all types of banks? Have banks changed their business model over time? Which barriers are likely to impede such mobility? Does changing business model pay off?

In this paper we address these questions using panel data for 524 European banks (EU28), both listed and non-listed, over the period between 2005 and 2016. Specifically, in order to identify which business choices are associated with higher bank performance and distance to distress, we run a set of OLS regressions wherein the explained variables are decomposed elements of ROA (e.g. interest income, interest expenses, net fees and commissions) and Z-score; as explanatory variables we test a variety of proxies that account for the multidimensional nature of business decisions: individual business choices (based on the literature), bank orientation (identified using principal components on a set of relationship banking proxies) and business model classification (obtained by using clustering methods on the individual business choices). Additionally, we perform univariate comparison of means tests between top and bottom performers. In order to assess whether the impact of business choices on profitability and distance to distress depends on the business model, we perform the OLS regressions using the sub-samples of each business model and run rolling regressions using the bank orientation as the mediating variable. Finally, we identify business model changes by computing the business model classification for each triennium (rather than the full sample period). In order to compute credible counterfactuals, we employ propensity score matching.

Our results suggest that the strategies followed by European banks may be mapped using a *continuum* of bank orientations (relationship banking) and four discrete business models (retail focused, retail diversified funding, retail diversified assets, large diversified), wherein, as expected, the retail focused model records the highest orientation towards relationship banking. We find that the ROA and Z-score of banks increase with the use of customer deposits and equity, and decrease with size. In line with this, banks pursuing relationship banking and following a retail focused business model tend to perform better than others. Furthermore, we find evidence of significant heterogeneity regarding the impact of several business choices on profitability and distance to distress. Namely, only banks with high orientation towards relationship banking tend to benefit from income diversification in terms of distance to distress and from trading assets in terms of profitability, while only such banks seem to be negatively affected by size. On the other hand, only banks with a very low orientation towards relationship banking seem to benefit from customer deposits in terms of profitability. Finally, we find that mobility barriers vary significantly across business models and, by comparing banks that change business model *vis-à-vis* their old peers, we show that on average changing from the retail diversified funding model to either the retail focused or the large diversified pays off in the medium term. We attribute this finding to the relatively low barriers of entry of customer deposits and trading assets. In general, we interpret these results as lending some support to the adaptation view of management (Child, 1972), as well as the implementation of forward-looking (BIS, 2018) and judgement-based supervision (Viñals *et al.*, 2010; Lastra, 2013). Importantly, we also find evidence that large diversified banks benefited from internal capital markets during the twin financial crisis in Europe (2008-10, 2011-13) by tapping into low-cost funding provided by subsidiaries.

This paper aims to contribute to the strand of literature which analyses banking business decisions in several ways. Firstly, we grasp the effects of business choices on profitability and distance to distress by taking into account three types of variables: individual business choices (e.g., Köhler, 2015), bank orientation (e.g., Mergaerts & Vander Vennet, 2016) and business model classification (e.g., Hryckiewicz & Kozłowski, 2017). Such an approach has the novelty of attempting to reconcile the concepts of banking business model with that of bank orientation. Given that such an attempt has yet to be performed in the literature, we dedicate part of our review to presenting the concepts of business model and bank orientation and discussing how the notions may be reconciled in a way that is meaningful for the literature on bank management. Moreover, the use of alternative types of variables provides a valuable source of confidence regarding our results, particularly given the complex nature of business models. Bearing this in mind, this paper is also the first to employ the method proposed by Marques & Alves (2020) to identify discrete banking business models, which combines the outputs of three clustering methods (Fuzzy C-Means, Self-Organizing Maps, Partitioning Around Methods). Given the absence of an established taxonomy of banking business models, the use of an ensemble of methods (rather than just one) is expected to increase the accuracy of the assignment of banks across business models relative to their *true*, unobserved, classification.

Secondly, this paper expands our understanding of the heterogeneous effects of business decisions on bank profitability and distance to distress by coupling two previously unreconciled methods: rolling regressions with bank orientation as the mediating variable (Mergaerts & Vander Vennet, 2016) and OLS regressions on sub-samples of banking business models (Köhler, 2015). Providing further insight into the heterogeneous effects of business decisions is important given that (i) an established result in the 2007-08 financial crisis literature is that some banks weathered the crisis better than others (e.g., Beltratti & Stulz, 2012); and (ii) the regulation and supervision of banks have become increasingly focused on implementing measures that are proportional to the supervised entities' business models (e.g., EBA, 2013).

Thirdly, to the best of our knowledge, along with Ayadi *et al.* (2020) this paper is one of the first to put forward a testing strategy for business model changes that relies on propensity score matching to compare the profitability of banks that change business model *vis-à-vis* their peers prior to the change. Specifically, propensity score matching allows us to compute a credible counterfactual to measure the effect of a given bank changing business model. This is a relevant concern as one cannot directly observe what the profitability of the bank would be had it not changed its business model; and because it is likely that some idiosyncratic features of the bank may simultaneously influence the likelihood of changing business model and its profitability. In other words, propensity score matching allows us to mitigate endogeneity concerns regarding the choice of business model. Our paper differs from Ayadi *et al.* (2020) in two meaningful ways. Firstly, the authors match all banks in the sample (first stage) and analyse the pooled business model changes (second stage); whereas we only match banks with the same *a priori* business models and analyse business model changes within each pair of source-destination business model. The relevance of our approach is backed by our findings, which show that the effects of business model changes vary significantly according to the source and destination business models. Secondly, we take on the stance that banks are not expected to change business models from one year to the next, as implicitly assumed by Ayadi *et al.* (2020), and as such use bank-triennium observations as the unit of analysis for business model changes.

Our fourth contribution is the identification of valid instrumental variables (IVs) for business decisions. This is quite relevant "as many empirical applications are characterized by the difficulty of finding strong IVs" (Clougherty *et al*., 2016: p.308). Particularly, we identify two IVs: proximity to financial centers and Lerner index; wherein the former instrument is an index developed in this paper which accounts for the proximity between the bank's headquarters (where strategic decisions take place) and the location of the closest financial centers (where one may expect to find the human and technological resources necessary to pursue certain bank strategies). Finally, we employ a GMM estimator as a robustness check, allowing us to account for the dynamic nature of profitability and distance to distress – an approach which has seldomly been used in this strand of the literature. We also perform sub-period analysis as a robustness check, which largely confirms the baseline results.

The findings in this paper bear relevant policy implications. Firstly, our results suggest that relying on stable funding sources, as required under the Basel III agreement (e.g. NSFR), has a positive impact on performance. Moreover, the general awareness demonstrated by the regulator regarding the need to ensure the proportionality of new regulatory requirements (EBA 2013) is in line with our findings regarding the heterogeneous effects of business choices, i.e. not all banks are equal. Finally, our results concerning the positive effects of business model changes in the medium to long-term may be seen as supporting the current bank supervision framework, which has increasingly relied on the use of scenario-based stress testing (BIS, 2018) and judgement-based supervisory practices (Viñals *et al.*, 2010; Lastra, 2013). Under such framework, bank supervisors are expected to have an understanding of how the business model may develop as a consequence of strategic choices made by the bank and/or the evolution of the business environment (Farkas, 2018).

The paper is structured as follows. **Section 2** provides a brief overview of the literature on the concepts of business model and bank orientation, and their link to profitability and distance to distress. **Section 3** presents the methodology. The dataset, variables and descriptive statistics are exposed in **Section 4**. **Section 5** presents and discusses the results. Robustness checks regarding endogeneity and persistency concerns are performed in **Section 6**, before **Section 7** concludes.

## 2. Literature review

### *2.1. The notion of business model in management and banking literature*

Although some authors trace the notion of business model to the inception of organized economic activity (Teece, 2010), Zott *et al.* (2011) place the onset of academic interest for the term business model in the context of the dot-com boom of the late 1990's. Since then, the interest of management literature for the business model has steadily grown, assuming different definitions and purposes according to the field of analysis (Zott *et al.*, 2011).

Within the field of strategic management (arguably the most matured field with regards to the exploration of the business model concept), one of most commonly accepted definitions of business model is that it constitutes the "management's hypothesis about what customers want, how they want it, and how an enterprise can best meet those needs, and *get paid for doing so*." (Teece, 2010: p.172). Bearing this in mind, strategic management papers have made use of the business model as a unit of analysis to investigate the ability of firms to record and sustain above peer profitability. For instance, Zott & Amit (2008) explore the business model as a contingency factor (Donaldson, 1996) and find that for firms operating with novelty-centered business models, the winning product market strategies seem to be those that emphasize differentiation, cost leadership, or early market entry. Parmigiani & Mitchell (2009), on the other hand, draw on the notion of business model as a set of activity complementarities (Milgrom & Roberts, 1995) to explore the longstanding debate regarding the boundaries of the firm, i.e. which components of the business model to perform within the firm and which to outsource. According to the authors, such decision is deemed to be fine-tuned over time, as firms often need to perform the activities before knowing whether they should outsource them. On a different note, Vidal & Mitchell (2013) resort to the concept of business model as a configuration that has to be fined-tuned in order to ensure the firm's survival, advocating for the perspective that the longstanding notion of 'first movers advantage' in reality should be replaced by the 'first survivors advantage', i.e. the first firm to adequately adjust its business model to the internal capabilities and needs of the market. Another strand of works has focused on the role of the business model as a representation tool for entrepreneurs (Doganova & Eyquem-Renault, 2009), allowing to build simplistic narratives (Perkmann & Spicer, 2010) and/or classify businesses in a concise and effective manner (Baden-Fuller & Morgan, 2010). Lastly, a strand has addressed the barriers to and effects of business model innovation (Chesbrough, 2010; Gambardella & McGahan, 2010).

In the banking literature, two aspects are common to most of the works using the notion of business model to study profitability and riskiness of banks: their multidimensional nature and their relatively long-term nature. For instance, Cavelaars & Passenier (2012: p.402) state that in banking the purpose of business model analysis "is to understand where the profit comes from and what risks the bank or the banking sector is exposed to in generating those profits". Mergaerts & Vander Vennet (2016: p.58), on other hand, equate the business model to a strategic group by suggesting that: "the concept of business models originates from the literature concerning strategic groups, i.e. sets of firms that are active in a single sector and use similar strategies. (...) that reflect the long-term choices of bank management with respect to assets, funding, capitalization and diversification." Another strand of literature positions the business model close to the concept of balance sheet intermediation (Martín-Oliver *et al*., 2017, Roengpitya *et al.*, 2014, 2017). For instance, Martín-Oliver *et al.* (2017, p.248) state that the "banking business model consists in a pattern of assets and liabilities adopted by one or several banks that differs from the pattern adopted by other banks, each with different combinations of expected return and risk.". Finally, Marques & Alves (2020 : p.69) argue that the previously stated definitions do not account for (i) the possibility that banks may have some level of affinity with more than one business model (fuzziness) and (ii) that business model changes may occur over time, and hence suggest an alternative definition of banking business model as "a predominantly stable and long-term oriented organizational configuration which is adopted, with different levels of association, by a significant share of banks, resulting from a set of observable and interconnected managerial choices". According to the authors, such a view is backed by the relatively novel fuzzy approach to strategic groups theory (DeSarbo & Grewal, 2008).

### *2.2. Linking the concepts of bank orientation and banking business model*

As stated by Degryse & Ongena (2007: p.399), bank orientation is about "the choice of relationship-based versus transactional banking". As for relationship banking, it is often seen as producing differentiated products, that require geographical proximity with the customers, as well as time and effort to customize the products to the customers' needs, which in turn allows banks to gain local market power and obtain information-based rents (Rajan, 1992; Boot, 2000). Transactional banking, on the other hand, takes advantage of economies of scale by servicing high volume-low customization transactions loans, that tend to yield lower net margins (DeYoung & Rice, 2004; DeYoung, 2010). Importantly, there is an open debate in the literature regarding the effects of competition in relationship banking, which may further enlighten the nature of this lending technology (Boot, 2000). On the one hand, more competition is seen as hindering relationship banking, as it may lead borrowers to change to other banks, reducing the expected lifespan of bank relationships. This *ex-ante* possibility may reduce the expected ability of banks to perform intertemporal subsidization of loan contracts, and as such may reduce the propensity for relationship banking. On the other hand, as discussed by Boot & Thakor (2000), banks may have the incentive to resort to relationship banking as a strategy to alleviate the additional competition, as such orientation is likely to produce a differentiating factor relative to other competitors.

The tensions between both theoretical views makes this an eminently empirical issue that has been tackled in several ways. While the preferred testing strategy is to use firm-bank relationships, wherein the researchers test the duration and uniqueness of the bank relationships to proxy for the level of relationship banking orientation (e.g., Berger & Udell, 1995; Degryse & Ongena, 2007; Elsas, 2005), the difficulty in accessing such detailed datasets has led some researchers to follow alternative strategies. For instance, Ewijk & Arnold (2014) perform factor analysis on a set of bank-level data regarding the number of branches, type of loans, size, funding structure and net interest margin – which could also be considered as potential proxies for the business model.

The similarity of empirical approaches used to identify bank orientation and business model may legitimately raise the question of what is common to (and what is different in) both concepts, and how they may be reconciled in a way that is useful to study bank performance. The first aspect which seems common to both concepts is their strategic nature, as ultimately decisions regarding both the business model and bank orientation are deemed to be taken at the highest instances of strategic decision-making and be part of the strategic plan. As such, it is desirable (and likely to occur) that decisions regarding the business model and the bank orientation are consistent (Miller, 1986). Secondly, the two concepts reflect relatively long-term strategies via which banks hope to improve their risk-return profiles.On the other hand, the notion of business model may be deemed to be more fit to reflect exposures to specific types of risks than bank orientation, given that it covers a wider variety of dimensions – such as trading book exposures (market risk) or the reliance on short-term wholesale debt (funding risk). Moreover, both concepts are also likely to differ regarding the type of data used as proxies. Namely, while the concept of business model may be convincingly proxied using financial statements data (e.g., Roengpitya *et al.*, 2014, 2017; Martín-Oliver *et al.*, 2017), the notion of bank orientation typically requires non-financial statements data (e.g. branch network) in order to capture the nature of the lending technology, i.e. the type of customer relationship and the information used to assess its credit worthiness (hard vs soft information).

In sum, both concepts are related to strategic long-term decisions that should be internally consistent among each other. In other words, the mismatch between bank orientation and business model may be an important finding in and of itself (e.g. a G-SIFI with a significant orientation towards relationship banking). Moreover, both concepts do not entirely overlap, as the scope of the analysis tends to be broader and more risk-oriented in the business model, while the informational content conveyed by bank orientation is likely to expand beyond balance sheet data.

### *2.3. Conceptual frameworks: strategic groups theory and bank intermediation theory*

The impact of business choices, particularly related with the business model and bank orientation, on the profitability and distance to distress of banks may be interpreted under two conceptual frameworks present in the management literature: strategic groups theory and agency theory.

According to the strategic groups theory (Porter, 1979), managers of firms operating in a given market are likely to undertake decisions regarding the same set of strategic dimensions, such as the distribution channel, the level of value chain integration and the geographical reach, which may lead to the formation of groups of firms operating under the same strategic guidelines. In turn, such decisions may involve investments which are difficult to revert, preventing firms from freely moving within the market's strategic space. Such barriers to mobility may be understood as entry barriers at an intra-market level and may drive performance heterogeneity. Other performance related hypotheses are linked to the notion that some groups may have more market power than others, due to their ability to manage strategic pressures (e.g. suppliers, customers, regulation) (McGee, 2006). In this paper we follow the approach proposed by Mergaerts & Vander Vennet (2016), by focusing our analysis on choices that are stable, long-term oriented and observable, namely those related with the asset and funding structures, diversification, size and capital. Additionally, under the strategic groups hypothesis we study whether business models perform differently and whether changing business model pays off in terms of profitability.

On the other hand, business choices are poised to bear implications in terms of the agency problems typically faced by banks[3] (Diamond, 1984). Particularly, choices related with the asset and funding structures are likely to affect in several ways the relations between the bank and its stakeholders, both on the right (e.g., depositors and debtholders) and left side of the balance sheet (e.g., loan borrowers). For instance, in normal times wholesale creditors may be expected to perform an efficient monitoring of banks (Calomiris, 1999); however, the monitoring incentives of wholesale lenders may become distorted in the presence of noisy public signals (Huang & Ratnovski, 2011). Additionally, diversifying into new activities and income streams may allow banks to capture valuable borrower information (Diamond, 1984) but may also significantly increase bank riskiness due to increased moral hazard (Boyd *et al.*, 1998) and lack of expertise and experience (Gennaioli *et al.*, 2012). Furthermore, while transaction costs are expected to be negatively related with size (Scholes *et al.*, 1976), increases in size may also generate additional agency costs given the incremental separation between the

[3] Consider two bank agency relations commonly referred to: debtholders-bank and bank-borrowers. Regarding the former, the debtholders (including depositors) act as principals by trusting their funds to the bank (agent) which invests these in loans and other assets. In return, the debtholders expect to receive a remuneration and, depending on the type of funding contract, may demand the timely reimbursement of their funds. Such pending threat acts as a monitoring device requirement (Diamond & Rajan, 2001). Concerning the latter, the bank (principal) invests funds in loans and other assets issued by the borrower (agent), which uses such funds to pursue investment goals. In exchange, the bank expects to receive interest payments or capital gains (e.g. in financial assets at fair value), and is able to monitor the borrower by using soft or hard information, depending on the type of bank orientation: relationship or transactional (Degryse & Ongena, 2007). If the borrower does not comply, the bank may (or not) be able to terminate the contract without losses, depending on debt seniority and collateral (Boot & Thakor, 2000).

control and ownership of the bank (Jensen & Meckling, 1976). Importantly, the optimal size is likely to vary according to the type of activities performed by the bank: transaction-based activities, such as trading and securitization, tend to bear more potential for economies of scale than relationship-based activities, such as SME finance, which require greater proximity with the customers (Berger *et al.*, 2005). Finally, two well established results in the finance literature regarding the agency issues between shareholders and debtholders (including depositors) are the following: shareholders have the incentive to increase risk-taking once debt has been issued (Jensen & Meckling, 1976) and such risk-taking may be expected to increase monotonically as shareholders decrease their 'skin in the game' (i.e. increase their leverage). As laid out by Jensen (1986) the agency costs that may arise from excess cash (such as the inefficient diversification into new business lines) may be offset by an increase in bank leverage (which reduces the free cash flow available for managerial discretion). As pointed out by the author, leverage is not a panacea, and banks already tend to be overly leveraged institutions (Haldane & Alessandri, 2009). In any case, such perspective shows us that managers may choose to operate a business model that yields a lower risk-return than the one preferred by shareholders, for instance because holding excess cash allows them to reap private benefits (empire building) and holding above optimal equity makes banks easier to manage (quiet life). In sum, the literature on the agency issues faced by banks provides mixed predictions regarding the effects of business model choices on agency costs (and bank profitability and riskiness), and hence deserves to be further studied.

### *2.4. Empirical literature on banking business choices*

The literature offers an abundant set of works testing the impact of each business choice on bank profitability and riskiness while holding the remaining choices constant (under the standard OLS assumption) – which we label as the 'isolated choices' approach. For instance, asset and funding structures (Demirgüç-Kunt & Huizinga, 2010), diversification (Stiroh & Rumble, 2006), size (Altunbas *et al.*, 2011; Davies & Tracey, 2014; Beccalli *et al.*, 2015; Curi & Lozano-Vivas, 2015) and capital (Beltratti & Stulz, 2012)[4].

This paper relates to a smaller and more recent strand of studies that has looked specifically into testing the effects that simultaneously determined choices regarding the business model components of banks (e.g. asset and funding structure, diversification, size and capital) have

[4] A review of the literature regarding each specific component of the business model (asset and funding structures, diversification, size, capital) and other elements of the banking business relevant for performance and distance to distress (risk culture, management quality, liquidity, ownership structure) is provided in **Sections 4.2.2** and **4.2.3**, respectively.

on their level of profitability and riskiness[5]. Using a large sample of European banks, Ayadi & De Groen (2015) find that banks operating with retail business models (i.e. with high values of customer deposits and loans to customers) tend to record a higher ROE and Z-score than other models. Conversely, using a cross-section sample of European banks in 2014, Farnè & Vouldis (2020) uncover that securities holding banks tend to exhibit a relatively higher risk-return profile than their peers, while traditional commercial banks record, on average, the lowest risk-returns. Hryckiewicz & Kozłowski (2017) document that the contribution to systemic risk is greater for banks operating with an investment model (i.e. high securities and low customer deposits). Flori *et al.* (2019), on the other hand, find that banks which simultaneously recorded concentrated asset structures (with high securities exposure) and a high ROA in the pre-crisis period, were more prone to distress than their peers. Similarly, De Haan & Kakes (2020) uncover that large investment banks recorded greater peak accumulated losses during the twin financial crisis period. Also, Köhler (2015) finds lower levels of risk-adjusted profitability and distance to distress of investment banks relative to commercial, savings and cooperative banks. Focused on a sample of European banks, between 2008 and 2015, Lucas *et al.* (2019) find significant heterogeneity in the effects of the financial crisis per business model. Mergaerts & Vander Vennet (2016) find that long-term retail orientation increases bank profitability and distance to distress. Finally, the two studies by Roengpitya *et al.* (2014, 2017) focus on samples of large international banks and document that the popularity of retail banking has increased in the post-crisis period and that, on average, banks following a traditional banking model have outperformed those with a trading model, both in terms of efficiency and stability of returns.

In general, such findings seem to point towards the existence of differences in profitability and distance to distress across business models, lending some support for the strategic groups hypothesis and the suggestion that agency problems may differ according to the business model. However, the literature survey also suggests that little attention has been devoted to the role of business model changes. Moreover, in these studies a methodological choice is made regarding the methods used to proxy for banking business models. Namely, whether to use individual choices (Demirgüç-Kunt & Huizinga, 2010), factor analysis (Mergaerts & Vander Vennet, 2016) or clustering analysis (Hryckiewicz & Kozłowski, 2017). However, each method seems to bring something new to the analysis which may be valuable for the overall investigation. For instance, analysing the impact of individual business choices allows us to identify which specific choices are driving the overall results; using dimensionality reduction

[5] While the study by Cernov & Urbano (2018) does not directly assess the profitability and distance to distress of each business model, the very significant size (5,292 credit institutions in Europe) as well as the innovative methodology make it also a relevant reference.

techniques mitigates potential multicollinearity and overfitting issues (Harrel, 2001); and clustering analysis allows us to perform peer group analysis. In this paper we adopt an agnostic perspective on this methodological issue, and investigate the relationship between business choices, profitability and distance to distress using three types of proxies, as described below.

## 3. Methodology

### *3.1. Identification of bank orientation and business models*

The bank orientation is identified by applying principal components analysis to a set of proxies for relationship banking previously used in the literature (e.g., Ewijk & Arnold, 2014). Particularly, we use as proxies for relationship banking the number of branches per total assets (which indicates the proximity of the bank to its customers), net margin (a higher value of which suggests the provision of customized, high value-added services) and the number of employees per total assets (in order to capture the relatively greater time and effort expected to be invested by relationship banks). The method used to identify business models follows the approach developed by Marques & Alves (2020), which may be summarized in the following way. Firstly, we perform principal component analysis on a selection of business model variables related with the assets and funding structures, diversification, size and capital. This step allows us to identify the components that will be used as inputs in the next step (clustering). Using principal components as inputs in clustering analysis (rather than the original variables) ensures that clustering is performed in an orthogonal space (Sharma, 1996) and enables us to focus on the most relevant relationships between business choices and, thus, mitigate the problem of data noisiness.

Secondly, we run clustering analysis using three alternative methods: Fuzzy C-Means (FCM), Self-Organizing Maps (SOM), and Partitioning Around Medoids (PAM), and combine the classification outputs of each algorithm into one single classification, using a majority consensus rule (ensemble). To determine the optimal number of clusters we rely on a set of internal selection criteria, namely, the Silhouette Width, the Calinski-Harabasz Index, the Davies-Bouldin Index and the Dunn Index[6]. Given the absence of an established taxonomy of discrete banking business models, the use of an ensemble of clustering methods (rather than a

[6] A detailed description of the clustering ensemble method, including each internal valuation criteira used, can be found in Marques & Alves (2020).

single method) is expected to increase the accuracy of the assignment of banks to business models relative to their *true*, unobserved, classification (Kuncheva, 2004).

### *3.2. Impact of business choices on bank performance and distance to distress*

We begin our analysis by testing the equality of business decisions between top and bottom performing banks, wherein top (bottom) performing banks are those that occupy the top (bottom) quartile of ROA for the cross-section sample.

Next, we run OLS regressions using three types of proxies (individual business choices, bank orientation and business model classification). This increases the confidence regarding our results, which may be particularly valuable given the complex and multivariate nature of business decisions. Following Baltagi & Griffin (1984), we perform two types of regressions: between regressions, i.e. OLS using the full sample mean per bank, which we interpret as long-term effects; and within regressions, i.e. OLS with bank-year fixed effects, interpreted as short-term effects. In order to ensure the brevity of our paper and because the results do not materially change, we only report the results for the between regressions. Namely, the between model is specified as follows:

$$Y_i = \alpha + \boldsymbol{\gamma} IC_i + \boldsymbol{\beta} X_i + \delta C_{\boldsymbol{i}} + \varepsilon_i \tag{1.1}$$

$$Y_i = \alpha + \boldsymbol{\gamma} BO_i + \boldsymbol{\beta} X_i + \delta C_{\boldsymbol{i}} + \varepsilon_i \tag{1.2}$$

$$Y_i = \alpha + \boldsymbol{\gamma} BM_i + \boldsymbol{\beta} X_i + \delta C_{\boldsymbol{i}} + \varepsilon_i \tag{1.3}$$

wherein $Y_i$ is the mean independent variable for each bank (ROA, Z-score, and sub-components of ROA and Z-score); α is the constant; $IC_i$ is the mean vector of individual business choices of bank $i$ (gross loans to customers, interbank lending, trading assets, customer deposits, interbank borrowing, wholesale funding, total derivatives, income diversification, total assets and total equity); $BO_i$ is the bank orientation of bank $i$ (relationship banking); $BM_i$ is a vector of dummies which identifies the business model classification of bank i; $X_{\mathrm{i}}$ is the mean vector of bank-level controls (excess loans, loan loss provisions to total assets, cost-to-income, net stable funding ratio, stakeholder dummy, listed dummy); $C_i$ is a vector of dummies identifying the country where the headquarters of bank i are located; $\gamma, \beta, \delta$ are the regression coefficients' vectors; and $\varepsilon_{\mathrm{i,t}}$ is the disturbance term. In our empirical setting we face a potential issue of model overfitting, given that our sample size is not very large (n=524) compared with the number of estimated parameters (eq.1.1: p=40, n/p=13.1). An overfitted model raises concerns regarding the validity of statistical inference, potentially yielding spurious associations (Harrel, 2001). In this regard, a common rule of thumb is that a "fitted regression model is likely to be reliable when the number of predictors (…) is less than n/10 or n/20" (Harrel, 2001: p.61). This means that the n/p ratio (13.1) is above the minimum threshold defined in the literature (10). In any case, we also run univariate analyses to check whether the main regression results are confirmed. Lastly, the use of dimensionality reduction techniques – as done in eq. (1.2) and (1.3) – has been pointed out as a way to mitigate the issue of model overfitting (Harrel, 2001), which in our view seems to support the approach followed in this paper to use alternative types of proxies to study banking business choices.

### *3.3. Heterogeneous effects of business choices on profitability and distance to distress*

In order to assess whether the impact of business choices on profitability and distance to distress depends on the business model, we draw on two testing strategies. First, we perform rolling regressions using the main bank orientation as the mediating variable (Mergaerts & Vander Vennet, 2016). The idea is that, if heterogeneity exists we may expect the coefficients of the individual business choices to change as banks adhere more (or less) closely to a given bank orientation. To perform such regressions, we divide the sample of 524 banks into three blocks of 174 observations (524/3), set our number of rolling regressions to 15 and obtain, as a result, a step size of 25 [(524-174)/(15-1)].

For the second testing strategy, we segment the full cross-section sample into different sub-samples according to the business model classification (Köhler, 2015). If there is heterogeneity in the relationship between business models and profitability and distance to distress, we expect to find significant differences in the regression coefficients across sub-samples. We also compute tests for the equality of coefficients across the business model sub-samples.

Given the smaller sample size of each regression in this sub-section, and in order to mitigate overfitting issues (Harrel, 2001), we re-specified the baseline model by replacing the country fixed effects (p=27) with three commonly used country-level controls (sovereign yield, GDP per capita and bank assets to GDP), thus significantly increasing the n/p ratio, in order to meet the minimum threshold defined in the literature.

### *3.4. Impact of changing business model on bank profitability*

The task of gauging the causal effect of changing business model on the profitability of a bank is prone to endogeneity issues, particularly self-selection bias (Ayadi *et al.*, 2020). Namely, the challenge is how to find a credible counterfactual that allows us to estimate the effect of a given bank changing business model *vis-à-vis* not changing business model. First, because we cannot directly observe what the profitability of the bank would be had it not changed its business model. Secondly, because it is likely that idiosyncratic features of the bank may simultaneously influence the likelihood of changing business model and the potential for future earnings.

To mitigate these issues, we apply propensity score matching (e.g., Casu *et al.*, 2013; Ayadi *et al.*, 2020). First, we compute the propensity score ($p$), defined as "the conditional probability of assignment to a particular treatment given a vector of observed covariates" (Rosenbaum & Rubin, 1983: p.41) in triennium $t-1$ for bank $i$:

$$p(X_{i,t-1}) = Pr(\,\Omega_{i,t} = 1 \mid X_{i,t-1}) \quad (2)$$

wherein $\Omega_{i,t}$ is a dummy that states bank $i$ changed business model in triennium $t$[7]; and $X_{i,t-1}$ is a set of pre-treatment independent variables which we expect to affect the likelihood of changing business model. The propensity score is estimated using a logit regression with triennium fixed effects. At this stage tests are performed in order to ensure that "observations with the same propensity score have the same distribution of observable (and unobservable) characteristics independently of treatment status" (Becker & Ichino, 2002: p.359). Next, a matching estimator is chosen that sets the manner in which treated and control observations are matched. After experimentation, we use the radius matching estimator (equal to 0.1), which enables us to identify multiple controls per treated observation. Finally, we estimate the Average Treatment Effect on the Treated (ATET) using the following model:

$$\tau = E\left(\Delta Y_{i,t}^{1} \,\middle|\, \Omega_{i,t} = 1, p(X_{i,t-1})\right) - E\left(\Delta Y_{i,t}^{0} \,\middle|\, \Omega_{i,t} = 0, p(X_{i,t-1})\right) \quad (3)$$

where $\Delta Y_{i,t}^{1}$ is the average change in bank performance (ROA) for all banks that changed business model in triennium $t$ (treated banks); and $\Delta Y_{i,t}^{0}$ is the change in performance for the set of matched banks. Moreover, we extend our baseline test to include the evolution of profitability with one triennium lag, given that we suspect that the effects of a structural change in business model are likely to exhibit a dynamic pattern.

[7] We identify the business model of each bank per triennium. Namely, we: (i) divide the full sample period (2005-16) into four trienniums: 2005-07 (T1), 2008-10 (T2), 2011-13 (T3) and 2014-16 (T4); (ii) compute the average value of the business model variables for each bank per triennium, and (iii) assign each bank-triennium observation to a specific business model by replicating the business model identification process described in **Section 3.1**. In this context, we label as business model change a pair of consecutive bank-triennium observations that are assigned to different business models.

## 4. Data

### *4.1. Sample selection*

Our sample includes 524 European banks, both listed and non-listed, from 2005 to 2016[8]. We collect year-end consolidated data from Bankscope and Orbis Bank Focus. The following criteria are applied: headquarters in an EU-28 country; total assets greater than 5 billion euros in at least one year during the period 2005-16; specialization: commercial, savings, cooperative, real estate & mortgage, investment, specialized governmental credit institution or bank holdings and holding companies; IFRS or Local GAAP accounting standards; both customer deposits and gross loans to customers greater than 5% of total assets; and data available for at least three consecutive years. We winsorize the variables at the 1% and 99% percentiles.

### *4.2. Selection of variables*

#### *4.2.1. Performance and riskiness variables*

In our analysis we use standard accounting measures of profitability and distance to distress, in order to ensure comparability with the extant literature (e.g., Köhler, 2015; Mergaerts & Vander Vennet, 2016; Hryckiewicz & Kozłowski, 2017). Regarding profitability, we employ 'pre-tax returns on average assets' ($ROAA_{i,t}$) defined as:

$$ROAA_{i,t} = \frac{\left(NII_{i,t} + NNII_{i,t} - OE_{i,t} - TIC_{i,t}\right)}{\left[\left(TA_{i,t} + TA_{i,t-1}\right)/2\right]} \tag{5}$$

in which $NII_{i,t}$ represents net interest income, i.e. interests received minus interests paid; $NNII_{i,t}$ is the value of non-net interest income, including net fees and commissions, net trading income and other income; $OE_{i,t}$ is the sum of operating expenses, namely staff expenses and other operating expenses; $TIC_{i,t}$ is total impairment charges, which include loan, securities and other credit impairment charges; and $\left[\left(TA_{i,t} + TA_{i,t-1}\right)/2\right]$ is the average total assets between years $t$ and $t-1$.

To capture the distance to distress of banking institutions, we use the Z-score, which has been widely used in banking literature:

$$Z_{i,t} = \left(\frac{TE_{i,t}}{\left[\left(TA_{i,t} + TA_{i,t-1}\right)/2\right]} + ROAA_{i,t}\right)/SDROAA_i \tag{6}$$

[8] A table with the full sample composition, per year, country and ownership type is presented in the Appendix, **Table A1**.

wherein $TE_{i,t}$ is total equity and $SDROAA_i$ is the standard deviation of $ROAA_{i,t}$ for each bank's full sample period.

### *4.2.2. Business choices variables*

In this section we identify variables used as proxies for banking business choices. All variables are taken from the financial statements, as these are well covered in the dataset. The definition of each variable is presented in **Table 1**.

**Asset structure.** The ratio of *gross loans to customers to total assets* measures the bank's level of engagement in traditional 'originate to hold' lending activities (Diamond, 1984). The ratio of *trading assets to total assets* captures the allocation of resources to financial assets. Banks engaged in trading activities are typically investment banks, however such activities may also be evidence of portfolio diversification strategies or search for yield. The ratio of *interbank lending to total assets*, on the other hand, reflects the involvement of banks in the creation of liquidity for other banking institutions. Evidence suggests that such involvement may be a significant source of counterparty and guarantee risks (Gorton & Metrick, 2012).

**Liability structure.** The ratio of *customer deposits to total assets* reflects the dependence of banks on the most traditional source of funding, also typically considered as the most stable source of funding due to the presence of deposit guarantee schemes (Diamond & Dybvig, 1983). The ratio of *interbank borrowing to total assets* includes mainly bank deposits and other money market funds which have been documented as fragile to negative shocks via refunding risk (Taylor & Williams, 2009). On the other hand, such funds may reflect the presence of internal capital markets, i.e. the borrower-lender relations of firms belonging to the same group. Under this notion, subsidiary banks are likely to face different incentives than those faced by standalone banks (De Haas & Lelyveld, 2010). The ratio of *wholesale funding to total assets* reflects the dependence of banks on market funding. This type of funding has become increasingly used by banks, for instance due to Basel rules on bail-in-able debt. However, a significant share of this type of funding is expected to be marked-to-market (e.g., trading liabilities), which may induce balance sheet volatility and riskiness.

**Diversification.** The ratio of *derivative instruments to total assets* includes both trading and standard interest-rate hedging derivatives. Given the level of expertise required to deal with certain complex derivative instruments, these are expected to absorb a significant share of human and technological resources (Blundell-Wignall *et al.*, 2014). The Herfindhal-Hirshman *income diversification* reflects the ability to diversify into fee-based financial services such as bancassurance, investment advice and credit card services (Elsas *et al.*, 2010) which may enable the improvement of the customers' screening and monitoring, due to the access to additional information, as well as to diversify risks (Diamond, 1984).[9]

**Size.** The (log) value of *total assets* may be considered an important banking business decision in the sense that different banking activities seem to bear different potential for economies of scale (DeYoung & Rice, 2004). In particular, the main intuition is that hard-information based activities, such as trading, wholesale funding and wholesale lending, are more prone to economies of scale than soft-information based activities, such as relationship lending, because hard-information activities are standardizable and require investments in specialized technologies and human resources and hence tend to be performed by larger banks (Hunter & Timme, 1986). Soft-information activities, on the other hand, tend to be performed less effectively in large organizations, for instance due to the presence of multiple layers of hierarchy that impede the effective communication of soft information from subordinates to superiors (Liberti & Mian, 2008). Importantly, some authors have argued that large banks benefit from a 'too-big-to-fail' (TBTF) subsidy which is deemed to be materialized in lower funding costs than those that would reflect the true cost of risk (Noss & Sowerbutts, 2012). On the other hand, such cost advantage may have been offset by the stricter capital requirements and higher supervisory expectations imposed on Global Systemically Important Financial Institutions (G-SIFI) since 2011 (FSB, 2019) – the opposing nature of both effects (TBTF subsidy and G-SIFI add-on requirements) have contributed to the recent interest in uncovering the empirical relationship between size and performance for large banks (Davies & Tracey, 2014; Beccalli *et al.*, 2015; Curi & Lozano-Vivas, 2015).

**Leverage.** The ratio of accounting *equity to total assets* is also expected to vary with other business choices, for a variety of reasons. For instance, large banks seem to benefit from TBTF status, which is likely to offset the risk premium of operating with lower equity (O'Hara & Shaw, 1990). Also, small regional banks are likely to face constraints in terms of asset growth and access to new sources of equity, which may yield a sub-optimal level of leverage. Finally, large diversified banks may be tempted to offset agency issues by offering relatively generous

[9] We acknowledge that some authors have explicitly refrained from including income statement variables as inputs to the business model identification, under the argument that balance sheet variables tend to be more stable than those included in the income statement (e.g., Roengpitya *et al.*, 2017). Our departure from this view, although not unique (Altunbas *et al.*, 2011; Mergaerts & Vander Vennet, 2016; Chiorazzo *et al.*, 2018) is based on the following view. Firstly, in the current low-for-long interest rates environment, banks have increasingly resorted to other sources of income for profitability – and as such income diversification may be seen as an increasingly important part of the banking business. Secondly, the risk of income diversification being volatile, becoming unfit to proxy for the long-term notion of business model is taken seriously and is mitigated by the fact that we use a composite measure of income diversification. In fact, as will be presented in the descriptive statistics table, we pay close attention to the ratio of between to within standard deviation (*ala* Mergaerts & Vander Vennet, 2016), which speaks to the relative stability of the measure over time.

buybacks and dividends to shareholders (Easterbrook, 1984), hence resulting in higher bank leverage.

### *4.2.3. Bank controls*

According to the literature, a set of additional bank-related variables are likely to play a role in explaining bank profitability and distance to distress, and hence we control for their impact in our analysis.

**Risk culture.** While there seem to be several sides to assessing the business risk culture of banks (Di Antonio, 2017), including the influence of national culture (Bussoli, 2017), in our empirical setting we are mainly focused on accounting for the credit risk culture of banks, which has been seen as a persistent determinant of performance, particularly during financial crises (Fahlenbrach *et al.*, 2012). In order to capture this effect we use two proxies. The first is *excess loans*, which is the difference between the bank's average growth of gross loans over the full period and the average growth recorded by the entire sample. The second is related with the value of *loan loss provisions to total assets*. This stream directly affects the bank's profit and, as a consequence, the capital base, and has been seen as highly pro-cyclical because it is determined based on the borrowers' outlook, which tends to be negative in recessions, and positive in recoveries (Huizinga & Laeven, 2019). Also, the procyclicality of loan loss provisions may impact loan mispricing (Bouvatier & Lepetit, 2012) and credit rationing (Jiménez *et al.*, 2017).

**Management quality.** According to one strand of the literature, managers may be seen as playing an important role in determining firm performance (Bertrand & Schoar, 2003). In banking, despite being a heavily regulated industry – which could be seen as an indicator that less room exists for strategic considerations – an increasing attention has been given by the regulator regarding the fit and proper assessment of board members (EBA & ESMA, 2017), suggesting that managerial ability may indeed constitute a significant factor for bank performance. In this paper we follow the existing literature that equates management quality to efficiency (e.g., Curi & Lozano-Vivas, 2020), by computing the *cost-to-income*. This ratio translates the banks' ability to transform inputs (operational costs) into outputs (operational revenues) and has the virtue of allowing for a straightforward comparison of inefficiency across banks.

**Liquidity.** In order to proxy for the exposure to liquidity risk of each bank, we compute an approximate value of the Net Stable Funding Ratio (NSFR), as described by the Basel Committee (BCBS, 2014). The expected relationship between the liquidity of a bank and its profitability is not a straightforward one. Namely, a higher NSFR may, in principle, reflect the cautious use of the bank's liquid resources in terms of illiquid assets, hence generating a sufficient buffer for the bank to pursue investment opportunities whenever they arise. However, a high NSFR could also reflect the general lack of opportunities of credit granting, which in turn deteriorates the bank's ability to generate income.

**Ownership structure.** We take into account the ownership structure of banks using two dummies. The first is related to the identification of *stakeholder* banks, in particular cooperative and savings banks. The literature has documented that stakeholder banks are subject to a different set of objectives than other banks, namely due to their commitment to a dual-bottom line and long-term focus on the preservation of the bank for future generations, both of which may lead to a more risk-averse profile (Fonteyne, 2007). Secondly, we identify *listed* banks, whose management is likely to be under greater market scrutiny, particularly if majority or institutional investors hold a significant part of the bank's claims (Grossman & Hart, 1988).

### *4.3. Descriptive statistics*

The descriptive statistics are presented in **Table 2**. We start our analysis by checking the mean values of ROA (0.54%) and confirming our suspicion that the European banking sector exhibits low levels of profitability. Moreover, the magnitude of the within standard deviation (relative to the between standard deviation) of ROA suggests that banks have endured significant shocks to profitability at the individual level over the sample period. This is sustained by observing **Figure 1**, which demonstrates how bank profitability has suffered two structural breaks over the last decade: 2008-09 (US subprime crisis) and 2011-12 (European sovereign debt crisis).

Next, we look at the asset and funding structures and find that asset allocation is mostly directed towards gross loans to customers (57.6%) and funding is mainly obtained via customer deposits (53.5%). This suggests that European banks tend to be oriented towards traditional retail banking. The average bank in our sample has approximately 220 branches and 3,092 employees[10]. We also find that, on average, banks in our sample do not comply with the Net Stable Funding Ratio requirements (NSFR>100%), which is admissible given that our sample period ranges between 2005 and 2016, i.e. before the NSFR implementation start date of 2018. All business choices exhibit a larger between standard deviation than within standard deviation, which supports the notion that business model features tend to show long-term stability.

[10] The mean ratio of branches per billion euros of total assets is 11.0 and the mean number of employees per billion euros of total assets is 154.6. Moreover, the mean total assets is 10^7.3 which is equivalent to close to 20 billion euros. Hence 11.0 x 20 = 220 and 154.6 x 20 = 3,092.

## 5. Results and discussion

### *5.1. Identification of bank orientation and business models*

Our first results are related to the identification of bank orientation using principal component analysis. In **Table 3**, the composition of the first retained component indicates the presence of large positive loadings of all the input variables (branches, employees and net margin). Proximity has been seen as an important ingredient to build long-term relationships with bank customers, as it allows to build tighter relationships and have access to critical soft information on the creditworthiness of customers (Liberti & Mian, 2008). For this reason, relationship banks may be expected to have a denser branch network than those performing transactional banking. On the other hand, the provision of taylor-made services to customers, and the corresponding time and effort spent by loan officers, may be expected to be much more evident in relationship banking than in transactional banking. Finally, the low volume and highly personalized services provided in relationship banking is likely to yield significantly higher net margins than the high volume-low personalization strategy followed by transactional banks. For these reasons, we label the retained component as 'relationship banking'. Note, however, that low values of this component may also be interpreted as transactional banking (e.g. Degryse & Ongena, 2007).

Next, we turn to the identification of discrete banking business models. For brevity reasons, the optimal number of clusters (business models) is based on untabulated results. In general, we find that, for a partition of four clusters ($J = 4$), the three clustering methods record high mean values of similarity of banks within the assigned business model *vis-à-vis* those assigned to other business models, as given by the highest value of average silhouette width (SW) for PAM (0.23) and the second highest for FCM (0.18) and SOM (0.19). Similarly, the $J = 4$ partition records the highest ratio of between to within cluster dispersion (Calinksi-Harabazs Index) for PAM (137.57) and the second highest for SOM and FCM (122.01 and 128.82, respectively). Based on these results, we conclude that the European banking sector may be characterized by the presence of four business models. This result is in line with the number of banking business models identified by previous studies (Ayadi & De Groen 2015; Roengpitya *et al.*, 2017; Martín-Oliver *et al.*, 2017).

The composition and popularity of each business model is presented in **Table 4**. The results show that when a business model records the highest or lowest mean value in comparison with other models, the number of significant pairwise differences is consistently two ($^{++}$) or three ($^{+++}$). This finding indicates that the business models are significantly different from each other. Namely, **BM1** records the highest mean value of customer deposits and gross loans to customers, as well as significantly higher mean values of relationship banking (and all of the input values, i.e. branches, employees and net interest margin) than the remaining models. For this reason **BM1** is described as *retail focused*[11]; **BM2** exhibits the second largest size and couples gross loans to customers with the highest exposure to wholesale funding, and as such is labelled as *retail diversified funding*; we name **BM3** as *retail diversified assets* because it combines the second highest mean value of customer deposits with the highest share of assets allocated to interbank lending; and **BM4** records the highest mean value of trading assets, derivatives, income diversification and size, and as such is termed *large diversified*[12].

### *5.2. Impact of business choices on bank profitability and distance to distress*

#### *5.2.1. Individual business choices*

**Asset structure. Table 5** shows that, on average, top performers exhibit significantly lower gross loans to customers than bottom performers do. Top banks also tend to record higher values of non-traditional assets, but the difference is not significant. In the same vein, the impact of asset structure variables on ROA and Z-score is generally insignificant, except for interbank lending which negatively affects both measures (**Table 6**). The regressions on the sub-components of ROA and Z-score help to understand such results. Regarding gross loans to customers, the positive effect on net interest income is offset by a negative effect of similar magnitude in terms of non-traditional sources of income. Concerning interbank lending, the negative impact on ROA stems from lower interest revenues, while the negative impact on Z-score results from a negative relation with ROA and equity. Finally, trading assets do not significantly impact any of the sub-components. Such results suggest that, in general, asset diversification does not significantly impact the profitability or distance to distress of banks, which is in line with the results obtained by Elsas *et al.* (2010). However, some studies have found different results from ours by focusing on certain types of banks. For instance, Mercieca *et al.* (2007) find that activity concentration tends to help small banks increase their distance to distress by enabling them to reap the benefits of long-term customer relationships; and Laeven & Levine (2007) document a diversification discount for a sample of large listed banks. To speak to this strand of the literature, we complement our baseline results with business model specific regressions in **Section 5.3**.

[11] A selection of examples of banks from each business model is presented in the Appendix, **Table A2**.

[12] According to the Financial Stability Board (FSB), between 2011 (first year of publication) and 2016, a total of 34 Global Systemically Important Financial Institutions (G-SIFI) were identified, wherein 17 where located in a European country belonging to our sample. Out of those 17 G-SIFI, 1 bank is missing from our sample (Nordea), but the remaining 16 were all classified into the large diversified model (BM4).

**Liability structure.** The results in **Table 5** show that top performing banks rely more on customer deposits than bottom banks do. The regression results in **Table 6** back this initial finding by showing that customer deposits contribute positively to ROA, whereas interbank borrowing and wholesale funding bear a negative and significant coefficient. Moreover, the latter source of funding also negatively affects the Z-score. The regressions on the sub-components tell us that the positive effect of customer deposits on ROA is induced by lower funding costs. Conversely, banks that use more interbank borrowing and wholesale funding tend to pay higher funding costs, which more than offset the savings obtained in terms of operating expenses. In line with other studies (e.g. Mergaerts & Vander Vennet, 2016) such results suggest that banks with a traditional funding structure have enjoyed a competitive advantage over their peers. A possible explanation may lie in the slower speed and smaller magnitude of adjustment of retail deposits to "noisy public signals" when compared to wholesale funds (Huang & Ratnovski, 2011).

**Diversification. Table 5** shows that top performers tend to make less use of derivatives than bottom banks. On the contrary, the regressions results in **Table 6** suggest that, after controlling for other drivers of profitability, the use of derivatives seems to be beneficial for profitability, mainly due to reduced interest expenses. A possible explanation for this result is that banks may mitigate the exposure to interest rate risk, for instance, by contracting vanilla interest rate swaps (Carter & Sinkey, 1998). We interpret the differences in the results of the equality of means test and OLS coefficients as suggesting the presence of heterogeneity in the use of derivatives, as the former test does not account for the effect of other business choices.

Regarding income diversification, the mean values are virtually the same for top and bottom performing banks (**Table 5**). In the same vein, the regressions in **Table 6** show that income diversification does not significantly impact ROA or the Z-score. Namely, the positive effect born on non-traditional income has a similar magnitude as the negative effect on net interest income. Such results seem to be in line with the lack of consensus in the literature, which points to different findings according to the type of banking organization. For instance, Beltratti & Stulz (2012) find a negative effect of income diversity on buy-and-hold stock returns during the 2007-08 crisis for a set of listed banks; whereas an opposite effect is found by Chiorazzo *et al.* (2008) for a sample of Italian banks, most of them not listed.

**Size.** Next, we find that top performing banks tend to be significantly smaller than the bottom banks (**Table 5**). In line with this, **Table 6** shows that size is negatively associated with ROA and the Z-score. The main driver of such results seems to be the negative effect of size on the generation of net fee income, which surpasses efficiency gains. Also, larger banks tend to hold less equity, contributing to the negative effect of size on the Z-score. These findings are in line with the literature (e.g. Beltratti & Stulz, 2012; Hryckiewicz & Kozlowski, 2017) and suggest that above a certain size, the costs of agency issues, such as empire building (Jensen & Meckling, 1976), are likely to exceed the gains due to economies of scale and scope (Scholes *et al.*, 1976).

**Capital.** The findings presented in **Table 5** indicate that top performing banks are significantly better capitalized than bottom banks. Moreover, the OLS estimates in **Table 6** indicate a strong positive relationship between equity and ROA. Namely, better capitalized banks tend to record lower interest expenses and to capture a greater share of non-traditional sources of income. The surveyed studies report similar results to ours: greater capital seems to increase bank profitability. A popular explanation for this relationship lies in the superior ability of well capitalized banks to pursue business opportunities (Athanasoglou *et al.,* 2008).

*5.2.2. Impact of bank orientation on bank profitability and distance to distress*

**Table 5** shows that top performing banks are more oriented towards relationship banking than bottom banks. Similarly, the coefficients presented in panel B of **Table 6** suggest that a long-term orientation towards relationship banking increases ROA and the Z-score. In particular, relationship banking positively affects the ability of banks to generate net interest income and net fees income – which more than offset the higher operating costs. Also, such banks tend to be better capitalized. In general, our findings are in line with those reported by Ewijk & Arnold (2014).

*5.2.3. Impact of business model classification on bank profitability and distance to distress*

The results reported in **Table 4** indicate that banks following the retail focused model (BM1) or the retail diversified assets model (BM3) tend to outperform the remaining banks. A similar ranking of business models is depicted in the OLS regressions (**Table 6**, panel C), with the exception that, after controlling for other sources of bank distress, it becomes apparent that the decision to operate with a retail focused model increases the Z-score relative to other models. These results are backed by **Figure 2**, which shows the evolution of profitability and distance to distress per business model over the sample period. Moreover, the differences in the magnitude of the dummy coefficients for each business model are economically significant. For instance, the coefficient of the dummy identifying banks that operate with a large diversified model (-0.264) accounts for nearly half of the ROA sample mean (0.264/0.54= 48.9%). Although to a lesser extent, a similar phenomenon seems to occur for the coefficient on the Z-score (0.621/2.84= 21.9%). The regressions using the sub-components of ROA and the Z-score suggest that the choice of operating with a retail diversified funding model (BM2) entails increased funding costs, greater impairment charges and lower ability to capture fee income. Regarding banks following the retail diversified assets model (BM3), we find that, relative to BM1 banks, these exhibit a trade-off between more efficient operations, and a lower ability to tap into interest income. Finally, concerning banks with a large diversified model (BM4), results indicate that the ability to capture additional trading income and to run more efficient operations is more than offset by significant difficulties related with lower interest and net fee income and higher funding and impairment costs – in what appears to be almost a perfect mirror image of the implications of pursuing a relationship banking strategy. Interestingly, however, when observing **Figure 2** we may see that the evolution of BM4 banks after 2011 seems particularly positive for both ROA and the Z-score when compared with other models. A possible explanation for this may lie in the specific regulatory framework set for G-SIFI beginning in 2011 (first year of publication of the G-SIFI list by the FSB). Further exploring this perspective may yield interesting results, which we do in **Section 6.3**.

*5.3. Heterogeneous effects of business choices on profitability and distance to distress*

To study the heterogeneous effects of business decisions, we focus our attention exclusively on the business choices that yield consistent results in the rolling and sample split regressions. Namely, trading assets, customer deposits, income diversification and size.

Regarding trading assets, the rolling regressions in **Figure 3** show that the impact on ROA is positive and significant only for banks with a high relationship banking orientation. Such a result finds support in the sample split regressions (**Table 7**) that show a positive and significant coefficient of trading assets on ROA for retail focused banks (BM1). Recall that in the full sample regressions trading assets do not bear a statistically significant impact on ROA. We interpret such findings as suggesting that some level of asset diversification, namely via trading assets, may be beneficial for retail focused banks.

Next, we find that customer deposits only bear a positive and statistically significant impact on ROA for banks with a very low relationship banking orientation (**Figure 3**). Similarly, the impact of customer deposits on ROA is positive and significant for large diversified banks (BM4) (**Table 7**). As previously commented, results in **Table 6** suggest that such an impact is likely to occur due to the beneficial effects of customer deposits on funding costs, net fees income and impairment charges – factors which, in turn, tend to significantly hinder the profitability for large diversified banks.

Income diversification, on the other hand, is only positively associated with a higher Z-score at high values of relationship banking orientation (**Figure 1**). Similarly, the positive coefficient of income diversification on the Z-score is statistically significant for retail focused banks (BM1) (**Table 7**). We relate such results to the findings obtained by Köhler (2015), which document a particularly large impact of non-interest income on the distance to distress of cooperative and savings banks, which tend to be relationship-oriented. A possible interpretation for this result steams from the standard observation that fee generating services performed by relationship banks are likely to be related to the lending activity of the bank, e.g. fees for processing credit payment and transactions, fees for the analysis of credit proposals, and the sale of mortgage-related insurance products. Critically, this result finds support in a body of relatively recent works that have dug deeper into the types of fee generating activities when exploring the relationship between income diversification and bank performance (Demirguç-Kunt & Huizinga, 2010; DeYoung & Torna, 2013). For instance, DeYoung & Torna (2013) find, for a set of US commercial banks (2008-10), that the impact of income diversification on the probability of distress depends on the type of fee generating activities. Namely, standard fee generating activities (e.g. securities brokerage, insurance sales) reduced the probability of distress, while asset-based activities (e.g. venture capital, investment banking, securitization) increased the likelihood of distress. Nonetheless, this may stand as a relatively counter-intuitive result. Hence, we further investigate the relationship between income diversification and the Z-score for relationship-oriented banks. Particularly, we extract the median values of each decile of the relationship banking index with respect to net fees and commissions and Z-score and compute the correlation between both measures. The untabulated result (+0.72) indeed suggests that as banks become more relationship-oriented the level of net fees and commissions tends to increase – note that, as expected for relationship banks, the range of values of net fees and commissions at which this positive correlation occurs is, nonetheless, relatively low (between 13.4% and 26.9% of total operating revenues).

Finally, we find that the impact of size on ROA is negative only for banks with a high level of relationship banking (**Figure 3**). In a similar vein, only retail focused banks record a negative and significant impact of size on ROA (**Table 7**). Both results suggest that size may hinder the superior ability of relationship banks to manage soft-information, for instance due to their multilayered hierarchical structure (Liberti & Mian, 2008).

### *5.4. Impact of changing business model on bank profitability*

The results in **Table 8** show that mobility rates vary considerably depending on the source and destination business models, suggesting that some business models have higher mobility barriers than others. For instance, banks operating under BM4, which tend to be larger than banks with other business models (**Table 4**), also record the lowest mobility rates. On the other hand, the relatively frequent changes from the retail diversified models (BM2 and BM3) to the retail focused model (BM1) suggest that over our sample period banks transitioned to a more traditional retail model. Roengpitya *et al*. (2017) analyse a sample of large global banks (2005-15) and find that a significant number of banks changed business model in the post-GFC period, particularly between 2007 and 2013. According to the authors, such changes may be attributed to the 2007-08 financial crisis, which "marked a distinct turning point in banks' strategic choices: it increased the appeal of the most traditional (...) business model" (Roengpitya *et al*., 2017: p.17).

To investigate if this trend is also observed in a sample of European banks, next we analyse the timing of the business model changes. Untabulated results indicate that the majority of the changes occurred in the 2014-16 period. More specifically, a total of 99 banks were found to operate under a different business model in 2014-16 *vis-à-vis* the model operated under in 2011-13, which corresponds to 20.9% of banks present in both trienniums (2008-10: 15.4%, 2011-13: 17.6%). Hence, when compared to the results reported by Roengpitya *et al.* (2017), it seems that the changes in European banks occurred at a relatively later stage than for global banks – which may be linked to the 2011-13 sovereign debt crisis that affected the European banking sector with more severity than other regions (Mink & De Haan, 2013).

Relatedly, another question that may arise is whether the timing of the business model changes significantly differs between listed and non-listed banks. In principle, managers of listed banks may be expected to be better equipped with market information, and hence could be in a better position to anticipate future trends. However, according to the quiet life hypothesis bank managers may also have lower willingness to undergo significant changes to the business, as these may be risky. Indeed, we find that while the percentage of banks that change business model is similar for listed and non-listed banks (16.5% and 18.5%, respectively), the timing of changes is not the same. Namely, the majority of the listed banks that changed business model did so during the GFC (2008-10, 42.5%), whereas for non-listed banks the majority changed business model after the crisis (2014-16, 44.7%). This seems to suggest that the speed of strategic decision making is greater in listed banks *vis-à-vis* their non-listed peers.

Next, we explore the determinants of business model changes (**Table 9)** and their effects on ROA (**Table 10**). To do so, we narrow our analysis to changes from less clearly defined business models (BM2 and BM3), i.e. business models that combine elements of both the retail focused and the large diversified models, to the more focused business models (BM1 and BM4). This approach may allow us to answer the general question of what occurs when a bank increases the focus of its strategy[13] to avoid getting "stuck in the middle" of alternative strategies (Porter, 1998: p.16). Regarding the determinants of changes reported in **Table 9**, we find that banks with mixed strategies (BM2 and BM3) are more likely to change to the focused business models (BM1 or BM4) when they exhibit (*ex-ante*) a smaller difference with respect to the key distinctive features of the focused models. In particular, the main distinctives features between BM2 and BM1 include the ability to capture customer deposits and the orientation towards relationship banking. Hence, it is logical that BM2 banks with an *ex-ante* higher level of customer deposits and commitment to building relationships are more likely to change to BM1 *vis-à-vis* other BM2 banks. As for BM2 and BM4, the key distinctive feature include the asset structure and size. Hence, it is understandable that *a priori* larger BM2 banks with relatively lower orientation towards customer lending are more prone to change to BM4. As for BM3 banks, the key balance sheet difference relative to retail focused banks (BM1) is located on the asset side, namely in the relative importance of the banking book – which is in line with the positive and significant coefficient of gross loans to customers on the likelihood of occurring a BM3 to BM1 change. Finally, the reliance on customer deposits and the size of the bank are the key features separating BM3 from the large diversified model (BM4) – which again is observable in the coefficients reported in **Table 9.**

As for the effects of business model changes on ROA, the results of the propensity score matching analysis in **Table 10** show two general findings[14]. Firstly, changing business model does not seem to pay off in the short-run (i.e. in the triennium that the change occurred) regardless of the source and destination business models. This is materialized in the absence of a statistically significant difference in '$ROA_{t-1}$ - $ROA_t$', for all types of business model changes. Secondly, we find that, in the triennium after the change occurred ('$ROA_{t+1}$ - $ROA_t$'), banks that changed from BM2 to either of the focused models (BM1 or BM4) recorded a significant improvement in profitability relative to their old peers. A possible reason for the lagged effect

[13] Additionaly, by taking this approach we also narrow our analysis on the types of business model changes with more cases, hence increasing the statistical power of the tests performed.

[14] In order to provide further confidence regarding the robustness of the PSM analysis, we present evidence on the quality of the matching performed in the Appendix (**Table A3**). Namely, for each sub-sample (BM2-BM1, BM2-BM4, BM3-BM1, BM3-BM4) we perform a test for the equality of means between treated and non-treated observations, before and after performing PSM, for each business model variable. The values presented in **Table A3** are the mean differences between treated and non-treated, as well as the tests' statistical significance. The table shows that, for the vast majority of comparisons performed (82.5% = 33/40), the mean differences between the treated and non-treated observations are smaller (in absolute terms) after employing PSM when compared to before PSM. Moreover, after implementing the PSM the mean differences become statistically insignificant for the main business choices that separate each pair of business models (when before PSM the differences were significant). For the pair "BM2-BM1" this occurs, for instance, with respect to wholesale funding and size; for 'BM2-BM4' this occurs for trading assets, customer deposits and size; and for the pair 'BM3-BM4' this happens for all funding-related variables, as well as size. We interpret these results as an indication that performing PSM is an important step to find credible counterfactuals and that the chosen PSM model is well suited.

may be related to the need to undergo significant investments in new resources that take their time to yield the expected returns. As for changes from BM3 to BM1 or BM4, no statistical difference in performance emerges from the data relative to other BM3 banks. Resorting to the notion of mobility costs (Porter, 1979), such differences in the outcomes of business model changes for BM2 and BM3 may be understood as suggesting that there are lower barriers to accessing customer deposits (which is the main difference between BM2 and BM1) and trading assets (one of the significant differences between BM2 and BM4) than to expand the loan portfolio (key difference between BM3 and BM1). Drawing on the literature regarding bank competition and loan quality, Ruckes (2004) argues that as the economic outlook improves, the likelihood of borrower default decreases, which negatively affects the profitability of screening loans. As a result, credit standards are lowered and the access to bank credit by low quality borrowers is facilitated. Such mechanism seems to describe nicely what we observe in the data. Namely, as previously noted, a significant share of BM3 banks changed to BM1 outside of the crisis period, at a time when the likelihood of default was lower. During that stage of the business cycle, as posited by Ruckes (2004), credit standards were likely lowered and, hence, in order to achieve credit growth, banks were forced to compete for lower quality loans, at reduced net margins – a mechanism that could explain why BM3 banks are likely to be unsuccessful when trying to improve profitability (*vis-à-vis* their old peers) by pursuing credit growth during the expansion stage of the business cycle. As such, we cannot confidently state that changing from business models with mixed strategies to those with a higher strategic focus necessarily induces higher profitability. Indeed, the data seems to rather indicate that the success of a change in bank strategy depends critically on the height of the mobility barriers (Porter, 1979). In any case, we see our results as broadly supporting the adaptation view of management, according to which the decisions taken by managers in response to changes in the competitive environment may positively influence the performance of firms (Child, 1972)[15].

## 6. Robustness checks

### *6.1. Endogeneity in bank orientation*

A legitimate concern regarding our research is the possibility that certain (unobserved) idiosyncratic features of banks may simultaneously influence their propensity to follow a given

[15] Conversely, the ecological view states that firms are better depicted as following a long-term strategy from which they are not supposed to deviate, given the substantial costs and added risks for their survival (Haveman, 1992).

bank orientation and the level of profitability and distance to distress (Clougherty *et al.*, 2016). We address this issue by employing 2SLS using two IVs that are expected to depict the access of banks to certain types of activities and funding sources, hence influencing bank orientation, and their impact on the outcome variables is foreseen to occur chiefly via this channel.

The first IV is *proximity to financial center*. The proposed rationale is that banks with strategic functions located farther away from financial centers are less likely to tap into the specialized resources (human and technological) required to follow certain market-oriented strategies. An opposing argument, however, could be that the choice of headquarters' location may be, in itself, a function of the proximity of strategic resources. While to the best of our knowledge there is no work that studies the costs of changing headquarters, anecdotal evidence suggests that such decisions are rarely made, as changing location is likely to bear high adjustment costs. In this sense, we suspect that this may be, in fact, a satisfactory instrument. In order to compute the *proximity to financial center* ($PFC_i$) we draw on the literature pertaining to gravitational models (e.g. Garrett *et al.*, 2005) and use the following specification:

$$PFC_i = \frac{1}{T} \times \sum_{t=1}^{T} \sum_{s=1}^{S} \frac{MV_{s,t}}{(1 + Dist_{i,s})} \tag{4}$$

wherein, $s$ corresponds to each of the $S$ stock exchanges located in the same or adjacent country as bank $i$'s headquarter; $MV_{s,t}$ represents the market valuation of stock exchange $s$ in year $t$ considering the equities listed as primary quotes in that stock exchange, obtained via Thomson Reuters Datastream ($T$ is the total number of years that bank $i$ is in the sample); and $Dist_{i,s}$ corresponds to the distance in hours of car travel between the cities where the bank $i$'s headquarters and stock exchange $s$ are located, obtained using the geocoding Stata program developed by Weber & Peclat (2017). The inverse and convex specification takes into account the distance-decay that may be expected to occur in knowledge spillovers (Basile *et al.*, 2012). Finally, $PFC_i$ is divided by the maximum value of $PFC$ in the sample and multiplied by 100.

The second instrument is the *Lerner index*. There is an ongoing debate regarding the effect of competition on bank orientation (Petersen & Rajan, 1995; Boot & Thakor, 2000; Degryse & Ongena, 2007). In particular, the discussion is whether competition potentiates or hinders the ability of banks to use private borrower information in order to extract *ex-post* rents, hence potentiating (or hindering) the incentives to pursue relationship banking (Rajan, 1992). Empirical findings are mixed. For instance, Degryse & Ongena (2007) find that bank branches that face more local competition are more likely to engage in relationship banking, whereas Petersen & Rajan (1995) uncover an opposite association. Despite the lack of consensus, both strands are aligned regarding the direction of causality: market competition drives bank orientation. Alternatively, one could equate the possibility that a change in bank $i$'s orientation may significantly impact the market's competitive structure. We address such potential for reverse causality by explicitly adopting the mainstream industrial organization view that a bank is not likely to single handedly change the market's competitive structure (Bain, 1951). By computing the Lerner Index, we are able to obtain a proxy for market competition at the bank-level (Beck *et al.*, 2013). The Lerner index is computed as follows:

$$Lerner_i = \frac{P_i - MC_i}{P_i} \tag{5}$$

wherein $P_i$ is proxied by the ratio of total revenues to total assets and $MC_i$ is the marginal cost of each bank, which we obtain using the specification defined by Berger *et al*. (2009).

The results in **Table 11** show that the F-test of (weak) instruments is rejected at the 1% level and the null hypothesis of overidentified restrictions is not rejected at the 5% level. Regarding the first-stage regression, we find that the proximity to financial centers decreases the propensity to follow a relationship banking strategy. Also, our results indicate that banks with lower competition are more likely to pursue relationship banking, which is in line with the standard view in the literature that bank competition may hinder the propensity for banks to invest in building relationships with informationally opaque firms (e.g. SME or start-ups) if there is a threat of increased competition in future states of the world, which undercut the monopolistic benefits of the relationship bank (Petersen & Rajan, 1995).

The second stage results lend support to our baseline regressions. Namely, we find a positive effect of pursuing relationship banking in terms of ROA and the Z-score. However, the magnitude of the coefficients is materially different from those obtained in the baseline model (ROA: 0.669 vs 0.268, baseline; Z-score: 0.447 vs 0.170, baseline), which supports the emerging role of endogeneity mitigation strategies in performance-related studies (Clougherty *et al*., 2016).

*6.2. Persistency in bank profitability and distance to distress*

Another source of potential estimation bias steams from the persistency of the outcome variables. In this regard, for instance, Goddard *et al*. (2011) analyse the persistency of bank profits in 65 countries using a system GMM estimator (Arellano & Bover, 1995) and report that the majority of countries record a significant AR(1). On the other hand, Fahlenbrach *et al*. (2012) show that the stock performance of banks during the 1998 crisis is a statistically significant predictor of their performance during the 2007-08 crisis.

We address this issue by employing a system GMM estimation (Arellano & Bover, 1995), which includes the lagged levels and differences of the dependent and independent variables. The consistency of this estimation strategy depends on checking the following tests: (i) the

AR(2) is not statistically significant and (ii) the instruments are not overidentified. We run the analysis using two types of proxies: individual business choices and bank orientation. We consider all variables as endogenous except for year fixed effects. After experimentation with alternative specifications, we exclude a set of bank controls used in the baseline specification, as including these variables resulted in the overidentification of the instruments. We attribute these results to the high correlation between certain control variables and the lagged dependent variable (e.g., cost-to-income, loan loss provisions).

The results in **Table 12** show that the Arellano-Bond test for AR(2) is not statistically significant for any of the regressions and the hypothesis of non-overidentification of the instruments is not rejected for any of the regressions. Also, we find that the coefficients for the lagged dependent variables are positive and statistically significant for all regressions. Regarding the effect of individual business choices on ROA and the Z-score (panel A), we find that the main baseline results remain unchanged, except for size (which becomes statistically insignificant). This finding suggests that incorporating the lag of ROA captures a significant part of the effect of size on ROA, which may be intuitively explained by the persistency of bank size. On the other hand, the results in panel B of **Table 12** show that the effect of relationship banking on ROA and the Z-score remains positive and significant.

*6.3. Sub-period analysis and internal capital markets*

Given the turbulence experienced during the sample period (2005-16) it seems relevant to check whether the main results are sensitive to different sub-periods of analysis. In other words, how did the determinants of performance and distance to distress of European banks evolve before, during and after the GFC and the sovereign debt crisis? To answer this question, we run the baseline models (1.1. and 1.2) on four sub-periods: 2005-07 (pre-crisis), 2008-10 (GFC), 2011-13 (sovereign debt crisis) and 2014-16 (post-crisis). In general, the results presented in Panel A of **Table 13** show that the baseline findings remain largely unchanged.

On the other hand, a strand of the literature devoted to studying the performance and riskiness of large listed banks (Guerry & Wallmeier, 2017; Curi & Murgia, 2018; Minton *et al.*, 2019) has documented the notion that the so-called diversification discount (Laeven & Levine, 2007) seems to have faded during the GFC period. One hypothesis that sustains this finding is the possibility that, during troubled times, financial conglomerates are able to tap into internal capital markets (Campello, 2002), particularly by obtaining low-cost funding from subsidiaries (De Haas & Lelyveld, 2010). To test this hypothesis, we focus on BM4 banks (Panel B of **Table 13**) and include an interaction term between customer deposits and the total number of subsidiaries of the bank. We find that the coefficient for the interaction term is positive and statistically significant for both ROA and the Z-score in the GFC and sovereign debt crisis periods (and not in the pre and post-crisis periods). Importantly, when we take the derivative of the equations with respect to customer deposits for both crises periods, and consider the mean value of subsidiaries (in natural log: GFC period=4.915, sovereign debt crisis period=4.523) we can conclude that the marginal effect of deposits is positive in both periods. For instance, for ROA, using the coefficients of regressions (10) and (11) of **Table 13**, we obtain the following effect:

$$Regression\ (10): \frac{\partial ROA}{\partial CD} = -0.014 + 0.005 \times \overline{Sub} = -0.014 + 0.005 \times 4.915 = 0.011$$

$$Regression\ (11): \frac{\partial ROA}{\partial CD} = -0.006 + 0.003 \times \overline{Sub} = -0.006 + 0.003 \times 4.523 = 0.008$$

Also, untabulated results using the decomposition of ROA indicate that the effect of the interaction term on ROA occurs chiefly via the reduction in interest expenses. These findings seem to corroborate the stated hypothesis, i.e. that large diversified banks (BM4) are likely to significantly benefit from the access to internal funding sources during crises periods.

Still regarding Panel B, we zoom in on the coefficient of size and find that the magnitude of the negative effect of size on ROA seems to have faded over time, becoming statistically insignificant in the post-crisis period. This finding is in line with recent post-GFC literature on large listed banks (Guerry & Wallmeier, 2017; Curi & Murgia, 2018; Minton *et al.*, 2019) and seems to be related to the greater opportunities that large banks have to diversify their sources of income and reduce costs. As for the Z-score, we find that the size coefficient actually becomes positively related with distance to distress in the post-crisis period. Given the relevance of the capital position for the calculation of the Z-score, we trace this result to the capital add-on buffers imposed on G-SIB banks since 2011 (FSB, 2019).

## 7. Conclusions

Over the past decade and a half the European banking sector has faced a number of challenges, having drawn the attention of academics, managers and supervisors to the long-term business choices of banks, related to size, asset and funding structures, diversification and capital, i.e. their business model. This paper has aimed to contribute to the literature on the elusive relationship between business choices and performance in several ways: (i) by testing a variety of proxies that account for the multidimensional nature of banking decisions, (ii) by combining a set of econometric methods to explore the heterogeneity of business choices, (iii) by putting forward a new testing strategy to study the effects of business model changes on profitability, and (iv) by developing a new valid instrument for strategic bank decisions that accounts for the distance between the bank's headquarters and the access to strategic resources ('proximity to financial centers').

Our results indicate that better performing banks tend to exhibit a traditional funding structure (mostly based on customer deposits), a small size and a high level of capital. In the same vein, better performing banks tend to focus on relationship banking. Additionally, our findings indicate that banks following a retail focused model record, on average, a higher profitability and distance to distress than banks following the remaining models. Moreover, the evidence collected suggests the presence of significant heterogeneity regarding the impact of several business choices on profitability and distance to distress. Namely, we find that only banks with high orientation towards relationship banking seem to benefit from higher levels of income diversification in terms of distance to distress and trading assets in terms of profitability, while only such banks seem to be negatively affected by size; on the other hand, only banks with a very low orientation towards relationship banking seem to benefit from customer deposits in terms of profitability. Finally, we find evidence that mobility barriers exist across business models, particularly related to size. Additionally, by comparing banks that change business model *vis-à-vis* their old peers, we uncover that on average changing from the retail diversified funding model to the retail focused or large diversified models improves performance in the medium term. In general, our results are robust to changes in the baseline specification in order to account for potential endogeneity and persistency issues (IV and GMM regressions). We also find evidence that large diversified banks benefited from internal capital markets during the twin financial crisis in Europe (2008-10, 2011-13) by tapping into low-cost funding provided by subsidiaries.

The findings in this paper bear several policy implications. Firstly, our results suggest that relying on stable funding sources, as required under the Basel III agreement (e.g. NSFR), has a positive impact on performance. Secondly, our findings regarding the heterogeneous effects of business choices on profitability and distance to distress seem to be in line with the emphasis on proportionality taken by recent regulatory initiatives in the post-GFC period (EBA 2013). Namely, the result that banks with different business choices seem to also bear differences in the ability to generate capital internally (via profits), seems consistent with the regulator's decision to grant to the competent supervisory authorities the power to adjust the capital requirements to the business specificities of each bank. In particular, under the Pillar 2 assessment, supervisors are required to analyse the short-run viability, as well as the long-term sustainability of the business choices of each bank, adjusting the prudential requirements accordingly (EBA, 2014). In other words, and despite the importance of ensuring a level playing field, our results seem to be in line with the current regulatory trend in suggesting that "not all types of bank have proven to be equal" in their ability to internally generate the capital needed to offset the prudential risks.

Finally, our results concerning the positive effects of specific types of business model changes seem to provide some support for the current forward-looking regulatory and supervisory framework, which has increasingly relied on the use of prospective and scenario-based stress testing (BIS, 2018) and also judgement-based supervisory practices (Viñals *et al.*, 2010; Lastra, 2013). As an example, we would argue that stress-testing, particularly in the context of certain regulatory processes (e.g. the internal capital adequacy assessment process, ICAAP) (BIS, 2009), allows supervisors to improve their understanding of how the business model may develop as a consequence of strategic choices made by the bank and/or the evolution of the business environment (Farkas, 2018). This approach also ultimately creates the conditions for decision-makers to preemptively react by adopting more sustainable and prudent business choices, such as the decision to shift to more stable funding sources.

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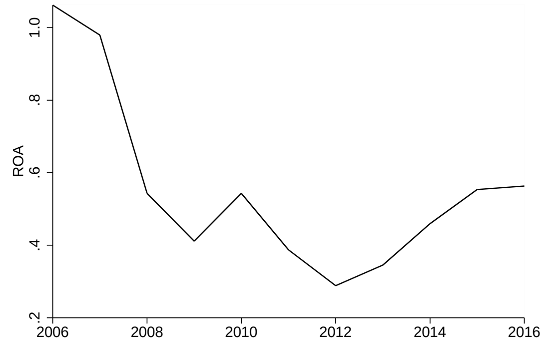
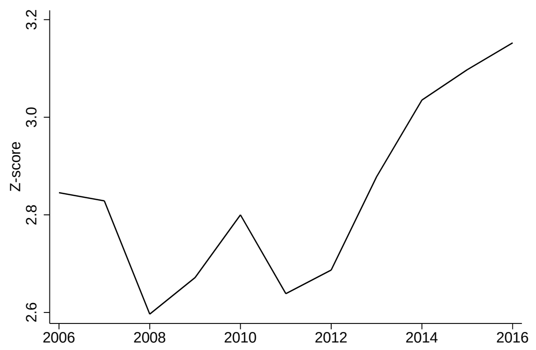
# Figures

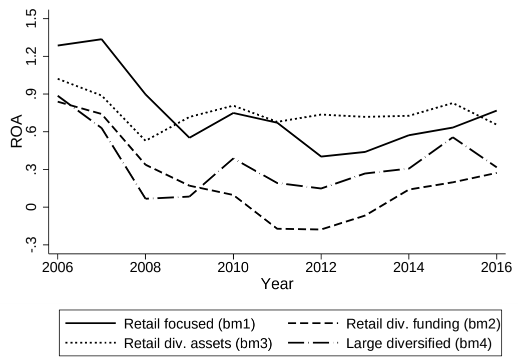
*Figure 1. Evolution of bank profitability and distance to distress*

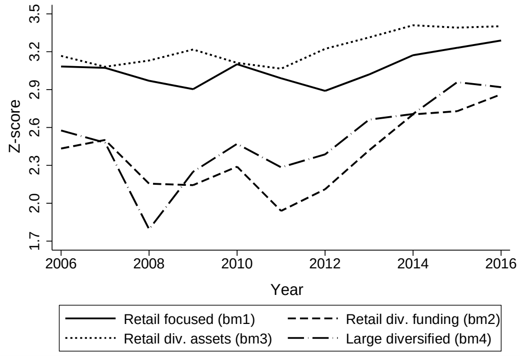



Notes: Mean values per year.

*Figure 2. Evolution of bank profitability and distance to distress per business model*




Notes: Mean values per year and business model classification.

*Figure 3. Heterogeneity of impact of individual business choices on profitability and distance to distress*


Notes: Rolling regressions using the first retained component (Relationship banking) as the mediating variable. Values presented are the coefficient estimates using cross-section OLS regression with bank and country controls on 15 sub-samples as a result of a window size of 174 (i.e., 1/3 of full sample size) and step size of 25. The full line represents the coefficient estimates; the bottom and lower dotted lines represent the 10% and 90% confidence intervals, respectively.

## Tables

*Table 1. Variables description*

| | Description | Unit |
|---|---|---|
| *Performance and riskiness* | | |
| ROA | Pre-tax profits on average assets. | % of avg. assets |
| Z-score | Total equity to total assets plus ROA in year t divided by the standard deviation of ROA for the full period. | Natural log |
| *Business model features* | | |
| Gross loans to customers | Gross loans and advances to customers. | % of total assets |
| Interbank lending | Sum of (i) net loans and advances to banks, (ii) reverse repos, securities borrowed and cash collateral. | % of total assets |
| Trading assets | Financial assets trading and at fair value through profit or loss. | % of total assets |
| Customer deposits | Customer deposits. | % of total assets |
| Interbank borrowing | Sum of (i) bank deposits, (ii) repurchase agreements, securities loaned & cash collateral. | % of total assets |
| Wholesale funding | Sum of (i) other deposits, (ii) short-term funding and debt securities (maturity < 1 year), (iii) long-term borrowings and debt securities at historical cost, (iv) subordinated liabilities, (iv) other long-term borrowing. | % of total assets |
| Total derivatives | Derivative financial instruments, asset and liability-side. | % of total assets |
| Income diversification | Herfindahl-Hirschman Index (HHI); total operating income (TOR) includes net interest income (NII), net fees and commissions (NFC), net trading income (NTI) and other income (OTH). As Elsas *et al.* (2010), absolute values of each component are used: $[1 - [(NII/TOR)^2 + (NFC/TOR)^2 + (NTI/TOR)^2 + (OTH/TOR)^2 ]]$. | HHI |
| Total assets | Log of average assets in thousand euros. | Log |
| Total equity | Total equity. | % of total assets |
| *Bank orientation* | | |
| Branches | Number of branches per billion euros of total assets. | Ratio |
| Employees | Number of employees per billion euros of total assets. | Ratio |
| Net margin | Ratio of net interest income to total assets. | % of total assets |
| *Bank controls* | | |
| Loan loss provisions | Impairment on loans and advances. | % of total assets |
| Excess loans | Growth of gross loans to customers of bank i in year t minus the average growth for the full sample in year t. | Percentage points |
| Cost to income | Total operating expenses to total revenues. | % of revenues |
| Net stable funding ratio | Following BCBS (2014), NSFR is computed as the ratio between the Available Funding (AF) and Required Funding (RF), wherein: AF = 90%*Customer deposits + 25%*Deposits from banks + 100%*Long-term funding + 100%*Loan loss reserves + 100%*Equity; RF = 100%*Gross loans to customers + 50%*Loans to banks + 50%*Securities + 50%*Derivatives + 100%*Other non-cash assets. | NSFR |
| Listed | Dummy 1 if bank is listed. | Dummy |
| Stakeholder | Dummy 1 if bank is cooperative or savings. | Dummy |
| *Other variables* | | |
| Lerner index | Difference between price and marginal cost divided by price. Following Berger *et al.* (2009) we proxy for price by using the ratio of total revenues to total assets; to compute the marginal cost we estimate a translog cost function using data regarding three inputs: labour, funding and fixed capital proxied, respectively, by staff expenses, interests paid and other operating expenses, each divided by total assets. | Index (0-1) |
| Financial center index | Sum of the market capitalization of stock exchanges located in the same (or adjacent) country as the bank's headquarter (considering equities listed as primary quotes), divided by 1 plus the distance in hours of car travel between the city where the bank's headquarters and the stock exchange (*vide* equation 4 of Section 6.1). | Index (0-100) |

Notes: Financial statement data was obtained from the Bankscope and Orbis databases; stock market data was obtained via Datastream; the Urban-Rural typology of each city was drawn from Eurostat.

*Table 2. Descriptive statistics*

| | N | Mean | SD within | SD between | SD overall | Min | Max |
|---|---|---|---|---|---|---|---|
| *Performance and riskiness* | | | | | | | |
| ROA | 4517 | 0.54 | 0.73 | 0.72 | 1.01 | -4.03 | 3.53 |
| Z-score | 5041 | 2.8 | 0.8 | 1.4 | 1.6 | -6.9 | 6.2 |
| *Business model features* | | | | | | | |
| Gross loans to customers | 5041 | 57.6 | 7.8 | 20.9 | 21.4 | 7.5 | 96.8 |
| Interbank lending | 5041 | 15.2 | 6.9 | 16.0 | 16.2 | 0.2 | 79.5 |
| Trading assets | 5041 | 3.6 | 3.8 | 6.1 | 7.0 | 0.0 | 39.1 |
| Customer deposits | 5041 | 53.5 | 7.5 | 22.8 | 22.7 | 6.3 | 91.9 |
| Interbank borrowing | 5041 | 17.3 | 6.9 | 14.8 | 15.2 | 0.0 | 72.7 |
| Wholesale funding | 5041 | 12.9 | 6.2 | 14.7 | 14.8 | 0.0 | 66.1 |
| Total derivatives | 5041 | 5.1 | 4.0 | 9.9 | 10.4 | 0.0 | 62.3 |
| Income diversification | 5041 | 47.9 | 7.2 | 12.1 | 13.7 | 8.2 | 71.0 |
| Total assets | 5041 | 7.3 | 0.1 | 0.6 | 0.7 | 6.1 | 9.2 |
| Total equity | 5041 | 7.1 | 1.8 | 4.2 | 4.3 | 0.9 | 27.9 |
| *Bank orientation* | | | | | | | |
| Branches | 5041 | 11.0 | 8.1 | 14.1 | 16.3 | 0.0 | 295.3 |
| Employees | 5041 | 154.6 | 98.2 | 212.3 | 241.6 | 0.0 | 4978.2 |
| Net margin | 5041 | 1.6 | 0.5 | 0.9 | 1.0 | 0.0 | 5.8 |
| *Bank controls* | | | | | | | |
| Loan loss provisions | 5041 | 0.41 | 0.49 | 0.49 | 0.68 | -0.41 | 4.14 |
| Excess loans | 4517 | 0.40 | 17.21 | 13.27 | 20.06 | -49.83 | 110.58 |
| Cost to income | 5041 | 64.4 | 15.4 | 17.1 | 21.9 | 11.9 | 169.3 |
| Net stable funding ratio | 5041 | 89.3 | 13.4 | 23.8 | 26.0 | 13.7 | 163.6 |
| Listed | 5041 | 0.19 | 0.00 | 0.37 | 0.39 | 0.00 | 1.00 |
| Stakeholder | 5041 | 0.24 | 0.00 | 0.43 | 0.43 | 0.00 | 1.00 |

Notes: Sample based on unbalanced panel data (2005-16). Variables winsorized at 1 and 99 percentiles. The total number of observations is different for ROA (n=4517) as we lose the first observation of each bank by dividing net income by average total assets and average total equity, respectively. Similarly, we lose the first observation of each bank when calculating excess loans (n=4517), as it is computed as a growth rate. Variables with mean values below 1 are reported with two decimals, while the remaining variables are reported with a single decimal.

*Table 3. Identification of bank orientation using principal component analysis*

| | Relationship banking |
|---|---|
| *Raw loadings* | |
| Branches | 0.848 |
| Employees | 0.692 |
| Net margin | 0.847 |
| *Variation explained* | |
| Sum of squared loadings | 1.384 |
| Variation explained (VE) | 0.638 |

Notes: The results are obtained using the full period average of each input variable for all banks (n=524). *Branches* is the number of branches per billion euros of total assets. *Employees* equates to the number of employees per billion euros of total assets. *Net margin* is calculated as the ratio of net interest income to total assets.

*Table 4. Composition and popularity of banking business models*

| | **Retail focused (BM1)** | **Retail div. funding (BM2)** | **Retail div. assets (BM3)** | **Large diversified (BM4)** |
|---|---|---|---|---|
| Number of banks | 203 | 124 | 109 | 88 |
| *Business model features* | | | | |
| Gross loans to customers | 68.3 (12.6)$^{++}$ | 67.6 (14.1)$^{++}$ | 35.6 (16.0)$^{++}$ | 40.1 (18.2)$^{++}$ |
| Interbank lending | 8.2 (5.4)$^{++}$ | 8.9 (6.3)$^{++}$ | 37.6 (19.1)$^{+++}$ | 16.7 (12.7)$^{+++}$ |
| Trading assets | 1.8 (3.4)$^{+}$ | 1.9 (2.5)$^{+}$ | 2.0 (4.9)$^{+}$ | 11.4 (8.9)$^{+++}$ |
| Customer deposits | 67.3 (13.4)$^{+++}$ | 37.5 (16.2)$^{+++}$ | 58.5 (23.0)$^{+++}$ | 29.3 (15.9)$^{+++}$ |
| Interbank borrowing | 11.5 (8.6)$^{+++}$ | 21.5 (16.6)$^{+}$ | 24.5 (19.7)$^{+}$ | 19.4 (10.3)$^{+}$ |
| Wholesale funding | 7.2 (6.5)$^{++}$ | 25.5 (17.0)$^{+++}$ | 4.5 (8.8)$^{++}$ | 20.5 (15.4)$^{+++}$ |
| Total derivatives | 1.4 (2.1)$^{++}$ | 3.8 (4.0)$^{+++}$ | 1.0 (2.9)$^{++}$ | 20.3 (14.5)$^{+++}$ |
| Income diversification | 47.2 (11.0)$^{++}$ | 43.2 (13.0)$^{++}$ | 46.6 (12.5)$^{+}$ | 55.1 (9.4)$^{+++}$ |
| Total assets | 7.0 (0.3)$^{++}$ | 7.5 (0.5)$^{+++}$ | 7.0 (0.4)$^{++}$ | 8.1 (0.7)$^{+++}$ |
| Total equity | 8.9 (4.5)$^{+++}$ | 6.0 (3.3)$^{+}$ | 6.7 (4.3)$^{++}$ | 5.2 (2.9)$^{++}$ |
| *Bank orientation* | | | | |
| Relationship banking | 0.8 (1.6)$^{+++}$ | -0.3 (1.1)$^{++}$ | -0.5 (0.4)$^{+}$ | -0.8 (0. 6)$^{++}$ |
| Branches | 15.9 (15.0)$^{+++}$ | 8.8 (15.9)$^{+}$ | 7.3 (15.3)$^{+}$ | 5.4 (6.5)$^{+}$ |
| Employees | 239.2 (297.4)$^{+++}$ | 100.1 (104.8)$^{+}$ | 79.9 (65.1)$^{+}$ | 60.6 (56.8)$^{+}$ |
| Net margin | 2.2 (1.0)$^{+++}$ | 1.3 (0.8)$^{++}$ | 1.2 (0.6)$^{+}$ | 1.0 (0.5)$^{++}$ |
| *Performance and distance to distress* | | | | |
| ROA | 0.68 (0.64)$^{++}$ | 0.27 (0.46)$^{++}$ | 0.67 (0.53)$^{++}$ | 0.33 (0.39)$^{++}$ |
| Z-score | 3.18 (1.14)$^{++}$ | 2.75 (1.09)$^{++}$ | 3.28 (0.96)$^{++}$ | 2.71 (0.88)$^{++}$ |

Notes: Mean values and standard deviation in brackets, except number of banks (count). The classification is obtained using the clustering ensemble of PAM, SOM and FCM classification output following a majority consensus rule. The input variables used in the clustering process are PC1 to PC5 for the full period, as identified in **Table 5**. For each variable, we compute the Tuckey HSD test for comparison of means per pair of business models, i.e. for a given variable the mean value of each business model is potentially different from the mean of the remaining three business models (only two, only one or none). The number of ($^{+}$) indicates the number of pairwise comparisons which are statistically different at the 5% level. All variables computed as percentage of total assets, except income diversification (HHI) and total assets (log).

*Table 5. Top vs bottom profitability: differences in individual business choices*

| | **Top** (1) | **Bottom** (2) | **Diff.** (3) |
|---|---|---|---|
| Number of banks | 89 | 117 | |
| *Performance and riskiness* | | | |
| ROA | 1.4 | -0.2 | 1.5*** |
| Z-score | 3.1 | 2.1 | 1.0*** |
| *Business model features* | | | |
| Gross loans to customers | 51.9 | 59.1 | -7.1** |
| Interbank lending | 17.8 | 14.9 | 3.0 |
| Trading assets | 3.6 | 3.1 | 0.5 |
| Customer deposits | 60.2 | 47.2 | 13.0*** |
| Interbank borrowing | 14.7 | 20.2 | -5.4*** |
| Wholesale funding | 7.7 | 16.5 | -8.8*** |
| Total derivatives | 3.5 | 6.3 | -2.8** |
| Income diversification | 48.2 | 48.1 | 0.1 |
| Total assets | 7.0 | 7.5 | -0.5*** |
| Total equity | 8.9 | 6.1 | 2.9*** |
| *Bank orientation* | | | |
| Relationship banking | 1.0 | -0.3 | 1.3*** |

Notes: Columns (1) and (2) show the mean values of banks that are cumulatively in the top (bottom) quartiles of ROA for the cross-section sample. In column (3) we present the difference between (1) and (2) as well as the p-value of the Tuckey HSD test for equality of means. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

*Table 6. Impact of business choices on bank profitability and distance to distress*

| | **ROA** | **Interest income** | **Interest expense** | **Net interest income** | **Net fee income** | **Net trading income** | **Other income** | **Staff expenses** | **Other op. expenses** | **Impairm. charges** | **Z-score** | **Total equity** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| *Panel A: Individual choices* | | | | | | | | | | | | |
| Gross loans to customers | -0.001 | 0.022*** | 0.012*** | 0.006*** | -0.006** | -0.002** | -0.002** | -0.001 | -0.004** | 0.000 | 0.004 | 0.009 |
| Interbank lending [(a)] | -0.003** | -0.024*** | -0.004 | -0.006*** | -0.000 | -0.001 | 0.000 | -0.002 | -0.001 | -0.001 | -0.006* | -0.035*** |
| Trading assets [(a)] | 0.000 | -0.009 | -0.009 | -0.003 | 0.009 | 0.004 | 0.005 | 0.007 | 0.011* | 0.002 | -0.013 | 0.020 |
| Customer deposits | 0.005*** | -0.006 | -0.017*** | 0.012*** | 0.004 | -0.000 | -0.006*** | 0.002 | 0.002 | -0.003 | -0.001 | -0.049*** |
| Interbank borrowing [(a)] | -0.003* | 0.004 | 0.011*** | -0.010*** | -0.001 | -0.001 | 0.007** | -0.004** | 0.003 | -0.001 | 0.002 | -0.004 |
| Wholesale funding [(a)] | -0.007*** | 0.012** | 0.025*** | -0.010*** | -0.007*** | 0.000 | 0.003 | -0.002 | -0.004** | 0.004** | -0.007** | -0.037*** |
| Total derivatives | 0.004* | -0.004 | -0.015** | 0.004 | 0.002 | 0.002 | -0.004 | 0.003 | -0.002 | 0.001 | 0.001 | -0.004 |
| Income diversification | 0.003 | -0.010 | -0.004 | -0.007** | 0.007 | 0.005*** | -0.005 | 0.002 | -0.007** | -0.003 | 0.006 | 0.031 |
| Total assets | -0.118*** | 0.034 | 0.154 | 0.070 | -0.196*** | -0.033 | -0.003 | -0.124*** | 0.006 | 0.029 | -0.231** | -2.553*** |
| Total equity | 0.042*** | -0.009 | -0.061*** | 0.051*** | 0.071*** | 0.013*** | 0.034*** | 0.048*** | 0.064*** | 0.002 | | |
| Number of observations | 524 | 477 | 523 | 524 | 523 | 498 | 510 | 521 | 524 | 469 | 524 | 524 |
| R-squared | 0.608 | 0.491 | 0.373 | 0.714 | 0.387 | 0.345 | 0.295 | 0.528 | 0.534 | 0.833 | 0.366 | 0.378 |
| Adjusted R-squared | 0.576 | 0.446 | 0.322 | 0.691 | 0.337 | 0.290 | 0.236 | 0.489 | 0.496 | 0.817 | 0.313 | 0.330 |
| | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) | (23) | (24) |
| *Panel B: Bank orientation* | | | | | | | | | | | | |
| Relationship banking | 0.268*** | 0.522*** | -0.051 | 0.494*** | 0.260*** | 0.010 | 0.186*** | 0.301*** | 0.389*** | 0.005 | 0.170*** | 1.585*** |
| Number of observations | 524 | 477 | 523 | 524 | 523 | 498 | 510 | 521 | 524 | 469 | 524 | 524 |
| R-squared | 0.645 | 0.500 | 0.268 | 0.798 | 0.307 | 0.244 | 0.258 | 0.600 | 0.614 | 0.829 | 0.356 | 0.368 |
| Adjusted R-squared | 0.620 | 0.463 | 0.217 | 0.784 | 0.258 | 0.189 | 0.205 | 0.573 | 0.587 | 0.816 | 0.312 | 0.325 |
| | (25) | (26) | (27) | (28) | (29) | (30) | (31) | (32) | (33) | (34) | (35) | (36) |
| *Panel C: BM classification* | | | | | | | | | | | | |
| Retail div. funding (BM2) | -0.264*** | 0.057 | 0.601*** | -0.437*** | -0.200** | 0.025 | 0.120 | -0.140** | -0.122 | 0.131** | -0.427*** | -2.010*** |
| Retail div. assets (BM3) | -0.063 | -0.886*** | -0.017 | -0.440*** | 0.166 | 0.024 | 0.022 | -0.168*** | -0.027 | -0.013 | -0.275** | -1.630*** |
| Large diversified (BM4) | -0.264*** | -0.571*** | 0.460** | -0.670*** | -0.217* | 0.086** | 0.061 | -0.258*** | -0.239*** | 0.074* | -0.621*** | -2.479*** |
| Number of observations | 524 | 477 | 523 | 524 | 523 | 498 | 510 | 521 | 524 | 469 | 524 | 524 |
| R-squared | 0.525 | 0.470 | 0.305 | 0.668 | 0.266 | 0.252 | 0.165 | 0.425 | 0.436 | 0.832 | 0.372 | 0.312 |
| Adjusted R-squared | 0.490 | 0.427 | 0.254 | 0.644 | 0.212 | 0.194 | 0.101 | 0.383 | 0.394 | 0.818 | 0.326 | 0.261 |

Notes: Values presented are the coefficient estimates using cross-section OLS regression with bank controls and country fixed effects. Regressions with bank fixed effects were also performed for ROA and Z-score, yielding similar results (available upon request). Regarding (a), due to multicollinearity issues, for each dependent variable we perform two regressions: (1) we exclude interbank lending, trading assets, interbank borrowing and wholesale funding; (2) we exclude gross loans to customers and customer deposits. For brevity reasons we report the estimates of (1) and include the excluded variables in (2) in the same column. White robust standard errors. ***, ** and * indicate statistical significance at the 1%. 5% and 10% level. respectively.

*Table 7. Individual business choices, profitability and distance to distress: heterogeneity analysis*

| | All | BM1 | BM2 | BM3 | BM4 |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Panel A: ROA* | | | | | |
| Gross loans to customers | -0.001 | $-0.004_{+}$ | $0.005^{*}_{+}$ | -0.001 | 0.001 |
| Interbank lending[a] | $-0.003^{**}$ | $0.006_{++}$ | $-0.008_{+}$ | $-0.006^{**}_{+}$ | -0.004 |
| Trading assets[a] | 0.000 | $0.023^{***}_{++}$ | 0.007 | $-0.015_{+}$ | $0.004_{+}$ |
| Customer deposits | $0.005^{***}$ | $0.007^{*}$ | 0.003 | $0.004^{**}$ | $0.006^{**}$ |
| Interbank borrowing[a] | $-0.003^{*}$ | $-0.014^{***}_{+++}$ | $0.001_{++}$ | $-0.006^{***}_{++}$ | $-0.003_{+}$ |
| Wholesale funding[a] | $-0.007^{***}$ | -0.004 | -0.002 | -0.004 | $-0.005^{**}$ |
| Total derivatives | $0.004^{*}$ | $0.030^{**}_{++}$ | $0.001_{+}$ | 0.007 | $0.000_{+}$ |
| Income diversification | 0.003 | 0.005 | $0.008^{*}$ | 0.003 | 0.006 |
| Total assets | $-0.118^{***}$ | $-0.190^{*}_{+}$ | -0.066 | $-0.144_{+}$ | $0.060_{++}$ |
| Total equity | $0.042^{***}$ | $0.036^{***}_{+}$ | $0.046^{**}_{+}$ | $0.052^{***}_{+}$ | $0.093^{***}_{+++}$ |
| Number of observations | 524 | 203 | 124 | 109 | 88 |
| R-squared | 0.608 | 0.589 | 0.358 | 0.466 | 0.607 |
| Adjusted R-squared | 0.576 | 0.565 | 0.295 | 0.406 | 0.550 |
| | (6) | (7) | (8) | (9) | (10) |
| *Panel B: Z-score* | | | | | |
| Gross loans to customers | 0.004 | -0.007 | 0.005 | 0.003 | -0.001 |
| Interbank lending[a] | $-0.006^{*}$ | $0.028^{**}_{++}$ | 0.000 | $-0.009_{+}$ | $0.003_{+}$ |
| Trading assets[a] | -0.013 | -0.010 | $0.029_{+}$ | $-0.042^{***}_{++}$ | $-0.008_{+}$ |
| Customer deposits | -0.001 | $-0.002_{+}$ | $-0.014^{*}_{+}$ | $-0.005_{+}$ | $0.013^{**}_{++}$ |
| Interbank borrowing[a] | 0.002 | $0.005_{+}$ | $0.002_{+}$ | $0.004_{+}$ | $-0.025^{***}_{++}$ |
| Wholesale funding[a] | $-0.007^{**}$ | 0.003 | 0.001 | $0.014_{+}$ | $-0.017^{**}_{+}$ |
| Total derivatives | 0.001 | -0.022 | -0.008 | -0.015 | 0.003 |
| Income diversification | 0.006 | $0.015^{**}$ | 0.006 | 0.002 | $0.019^{**}$ |
| Total assets | $-0.231^{**}$ | -0.125 | 0.299 | 0.356 | -0.024 |
| Total equity | | | | | |
| Number of observations | 524 | 203 | 124 | 109 | 88 |
| R-squared | 0.355 | 0.388 | 0.348 | 0.141 | 0.393 |
| Adjusted R-squared | 0.304 | 0.357 | 0.290 | 0.033 | 0.314 |

Notes: Values presented are the coefficient estimates using cross-section OLS regression with bank and country controls. We perform tests for the equality of coefficients for pairs of business model sub-samples. (+): number of statistically significant different pairs at 10% level. (a): due to multicollinearity issues, for each dependent variable we perform two separate regressions: (1) we include all business model features except for interbank lending, trading assets, interbank borrowing and wholesale funding; (2) we exclude gross loans to customers and customer deposits. For brevity reasons we report the estimates of (1) and include the excluded variables in (2) in the same column. Inference based on White robust standard errors. ***, ** and * indicate statistical significance at the 1%. 5% and 10% level. respectively.

*Table 8. Mobility rates per business model*

| | BM1 to BM2 | BM1 to BM3 | BM1 to BM4 | BM2 to BM1 | BM2 to BM3 | BM2 to BM4 |
|---|---|---|---|---|---|---|
| Possible business model changes (1) | 469 | 469 | 469 | 327 | 327 | 327 |
| Actual business model changes (2) | 24 | 35 | 4 | 53 | 7 | 34 |
| Adjusted mobility rate (2/1) | 0.051 | 0.075 | 0.009 | 0.162 | 0.021 | 0.104 |
| | **BM3 to BM1** | **BM3 to BM2** | **BM3 to BM4** | **BM4 to BM1** | **BM4 to BM2** | **BM4 to BM3** |
| Possible business model changes (1) | 256 | 256 | 256 | 219 | 219 | 219 |
| Actual business model changes (2) | 27 | 8 | 12 | 5 | 14 | 7 |
| Adjusted mobility rate (2/1) | 0.105 | 0.031 | 0.047 | 0.023 | 0.064 | 0.032 |

Notes: (1) number of consecutive bank-triennium observations. The classification is obtained using the ensemble classification output following a majority consensus rule for each triennium. To illustrate how we compute the number of business model changes, consider a bank that is present in four trienniums in our sample (last column) and we obtain the following clustering (ensemble) results: T1=BM1, T2=BM2, T3=BM1, T4=BM1. In this case we consider two business model changes (T1-T2 and T2-T3).

*Table 9. Determinants of business model changes*

| | BM2 to BM1 | BM2 to BM4 | BM3 to BM1 | BM3 to BM4 |
|---|---|---|---|---|
| Relationship banking | 0.321** | -0.153 | 1.281*** | -0.905 |
| Gross loans to customers | -0.028* | -0.027* | 0.060*** | -0.022 |
| Customer deposits | 0.114*** | -0.027* | 0.017 | -0.060*** |
| Total assets | -1.736*** | 1.200*** | -0.144 | 2.504*** |
| Nbr. of observations (changes) | 327(53) | 327(34) | 256(27) | 256(12) |
| Likelihood ratio (chi-square test) | 66.64*** | 25.05*** | 43.81*** | 37.75*** |
| Pseudo R-squared | 0.230 | 0.115 | 0.254 | 0.390 |

Notes: The values reported are the coefficients of logit regressions. The explained variable is business model change. Each column represents a different combination of source and destination business model. To illustrate how we compute the number of business model changes, consider a bank that is present in four trienniums in our sample (last column) and we obtain the following clustering (ensemble) results: T1=BM1, T2=BM2, T3=BM1, T4=BM1. In this case we consider two business model changes (T1-T2 and T2-T3). ***, ** and * indicate statistical significance at the 1%. 5% and 10% level. respectively.

*Table 10. Impact of changing business model on profitability: propensity score matching*

| Type of BM change | Time frame | ATET | Treated | Controls |
|---|---|---|---|---|
| **BM2 to BM1** | $ROA_t$ - $ROA_{t-1}$ | -0.231 | 52 | 190 |
| | $ROA_{t+1}$ - $ROA_t$ | 0.875*** | 33 | 126 |
| **BM2 to BM4** | $ROA_t$ - $ROA_{t-1}$ | 0.195 | 34 | 192 |
| | $ROA_{t+1}$ - $ROA_t$ | 0.452*** | 10 | 97 |
| **BM3 to BM1** | $ROA_t$ - $ROA_{t-1}$ | 0.246 | 23 | 142 |
| | $ROA_{t+1}$ - $ROA_t$ | 0.405 | 11 | 86 |
| **BM3 to BM4** | $ROA_t$ - $ROA_{t-1}$ | 0.095 | 12 | 76 |
| | $ROA_{t+1}$ - $ROA_t$ | 0.439 | 3 | 7 |

Notes: Values reported are the average treatment on the treated (ATET) of banks that changed business model in triennium t using Radius Matching, r=0.10. ***, ** and * indicate statistical significance at the 1%. 5% and 10% level. respectively.

*Table 11. Endogeneity in the choice of bank orientation: IV regressions*

| | First stage regression | Second stage regressions | |
|---|---|---|---|
| | **Relationship banking** | **ROA** | **Z-score** |
| | (1) | (3) | (4) |
| *Instrumental variables* | | | |
| Proximity to financial center | -0.004** | | |
| Lerner index | 4.012*** | | |
| *Instrumented variables* | | | |
| Relationship banking | | 0.669*** | 0.447*** |
| Number of observations | 524 | 524 | 524 |
| R-squared | 0.740 | | |
| F-test of instruments (p-value) | 0.000 | | |
| Stock-Yogo's min. eigenvalue | 93.405 | | |
| Wald Chi-square test (p-value) | | 0.000 | 0.000 |
| Sargan test overid. (p-value) | | 0.104 | 0.350 |

Notes: The values presented are the coefficient estimates of cross-section IV regressions with bank controls and country fixed effects. Results reported using robust standard errors. ***, ** and * indicate statistical significance at the 1%. 5% and 10% level, respectively. The Stock-Yogo's critical value for 2SLS size of nominal 5% Wald test considering a 15% relative bias is 8.18 (which should be compared with the reported minimum eigenvalue).

*Table 12. Persistency of profitability and distance to distress: System GMM*

| | **ROA** | **Z-score** |
|---|---|---|
| *Panel A: Individual business choices* | | |
| Y (t-1) | 0.203*** | 0.377*** |
| Gross loans to customers | -0.012** | -0.004 |
| Interbank lending[a] | -0.005 | 0.002 |
| Trading assets[a] | -0.018* | -0.012 |
| Customer deposits | 0.025*** | 0.012* |
| Interbank borrowing[a] | -0.020*** | -0.033*** |
| Wholesale funding[a] | -0.026*** | -0.009 |
| Total derivatives | 0.007 | -0.010 |
| Income diversification | -0.017*** | -0.005 |
| Total assets | -0.096 | 0.154 |
| Total equity | 0.157*** | |
| Number of observations | 3993 | 4517 |
| Number of banks | 523 | 524 |
| Number of instruments | 37 | 33 |
| Wald Chi-square test (statistic) | 327.3 | 181.7 |
| Hansen test (p-value) | 0.108 | 0.269 |
| A-B test for AR(1) (p-value) | 0.000 | 0.000 |
| A-B test for AR(2) (p-value) | 0.650 | 0.697 |
| *Panel B: Bank orientation* | | |
| Y (t-1) | 0.141** | 0.409*** |
| Relationship banking | 0.264* | 0.537* |
| Number of observations | 3993 | 4517 |
| Number of banks | 523 | 524 |
| Number of instruments | 21 | 21 |
| Wald Chi-square test (statistic) | 461.3 | 135.4 |
| Hansen test (p-value) | 0.307 | 0.482 |
| A-B test for AR(1) (p-value) | 0.494 | 0.879 |
| A-B test for AR(2) (p-value) | 0.947 | 0.770 |

Notes: The values presented are the coefficient estimates of a system GMM, following Arellano & Bover (1995) with bank controls and year fixed effects (unreported). For the first differences equation we use as instruments the first and second lags of the independent variables; for the levels equation we use as instruments the differentiated first and second lags of the independent variables. ***, ** and * indicate statistical significance at the 1%. 5% and 10% level, respectively.

*Table 13. Sub-period analysis: impact of business model features on performance and distance to distress*

| | ROA | | | | Z-score | | | |
|---|---|---|---|---|---|---|---|---|
| | **2005-07** | **2008-10** | **2011-13** | **2014-16** | **2005-07** | **2008-10** | **2011-13** | **2014-16** |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Panel A: All banks* | | | | | | | | |
| Gross loans to customers | 0.002 | 0.000 | -0.001 | -0.002 | -0.005** | 0.000 | 0.008*** | 0.000 |
| Interbank lending[a] | -0.004* | -0.003** | -0.002 | -0.003*** | 0.003 | -0.001 | -0.005 | -0.003 |
| Trading assets[a] | 0.005 | -0.002 | 0.004 | 0.000 | -0.009** | 0.000 | -0.008* | -0.011*** |
| Customer deposits | 0.005*** | 0.008*** | 0.005*** | 0.008*** | 0.009*** | 0.011*** | 0.004* | 0.003 |
| Interbank borrowing[a] | -0.006*** | -0.008*** | -0.006*** | -0.008*** | -0.009*** | -0.012*** | -0.005 | -0.001 |
| Wholesale funding[a] | -0.009*** | -0.009*** | -0.006*** | -0.009*** | -0.011*** | -0.018*** | -0.009** | -0.008* |
| Total derivatives | -0.001 | 0.006*** | 0.004** | 0.002 | 0.004 | -0.001 | -0.005 | -0.010*** |
| Income diversification | 0.011*** | 0.008*** | 0.006*** | 0.004*** | -0.004 | 0.005 | 0.009** | 0.005* |
| Total assets | -0.066 | -0.088*** | -0.092*** | 0.010 | -0.204*** | -0.299*** | -0.209*** | -0.023 |
| Total equity | 0.075*** | 0.073*** | 0.081*** | 0.076*** | | | | |
| Number of observations | 672 | 1155 | 1341 | 1349 | 1048 | 1226 | 1408 | 1359 |
| R-squared | 0.498 | 0.592 | 0.662 | 0.619 | 0.080 | 0.271 | 0.371 | 0.187 |
| | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| *Panel B: Large diversified (BM4)* | | | | | | | | |
| Gross loans to customers | 0.005** | 0.001 | -0.003 | -0.002 | -0.002 | -0.010 | -0.016** | -0.004 |
| Interbank lending[a] | -0.009** | -0.007** | -0.008*** | 0.000 | -0.004 | 0.008 | 0.012 | 0.014* |
| Trading assets[a] | 0.000 | -0.003 | -0.003 | 0.008** | 0.001 | 0.011 | 0.017 | 0.006 |
| Customer deposits | -0.006 | -0.014*** | -0.006** | 0.003 | -0.009 | -0.015 | 0.005 | 0.012 |
| Customer deposits x Subsidiaries | 0.003 | 0.005*** | 0.003*** | 0.001 | 0.005** | 0.010*** | 0.004 | -0.002 |
| Interbank borrowing[a] | -0.009** | -0.005 | 0.002 | -0.008** | -0.021*** | -0.057*** | -0.015 | -0.026*** |
| Wholesale funding[a] | -0.003 | -0.006*** | -0.004*** | -0.006 | -0.010 | -0.019** | -0.018** | -0.004 |
| Total derivatives | 0.001 | 0.003* | -0.001 | -0.003 | -0.010 | 0.005 | -0.002 | 0.002 |
| Income diversification | 0.011** | 0.000 | 0.001 | 0.000 | 0.006 | 0.003 | 0.011 | 0.012** |
| Total assets | -0.176* | -0.333*** | -0.138* | 0.087 | -0.269** | -0.585*** | 0.05 | 0.290* |
| Total equity | 0.111*** | 0.069*** | 0.072*** | 0.093*** | | | | |
| Number of observations | 115 | 204 | 227 | 219 | 181 | 216 | 236 | 220 |
| R-squared | 0.736 | 0.767 | 0.826 | 0.729 | 0.128 | 0.260 | 0.437 | 0.280 |

Notes: Values presented are the coefficient estimates using cross-section OLS regression with bank and country controls. (a): due to multicollinearity issues, for each dependent variable we perform two separate regressions: (1) we include all business model features except for interbank lending, trading assets, interbank borrowing and wholesale funding; (2) we exclude gross loans to customers and customer deposits. For brevity reasons we report the estimates of (1) and include the excluded variables in (2) in the same column. Inference based on White robust standard errors. ***, ** and * indicate statistical significance at the 1%. 5% and 10% level. respectively.

## Appendix

*Table A1. Sample composition*

| | Banks | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | Bank-year obs. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Country* | | | | | | | | | | | | | | |
| Austria | 40 | 22 | 32 | 32 | 33 | 34 | 35 | 36 | 36 | 38 | 39 | 37 | 36 | 410 |
| Belgium | 16 | 10 | 11 | 11 | 11 | 11 | 11 | 11 | 12 | 13 | 15 | 13 | 12 | 141 |
| Bulgaria | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 24 |
| Croatia | 3 | 2 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 35 |
| Cyprus | 5 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 5 | 5 | 5 | 4 | 4 | 44 |
| Czech Republic | 10 | 7 | 7 | 7 | 8 | 9 | 9 | 9 | 9 | 10 | 10 | 10 | 10 | 105 |
| Denmark | 8 | 6 | 6 | 6 | 6 | 7 | 7 | 8 | 8 | 8 | 8 | 8 | 7 | 85 |
| Estonia | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 24 |
| Finland | 11 | 4 | 5 | 5 | 7 | 7 | 6 | 6 | 7 | 9 | 10 | 10 | 10 | 86 |
| France | 68 | 38 | 42 | 48 | 50 | 49 | 61 | 64 | 62 | 64 | 63 | 48 | 46 | 635 |
| Germany | 97 | 60 | 72 | 74 | 79 | 82 | 88 | 87 | 88 | 90 | 87 | 82 | 77 | 966 |
| Greece | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 48 |
| Hungary | 8 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 8 | 8 | 8 | 8 | 8 | 89 |
| Ireland | 13 | 8 | 8 | 8 | 8 | 8 | 9 | 10 | 11 | 11 | 10 | 8 | 8 | 107 |
| Italy | 46 | 33 | 37 | 39 | 39 | 41 | 41 | 44 | 44 | 44 | 43 | 41 | 40 | 486 |
| Latvia | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 12 |
| Lithuania | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 24 |
| Luxembourg | 27 | 14 | 15 | 20 | 20 | 20 | 23 | 23 | 22 | 24 | 23 | 21 | 21 | 246 |
| Malta | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 24 |
| Netherlands | 24 | 11 | 12 | 14 | 16 | 15 | 16 | 18 | 19 | 20 | 21 | 19 | 18 | 199 |
| Poland | 14 | 11 | 12 | 12 | 12 | 13 | 13 | 14 | 14 | 14 | 14 | 14 | 13 | 156 |
| Portugal | 12 | 7 | 9 | 9 | 9 | 10 | 10 | 11 | 11 | 11 | 12 | 11 | 11 | 121 |
| Romania | 6 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 6 | 6 | 6 | 6 | 64 |
| Slovakia | 5 | 3 | 3 | 3 | 3 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 5 | 48 |
| Slovenia | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 24 |
| Spain | 32 | 13 | 13 | 14 | 17 | 18 | 26 | 30 | 29 | 30 | 29 | 27 | 25 | 271 |
| Sweden | 11 | 5 | 5 | 5 | 5 | 5 | 6 | 7 | 8 | 9 | 11 | 11 | 11 | 88 |
| United Kingdom | 53 | 31 | 35 | 36 | 35 | 35 | 36 | 43 | 46 | 47 | 46 | 45 | 44 | 479 |
| *Listed* | | | | | | | | | | | | | | |
| Yes | 88 | 70 | 73 | 75 | 78 | 79 | 82 | 86 | 87 | 86 | 86 | 86 | 85 | 973 |
| No | 436 | 245 | 284 | 301 | 313 | 322 | 352 | 372 | 379 | 398 | 397 | 360 | 345 | 4068 |
| *Stakeholder* | | | | | | | | | | | | | | |
| Yes | 124 | 75 | 83 | 88 | 92 | 94 | 111 | 118 | 119 | 122 | 121 | 103 | 101 | 1227 |
| No | 400 | 240 | 274 | 288 | 299 | 307 | 323 | 340 | 347 | 362 | 362 | 343 | 329 | 3814 |
| **Total** | **524** | **315** | **357** | **376** | **391** | **401** | **434** | **458** | **466** | **484** | **483** | **446** | **430** | **5041** |

Notes: Unbalanced panel data. Stakeholder refers to cooperative or savings banks.

*Table A2. Selection of banks per business model*

| | **Business model features** | | | | | | | | | | **Bank orientation** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Name** | **GL** | **TR** | **IL** | **CD** | **IB** | **WF** | **TD** | **ID** | **TA** | **TE** | **RB** | **BR** | **EM** | **NM** |
| *Retail focused (BM1)* | | | | | | | | | | | | | | |
| Banco di Sardegna (IT) | **74.9** | 4.4 | 15.8 | **66.3** | 3.7 | 16.7 | 0.1 | 47.4 | 7.1 | 9.3 | **1.3** | **30.3** | **148.3** | **2.5** |
| Société Marseillaise de Crédit (FR) | **73.7** | 0.0 | 19.5 | **82.8** | 7.2 | 0.1 | 0.0 | 55.9 | 6.7 | 6.5 | **1.4** | **18.0** | **226.6** | **2.9** |
| Volksbank Mittelhessen (DE) | **58.8** | 0.0 | 11.7 | **76.9** | 7.7 | 6.6 | 0.0 | 44.2 | 6.7 | 6.8 | **0.6** | **10.1** | **192.1** | **2.3** |
| *Retail diversified funding (BM2)* | | | | | | | | | | | | | | |
| Aareal Bank (DE) | **61.3** | 0.7 | 4.7 | 40.4 | 8.2 | **39.0** | 9.8 | 45.2 | 7.6 | 4.7 | -0.7 | 2.3 | 58.5 | 1.2 |
| Banco Santander Totta (PT) | **70.7** | 2.8 | 9.2 | 46.3 | 21.5 | **20.0** | 8.0 | 55.7 | 7.6 | 6.3 | -0.2 | 9.8 | 97.6 | 1.5 |
| Unione di Banche Italiane (IT) | **76.0** | 2.1 | 3.5 | 41.9 | 9.5 | **33.3** | 2.0 | 50.3 | 8.1 | 9.2 | 0.2 | 14.9 | 103.4 | 1.8 |
| *Retail diversified assets (BM3)* | | | | | | | | | | | | | | |
| Banco Pastor (ES) | 42.6 | 0.0 | **52.0** | **78.0** | 13.5 | 1.4 | 1.3 | 33.6 | 7.1 | 5.2 | -0.2 | 11.0 | 87.4 | 1.5 |
| CheBanca (IT) | 33.0 | 0.0 | **56.5** | **74.5** | 22.4 | 0.0 | 0.3 | 35.0 | 7.1 | 1.7 | -0.9 | 4.3 | 67.1 | 0.8 |
| CEP de Loire-Drôme-Ardèche (FR) | 40.6 | 0.0 | **44.8** | **71.8** | 18.5 | 1.0 | 0.0 | 55.0 | 7.0 | 5.7 | -0.3 | 9.6 | 122.1 | 1.2 |
| *Large diversified (BM4)* | | | | | | | | | | | | | | |
| Deutsche Bank (DE) | 19.8 | **17.8** | 9.5 | 28.1 | 5.8 | 13.8 | **55.4** | **62.8** | **9.0** | 2.9 | -0.7 | 0.7 | 87.6 | 1.2 |
| ING Belgium (BE) | 46.6 | **8.1** | 12.0 | 52.7 | 16.0 | 3.9 | **29.6** | **45.9** | **8.2** | 6.0 | -0.6 | 3.7 | 48.1 | 1.5 |
| Crédit Agricole (FR) | 21.5 | **20.5** | 26.4 | 29.4 | 12.7 | 22.9 | **15.8** | **67.3** | **9.0** | 3.3 | -0.9 | 0.0 | 50.0 | 1.1 |

Notes: In **bold** main distinctive features of each business model as described in **Table 4**. GL – Gross loans to customers, TR – Trading assets, IL – Interbank lending, CD – Customer deposits, IB – Interbank borrowing, WF – Wholesale funding, TD – Total derivatives, ID – Income diversification, TA – Total assets (log), TE – Total equity, RB – Relationship banking, BR – Number of branches, EM – Number of employees, NM – Net margin.

*Table A3. Sensitivity analysis: mean differences tests before and after implementing propensity score matching*

| | Obs.[(1)] | GL | TR | IL | CD | IB | WF | TD | ID | TA | TE |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **BM2 to BM1** | | | | | | | | | | | |
| (1) Before PSM | 53(274) | 1.4 | -0.6 | -2.4* | 13.0* | -4.9* | -8.1* | -0.7 | 3.1 | -0.2* | 0.6 |
| (2) After PSM | 52(190) | -0.5 | -0.7* | -1.2 | 4.5* | -1.8 | -2.9 | -0.6 | 0.2 | -0.1 | 0.5 |
| Diff. \|(2)\|-\|(1)\| | | **-0.9** | 0.1 | **-1.2** | **-8.5** | **-3.1** | **-5.2** | **-0.1** | **-2.9** | **-0.1** | **-0.1** |
| **BM2 to BM4** | | | | | | | | | | | |
| (3) Before PSM | 34(293) | -9.7* | 1.1* | 4.6* | -6.7* | -2.9 | 5.5 | 4.6* | 4.0 | 0.3* | 0.1 |
| (4) After PSM | 34(192) | -6.7* | 0.9 | 4.6* | -5.4 | -1.0 | 3.5 | 3.9* | 4.0 | 0.1 | 0.7 |
| Diff. \|(4)\|-\|(3)\| | | **-3.0** | **-0.2** | **0.0** | **-1.3** | **-1.9** | **-2.0** | **-0.7** | **0.0** | **-0.2** | 0.6 |
| **BM3 to BM1** | | | | | | | | | | | |
| (5) Before PSM | 27(229) | 13.8* | 1.1 | -16.6* | 3.3 | -3.4 | -0.5 | 1.2* | 1.2 | 0.0 | 1.3 |
| (6) After PSM | 23(142) | 6.7* | 0.5 | -12.4* | -0.8 | -1.2 | 1.7 | 1.8* | 0.5 | 0.0 | 0.3 |
| Diff. \|(6\|-\|(5)\| | | **-7.1** | -0.6 | **-4.2** | **-2.5** | **-2.2** | 1.2 | 0.6 | **-0.7** | **0.0** | **-1.0** |
| **BM3 to BM4** | | | | | | | | | | | |
| (7) Before PSM | 12(244) | -9.2 | 1.2 | 1.7 | -34.1* | 20.4* | 9.9* | 0.8 | -0.7 | 0.4* | -0.9 |
| (8) After PSM | 12(76) | -5.3 | 1.5 | 2.2 | -9.5 | 4.3 | 3.6 | 0.4 | 0.3 | 0.1 | -0.1 |
| Diff. \|(8\|-\|(7)\| | | **-3.9** | 0.3 | 0.5 | **-23.6** | **-16.1** | **-6.3** | **-0.4** | **-0.4** | **-0.3** | **-0.8** |

Notes: Values presented are the mean differences between treated and non-treated observations for the set of business models. This is done for each type of business model change presented in **Tables 9 and 10**, for two settings: "Before PSM", i.e. before employing propensity score matching, and "After PSM". In each case we perform Tuckey HSD test for the equality of means, wherein * indicates statistical significance at the 5% confidence level. In **bold** we identify the cases where the mean differences, in absolute terms, are smaller after employing PSM. (1) Within brackets: number of non-treated observations, outside brackets: number of treated observations. GL – Gross loans to customers, TR – Trading assets, IL – Interbank lending, CD – Customer deposits, IB – Interbank borrowing, WF – Wholesale funding, TD – Total derivatives, ID – Income diversification, TA – Total assets (log), TE – Total equity.