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‘ONE SIZE DOES NOT FIT ALL’: LINKING THE DIVERSITY OF BUSINESS MODELS TO PERFORMANCE AND RESILIENCE IN THE BANKING SECTOR

by

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BIOGRAPHICAL NOTE

Bernardo was born in Porto in 1986. In 2007 he concluded his undergraduate degree in Economics at the Portuguese Catholic University in Porto (UCP-Porto); and in January 2010 he defended his Master thesis in Economics, at the same University.

In parallel, he started to work as a management consultant at Deloitte in September 2008, where, for six years, he participated in a wide variety of strategic and operational projects for banks and insurance companies in Portugal, Angola and Denmark.

In September 2014, Bernardo switched from the consulting to the academic world, becoming a full-time assistant lecturer at *Católica Porto Business School* (CPBS), where he has since taught finance and economics courses at the undergraduate level, including *Money and Financial Markets*, *Corporate Finance*, and *Managerial Economics* – while pursuing his PhD at the Faculty of Economics of the University of Porto, since September 2015.

In 2016 and 2017, he published, in co-authorship, two large-scale reports on the cooperative banking sector in Portugal, commissioned to the Center for Applied Studies in Economics and Management (CEGEA) at UCP – it was during the preparation of these reports that Bernardo first came in contact with the notion of banking business model.

In early 2018, Bernardo visited the Rotterdam School of Economics, where, for two weeks, he received guidance regarding state-of-the art multivariate data analysis techniques under Professor Groenen. Later that year, he was awarded the Oliveira Marques Award for best PhD project in *Corporate Finance*. In the same year he received a PhD scholarship from *Fundação para a Ciência e Tecnologia*.

In June 2019 he was awarded the prize for best poster at the 6th Young Finance Scholars Conference at the University of Sussex. Since September 2020 he is a PhD trainee at the European Central Bank, at DG Microprudential Supervision III.

Bernardo is married and has a 2 year old boy, who will soon be joined by a little sister.

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ABSTRACT

Rising concerns about the riskiness and lack of profitability of banks have motivated recent debates in literature regarding the classification and analysis of banking business models, as well as the adoption of business model specific regulation and supervision.

The thesis aims to contribute to the current debates and to improve the quality of regulation and supervision of banks by producing three empirical studies. The first paper develops a novel definition and method to identify banking business models that accommodate two empirical observations: (i) the possibility that banks may have some level of affinity with more than one business model, e.g. following a merger with another bank, and (ii) banks may choose to change their business model. In the second paper, we test which business model choices are associated with higher profitability and resilience, using three alternative proxies for business model choices (individual features, bank orientation, business model classification). The paper also explores the heterogeneity of the relationship between business models and performance, as well as the effects of changing business model – while close attention is given to endogeneity issues. The final paper tests the link between the country-level diversity of business models and banking sector resilience and explores differences between market and bank-based financial systems. Innovatively, we equate the composition of business models at the country-level to a portfolio selection exercise.

In a nutshell, the main results in this thesis suggest that (i) the European banking sector is populated by four distinct business models, (ii) banks operating with a traditional retail-oriented model (based on customer deposits and lending) have outperformed others, and (iii) business model diversity is found to positively affect resilience, particularly for market-based financial systems. In each paper we have identified a set of contributions to micro and macroprudential supervision. In general, our findings are in tune with the current trend in banking regulation and supervision, which have adopted the concept of banking business model at their core.

RESUMO

A crescente atenção dedicada à exposição ao risco e à fraca rendibilidade das entidades bancárias tem motividado discussões recentes na literatura sobre a classificação e análise de modelos de negócio bancário, assim como a adopção de regulação e supervisão que são sensíveis ao modelo de negócio da entidade supervisionada.

A tese tem como objectivo contribuir para este debate e para a melhoria da regulação e supervisão bancária através da produção de três artigos com enfoque no sector bancário Europeu. No primeiro artigo é desenvolvido uma nova definição e método de identificação modelos de negócio bancário que acomoda duas observações empíricas: (i) a possibilidade dos bancos se assemelharem a mais do que um modelo de negócio, e,g, após um processo de fusão, e (ii) os bancos podem escolher alterar o seu modelo de negócio. No segundo artigo é testada a relação entre as escolhas de modelo de negócio e a rendibilidade e resiliência de bancos, através da aplicação de três medidas alternativas referentes às escolhas de modelo de negócio (características individuais, orientação bancária, e modelo de negócio). O segundo artigo explora ainda a heterogeneidade da relação entre modelos de negócio e rendibilidade, assim como os efeitos de alterar o modelo de negócio na sua rendibilidade. No último artigo é testada a ligação entre a diversidade de modelos de negócio e a resiliência de cada sector bancário, sendo ainda exploradas as diferenças entre tipologias de sistemas financeiros (mercado *vs* sistema bancário). De forma inovadora, a análise da composição de modelos de negócio bancário a nível nacional é equiparada a um exercício de selecção de carteiras.

Em suma, os principais resultados da tese sugerem que (i) o sector bancário europeu é composto por quatro modelos de negócio distintos, (ii) os bancos a operar com um modelo de negócio focado no retalho (orientado à captação de depósitos de clientes e concessão de crédito) registaram um desempenho melhor que os seus pares, e (iii) a diversidade de modelos de negócio afecta positivamente a resiliência do sector bancários, particularlmente nos sistemas financeiros com orientação para o mercado. Em cada estudo foram identificadas recomendações para a supervisão macro e microprudencial. Em geral, os resultados obtidos validam a atual tendência de supervisão e regulação bancária, em que a noção de modelo de negócio tem assumido um lugar central.

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ABBREVIATIONS

2SLS	Two-Stages Least Squares
3SLS	Three-Stages Least Squares
ARI	Adjusted Rand Index
BM	Business model
BO	Bank orientation
CHI	Caliński-Harabasz Index
CRD	Capital Requirements Directive
DBI	Davies-Bouldin Index
DI	Dunn index
EBA	European Banking Authority
FCM	Fuzzy C-Means
GFC	Global Financial Crisis of 2007-09
GMM	General Moments Method
HC	Hierarchical Clustering
HHI	Herfindahl-Hirschman Index
IV	Instrumental Variable
JI	Jaccard Index
MBC	Model Based Clustering
MDA	Multivariate Data Analysis
NSFR	Net Stable Funding Ratio
PAM	Partitioning Around Medoids
PCM	Percentage of Cluster Membership
PSM	Propensity Score Matching
RI	Rand Index
SM	Simple Matching
SGT	Strategic Groups Theory
SOM	Self-Organizing Map
SW	Silhouette Width
SREP	Supervisory Review and Evaluation Process

To Catarina, Bernardo and Leonor.

"Banks serve different *functions*
and, therefore, face different *risks*.
Another way of saying this is that
banks' *business models* can vary."

Andy Haldane
Fariborz Moshirian
Luci Ellis

INTRODUCTION

Motivated by the relevance of the economic *functions* performed by the banking sector (Bencivenga & Smith, 1991) but also by the severity of banking crises (Laeven & Valencia, 2018), the aftermath of the 2007-09 global financial crisis (GFC) has seen a growing number of empirical studies focus on understanding the *risks* and vulnerabilities of banks by adopting a holistic view of the banking firm. In most studies, such holistic perspective is achieved by employing advanced data analysis techniques that capture, in a single indicator, the multidimensional nature of long-term business choices, such as those related with size, asset and funding structures, diversification, and capital – i.e. the *business model* (e.g. Ayadi *et al.*, 2011; Roengpitya *et al.*, 2014, 2017; Mergaerts & Vennet, 2016; Martín-Oliver *et al.*, 2017; Chiorazzo *et al.*, 2018; De Haan & Kakes, 2019).

The notion of business model has also attracted the attention of bank regulators and supervisors in the post-GFC period. In Europe, for instance, an effort has been made in recent years to incorporate a business model specific recommendation originally identified in the Liikanen report, and transposed to the CRD IV, according to which "capital requirements must be targeted at the risks inherent in different bank business lines and business models" (Liikanen, 2012: p. 71). In this context, since 2016 the viability and sustainability of the business model of supervised entities has become one of the elements that directly impacts the supervisor's decision regarding the level of Pillar 2 capital requirements (P2R) and guidance (P2G), under the Supervisory Review and Evaluation Process (SREP) (EBA, 2014). In other words, if a supervised entity is seen to operate a riskier business model, the competent supervisor has the mandate to set a higher P2R and P2G to cover business risks.

Against this backdrop, this thesis is comprised of three papers that aim to achieve the following overarching objectives. Firstly, to contribute to the development of literature on banking business models. Secondly, to contribute to the literature on the management of banking firms, by exploring the implications of different business models designs in terms of profitability and resilience; and, thirdly, to contribute to the improvement of business model specific-regulation and supervision of the banking sector.

Although no unique view exists on the definition of business model (Zott *et al.*, 2011), research on banking business models finds theoretical support on strategic groups theory, according to which the existence of mobility barriers within industries helps to explain the formation of groups of firms with similar long-term strategic choices (Caves & Porter,1977; Porter, 1979). In the case of banks, such strategic choices have been proxied by observable, financial statement data such as size, type of activities, funding sources, diversification, and capital (e.g., Amel & Rhoades, 1988; Halaj & Zochowski, 2009). Importantly, much of the usefulness of strategic groups theory to our empirical context lies in the fact that it is significantly better at accommodating the longstanding heterogeneity observed in the banking sector than the 'shared profits' narrative proposed by standard microeconomic theory (Bain, 1956).

Another key theoretical reference for the study of banking business models is bank intermediation theory, which in general may be seen as bundling insights from agency theory, transaction costs theory and asymmetric information theory applied to banking. According to this theory, banks are ultimately seen as intermediaries between stakeholders in the right (e.g. depositors, debtholders) and left side of the balance sheet (e.g. loan borrowers) (Diamond, 1984; Merton, 1995), giving rise to a set of coordination problems that may be mitigated or aggravated according to the contractual arrangements between the stakeholders and the bank. Given the balance sheet focus of banking business model analysis, we are able to draw on (and contribute to) the longstanding results achieved under bank intermediation theory. For instance, we know that in normal times wholesale creditors are 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). Under business model analysis, such result (focused on the funding structure of the bank) would be complemented by checking the level of liquidity on left side of the balance sheet, allowing a better assessment of the bank's actual exposure to liquidity risk (when compared to only analyzing the right side of the balance sheet).

Finally, several of the business choices that banks face concern diversification (e.g. asset and funding structures), and as such Markowitz's portfolio selection theory (1952) stands as a key theoretical reference. In particular, the notion that banks may choose specific combinations of bank activities and funding sources based on an expected level of risk-return, provides a viable explanation for some of the heterogeneity observed in the risk-return levels of the banking sector. On the other hand, as suggested by Jiménez & Mencía (2009), seemingly uncorrelated bank assets and funding sources may become highly correlated under systemic distress due to the presence of unobserved, latent factors (Duffie *et al.*, 2009). Importantly, such disparities between the results of the base and adverse scenarios stand as a key source of insights that we draw upon when performing our analysis.

To further illustrate the concept of banking business model, we provide an overview of the two most commonly identified business models in literature: the retail model and the investment model. Briefly put, the retail model tends to be followed by smaller banks that perform traditional intermediation, i.e. the transformation of customer deposits into loans to customers. Such banks are often specialized in SME and household financing, and typically exhibit a narrow focus on net interest income. The investment model, on the other hand, tends to be operated by larger banks with a diversified balance sheet, that mostly provide services to large corporates and wholesale customers. Such banks tend to be significantly exposed to trading assets and derivatives, and are highly leveraged (e.g., Ayadi *et al.*, 2015, 2016; Hryckiewicz & Kozłowski, 2017; De Haan & Kakes, 2019).

This thesis aims to contribute to three open debates in literature.

The first debate concerns the method used to identify banking business models. Our survey of literature suggests that studies in this strand often lack a formal definition of banking business model that underpins the analysis (Cosma *et al.*, 2017). Relatedly, the methods used to identify business models vary significantly, and may be seen as including significant shortcomings. For instance, some papers use private datasets and expert judgement to identify banking business models, an approach which is not possible to replicate (Köhler, 2015; Cernov & Urbano, 2018). Other papers employ dimensionality reduction, such as factor analysis, falling short of producing a classification, which is a key requirement for practitioners (Van Ewijk & Arnold, 2014; Mergaerts & Vennet, 2016; De Haan & Kakes, 2019). Another strand uses hard clustering methods, yielding low quality and stability of clusters, which raise concerns regarding the usefulness of this approach (Ayadi *et al.*, 2011, 2015, 2016, 2018; Roengpitya *et al.*, 2014, 2017; Hryckiewicz & Kozłowski, 2017, Martín-Oliver *et al.,* 2017). Moreover, none of the methods used thus far incorporate the insights from fuzzy strategic groups theory, according to which some banks may choose to combine features of different business models following, for instance, a merger or acquisition (DeSarbo & Grewal, 2008). Additionally, when reviewing the literature on unsupervised clustering methods, we find a relatively novel approach that has been used in other finance related contexts, such as bankruptcy prediction (Davalos *et al.*, 2014) and credit scoring (Abellán & Castellano, 2017), but is yet to be applied in business model analysis. The method in question is clustering ensemble, which "combines the information provided by the partitions" of different clustering methods (Jain, 2010: p.660) and is expected to increase the accuracy of the classification relative to its *true*, unobserved, value. Hence, for the sake of bringing further clarity to research on business model analysis, the thesis aims to answer the following research questions:

RQ1: What is the definition of banking business model? Which method is more robust to classify business models? Which banking business models exist?

In this context, the first paper (which addresses RQ1) has the following goals. Firstly, to expand the definition of business model in order to explicitly incorporate (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. Secondly, the paper aims to apply the clustering ensemble approach to the identification of banking business models, as well as to develop a strategy to measure their fuzziness and stability over time. Thirdly, the paper seeks to identify how many banking business models exist in Europe, what are their distinctive features, and to describe their fuzziness and stability over time. In putting forward this new method, the paper also seeks to contribute to the improvement of the approach used by micro-prudential supervisors in Europe to identify the business models of supervised banks.

The second debate focuses on the relationship between business model choices and bank profitability and distance to distress. In a nutshell, our overview of literature suggests the existence of four gaps in literature.

The first gap refers to the missing link between the results obtained using individual features (e.g. size, loans to customers, deposits, revenue diversification) and the multivariate approach (e.g. bank orientation using retained principal components, business model classification). A failure to bridge this gap may cast doubts on the relevance of using business model as unit of analysis, given that the majority of hypothesis in literature are focused on the sub-components of the business model. For instance, the 'efficiency hypothesis' states that profitability may increase with bank *size*, via economies of scale and scope (Scholes *et al.*, 1976). Similarly, portfolio selection theory suggests that *diversification*, i.e. the combination of assets (or funding sources) from different risk classes, may reduce the risk for a given level of expected return (Markowitz, 1952). Finally, while the Modigliani-Miller theorem of perfectly adjusted *capital* structures (Modigliani & Miller, 1958) is likely to fail in the banking industry, as bankruptcy costs are not zero and the existence of deposit guarantee schemes makes depositors less prone to react to bank risk (Diamond & Dybvig, 1983; Rajan, 1992), this implies that, in theory, there is room for an optimal bank capital structure to emerge (Miles *et al.*, 2013). In this regard, Mergaerts & Vennet (2016) have been the only authors to explicitly link the individual features and the multivariate approaches – yielding noticeable results. For instance, the authors are able to trace the underlying drivers of the positive impact of retail orientation on bank profitability to the superior risk management abilities (via lower loan loss provisions) and cheaper funding (via customer deposits) of retail banks.

The second gap steams from a general lack of studies exploring the heterogeneous effects of business choices on bank profitability and riskiness. This is a relevant gap given the interesting, but often mixed, results obtained in this regard. For instance, Köhler (2015) finds that income diversification increases distance to distress for retail-oriented banks and decreases for investment-oriented banks; whereas, customer deposits are found to be particularly relevant for retail-oriented banks. Conversely, Mergaerts & Vennet (2016) document that the positive effect of deposits on profitability is particularly relevant for banks with low retail-orientation, and argue that this may be seen as evidence of the stabilizing effects of customer deposits on non-retail banks (Huang & Ratnovski, 2011).

The third gap is related to the scarcity of studies on the impact of business model changes on bank profitability. To the best of our knowledge, only one paper has directly addressed this issue. Particularly, Ayadi *et al.* (2018) employ Propensity Score Matching (PSM) and find that the impact of changing business model is negative in the year of the change and positive in the subsequent years. Relatedly, Roengpitya *et al.* (2017) find some evidence that in the post-GFC period there has been a return of banks to the traditional retail model. This gap seems particularly relevant given the potential role of business model changes in the build-up of risks and vulnerabilities in the banking sector in the pre-GFC period (Liikanen, 2011).

The final gap is related to the general absence, from most works, of a convincing strategy to mitigate endogeneity concerns. More specifically, performance related literature has cast serious doubts concerning the exogeneity of strategic variables, suggesting the adoption of techniques (e.g. two-stages least square, 2SLS) (Clougherty *et al.*, 2016) that go well beyond lagging explanatory variables (e.g. Mergaerts & Vennet, 2016). The abovementioned gaps in literature lead us to focus on the following research questions:

RQ2: Which business choices are more likely to increase bank profitability and resilience? Is it expected that such choices yield similar results for banks with different business models? Have banks changed their business model over time? Which barriers are likely to impede such mobility? Does changing business model pay-off?

In this regard, the second paper (which focuses on RQ2) has the following objectives. The first goal is to use the business model as the unit of analysis to test several hypotheses regarding bank profitability and distance to distress (e.g. efficiency, diversification, capital structure). Secondly, the paper aims to test the existence of heterogeneous effects of business model decisions on bank profitability and distance to distress, and to enhance the current testing framework. Additionally, the paper seeks to provide further evidence on the impact of business model changes on bank profitability. Finally, the paper aims to implement testing strategies that mitigate the endogeneity and autocorrelation concerns that arise in performance related studies.

The third and final debate addresses the link between the country-level diversity of banking business models and banking sector resilience. In this regard, our review indicates the existence of a gap in empirical literature, which is particularly relevant given the density, but also the lack of consensus, of theoretical works in this domain. More specifically, the link between the diversity and resilience of banking systems is bound to be intertwined with the notions of diversification and market power (Baum *et al.,* 2020). Briefly put, some authors argue that as banks diversify their business they tend to become more alike, hence reducing the variety of bank types operating in the banking system, i.e. its diversity (e.g., Wagner, 2011). In parallel, the diversity of a banking system may be expected to jointly impact: (i) the resilience, via reduced bank contagion (e.g., Acharya & Yorulmazer, 2007), and (ii) the market power, via potentially mixed effects on the likelihood of collusive agreements and strategic interdependence (Porter, 1979). Finally, both diversification and market power are expected to directly affect resilience, via their own channels. This empirical context sets up well for a simultaneous equation approach. To the best of our knowledge, the work done by Baum *et al.* (2020) stands as the only to directly address the 'diversity-resilience' nexus in the banking. The paper provides interesting insights on how diversity may be measured, by drawing on ecology literature, but its narrow focus on ownership structures falls short of the holistic approach to bank risks and vulnerabilities proposed by business model analysis.

Additionally, the idea that banking systems may be decomposed into market shares held by banks operating with different business models may be seen as similar to the approach used by a portfolio manager selecting the weights to attribute to each asset class. Also, the most common measure of bank resilience (Z-score) bears the same denominator (deviation of returns) as the most common measure used in portfolio analysis (Sharpe Ratio). Both intuitions lead us to draw on portfolio selection theory (Markowitz, 1952) to study the diversity and composition of efficient portfolios of country-level banking business models. Such expansion of the standard application of portfolio theory to country-level analyses is not new. For instance, Ben-Bassat (1980) studies the composition of currencies held by the central banks of different countries using efficient portfolios. However, to the best of our knowledge such approach has never been applied to the study of banking sector resilience. Finally, given the focus of this topic on the structure of the banking system, it shares common ground with the longstanding debate regarding the financial stability of market and bank-based systems (Allen & Gale, 2000). The thesis focuses on the following research questions:

RQ3: Does the diversity of business models in the banking system impact its resilience? What is the optimal composition of banking business models in terms of resilience? Do the answers to the previous questions vary for market and bank-based systems?

In this context, the third paper (addressed at RQ3) seeks the following goals. Firstly, to provide empirical evidence on the simultaneous relationship between business model diversity, diversification, market power and resilience. Secondly, the paper aims to contribute to literature on the types of financial system, by testing whether the effects of diversity on resilience differ for market and bank-based systems. Thirdly, the paper aims to expand the traditional scope of portfolio selection theory to the study of diversity and composition of efficient portfolios of banking business models. Relatedly, the paper seeks to contribute to the macroprudential supervision, by providing preliminary evidence on the usefulness of monitoring the correlation of returns among market players as a potential early warning tool.

The three papers in this thesis are interrelated in several ways. Firstly, they all use the business model as the main unit of analysis. This becomes apparent by the fact that the method developed in the first paper to identify banking business models is used as a key methodological step in the remaining two papers. Relatedly, the number (and description) of the banking business models identified for the sample of European banks is identical in all papers. Additionally, the results obtained in the first paper regarding the fuzziness and persistency of business models over time, feed into the analysis of business model changes performed in the second study. Finally, while the policy implication of the first two papers are relevant for microprudential supervision and the third paper contributes mostly to macroprudential policy, all papers share the same conceptual frameworks laid out by strategic groups theory, bank intermediation theory, and portfolio selection theory.

The rest of the thesis is structured as follows. In **Chapter 1** we present the first paper, regarding the identification of banking business models. The second paper, focused on the relationship between the business models, profitability, and riskiness of European banks, is featured in **Chapter 2**. **Chapter 3** comprises the third paper, which addresses the link between the country-level diversity of business models and resilience in the banking sector. In the final section we summarize the main findings, highlighting the contribution of each paper to the overall **Conclusion** of the thesis.

CHAPTER 1.

Using clustering ensemble to identify banking business models[1]

1.1. Introduction

This paper deals with the special methodological requirements that emerge from the task of business model identification – a task which has gained particular relevance in the context of recent efforts to reform the regulation and supervision of banks in Europe (EBA, 2014; ECB, 2018). In particular, policymakers and researchers have become increasingly focused on grouping banks based on the similarity of their business model choices (such as size, types of activities, funding, and diversification). However, in doing so, they have faced significant challenges in finding clearly separated and homogenous clusters. This occurs chiefly because business choices are likely to follow a fuzzy, rather than a crisp, logic – e.g. some banks may choose to combine features of different business models following a merger or acquisition (DeSarbo & Grewal, 2008).

In general, by applying clustering analysis to the business choices of banks one may hope to achieve two main goals. First, to obtain an objective and stable taxonomy of business model classifications, which in turn may be used by supervisors to monitor the performance of banks in each business model (e.g. by identifying outliers) – in line with the guidelines for the Supervisory Review and Evaluation Process (EBA, 2014). Secondly, to obtain a better insight into the competitive structure of the banking sector, as banks with similar business choices may be expected to compete more intensely among themselves (Porter, 1979). The former goal (i.e. attaining an objective and stable taxonomy of business models) seems particularly timely given that the method currently used by supervisors to identify business models (expert judgement) may lead to inconsistencies and potential conflict of interests. In particular, under the principle of proportionality different banking business models may be expected to entail different degrees of monitoring effort for the supervisor. Hence, if the

[1] This chapter has been published in an international peer-reviewed journal – *vide* Marques & Alves (2020).

allocation of banks to business models is based on the subjective assessment of supervisors, under first principles these may have the incentive to allocate banks into business models which are easier to monitor or subject to stricter regulatory requirements (e.g. higher capital requirements). The same rationale may be applied to business model self-reporting by banks. In this context, we argue that finding an objective and reliable method to allocate banks into business models is paramount for the implementation of business model specific regulation and supervision.

The use of clustering analysis to identify banking business models, however, bears significant challenges of its own, including those related with the choice of method. For instance, a recent strand of research has relied exclusively on hard clustering methods (e.g., Hierarchical Clustering, HC) to identify the business models of banks, failing to apply methods that enable banks to have some affinity with more than one business model, such as Fuzzy C-Means. For instance, Mergaerts & Vennet (2016) apply HC on seven business model variables for a sample of European banks (1998-2013) and report an average silhouette width of 0.20 for a partition in three clusters, a value which is below the threshold of 0.25 for minimum quality of clustering as proposed by Kaufman & Rousseeuw (1990). Similarly, Martín-Oliver *et al.* (2017) apply HC on six variables for a sample of Spanish banks and report persistency levels of business model classification across consecutive periods (1999-2002 vs 2003-07) which range from 10.4% (lowest) to 85.7% (highest). In our view, both studies raise some concerns regarding the usefulness and reliability of results that are obtained by applying hard classification methods to the identification of banking business models.

Conversely, by using fuzzy clustering to identify banking business models one may be able to measure the similarity that each bank holds with the prototypical models (i.e. percentage of cluster membership). In turn, such measure may be used in several empirical contexts in business model analysis, such as (i) the identification of whether a bank combines features of more than one business model, and which models those are; (ii) the use of the measure in its original format, i.e. continuous value from 0 to 1, as an explanatory variable in performance and riskiness related fixed effects regression (not possible when the business model assignment is stable and discrete); and (iii) its conversion into a discrete measure, 0 or 1, based on the business model with which the bank has the highest percentage of membership, enabling, for instance, a supervisor to identify peer groups of banks based on their business model.

In this paper we contribute to literature in several ways. Firstly, we provide a formal definition of 'banking business model' grounded on strategic management literature, namely the configurational approach (Miller, 1976) as well as strategic groups theory (Reger & Huff, 1993; DeSarbo & Grewal, 2008). Secondly, by applying principal components analysis to an array of banking variables, we identify five strategic dimensions along which banks assume a long-term position relative to their peers (Galbraith & Shendel, 1983). Thirdly, based on the notion of consensus based classification (Kuncheva, 2004), we identify the business models of European banks using an ensemble of three unsupervised clustering methods: Fuzzy C-Means (Bezdek *et al.*, 1984), which allows us to handle fuzzy clustering; Self-Organizing Maps (Kohonen, 1997), which yield intuitive visual representations of the clusters; and Partitioning Around Medoids (Kaufman & Rousseeuw, 1990), which circumvents the presence of data outliers. Fourthly, we examine the level of similarity of banks operating with the same long-term business model (core vs non-core banks). Finally, we provide some evidence regarding the level of persistency of banks in terms of their business model, as well as examine the factors that influence the likelihood of non-persistency per business model.

Briefly put, our approach begins with the implementation of principal component analysis with the aim of identifying a set of business model components. This step allows us to perform clustering on a space with orthogonal dimensions, as well as to focus on the most relevant relationships between business model choices and, thus, hopefully mitigate the problem of data noisiness. The second step is to run three clustering methods – Partitioning Around Medoids (PAM), Fuzzy C-Means (FCM) and Self-Organizing Maps (SOM) –, combine their classification output and assign each bank to the business model (cluster) with the majority of the 'votes' (clustering ensemble). Next, we label a bank as 'core' in a given business model if (i) the ensemble is unanimous (e.g. if the three methods assign the bank to the same business model) and (ii) the silhouette width using the clustering ensemble classification is above a threshold identified in literature. Finally, we look for persistent banks by dividing the full sample period (2005-16) into four trienniums (2005-07, 2008-10, 2011-13 and 2014-16), identifying the business model of banks for each triennium separately (using triennium average values) and looking for banks for which the business model is the same in all the trienniums in which the bank is present in the sample.

By applying our method to the context of the European banking industry (2005-16), we find evidence of four banking business models: retail focused, retail diversified funding, retail diversified assets and large diversified. Importantly, we test the stability of classification using alternative sub-sampling methods and find that the stability of classification is significantly higher when testing the samples of core banks, and core and persistent banks when compared to tests with the full sample. Also, we find that the mean values of key dimensions of each banking business model change significantly when using the sample of core and persistent banks when compared to other banks. These results (stability and mean difference) may be seen as evidence of the suitability of our approach to identify banking business models.

This paper is structured in the following way. In **Sections 1.2** and **1.3**, we survey applications of the ‘business model’ concept in banking regulation and recent literature on methods used to identify banking business models, respectively. A conceptual framework for banking business models is established in **Section 1.4**. **Section 1.5** provides an overview of key concepts in the ‘clustering ensemble’ approach, as well as a brief description of the classification methods used in the paper. The dataset is presented and described in **Section 1.6**. In **Section 1.7**, we identify the procedures used in our methodology. **Section 1.8** deals with the results and discussion and **Section 1.9** presents robustness checks. In the final section, we conclude and identify opportunities for future research. For brevity reasons, we include the description of the clustering algorithms and valuation criteria in the appendix.

1.2. The relevance of business models in bank regulation and supervision

The importance of monitoring the different aspects of banking business models has been stressed in recent efforts to reform the regulation and supervision of banks. For instance, in the ‘High-Level Expert Group’s report on reforming the structure of the EU banking sector’, also known as Liikanen Report (2012), an entire section is dedicated to the analysis of banking business models in the EU (pp.32-66), concluding that: "while all types of bank business model have been affected in the crisis, some characteristics have proven less resilient than others. The main bank failures have been attributed to overreliance on short-term wholesale funding, excessive leverage, excessive trading/derivative/market activity (...)". (p.32).

Additionally, business model analysis has become a key procedure in the Supervisory Review and Evaluation Process (SREP)[2] since its implementation on January 1, 2016. In particular, according to the European Banking Authority's (EBA) guidelines for the SREP, supervisors are required to monitor, assess and challenge the business models of supervised entities (EBA, 2014). On the other hand, the business model is depicted as a key element for the implementation of the principle of proportionality by supervisors in CRD IV[3], which, among other things, mandates the EBA to assess the impact of new liquidity and leverage requirements on different banking business models (EBA 2013, 2015, 2016).

Lastly, two instances further illustrate the recent attention attributed by regulators and supervisors to banking business models: the identification of business model and profitability risk as a top priority for the 'Single Supervisory Mechanism' (SSM) between 2016 and 2018 (ECB, 2018); and the approval by the US Congress of the 'Financial CHOICE Act' regulatory package in August 2017, which, among other things, reduces the reporting burden of traditional banking organizations, i.e. banks following a traditional business model.

1.3. Literature review: methods used to identify banking business models

Recent literature reports four methods to identify the business models of banks. The first method is to apply discretionary rules on a set of business model proxies (Curi *et al.* 2015;

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[2] The SREP is an annual process carried out by supervisors (national central bank or ECB, according to the systemic relevance of the entity) with the goal of reviewing whether the arrangements, strategies, processes and mechanisms implemented by the supervised entities are in compliance with recent legislation (e.g. CRD IV).

[3] The term 'CRD IV' is used in banking literature and regulation to refer to the Capital Requirements Directive (Directive 2013/35/EU) and the Capital Requirements Regulation (Regulation no. 575/2013), jointly approved by the EU Parliament in April, 2013 and with effect since January, 1, 2014, which constitute the transposition to EU law of the post-crisis global regulatory reform, 'Basel III Agreement' (BCBS, 2011).

Chiorazzo *et al.*, 2018). Curi *et al.* (2015), for instance, use three measures of Herfindhal-Hirshman diversification (asset, funding, and income) and, based on the graphical observation of the estimated distributions of each variable, apply threshold values (0.35, 0.35, 0.30, respectively) below which the banks are labelled as following a focused business model. For a sample of foreign banks located in Luxembourg, the authors find that banks that are cumulatively classified as focused on each of the three dimensions are more efficient than their peers. Methodologically, such approach is simple to replicate and intuitive. However, the methods used may be seen as excessively discretionary, and often authors do not provide any evidence of the quality of the groupings (or clusters), fuelling some doubts regarding the similarity of the banks in each group.

The second method is to apply dimensionality reduction techniques to account for the multivariate and simultaneous nature of business model choices (Van Ewijk & Arnold, 2014; Mergaerts & Vennet, 2016; De Haan & Kakes, 2019). After applying hierarchical clustering and finding clusters with low quality (silhouette width of 0.2 for a partition in three clusters), Mergaerts & Vennet (2016) apply factor analysis on seven business model variables and retain two factors: retail-orientation and diversification. Moreover, the authors account for the long-term nature of business models by using an econometric approach (Mundlak estimator) which separates the between and within effects of each factor on profitability and riskiness, wherein the between effect is attributed to the business model. In general, this method seems to allow an adequate grasp of the interconnections between business model choices and is able to separate long- and short-term effects of business models. However, it fails to produce a business model classification, which may impair the ability for supervisors to analyse the performance and riskiness of peer groups.

The third method is to use expert judgement to identify business models (Köhler, 2015; Cernov & Urbano, 2018). In this strand, Cernov & Urbano (2018) combine a qualitative step (*expert*) with a quantitative step (*unsupervised clustering*) to define business models. Namely, in the first step, using the EBA's business model classification, which is comprised of sixteen models, supervisors are asked to assign each supervised entity to a business model; in the second step, using ten business model variables, the authors map the main activities and funding sources of each model and remove redundant business models, narrowing the initial set of sixteen business models to eleven. The authors argue that this approach allows us to challenge the initial business model classification of some banks. For instance, the approach identifies large diversified banks, such as ‘Crédit Agricole Group’, as outliers in the initial model of cooperative banks/saving and loans associations and recommends it to be re-classified under the cross-border universal banks model. In our view, this approach is able to expand the typical scope and depth of the information used to classify business models. However, the collection of such granular data is often costly, inaccessible and/or self-reported, which may impede cross-study comparisons.

The fourth and final method consists in employing hard clustering algorithms (Ayadi *et al.*, 2011, 2015, 2016, 2018; Roengpitya *et al.*, 2014, 2017; Hryckiewicz & Kozłowski, 2017, Martín-Oliver *et al.*, 2017). For instance, Martín-Oliver *et al.* (2017) employ hierarchical clustering with Ward’s method on a sample of Spanish banks using different sub-periods and find four business models (retail-deposits, retail-balanced, retail-diversified, and retail-market). The authors document that small cooperative banks that migrated to more risky business models before the crisis suffered higher losses during the crisis than shareholder banks with the same business model. However, the level of persistency of classifications in different periods is very low. For instance, 56.3% of the bank’ assets that followed a ‘retail-balanced model’ in the 1999-2002 sub-period, migrated to the ‘retail diversified model’ in the 2003-2007 sub-period, whereas only 10.4% remained in the same cluster. Similarly, in the ‘retail-deposits’ and ‘retail-diversified’ models, only 28.6% and 15.4% of banks’ assets remained in the same cluster in consecutive sub-periods. These results provide a strong indication of the presence of issues regarding cluster quality and suggest that the use of fuzzy clustering methods is perhaps more appropriate to capture the business models of banks.

In sum, we retain two main issues that have been mishandled in recent banking literature: the general lack of a conceptual framework that clearly guides the methodology used to identify business models; and the inadequate use of hard clustering techniques to model data which is likely to have a positive association with more than one cluster. In the next sections, we aim at contributing to mitigate these issues by providing a definition of ‘banking business model’; and by proposing an approach to identify business models which combines the results of alternative clustering methods.

1.4. Definition of banking business model

The banking literature has provided several definitions of business model. For example:

- “We (...) define a business model as a simplified representation of the activities that a bank performs to make money.” (Cavelaars & Passenier, 2012: p.404);
- “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.” (Mergaerts & Vennet, 2016: p.58);
- “A 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.” (Martín-Oliver *et al.*, 2017: p.248).

These citations illustrate that there is no unique definition of business model (Zott *et al.*, 2011). Moreover, they showcase that the banking literature has not accounted for the fuzzy nature of business models. For that reason, we offer an alternative definition of ‘banking business model’ which attempts to overcome this, and other misconceptions identified in the literature review (e.g. lack of stability of business models over time). Namely, we define a ‘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.

More specifically, a banking business model is expected to be “predominantly stable and long-term oriented” in the sense that key strategic decisions are likely to bear significant investments which impose mobility barriers on banks, impeding them to freely shift across business models – an insight which is borrowed from strategic groups theory (Porter, 1979: p.214). On the other hand, when we state that a business model may be seen as an "organizational configuration (...) adopted by a significant share of banks" we allude to the configurational approach (Miller, 1986). In particular, to the notion that: "(...) elements of strategy, structure and environment often coalesce or configure into a manageable number of common, predictively useful types that describe a large proportion of (...) organizations." (Miller, 1986: pp.235-236). The fuzzy nature of business models is explicitly incorporated in our proposed definition of banking business model when we state that banks may exhibit "different levels of association" with one or more business models. This idea is borrowed from the fuzzy approach to strategic groups theory (Reger & Huff, 1993; DeSarbo & Grewal, 2008). For instance, Reger & Huff (1993) suggest that, based on the level of agreement among industry participants regarding the allocation of a firm to a strategic group, it is possible to segment the firms into core ("that are tightly associated and define the basic 'recipe' of a strategic group"), secondary ("that implement the strategic group recipe less consistently than core firms") and transient ("whose strategies are changing from one strategic position to another, but along dimensions common to other firms in the industry") (Reger & Huff, 1993: p. 117). In order to be able to replicate the clustering results, our definition requires business model choices to be "observable" – by this we mean that the variables used to proxy for business model choices should, preferably, be publicly available. Finally, we require business model choices to be "interconnected" in order to incorporate Miller's (1996) concerns regarding the need for configurational studies to provide an explanation of "why and how" the elements of the configuration relate and complement with each other. In this study we explore the "why and how" in two ways: (i) by surveying banking theory and recent empirical studies for predictions regarding the way that some business model choices are expected to be interconnected; and (ii) by following Galbraith & Shendel (1983) and applying principal component analysis to extract the main business model components (note that the rationale underlying the use of principal component analysis is discussed in the introduction to the methodology section).

Importantly, this definition of business model embodies two notions that are at the heart of our proposed methodology. Firstly, the possibility that banks may vary in terms of the similarity of association relative to the most representative banks in the assigned business model, hence allowing for a distinction between core and non-core banks. Secondly, although we define business model as a ‘predominantly stable and long-term oriented’ concept, the choice of wording (‘predominantly’) deliberately makes way for the possibility of banks changing business models over time and, thus, the distinction between persistent and non-persistent banks. Both concepts, in our view, would make it ideal for us to select a clustering method that may, cumulatively, (i) capture the fuzzy logic of business models, (ii) yield an intuitive visualization of the clusters and (iii) circumvent the potential presence of data outliers. In the next section, we describe three methods that have been used in literature to address each of these requirements, and provide an overview of literature on the method that combines the outputs of different clustering methods (i.e. clustering ensemble).

1.5. Clustering methods and clustering ensembles

1.5.1. Fuzzy clustering

Fuzzy logic is founded on the idea that, in some real world clustering problems, the membership of a data point to a given configuration or object may be nuanced and hence a binomial membership function is likely to be oversimplistic (Zadeh, 1965). According to this logic, in some situations the assignment of data points to clusters may be better depicted as a continuous function, truncated between 0 and 1, whereby the nearer the membership value is to unity, the higher the similarity between the observation and the cluster.

The application of fuzzy logic to clustering was popularized with the Fuzzy C-Means algorithm (FCM), initially formulated by Dunn (1974) and improved by Bezdek *et al.* (1984). In FCM, data is clustered into a pre-determined total number of clusters by iteratively minimizing the weighted within group sum of squared errors, where the fuzzified membership of a data point to each cluster j ($\mu_{i,j}^{m}$) is the weighting scheme. The FCM objective function is:

$$\min F = \sum_{i=1}^{n} \mu_{i,j}^{m} d^2\left(\vec{x}_i, \vec{v}_j\right)$$

Wherein m is the fuzzifier ($m > 1$), $\vec{x}_i$ is the data vector for each bank (of size $1 \times k$, where k are the number of input features), $\vec{v}_j$ is the vector of cluster centers ($1 \times k$), and d is the dissimilarity measure. The total number of clusters (J) and m are pre-determined. Regarding J, researchers may test the quality of different partitions using alternative valuation criteria such as the silhouette width (Rousseeuw, 1987) or the Caliński-Harabaz index (Caliński & Harabasz, 1974). Concerning the choice of m, Bezdek *et al.* (1984) state that algorithms tend to perform well for fuzzifiers between 1.5 and 2.5.

Despite being subject to various revisions, Bezdek's original FCM algorithm is still widely used in a variety of fields, including in banking, where it has been applied to bankruptcy forecasting (Alam *et al.*, 2000; de Andrés, 2011; Martin *et al.*, 2011), branch efficiency (Azadeh *et al.*, 2010), credit card issuance (Hsu, 2000), retail churn prediction (Popović & Bašić, 2009), credit scoring (Michalopoulos *et al.*, 2002) and currency crisis prediction (Marghescu *et al.*, 2010).

1.5.2. Self-Organizing Maps

Another method that has been used in literature to deal with high-dimensional fuzzy data is Self-Organizing Maps (SOM). Introduced by Kohonen (1997), SOM is a form of artificial neural network that reduces dimensionality by projecting high-dimensional data (input layer) onto a two-dimensional space (output layer or lattice), using the concept of neurons (i.e. clusters). Each neuron is differentiated from the remaining neurons by a vector of weights attributed to the input variables (codebook vector). This vector is the result of the algorithm's training process (*vide* **Appendix 1.1**). Briefly put, the training process consists in identifying, sequentially and for each data point, the neuron that is closest to a given point (winning neuron), based on the weights vector. Each assignment leads the neuron to update its codebook vector, as well as the vector of neighbour neurons (although to a lesser degree).

Importantly, the information contained in the vector of each neuron can be used to build effective visualizing tools. In SOM, each data point is assigned to a single neuron, which may be seen as contrary to fuzzy logic. In order to circumvent this issue, we use the Silhouette Width (SW) to compare the distance between each data point, the remaining data points in the assigned neuron and the data points assigned to the closest neighbour neuron. In our paper, the SW is one of the measures used to account for the fuzziness of the clustering output, in the sense that we expect banks that are close to the data points assigned to other business models (i.e. with low SW) to record some affinity with more than one business model (i.e. high fuzziness). Finally, in addition to the number of 'neurons' (or clusters), the SOM algorithm also requires the pre-definition of a number of other parameters – such as the shape of the lattice, the distance function, the number of times the algorithm is re-run, the radius and the learning rate – which are often defined after experimentation with alternative specifications (Curry *et al.*, 2001; Budayan *et al.*, 2009).

The seminal applications of SOM in finance-related literature cover a variety of topics including bankruptcy prediction (Back *et al.*, 1995) and financial diagnosis (Serrano-Cinca, 1996; Deboeck, 1998; Kiviluoto & Bergius, 1998). More recent applications include, for instance, the use of SOM as a tool for macroprudential supervision (Sarlin, 2016) and the prediction of currency crisis (Sarlin & Marghescu, 2011).

1.5.3. Partitioning Around Medoids

The Partitioning Around Medoids, or k-medoids (PAM), method is an iterative, partitional algorithm which groups data into a pre-determined number of clusters, k, by finding a representative data point or medoid and assigning data points to the nearest (or least dissimilar) medoid (Kaufman & Rousseeuw, 1990). Comparatively to the k-means algorithm (MacQueen, 1967), PAM uses an actual data point (medoid) as the cluster centre, rather than the cluster mean (centroid).

This method has been deemed more adequate for some data structures, such as fuzzy data. Also, it allows us to document the representative (medoid) banks of each business model. The study of banking-related topics with the aid of PAM has been scarce and mostly oriented towards client segmentation (Liu *et al.*, 2010; Aryuni *et al.*, 2018). An exception to this has been the study by Hryckiewicz & Kozłowski (2017), who apply PAM on a sample of large banks operating in 65 countries. Their findings suggest that, during the financial crisis, banks that adopted an investment model contributed to the accumulation of systemic risk due to their reliance on wholesale funding.

1.5.4. Clustering ensembles

A recent stream of research in classification literature "combines the information provided by the partitions" of different clustering methods (Jain, 2010: p.660). As an illustration, if we compare a clustering result to a medical diagnosis, the clustering ensemble approach equates to combining the diagnoses performed by a variety of experts (clustering methods), based on a given consensus scheme, into a single medical diagnosis (ensemble), under the expectation that the robustness/accuracy of the ensemble diagnosis is improved as a result. Kuncheva (2004) refers three consensus schemes: unanimity, simple majority, and plurality[4]. When using the unanimity scheme, a given observation is only assigned to a cluster if all the methods in the ensemble produce the same, unanimous classification; in the simple majority scheme, the observation is only classified in a cluster if the majority of methods assign the same classification; and, finally, the plurality scheme states that an observation is assigned to the cluster which receives the largest share of classifications among the methods in the ensemble. A number of methods have been used to handle ties (e.g. Ravikumar & Ravi, 2006). An established, and intuitive, result in literature is that the performance of clustering ensembles is expected to improve with the diversity of clustering methods (Kuncheva, 2004).

The application of the clustering ensemble approach to banking has gained increasing attention over recent years, with particular focus on bankruptcy prediction (Alam *et al.*, 2000; Ravikumar & Ravi, 2006; De Andrés *et al.*, 2011; Davalos *et al.*, 2014) and credit scoring (Ala'raj & Abbod, 2016; Abellán & Castellano, 2017). For instance, Alam *et al.* (2000) combine FCM, SOM and competitive neural network to form an ordinal ranking regarding the likelihood of bank failure. Budayan *et al.* (2011), on the other hand, study the presence of hybrid strategic groups in Turkish construction firms by performing FCM, using cluster membership values as inputs to k-means, and visually representing the results using SOM.

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[4] Onan (2019) provides an overview of recently developed consensus schemes such as homogenous and heterogeneous consensus clustering-based undersampling scheme.

The authors find three pure strategic groups and two hybrids. Our study relates to this strand of research in the sense that we cumulatively apply PAM, FCM and SOM to a single setting. However, our method to identify banking business models combines the actual classification of the three methods, which relates more closely to the 'ensemble' approach than the paper by Budayan *et al.* (2011). Moreover, we also provide two additional layers of classification: the identification of core (and non-core) banks, and persistent (and non-persistent) banks. Finally, we provide evidence of the robustness of our approach across a variety of checks.

1.6. Data

1.6.1. Sample selection

Our sample includes 524 European banks, both listed and non-listed, from 2005 to 2016. We collect year-end consolidated data from Bankscope and Orbis Bank Focus. The following criteria are applied:

- headquarters in 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;
- data available for at least three consecutive years.

Although we apply the correct consolidation code filter according to the Bankscope/Orbis standards, in some cases, it is still possible to find both the bank entity and the holding company entity of the same group (e.g., HSBC Holdings Plc and HSBC Bank Plc). In such cases, we keep the bank entity and remove the holding company because we are mainly interested in studying the banking business. Regarding cooperative networks, we opt to remove cooperative entities operating in the lowest tier because, in most cases, the autonomy of these entities to set long-term strategic choices is reduced. This means that we only exclude the local cooperatives whenever groups have more than one tier. For instance, the Crédit Agricole Group (CAG) consists of a three tier cooperative network which includes the top tier cooperative, regional banks, and local banks; for this study we only keep CAG's entities belonging to the top tier and regional banks. We winsorize the variables at the 1% and 99% percentiles.

1.6.2. Business model variables

In this section we identify ten variables that have been used in extant studies to identify banking business models. 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 1.1**.

Table 1.1. Variables description

	Description
Balance sheet structure	
Gross loans to customers	Gross loans and advances to customers.
Trading assets	Financial assets trading and at fair value through profit or loss.
Interbank lending	Sum of (i) net loans and advances to banks, (ii) reverse repos, securities borrowed and cash collateral.
Customer deposits	Customer deposits.
Interbank borrowing	Sum of (i) bank deposits, (ii) repurchase agreements, securities loaned and cash collateral.
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.
Diversification	
Total derivatives	Derivative financial instruments, asset and liability-side.
Income diversification	Following Elsas *et al.* (2010), income diversification is computed as a Herfindahl-Hirschman Index (HHI). In banking, total operating income (TOR) includes net interest income (NII), net fees and commissions (NFC), net trading income (NTI) and other income (OTH). We use the absolute values of each component: $[1 - [(NII/TOR)^2 + (NFC/TOR)^2 + (NTI/TOR)^2 + (OTH/TOR)^2]]$.
Size	
Total assets	Log of total assets in thousand euros.
Leverage	
Total equity	Total equity.

Notes: All variables computed as percentage of total assets, except income diversification (HHI) and total assets (log). Data is obtained from the Bankscope and Orbis databases.

Balance sheet 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, in line with the notion of banks as delegated monitors (Diamond, 1984). The ratio of *trading assets* to total assets captures the allocation of resources to financial assets at fair value. Banks engaged in such 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 short-term liquidity. While such operations constitute a key component of market liquidity for banking institutions, evidence shows that they may be a significant source of counterparty and guarantee risks (Gorton & Metrick, 2013). 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; Rajan, 1992). The ratio of *interbank borrowing* to total assets includes mainly bank deposits and other money market funds which have been documented as more 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 bank's ability to diversify into fee-based financial services such as bancassurance, investment advice and credit card services (Elsas *et al.*, 2010) which enable it to improve the screening and monitoring of customers due to access to additional information as well as to diversify risks (Diamond, 1984).

Size. The value of *total assets* may be an important indicator of banking business models in the sense that different banking activities seem to bear different potential for economies of scale (De Young, 2000). 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 are 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).

Leverage. The ratio of accounting *equity* to total assets is also expected to vary with the choice of other business model variables, for a variety of reasons. For instance, large banks seem to benefit from too-big-to-fail state subsidies, which are likely to offset the excess risk premium of operating with lower than optimal 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 buybacks and dividends to shareholders (Easterbrook, 1984), hence resulting in higher bank leverage.

1.6.3. Descriptive statistics and principal component analysis

The descriptive statistics presented in **Table 1.2** are based on full period average values, which allows us to account for the long-term nature of business model choices. The indicators show that asset allocation is mostly directed towards gross loans to customers (56.6%) and funding is mainly obtained via customer deposits (52.0%). This suggests that, on average, European banks are oriented towards traditional retail intermediation. Also, some variables display a substantially larger mean than median values (trading assets, mean: 3.5% and median: 0.8%; total derivatives, mean: 5.1% and median: 1.3%). This indicates that the distributions have significant right-sided skewness. In other words, a small share of observations has large values, and a large share of observations have low values. In general, this seems to support the notion that while traditional retail intermediation prevails in European banking, significant heterogeneity may be observed across banks.

Table 1.2. Descriptive statistics

	Mean	**SD**	**Min.**	**Median**	**Max**
Gross loans to customers	56.6	20.9	7.4	60.9	95.9
Trading assets	3.5	6.1	0.0	0.8	39.6
Interbank lending	15.9	16.0	0.2	10.5	79.7
Customer deposits	52.0	22.8	6.2	55.0	92.0
Interbank borrowing	17.9	14.8	0.0	14.1	72.9
Wholesale funding	13.2	14.6	0.0	8.8	65.9
Total derivatives	5.1	9.5	0.0	1.3	56.4
Income diversification	47.5	12.1	10.5	50.4	68.5
Total assets	7.3	0.6	6.1	7.1	9.0
Total equity	7.1	4.2	0.9	6.4	28.6

Notes: Sample based on full-period average for each bank (524 observations). Variables winsorized at 1 and 99 percentiles. All variables computed as percentage of total assets, except income diversification (HHI) and total assets (log).

Table 1.3 presents the principal component analysis results. Literature has pointed several advantages regarding the use of the retained principal components in clustering *vis-à-vis* using the original variables. Firstly, using the retained components allows us to perform clustering on a space with orthogonal dimensions, given that they are uncorrelated, which is a desirable feature when using the Euclidean distance to compute dissimilarities (Sharma, 1996). Secondly, such approach narrows the focus of the analysis on the most relevant relationships between business model choices and, thus, mitigate the problem of data noisiness in strategy variables (Galbraith & Shendel, 1983). Related to this, we interpret each retained component as a strategic dimension along which banks assume a long-term position relative to their peers. On the other hand, the main disadvantage of using the retained components is loss of information. However, we argue that the abovementioned benefits of using the components outweigh the issue of loss of information, particularly if the retained components explain a significant share of the variation of the original variables. For this reason, we retain a number of components that ensures that the total variation explained is

Table 1.3. Principal component analysis

	(1) Full period, 2005-16					(2) T1, 2005-07					(3) T2, 2008-10					(4) T3, 2011-13					(5) T4, 2014-16				
	PC1 *div*	**PC2** *tlen*	**PC3** *sfun*	**PC4** *sol*	**PC5** *ifun*	**PC1** *div*	**PC2** *tlen*	**PC3** *ifun*	**PC4** *sol*	**PC5** *sfun*	**PC1** *div*	**PC2** *tlen*	**PC3** *sfun*	**PC4** *ifun*	**PC5** *sol*	**PC1** *sfun*	**PC2** *tlen*	**PC3** *div*	**PC4** *sol*	**PC5** *ifun*	**PC1** *sfun*	**PC2** *tlen*	**PC3** *ifun*	**PC4** *sol*	**PC5** *div*
Rotated factor loadings																									
Gross loans to customers	-0.34	**0.88**				-0.32	**0.87**				-0.33	**0.88**					**0.91**	-0.30				**0.90**			-0.36
Trading assets	**0.78**	-0.15				**0.84**					**0.80**					-0.12	-0.20	**0.75**			-0.15	-0.22	-0.21		**0.73**
Interbank lending	-0.12	**-0.89**	0.11		0.17	-0.17	**-0.86**	0.21		0.16	-0.14	**-0.90**	0.12	0.17		0.11	**-0.92**	-0.13		0.12		**-0.92**	0.19		-0.14
Customer deposits	-0.28		**0.74**		**-0.58**	-0.26		**-0.54**		**0.77**	-0.26		**0.73**	**-0.60**		**0.69**		-0.26		**-0.64**	**0.81**		**-0.53**		-0.24
Interbank borrowing		-0.14			**0.97**		-0.14	**0.98**	-0.11			-0.11		**0.98**						**0.98**		-0.12	**0.95**		
Wholesale funding		0.13	**-0.87**	-0.17			0.14		-0.13	**-0.90**			**-0.92**	-0.11	-0.13	**-0.92**	0.11		-0.14		**-0.90**	0.10		-0.14	-0.13
Total derivatives	**0.71**	-0.14	-0.35	-0.24		**0.71**			-0.18	-0.23	**0.74**		-0.25		-0.28	-0.32	-0.16	**0.67**	-0.38		-0.39	-0.15		-0.46	**0.59**
Income diversification	**0.69**		0.38		0.15	**0.69**		0.23	0.15	0.17	**0.67**		0.22			0.22	0.12	**0.71**			0.23		-0.16		**0.72**
Total assets	0.47	0.11	-0.38	**-0.55**		**0.55**			-0.41	-0.45	0.45		-0.45		**-0.52**	-0.34		0.40	**-0.64**		-0.27	0.11		**-0.70**	0.35
Total equity				**0.94**					**0.99**						**0.95**		0.11	0.14	**0.88**					**0.83**	0.21
Variation explained																									
Sum of squared loadings	1.64	1.36	1.23	1.05	0.93	1.68	1.41	1.19	1.02	0.90	1.66	1.37	1.23	1.07	0.90	1.65	1.29	1.23	1.05	0.96	1.59	1.27	1.20	1.08	1.00
Variation explained (VE)	27.0	18.4	15.2	11.1	8.7	28.4	20.0	14.3	10.4	8.2	27.4	18.8	15.2	11.5	8.0	27.3	16.8	15.2	11.0	9.1	25.2	16.3	14.5	11.7	9.9
Cumulative VE	27.0	45.4	60.7	71.8	80.5	28.4	48.4	62.6	73.1	81.2	27.4	46.2	61.4	72.9	80.9	27.3	44.1	59.2	70.2	79.3	25.2	41.5	56.0	67.6	77.5
N	524					376					441					495					483				

Notes: The results in (1) are obtained using the full period average of each input variable for all banks (n=524). For the remaining results (2-5), we compute the triennium average value of the input variables observed by the banks present in the sample in at least one year of each triennium. Hence, the last line of the table represents the number of banks present in the sample in each triennium. Component loadings rotated using Varimax rotation. In **bold**, variables with higher than 0.5 loadings per component (absolute value). Input data standardized. Labels of the principal components: *div*: diversification, *tlen*: traditional lending, *sfun*: stable funding, *sol*: solvency, *ifun*: interbank funding.

greater than 80%. We also perform a Varimax rotation in order to increase the interpretability of the components. **Table 1.3** is divided into five groups of columns, each indicating a different sample period. As discussed in the methodology section, the full period sample (2005-16) is used to classify the long- term business model of banks, whereas the triennium samples (T1: 2005-07, T2: 2008-10, T3: 2011-13, T4: 2014-16) are used to assess the persistency of business models. In order to ensure comparability, we retain the same number of components for all sample periods, which allows us to cover close to 80% of the variation explained in all trienniums (T1: 81.2%; T2: 80.9%; T3: 79.3%; 77.3%).

In general, the retained components are the same across sample periods, however the relevance of some components (and hence their order) has shifted over time. Taking the components derived from the full period mean values as the reference, i.e. column (i), the first component is loaded positively by trading assets, derivatives and income diversification – and, thus, may be interpreted as a business orientation towards 'diversification' (div). The second component is loaded positively by gross loans to customers and negatively by interbank lending. Hence, we interpret the second component as an orientation towards 'traditional lending' (tlen). The third component is loaded positively by customer deposits and negatively by wholesale funding, which indicates an orientation which is focused on 'stable funding' (sfun). The fourth component is loaded positively by equity and negatively by total assets, suggesting a 'solvency' oriented policy (sol). Finally, the fifth component is loaded positively by interbank borrowing and negatively by customer deposits, which indicates an orientation towards 'interbank funding'. In comparison with extant studies, the top three components are in line with those found in literature. For instance, Van Ewijk & Arnold (2014) retain factors related with traditional funding and traditional lending; Mergaerts & Vennet (2016) retain factors associated with retail orientation and diversification; and De Haan & Kakes (2019) label the retained factors as 'big investment banks' and 'retail banks'. Regarding the bottom two components (solvency and interbank funding), a possible explanation for their novelty (in relation to comparable studies) is likely related with the higher cut-off value of cumulative proportion of variation explained (CPVE) used in our study. For instance, De Haan & Kakes (2019) report a CPVE of 69.7%, which compares with 80.5% for our study.

When we analyse each sub-period separately, it is possible to identify a significant shift in the order of two components which takes place in the 2011-16 period. Namely, the 'diversification' component significantly loses relevance (i.e. the variation explained drops from 28% in 2005-07 to 10% in 2014-16), whereas as the 'stable funding' component gains relevance (i.e. the variation explained increases from 8% in 2005-07 to 25% in 2014-16). In our view, such result is informative and in line with the recent events that took place in the banking sector. In particular, we interpret this shift as indicating that funding related choices have become more important sources of strategic variation among European banks in recent years. This result has been documented in extant literature (e.g. Roengpitya *et al.*, 2017) and is likely related with the implementation of the funding-related Basel III requirements, specifically the Net Stable Funding Ratio and the Liquidity Coverage Ratio (BCBS, 2011).

1.7. Methodology

The method used to identify banking business models may, in general, be summarized in the following way: first, we perform clustering analysis with alternative algorithms based on the retained components to identify the optimal number of business models, and combine the classification outputs of each algorithm into one single assignment, using a majority consensus rule (clustering ensemble); then, we apply a set of criteria to identify core banks, using a stricter consensus rule (unanimity) and information regarding the quality of clustering (silhouette width); finally, we identify as persistent banks those that hold the same business model classification for all the sample periods. Below we detail the methodological decisions made in each step.

1.7.1. Classification of banking business models (clustering ensemble)

In order to classify and describe the business models we apply the following procedure:

1. Using the retained components as inputs (full period mean values), run the three clustering methods: Partitioning Around Medoids (PAM), Fuzzy C-Means (FCM), and Self-Organizing Maps (SOM) (each algorithm is presented in **Appendix 1.1**). For

parsimony, we run the algorithms for a range of 3 to 9 clusters. Several decisions are made at this stage:

– Distance measure (PAM, FCM, SOM): Euclidean distance;

– Fuzzifier (FCM): 2 (following the default value in ‘ppclust’ R package[5]);

– Grid size (SOM), we adapt the grid configuration to enable us to represent the range of 3 to 9 clusters (J). Namely, for J=3: 3x1, for J=4: 2x2, for J=5: 5x1, for J=6: 3x2, for J=7: 7x1, for J=8: 4x2, for J=9: 3x3;

– Neighbourhood radius/type and topology (SOM): radius 0.5 (minimum) and 1.0 (maximum), gaussian function type and rectangular topology (defined after experimentation with alternative specifications);

– Type of learning algorithm and initialization (SOM): batch with linear initialization, i.e. the algorithm defines the initial data point weights matrix by using “the linear grids upon the first two principle components direction” (Chair & Charrad, 2017: p.2), which allows for a deterministic, and hence reproducible, clustering output.

In FCM, each observation is assigned to the cluster for which it has the highest coefficient of membership. For each bank, collect the silhouette width (SW) using PAM, FCM, and SOM and the percentage of cluster membership (PCM) using FCM.

2. Select the optimal number of clusters for each method by examining four criteria: average silhouette width (SW), Caliński-Harabasz index (CHI), Davies-Bouldin index (DBI) and Dunn index (DI) (*vide* the description of each criterion in **Appendix 1.3**). In particular, for each method we rank the results obtained for each partition (J=3 to J=9) and count the number of times each partition is ranked as the best (#1) or second best (#2) value in each criterion. The partition with the highest count of #1 and #2 is labelled as the optimal number of clusters.

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[5] The list of all R packages used in the paper are included in the **Appendix 1.2**.

3. Combine the clustering assignment of each method into one single assignment (clustering ensemble step). To do so, compute the 'voting results' for each bank, i.e. the count of classifications (1, 2, or 3) of a given bank in each business model and apply a majority consensus rule. That is, a bank is assigned to the business model for which the count of classifications is higher. For example, a bank may be classified as operating with business model BM1 by two methods (BM1 count = 2) and BM3 by the other method (BM3 count = 1). In this case, the bank is assigned to business model BM1(as 2 > 1). When there is a tie (i.e. each method assigns the bank to a different business model), we follow the assignment made by the method with the highest silhouette width for that specific bank.
4. Assess the similarity of business model classifications between the ensemble classification and each of the alternative clustering methods (PAM, FCM, SOM) by computing the cross-tabulation of clustering results. In order to match the classes of each clustering method, we analyse the clusterwise mean values of each clustering output. The similarity of classifications is assessed using simple matching, the Rand Index, the Adjusted Rand Index and the Jaccard index. The first two measures allow us to have an intuitive description of classification similarity; the third measure corrects the original Rand index for randomness; and the Jaccard index only considers as similar classifications those that are 'true positives', whereas the Rand index also considers true negatives. The simple matching method is the only method that directly uses the elements of the cross-tabulation and is computed as the sum of similar business model classification (elements in the diagonal) divided by the total number of elements. The remaining indices (Rand index, Adjusted Rand index and Jaccard index) are computed based on pairs of elements. For brevity reasons, we refer the specification of these indices to the work by Milligan & Cooper (1986) – which is also used as the main reference paper for the R package used in this analysis ('clues'). We also run Pearson's Chi-Square Independence Test.
5. Finally, describe the composition of each business model by computing the mean and standard deviation of business model variables for each cluster (business model). Test for differences in the mean values between pairs of business models using the Tuckey

HSD Test. For each variable, identify the cluster with the highest and lowest values. We label as a 'cluster distinguishing feature' those variables for which a cluster records the highest or lowest value, and its mean is statistically significant from one or more extant clusters.

1.7.2. Identification of core banks

The identification of 'core' (and 'non-core') banks is made in the following way:

1. Use the clustering ensemble obtained for the cross-section sample (*vide* **Section 1.7.1**, step 5) and compute the silhouette width for each bank.
2. Label as 'core' the banks that cumulatively meet the following criteria:
   - **Criterion 1.** Unanimity scheme, i.e. the bank is classified in the same business model using the three clustering methods (3 out of 3). The choice of the unanimity scheme, which is more restrictive than the alternative schemes, allows us to obtain a lower propensity for Type I error, although at the expense of a higher likelihood of Type II error. We take this decision given the focus of this step in the identification of those banks that clearly belong to a given business model. In other words, we decide to adopt such voting scheme because we place special importance in increasing the level of confidence regarding the accuracy of the classification attributed to banks labelled as core;
   - **Criterion 2.** The bank records a silhouette width (clustering ensemble) above 0.2. This limit is based on the threshold values of average silhouette width as proposed by Kaufman & Rousseeuw (1990).
3. Check the fuzziness of core and non-core banks by comparing the following metrics:
   - average values of the first- and second-best cluster memberships (PCM1 and PCM2), wherein PCM1 and PCM2 correspond to the top two membership scores obtained via FCM for each bank;
   - difference between PCM1 and PCM2;

– Herfindahl-Hirschman Index of cluster memberships, computed as the sum of squared PCMs (i.e. PCM1^2 + ... + PCMJ^2) for each bank;

– average silhouette width based on the ensemble classification for each bank.

For each metric, we compute the Tuckey HSD test for comparison of means between the two sub-samples: core and non-core banks.

1.7.3. Identification of persistent banks

The following procedure is used to separate 'persistent' from 'non-persistent' banks:

1. Compute the clustering ensemble for each 'triennium sample'. Namely, we perform principal component analysis and clustering with alternative methods for each triennium sample: 2005-07 (T1), 2008-10 (T2), 2011-13 (T3) and 2014-16 (T4).
2. Assess the general persistency of business model classification for each method over consecutive trienniums. In order to do this, for each method, organize the classification results so that each row represents a bank specific pair of classifications obtained in consecutive trienniums. To illustrate this, if a given bank (e.g., A) is present in our dataset in four trienniums (T1 to T4), we compute the clustering method (e.g., FCM) for each triennium separately and transform the results into three pairs of consecutive business model: 'A.FCM.T1-T2', 'A.FCM.T2-T3', 'A.FCM.T3-T4'. We compute the Rand Index, the Adjusted Rand, the Jaccard (Milligan & Cooper, 1986) and the Chi-Square Independence Test for each method.
3. Label as a 'persistent bank' those banks for which the business model classification (ensemble) is the same across all trienniums.
4. For the sub-set of 'non-persistent banks', investigate the number of changes per bank. This step allows us to understand whether non-persistency derives from business policy changes (if the majority of non-persistent banks change their business model once) or, on the contrary, from the inability of our approach to capture the business models in a consistent fashion over time. Such analysis may be seen as a time-varying adaptation of the concept of "frustrated clustering" proposed by Gates *et al.* (2019),

which refers to observations that the method "cannot consistently decide on a grouping" (p.8).

5. Identify the distinctive features of non-persistent banks (relative to persistent ones) by comparing banks that changed their business model in a given triennium $(\mathrm{t}+1)$ with other banks that held the same business model in the triennium prior to the change (t) and did not change their business model in $\mathrm{t}+1$, with respect to the features exhibited by both banks in triennium t. To undergo this analysis, we run Bayesian logistic regressions (J regressions, i.e. one per business model prior to change) using a sample of bank-triennium observations. The model specification is as follows:

$$Prob\left(Y_{i,t+1}^{j}=1\right)=1-\Lambda(\alpha+\boldsymbol{\beta}\mathbf{X}_{\mathbf{i,t}}+\boldsymbol{\gamma}BM_{i,t+1}+\boldsymbol{\tau}Triennium_{t}+\delta Fuzziness_{i,t}+\varepsilon_{i,t}) \qquad (1.1)$$

In which $\mathrm{Y}_{\mathrm{I,t+1}}^{j}$ is a dummy which takes on the value 1 if bank i changes its business model from j in triennium t to another business model $(-j)$ in triennium $\mathrm{t}+1$ and assumes the value 0 if the bank remains in business model j, wherein t = 2005-07, 2008-10, 2011-13 and 2014-16; α is the model constant; $\mathrm{X}_{\mathrm{I,t}}$ is the vector of business model variables observed in triennium t for each bank i; $\mathrm{BM}_{\mathrm{I,t+1}}$ is the destination business model of bank i, which for banks that change business model will be $-j$ and for the persistent banks will be j. Notice that the aim is to capture forward looking fixed effects that are specific to the business model change direction. For instance, a bank that changes from a retail diversified funding model to a retail focused model is expected to have previously invested in technology to capture customers deposits (Berger *et al.*, 2005a); $Triennium_{\mathrm{t}}$ is a dummy for the triennium and is used to capture period specific fixed effects (e.g. new regulation or a financial crisis); $Fuzziness_{\mathrm{t}}$ is 1 minus the difference between the top two percentages of business model membership in t for each bank i, i.e. 1 – (PCM1 – PCM2); $\beta, \gamma, \tau, \delta$ are the regression coefficients; and $\varepsilon_{\mathrm{I,t}}$ is the disturbance term.

1.8. Results and discussion

1.8.1. Banking business models

Table 1.4 displays the results of the selection criteria for each partition and method. In general, the results seem consistent across clustering methods. For instance, for a partition of four clusters ($J = 4$) the three 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

Table 1.4. Selection criteria: number of business models

	ASW	SW>0.5	SW<0	CHI	DBI	DI	Count of #1 rank	Count of #2 rank
FCM								
J=3	**0.23**	**8.21**	18.70	**133.89**	1.65	0.039	3	0
J=4	**0.18**	0.00	**18.32**	**128.82**	1.59	**0.049**	1	3
J=5	0.15	0.00	**17.94**	119.25	1.92	0.036	1	0
J=6	0.14	0.00	20.99	108.96	1.63	0.021	0	0
J=7	0.13	0.00	23.47	105.95	**1.40**	0.036	0	1
J=8	0.10	0.00	27.29	96.20	**1.36**	0.025	1	0
J=9	0.09	0.00	30.53	87.21	2.09	**0.040**	0	1
SOM								
J=3	0.11	0.00	20.61	110.96	1.68	**0.041**	0	1
J=4	**0.19**	**1.15**	19.27	**122.01**	1.51	0.032	1	2
J=5	**0.21**	0.00	**13.36**	**127.57**	**1.14**	0.039	3	1
J=6	0.11	0.00	27.67	86.66	1.46	0.019	0	0
J=7	0.14	0.00	**17.56**	98.67	**1.05**	**0.045**	2	1
J=8	0.11	0.00	26.34	97.20	1.18	0.024	0	0
J=9	0.07	0.00	35.31	74.05	1.33	0.036	0	0
PAM								
J=3	0.15	0.00	**9.54**	114.21	1.47	0.042	1	0
J=4	**0.23**	**1.53**	10.50	**137.57**	1.44	0.036	3	0
J=5	0.21	0.00	9.92	126.00	1.27	0.036	0	0
J=6	0.19	**0.38**	12.60	123.25	1.10	**0.044**	0	2
J=7	**0.21**	**0.38**	**9.54**	**129.94**	**1.09**	**0.049**	2	4
J=8	0.20	0.00	14.31	123.44	**0.96**	0.042	1	0
J=9	0.20	0.00	14.69	117.15	1.23	0.042	0	0

Notes: Results of running the PAM, SOM and FCM algorithms on the full period average sample, with inputs PC1 to PC5 for different number of clusters (J). Selection criteria: Average Silhouette Width (ASW), percentage of observations with SW greater than 0.5 (SW>0.5) and lower than 0 (SW<0), Calinski-Harabasz Index (CHI), Davies-Bouldin Index (DBI) and

Dunn Index (DI). The partitions with the top values (#1 and #2) for each criterion are presented in **bold.** Note that the best partitions minimize SW<0 and DBI and maximize the remaining criteria (*vide* **Appendix 1.3**).

for FCM (0.18) and SOM (0.19). Similarly, the $J = 4$ partition records the highest ratio of between to within cluster dispersion (Caliński-Harabasz Index) for PAM (137.57) and the second highest for SOM and FCM (122.01 and 128.82, respectively). Moreover, we may observe $J = 4$ is identified as the partition with the highest count of #1 ranked criteria for PAM (3) and the highest count of #2 ranked criteria for FCM (3) and SOM (2). Based on these results, we conclude that the optimal number of clusters is $J = 4$. In other words, our findings suggest that the European banking sector may be characterized by the presence of four distinct banking business models. This result is in line with the number of banking business models identified by previous studies (Roengpitya *et al.*, 2017; Ayadi *et al.*, 2015; Martín-Oliver *et al.*, 2017). Also, we note that in line with the results of Mergaerts & Vennet (2017), the values of average silhouette width are below the threshold of 0.25 for minimum quality of clustering as proposed by Kaufman & Rousseeuw (1990). In our framework, such findings support the notion that some banks may be combining the 'recipes' of different business models (non-core banks) and/or have changed their business model in the sample period (non-persistent) – two analysis which are conducted in the sections below.

Next, **Table 1.5** describes the composition and popularity of each banking business model, using the clustering ensemble approach[6]. The table shows the mean values (and standard deviation) of all business model variables, as well as the results of the test for mean differences across pairs of business model. In general, results show that when a business model records the highest or lowest mean value in comparison with the other models, the number of significant pairwise differences is consistently two ($^{++}$) or three ($^{+++}$). This finding indicates the ability of the ensemble to significantly differentiate between banking business models. Taking each business model separately, we observe that:

- **BM1** is followed by 203 banks (38.7% of the total number of banks), making it the most popular configuration. This model records the highest mean value of customer deposits (67.3%) and total equity (8.9%) and the lowest value of interbank borrowing

[6] A similar table the with classifications obtained for each method (separately) may be found in **Appendix A4**.

(8.9%). Moreover, along with BM2, BM1 registers the highest mean value of gross loans to customers (68.3%). We label BM1 as '*retail focused*' model;

- **BM2** comprises 124 banks (23.7%). As a whole, banks included in BM2 exhibit the highest mean value of wholesale funding (25.5%) and second largest size (7.5, log). Additionally, *ex-aequo* with BM1, BM2 records the highest value of gross loans to customers (67.6%). We label BM2 as '*retail diversified funding*' model;

Table 1.5. Composition of business models: clustering ensemble

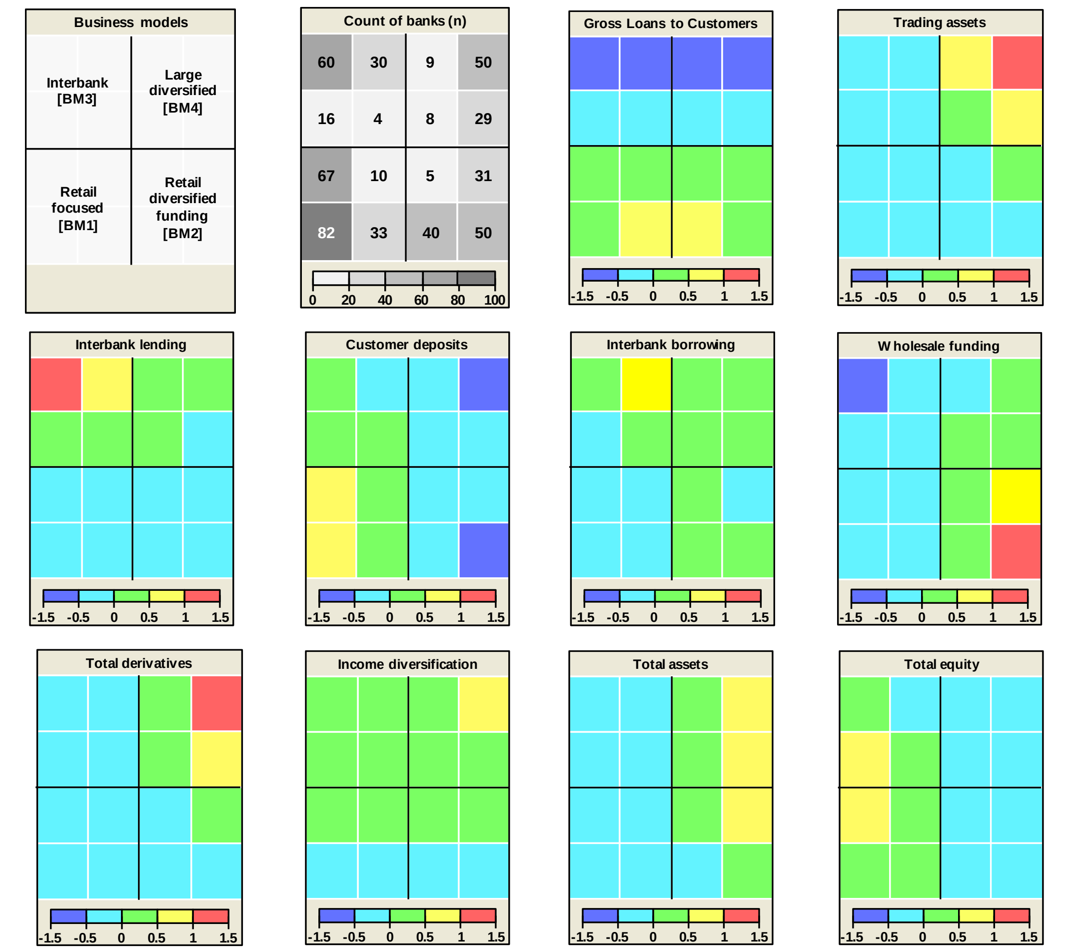
	BM1	**BM2**	**BM3**	**BM4**
Number of banks	203	124	109	88
Gross loans to customers	68.3 (12.6)$^{++}$	67.6 (14.1)$^{++}$	35.6 (16.0)$^{++}$	40.1 (18.2)$^{++}$
Trading assets	1.8 (3.4)$^{+}$	1.9 (2.5)$^{+}$	2.0 (4.9)$^{+}$	**11.4 (8.9)**$^{+++}$
Interbank lending	8.2 (5.4)$^{++}$	8.9 (6.3)$^{++}$	**37.6 (19.1)**$^{+++}$	16.7 (12.7)$^{+++}$
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)$^{++}$	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)$^{++}$

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 (*vide* **Appendix 2.4** for detailed results per method). The input variables used in the clustering process are PC1 to PC5 for the full period, as identified in **Table 2.3**. 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. Values in **bold** indicate the business models with the highest and lowest mean values for each variable, when the number of crosses is ($^{+++}$). All variables computed as percentage of total assets, except income diversification (HHI) and total assets (log).

- **BM3** includes 109 banks (20.8%). This model records the second highest value of customer deposits (58.5%), the highest mean value of interbank lending (37.6%) and lowest loans to customers (35.6%). We name BM3 as '*retail diversified assets*' model;

- **BM4** is followed by 88 banks (16.8%), making it the least common model. BM4 shows the highest mean value of trading assets (11.4%), total derivatives (20.3%), income diversification (55.1, HHI), and size (8.1, log). Moreover, BM4 records the lowest mean value of customer deposits (29.3%), which makes it the least traditional and more diversified business model. We name BM4 as '*large diversified*' model.

Figure 1.1. Self-organizing map of business model features



Notes: The frontier between business models was obtained by performing the clustering ensemble approach on the codebook vectors. The values presented for each variable, ranging from -1.5 to +1.5, correspond to the codebook vectors obtained by performing a batch SOM on the full list of business model variables (standardized).

In general, such distribution of banks across business models, as well as the description of each model, is in line with the results obtained by Ayadi *et al.* (2015). Next, we provide a novel visual representation of banking business models by using SOM (**Figure 1.1**). In order to obtain a richer representation, we modify the SOM used in the clustering ensemble by expanding the SOM grid from 2x2 to 4x4. Then, we cluster the SOM code vectors and map the four banking business models, which are identified in the top-left map of **Figure 1.1** (labelled 'Business models'). Observing the maps of business model features, we may see that the results are consistent with those described in **Table 1.5**. Particularly, the panel corresponding to BM1 (retail focused) shows high values (in yellow and green) for gross loans to customers, customer deposits and equity, and also contains the largest number of banks. In the same line, BM2 (retail diversified funding) registers high values of gross loans to customers, wholesale funding and size. BM3 (retail diversified assets) records low values in gross loans to customers and high values in interbank lending, interbank borrowing and customer deposits. Lastly, BM4 (large diversified) records high values of trading assets, derivatives, income diversification and size. Interestingly, the 'neurons' located in the four extreme corners of each map seem to adhere more closely to each 'typical' business model configuration. On the contrary, the 'neurons' located in the centre part of each map seem to be less well-defined, exhibiting some features that adhere less closely to each archetypal business model. For instance, in the panel corresponding to BM1 (retail focused), the 'neuron' located closest to the centre exhibits relatively lower values than the corner 'neuron' in terms of gross loans to customer, customer deposits and total equity, and higher values in terms of income diversification. Overall, we view these results as suggesting that banks may have different levels of adherence to their assigned banking business model, an analysis which we explore in more detail in the next section.

Finally, we perform the cross-tabulation of the business model classifications obtained in the ensemble and each method in order to assess the suitability of methods included in our ensemble. In the upper panel of **Table 1.6**, we test the classification similarity of the pair ensemble/FCM and find that 94.7% of the banks in our sample record the same business model classification in both methods (simple matching). Moreover, the Rand index (RI) of 0.943 indicates that 94.3% of the 132 026 unordered pairs of observations [524(524-1)/2] include elements that are either (i) both classified in the same business model by both methods (true positives) or (ii) both classified in different business models by both methods (true negatives) – a value which reduces slightly to 0.857 when adjusting for chance

Table 1.6. Similarity of business model classifications per pair of methods

	Ensemble				
FCM	BM1	BM2	BM3	BM4	Total
BM1	**184 (99.5%)**	0 (0.0%)	1 (0.5%)	0 (0.0%)	185 (100%)
BM2	18 (13.4%)	**116 (86.6%)**	0 (0.0%)	0 (0.0%)	134 (100%)
BM3	1 (0.9%)	6 (5.2%)	**108 (93.9%)**	0 (0.0%)	115 (100%)
BM4	0 (0.0%)	2 (2.2%)	0 (0.0%)	**88 (97.8%)**	90 (100%)
Total	203 (38.7%)	124 (23.7%)	109 (20.8%)	88 (16.8%)	524 (100%)
Simple matching	0.947				
Rand index (adj.)	0.943 (0.857)				
Jaccard index	0.811				
Chi^2	1154.8***				
SOM					
BM1	**198 (99.5%)**	0 (0.0%)	1 (0.5%)	0 (0.0%)	199 (100%)
BM2	0 (0.0%)	**103 (98.1%)**	2 (1.9%)	0 (0.0%)	105 (100%)
BM3	5 (4.7%)	0 (0.0%)	**101 (95.3%)**	0 (0.0%)	106 (100%)
BM4	0 (0.0%)	21 (18.4%)	5 (4.4%)	**88 (77.2%)**	114 (100%)
Total	203 (38.7%)	124 (23.7%)	109 (20.8%)	88 (16.8%)	524 (100%)
Simple matching	0.935				
Rand index (adj.)	0.947 (0.866)				
Jaccard index	0.823				
Chi^2	948.9***				
PAM					
BM1	**203 (88.3%)**	23 (10.0%)	4 (1.7%)	0 (0.0%)	230 (100%)
BM2	0 (0.0%)	**101 (70.6%)**	2 (1.4%)	40 (28%)	143 (100%)
BM3	0 (0.0%)	0 (0.0%)	**103 (100%)**	0 (0.0%)	103 (100%)
BM4	0 (0.0%)	0 (0.0%)	0 (0.0%)	**48 (100%)**	48 (100%)
Total	203 (38.7%)	124 (23.7%)	109 (20.8%)	88 (16.8%)	524 (100%)
Simple matching	0.868				
Rand index (adj.)	0.892 (0.741)				
Jaccard index	0.691				
Chi^2	972.1***				

Notes: Count of banks per business model classification over pairs of clustering methods. The values in brackets are the percentage of each line total. Simple matching is computed as the number of observations with the same classification divided by the total number of observations. Remaining similarity measures are described in detail in Milligan & Cooper (1986), namely: the Rand Index is measured as the proportion of pairs of observations labelled as true positive and true negative divided by the total number of pairs of observations (Rand, 1971); the Adjusted Rand Index corrects the original Rand Index for randomness (Hubert & Arabie, 1985); the multi-class mean Jaccard index is defined as the proportion of pairs labelled as true positives divided by the total number of pairs of observations excluding true negatives (Jaccard, 1901). Finally, we compute the Pearson's Chi-Square independence test. *, ** and *** indicate the statistical significance at the 10%, 5% and 1% levels, respectively. Classifications are obtained using PC1 to PC5 as input variables.

(Adjusted Rand Index, ARI). The main sources of dissimilarity steam from 18 banks which are classified as BM2 by FCM and as BM1 by the ensemble. In the middle panel, the pair ensemble/SOM shows a similar simple matching score to that of FCM (93.5%), but presents higher values for other similarity measures, including ARI (0.866). In the lower panel, the pair ensemble/PAM also shows high values for the measures of similarity, despite displaying the lowest ARI (0.741). Finally, the null hypothesis of statistical independence of the classifications is rejected at a 1% level for all methods. In general, we interpret these results as supporting our approach, in the sense that (i) the similarity of classification between the ensemble and each method seems sufficiently high to give us some confidence that the classifications are not spurious; (ii) the sources of dissimilarity differ across pairs of methods, indicating the presence of diversity which is seen as a positive attribute of ensemble compositions (Kuncheva, 2004).

Table 1.7. Core banks per business model

	Total	BM1	BM2	BM3	BM4
Criterion 1. Same BM classification across all methods ('unanimity')					
FCM=PAM	427 (81.5%)	184	93	102	**48**
SOM=FCM	468 (89.3%)	**180**	100	100	88
PAM=SOM	422 (80.5%)	198	**80**	**96**	**48**
(a) PAM=SOM=FCM	400 (76.3%)	180	77	95	48
Criterion 2. Silhouette Width above 0.2 for the clustering ensemble					
FCM	276 (52.7%)	169	**36**	32	39
SOM	266 (50.8%)	**155**	40	**30**	41
PAM	316 (60.3%)	200	50	33	**33**
(b) Ensemble	281 (53.6%)	172	37	31	41
Core banks (a, b)	273 (52.1%)	170	33	31	39

Notes: Results for each criterion are computed separately from other criteria, except in the last line (a, b). For each criterion (1 and 2) and business model (BM1, BM2, BM3, BM4) we identify the most restrictive method (PAM, SOM or FCM) in **bold**, i.e. the method which identifies the lowest number of banks that meet the criterion.

1.8.2. Core banks and fuzziness analysis

Next, we are interested in discriminating between core and non-core banks. **Table 1.7** identifies the number of core banks per business model. In the upper panel (criterion 1), the results indicate that 400 banks are classified in the same business model by the three methods. In the lower panel (criterion 2), the assessment of partition quality is similar across the different methods. In particular, the percentage of banks with a silhouette width above 0.2 ranges from 50.8% (SOM) to 60.3% (PAM). For the clustering ensemble, the number of banks that meet this criterion is 281 (53.6%).

Also, we find that in each criterion the methods that yield the lowest number of similar classifications per business model vary considerably. For instance, for criterion 2, PAM is more restrictive for BM4 (i.e. identifies a lower number of BM4 banks), SOM is more restrictive for BM1 and BM3 and FCM is more restrictive for BM2. We interpret these results as an indication of the suitability of the choice of clustering methods due to their diversity (Kuncheva, 2004). Importantly, when imposing criterion 1 and 2 we identify a total of 273 core banks (52.1% of total banks). Also, when comparing the distribution of core banks per business model relative to the full sample, we observe significant differences across business models. Namely, BM1 banks represent a significantly higher share of the sample of core banks (62.3%) when compared to the full sample (38.7%); BM4 banks represent a similar share; and BM2 and BM3 banks represent a significantly lower share (12.1% vs 23.7%, and 11.4% vs 20.8%, respectively). This finding seems to suggest that a bank following a retail focused (BM1) or trading (BM4) model is more likely to follow the 'standard' group strategy, whereas banks allocated to the retail diversified funding (BM2) or retail diversified assets (BM3) models may be more prone to operate less tightly under the peer group's typical business strategy.

Following this line of inquiry, next we compare the core and non-core banks in terms of their level of adherence (or fuzziness) to the assigned business model (**Table 1.8**). Firstly, we compare the average values of the first- and second-best percentage of cluster membership (PCM1 and PCM2, obtained via FCM) for core and non-core banks. As expected, the results show that core banks record a significantly higher value of PCM1 (0.52 vs 0.43) and a lower value of PCM2 (0.23 vs 0.26) than non-core banks do. In line with this, the difference between PCM1 and PCM2 (third line) is significantly higher for core banks (0.29) than for non-core banks (0.17). Similarly, core banks record a higher concentration of cluster memberships (0.38) and a higher silhouette width (0.34) than non-core banks do (0.32 and 0.05, respectively). Interestingly, in comparison to the only other study which reports the silhouette width in the identification of banking business models, the average silhouette width of core banks is significantly higher than the one reported by Mergaerts & Vennet (2016), which ranges between 0.14 to 0.20 for a 3 to 6 clusters' partition. We interpret these results as an indication that, for banks labelled as core, the assignment to a single, discrete business model is, on average, appropriate, whereas it may be more suitable to depict non-core banks as following a combination of 'recipes' of different business models. Moreover, untabulated results show that the majority of non-core banks with below mean PCM1-PCM2 (<0.17) seem to be better depicted as combining the retail focused model (BM1) with either the retail diversified funding (BM2: 48) or the retail diversified assets (BM3: 24) models.

Table 1.8. Fuzziness analysis: core versus non-core banks

	Core	**Non-core**	**Diff.**
First best cluster membership (PCM1)	0.52 (0.12)	0.43 (0.12)	0.09***
Second best cluster membership (PCM2)	0.23 (0.06)	0.26 (0.05)	-0.04***
PCM1 - PCM2	0.29 (0.17)	0.17 (0.16)	0.13***
Herfindahl-Hirschman Index (HHI)	0.38 (0.1)	0.32 (0.08)	0.05***
Average Silhouette Width (ASW)	0.34 (0.08)	0.05 (0.11)	0.29***
Number of banks	273	251	

Notes: Mean values and standard deviation in brackets, except number of banks (count). The first- and second-best cluster memberships (PCM1 and PCM2) correspond to the top two membership scores obtained via FCM for each bank. In other words, for each bank we identify the business models with which the bank has the two highest membership scores and label them as PCM1 and PCM2 respectively. Note that the sum of all membership scores per bank is 1. A core bank is expected to record a higher PCM1 and a lower PCM2 than non-core banks. The 'PCM1-PCM2' is computed as the difference between the top two membership scores for each bank. A core bank is expected to record a higher PCM1-PCM2 than non-core banks. The 'Herfindahl-Hirschman Index' is computed as the sum of squared PCMs (i.e. PCM1^2 + PCM2^2 + PCM3^2 + PCM4^2) for each bank. A core bank is expected to record a higher HHI than non-core banks. The Average Silhouette Width (ASW) is based on the ensemble classification for each bank and is calculated as the difference between the average distance to banks in the closest neighbor business model minus the average distance to banks in the assigned business model, divided by the maximum of the two distances. A core bank is expected to record a higher ASW than non-core banks. For each metric, we compute the Tuckey HSD test for comparison of means between the two sub-samples: core and non-core banks. Results are reported in the final column. *, ** and *** indicate the statistical significance of the difference at the 10%, 5% and 1% levels, respectively.

1.8.3. Persistent banks

The first step in the persistency analysis is to assess the general level of persistency of business model classifications. Using the Rand index, **Table 1.9** shows that 83.2% of pairs of consecutive triennium observations are classified in the same business model.

Furthermore, the null hypothesis of independence of classification over consecutive trienniums is rejected for all methods. As expected, these values are relatively lower when adjusting for chance (Adjusted Rand index). In other words, the proportion of pairs of bank-triennium observations that cumulatively change business model may be non-negligible. In sum, while the general results indicate that our approach is able to capture the long-term stable nature of business models, evidence also suggests that a significant share of banks in our sample changed business model in the period between 2005 and 2016. While such finding is in line with extant literature (e.g. Martín-Oliver *et al.*, 2016; Roengpitya *et al.*¸2017), it fuels our quest to understand more precisely what share of banks is non-persistent, how many times do non-persistent banks changed business model during the 2005-16 period and which features of banks potentiate such changes.

Table 1.9. Persistency of business models in consecutive trienniums

	Ensemble (t+1)				
Ensemble (t)	BM1	BM2	BM3	BM4	Total
BM1	406 (**82.7%**)	53 (10.8%)	27 (5.5%)	5 (1.0%)	491 (100%)
BM2	24 (8.6%)	233 (**83.5%**)	8 (2.9%)	14 (5.0%)	279 (100%)
BM3	35 (13.6%)	7 (2.7%)	209 (**81.0%**)	7 (2.7%)	258 (100%)
BM4	4 (1.6%)	34 (14%)	12 (4.9%)	193 (**79.4%**)	243 (100%)
Total	469 (36.9%)	327 (25.7%)	256 (20.1%)	219 (17.2%)	1271 (100%)
Simple matching	0.819				
Rand index (Adj.)	0.832 (0.578)				
Jaccard index	0.530				
Chi^2	2202.4***				

Notes: Count of bank-triennium observations per business model classification over pairs of consecutive trienniums. The total number of observations (1271) corresponds to the sum of banks in each of the first three trienniums (T1:376, T2:441, T3:495) minus the banks that exited the sample in the last three trienniums (T2:6, T3:13, T4:22). Values presented in brackets are a percentage of the row total. Simple matching is computed as the number of observations with the same classification divided by the total number of observations. Other similarity measures follow Milligan & Cooper (1986): the Rand Index is measured as the proportion of pairs labelled as true positive or true negative divided by the total number of pairs of observations (Rand, 1971); the Adjusted Rand Index corrects the original Rand Index for randomness (Hubert & Arabie, 1985); the multi-class mean Jaccard index is defined as the proportion of pairs labelled as true positives divided by the total number of pairs of observations excluding true negatives (Jaccard, 1901). Finally, we perform Pearson's Chi-Square independence test. *, ** and *** indicate the statistical significance at the 10%, 5% and 1% levels, respectively.

The identification of persistent banks per pair of consecutive trienniums is detailed in **Table 1.10**. Particularly, in the first three lines we identify the number of banks with the same business model classification in each pair of consecutive trienniums (T1 and T2, T2 and T3, T3 and T4). This step unveils the exact evolution of persistency across pairs of trienniums. The results indicate that the persistency of business model classifications remains stable throughout the sample period (T1 and T2: 82.4%, T2 and T3: 84.6%, T3 and T4: 79.1%). In general, our findings compare favourably with the persistency levels of business model classifications reported by Martín-Oliver *et al.* (2017), which range from 10.4% (lowest) to 85.7% (highest) for a sample of Spanish banks, using a single clustering method (hierarchical clustering) and comparing the periods 1999-2002 and 2003-07. We view this result as supporting the notion that the ensemble approach is less pliable to clustering stochasticity than using each method separately. Importantly, the results for the full sample period show that 63.6% of banks (n=321) are classified in the same business model in all trienniums. Finally, we observe that the distribution of persistent banks per business model is similar to the full sample (BM1: 41.7%, BM2: 19.3%, BM3: 19.3%, BM4: 19.6%).

Table 1.10. Persistent banks per business model and period

	N	Persistent	BM1	BM2	BM3	BM4
T1 and T2	370	305 (82.4%)	108	83	55	59
T2 and T3	428	362 (84.6%)	137	82	77	66
T3 and T4	473	374 (79.1%)	161	68	77	68
All trienniums (**persistent banks**)	505	321 (63.6%)	134	62	62	63
Core and persistent banks	505	211 (41.8%)	130	22	25	34

Notes: Number of banks with the same business model classification across consecutive trienniums. A persistent bank records the same business model in every triennium it is present in the sample. The full sample period is divided in four trienniums: 2005-07 (T1), 2008-10 (T2), 2011-13 (T3) and 2014-16 (T4). The clustering is obtained using the ensemble approach for each triennium separately. The sample size for each pair of consecutive trienniums is presented in the first column (N). Note that the number of banks considered in the fourth line ('All trienniums') is 505, rather than 524 (original full sample), because 19 banks are present in only one triennium in our sample and hence were excluded from the analysis of business model persistency. The percentage value presented in the column 'Persistent' for each period is calculated as the number of banks with the same business model classification divided by the sample size (N) for the period (e.g. T1 and T2 = 305/370=82.4%).

A possible concern regarding these results is whether the changes in business model made by the non-persistent banks reflect actual changes in business policy or, rather, reveal fragilities in our clustering approach to adequately capture the business models of banks. To address this concern, we analyse the number of business model changes per bank. The intuition behind this analysis is that one-off changes are more likely to reflect clear policy changes, whereas multiple changes indicate the presence of clustering stochasticity. **Table 1.11** shows that 79.3% of banks record one-off changes in the sample period (146 of 184 non-persistent banks), even though they are mostly present in 3 or 4 trienniums in our sample. Alternatively, when considering all the banks in the sample, the number of banks that change more than once is only 7.3%. In our view, these findings attest that the approach followed is able to capture actual business policy changes. Regarding the banks with multiple business model changes (n=38), these banks record high values of fuzziness (mean PCM1=0.41, PCM2=0.28, PCM1-PCM2=0.13, HHI=0.32, SW=0.06) which suggest that they are likely combining the 'recipes' of more than one business model. Another possible explanation for multiple business model changes may lie in the structural shifts that have occurred in the banking sector during our sample period (2005-16), including the global financial crisis, the sovereign debt crisis and the implementation of new regulatory requirements under the Basel III Accord with significant impacts on the business model choices of banks (e.g. Net Stable Funding Ratio, Liquidity Coverage Ratio, Leverage Ratio).

Table 1.11. Number of business model changes

	Total	**Nbr. of trienniums bank is present in the sample**			
		1	**2**	**3**	**4**
Total banks	524	19	80	84	341
Banks with no changes*	340	19	64	53	204
Banks with changes	184 (100%)		16	31	137
1 change	146 (79.3%)		16	26	104
2 changes	30 (16.3%)			5	25
3 changes	8 (4.3%)				8

Notes: 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 record two business model changes. * Note that the 'Total' obtained for the row '0 changes' (n=340) corresponds to the number of 'persistent banks' identified in **Table 1.10** (n=321) plus 19 banks which are present in only 1 triennium in our sample, and hence were excluded from the persistency analysis in **Table 1.10**.

Finally, we may be interested in investigating the distinctive features of non-persistent (relative to persistent) banks. In other words, which features significantly impact the likelihood of a bank changing its business model? To study this, we perform a logistic regression wherein the explained variable is a dummy which takes on the value 1 if the bank changes its business model in a given triennium. The explanatory variables are all the business model variables. In brief, the results presented in **Table 1.12** seem to suggest that the impact of some variables on the likelihood of a business policy change is significantly different across business models.

Table 1.12. Likelihood of non-persistency: logistic regressions

	BM1	**BM2**	**BM3**	**BM4**
Gross loans to customers	-0.02	-0.04**	0.07***	0.01
Trading assets	0.03	-0.14*	0.02	-0.01
Interbank lending	-0.02	-0.03	-0.06***	-0.04
Customer deposits	-0.12**	0.06**	0.03	0.05
Interbank borrowing	0.01	-0.04*	0.00	-0.06
Wholesale funding	0.09	-0.05**	0.04	0.00
Total derivatives	0.08	-0.10	0.08	0.02
Income diversification	0.02	0.02	0.00	0.04
Total assets	1.55**	-1.48***	0.47	-2.30***
Total equity	-0.27***	0.05	0.11	-0.05
Fuzziness	1.73	4.54***	2.41*	0.60
Bank-triennium obs. (non-persist.)	469 (63)	327 (94)	256 (47)	219 (26)
AIC	147.86	220.40	139.86	52.25
McFadden's Pseudo R^2	0.687	0.520	0.558	0.873

Notes: Values presented are the coefficient estimates of a pooled Bayesian logistic regression with fixed effects for the trienniums and post-change business model. Explained variable: for each bank-triennium observation we label as non-persistent (dummy = 1) if a change occurs in the business model in the next triennium and label as persistent (dummy=0) if the business model remains the same. Explanatory variables: business model variables, and 'business model fuzziness' given by 1 minus the difference of the top two percentage of cluster membership in t, i.e. 1 – (PCM1 – PCM2). Fixed effects included: triennium and business model recorded in t+1. Predictors with statistically significant positive values are positively correlated with the likelihood of a bank being non-persistent, whereas predictors with a statistically significant negative value are inversely related with such likelihood. McFadden's Pseudo R^2 = 1−[ln(LM)/ln(L0)] wherein ln(LM) is the log-likelihood of the fitted model and ln(L0) is the log-likelihood of the model with the intercept as the only predictor. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Namely, for retail focused banks (BM1) the likelihood of a business policy change increases significantly with size. In a way such result may seem counter intuitive, in the sense that large banks could be expected to be less mobile given the amount of resources invested in their activity. In other words, one could suspect that larger banks are subject to higher mobility barriers than their smaller peers (Caves & Porter, 1977). However, recall that, on average, BM1 banks are relatively small (mean total assets: 7.0, log) and, as such, an increase in size may represent an opportunity to have access to alternative sources of diversification and market funding with the goal, for instance, of reducing funding costs (Huang & Ratnovski, 2011) or signalling creditworthiness (Demirguc-Kunt & Huizinga, 2010). The signal and significance of the coefficient of size for BM1 banks, provides some support for the ‘size as opportunity’ rather than ‘size as barrier’ narrative. On the other hand, larger values of deposits and equity seem to deter retail banks away from changing their business model. Such barriers to mobility seem to reflect the fact that equity and customer deposits are often labelled as the most stable sources of bank funding – for the latter, this has become particularly true since the introduction of deposit guarantee schemes in the 1930s (Diamond & Dybvig, 1983; Rajan, 1992).

For retail diversified funding banks (BM2), which contrary to BM1 are, on average, among the largest in our sample, increases in size seem to reduce the likelihood of mobility – which is consistent with the ‘size as opportunity’ explanation presented above. Also, with the remaining business model variables held constant, both loans to customers and wholesale funding seem to impede mobility. On the other hand, BM2 banks with higher customer deposits are more likely to change their business model. In line with this, untabulated results indicate that the main destination of non-persistent BM2 banks is BM1 (53 in 94 BM shifts). This finding suggests that shifts from BM2 to BM1 do not occur in a short period of time, and require a smooth transition which is visible in the high values of customer deposits observed in the triennium that precedes the actual business model change – an observation that is consistent with the notion that retail banking requires investments in customer proximity which are likely to take some time to become productive (Berger *et al.*, 2005a). Importantly, note that this result is not driven by banks that operate with mixed business models, given that we control for the business model fuzziness (which as expected is positively correlated with non-persistency). In a similar vein, the majority of non-persistent banks following the retail diversified assets model (BM3) transit to BM1 (27 out of 47). By looking at the regression coefficients in **Table 1.12** we observe that the propensity to change business model in BM3 banks increases for banks with larger lending portfolios. Again, in line with the explanation put forward for BM2 non-persistent banks, we view this finding as supporting the idea that prior to shifting to the retail focused model, banks are required to invest in retail specific technology that takes some time to yield results. Finally, the only significant feature of non-persistent banks with a large diversified business model (BM4) is their smaller size – which seems to support the notion that the possibility of attaining significant economies of scale in transactional banking is likely driving the long-term persistency of large diversified banks (Van Ewijk & Arnold, 2014).

1.9. Robustness checks

1.9.1. Different sub-samples

A possible concern regarding our clustering approach may be whether the business model classifications (ensemble, core, persistent) hold after imposing disturbances to the baseline sample. In order to test this, we start by drawing 100 random sub-samples without replacement, imposing a 1% disturbance on the baseline sample ($d_1 = 1\%$). In other words, each sub-sample comprises 99% of the total observations in the baseline sample, i.e. n=519. Then, we run our business model classification approach on each sub-sample and test the similarity of classifications (ensemble, core, persistent) relative to the classifications obtained for the baseline sample. We use four similarity measures: simple matching, Rand index, Adjusted Rand index and Jaccard index. Results are reported as the mean similarity across sub-samples. Finally, we repeat this procedure using different sub-sample sizes, namely comprising 95% and 90% of total observations in the baseline sample, d_2 and d_3 respectively (with the same number of random sub-samples each, i.e. 100).

Table 1.13 shows that, when imposing a 1% disturbance on the baseline sample (upper panel), the ensemble classification remains virtually unchanged (SM = 0.988, RI = 0.987, ARI=0.967, JI=0.956). Similar results are found when focusing on the identification of core and persistent banks, although at relatively lower levels (e.g., RI = 0.955 and 0.897, respectively). In the same line, the vast majority of business model classifications perform well when imposing 5% and 10% disturbances on the baseline sample (middle and lower panels). In particular, the RI ranges from 0.807 to 0.966 for all types of classification (ensemble, core, persistent). As expected, as the disturbances become larger, the similarity of classifications with the baseline sample reduce for all measures (e.g. Gates, *et al.*, 2019). This result suggests that, although the approach handles small disturbances well, practitioners should strive to use a stable sample in a scenario where business model analysis is performed in a time-varying setting (e.g. monitoring the evolution of performance and riskiness of banks per business model over time).

Table 1.13. Stability of business model classification for different sub-samples

	Simple matching	Rand index	Adj. Rand index	Jaccard index
d_1=1% (n=519)				
Ensemble classification	0.988	0.987	0.967	0.956
Core vs non-core	0.975	0.955	0.909	0.922
Persistent vs non-persistent	0.945	0.897	0.794	0.823
d_2=5% (n=498)				
Ensemble classification	0.967	0.966	0.915	0.888
Core vs non-core	0.938	0.892	0.783	0.821
Persistent vs non-persistent	0.912	0.840	0.679	0.735
d_3=10% (n=472)				
Ensemble classification	0.914	0.954	0.886	0.853
Core vs non-core	0.954	0.860	0.720	0.774
Persistent vs non-persistent	0.891	0.807	0.614	0.689

Notes: We test the stability of our classification approach using three sets of 100 random sub-samples drawn from the baseline sample without replacement. Each set has a different sub-sample size: 99% of the baseline sample (d_1, n=519), 95% (d_2, n=498) and 90% (d_3, n=472).We report the mean value of each measure obtained for the three sets of samples. Simple matching is computed as the number of observations with the same classification divided by the total number of observations. Remaining similarity measures are described in detail in Milligan & Cooper (1986), namely: the Rand Index is measured as the proportion of pairs labelled as true positive or true negative divided by the total number of pairs of observations (Rand, 1971); the Adjusted Rand Index corrects the original Rand Index for randomness (Hubert & Arabie, 1985); the multi-class mean Jaccard index is defined as the proportion of pairs labelled as true positives divided by the total number of pairs of observations excluding true negatives (Jaccard, 1901).

1.9.2. Different clustering methods

Another potential source of concern may lie in the choice of methods included in the ensemble. In order to test whether the combination of methods significantly impacts the classification results, we remove one of the original methods at a time (PAM, SOM, FCM) replacing it with one of two alternative methods discussed in literature related with banking business models and strategic groups (Zúñiga-Vicente & Vicente-Lorente, 2006; Martín-Oliver *et al.*, 2017; Mergaerts & Vennet, 2016): Hierarchical Clustering (HC) and Model Based Clustering (MBC). This produces the following six alternative combinations of methods: HC/SOM/FCM, PAM/HC/FCM, PAM/SOM/HC, MBC/SOM/FCM, PAM/MBC/FCM, and PAM/SOM/MBC.

The (untabulated) results show that, on average, 91.4% of the observations retain the same classification using the alternative and the original combinations of methods (max. similarity: 98.3%, MBC/SOM/FCM; min. similarity: 87.4%, PAM/SOM/MBC). This finding suggests that the clustering results are not significantly dependent on the choice of methods. Importantly, there are fundamental reasons for why we use the original combination of methods (PAM/SOM/FCM). Firstly, the combination has been used in extant literature (Alam *et al.*, 2000; Budayan et al., 2011). Secondly, the classification obtained with PAM is not prone to outliers and yields a deterministic solution. Thirdly, the FCM method yields information on the best and second-best cluster assignments per bank, a result which is a central input in the fuzziness analysis. And, finally, SOM yields particularly informative graphical representations for banking business model analysis as presented in **Figure 1.1**.

On the other hand, the choice of methods may also impact the identification of core banks. To test whether this is the case, we run a similar experiment to the one presented above, i.e. we remove one of the original methods at a time (PAM, SOM, FCM) and replace it with HC and MBC, iteratively. The results show that 92.3% of the banks are labelled in the same category (core or non-core) using the alternative and the original combinations of methods (max. similarity: 95.6%, MBC/SOM/FCM; min. similarity: 89.1%, PAM/SOM/HC). Similarly, we test the impact of using the different combinations of methods on the identification of persistent banks. On average, 82.2% of banks are labelled in the same category (persistent or non-persistent) when compared to our original ensemble (max.: 89.7%, MBC/SOM/FCM; min.: 76.0%, PAM/SOM/MBC). Both findings may be interpreted as an indication that the identification of core and persistent banks is not significantly impacted by the choice of methods.

1.9.3. Clustering with the original variables

Next, we assess whether the approach is insensitive to the decision regarding the use of original variables versus retained principal components. To do this, we run our clustering ensemble approach using the original variables, rather than the retained components, as inputs, and check (i) the similarity of classifications and (ii) the business model composition.

Regarding (i), the untabulated results indicate that 85.5% of the observations are labelled in the same business model using the original variables and the retained components. Regarding (ii), the composition of business models using the original variables seems relatively similar to the one which results from using the retained components as inputs (**Table 1.6**). Namely:

- **BM1** (*retail focused*): loans to customers (65.4%), customer deposits (68.9%);
- **BM2** (*retail div. funding*): loans to customers (71.5%), wholesale funding (24.0%);
- **BM3:** (*retail div. assets*): interbank lending (35.8%), customer deposits (58.6%);
- **BM4** (*large diversified*): trading assets (8.7%), derivatives (15.6%), income diversification (51.6, HHI) and total assets (7.9, log).

Both results (classification similarity and composition) seem to suggest that, in fact, our approach is not entirely insensitive to the choice of inputs (retained components versus original variables). For this reason, we have explained with particular care the decision to use the retained components as inputs in the clustering process (*vide* **Section 1.6.3**).

1.9.4. Business model interpretation after core and persistency treatments

An additional concern we may face is whether using the treated samples leads to a loss of interpretation of the business models or, rather, contributes to an increased clarity of interpretation. To answer this concern we examine whether the mean values of core and persistent banks (C&P) are significantly different from the mean values of other banks (i.e. non-core, non-persistent, or both) per business model, and assess whether the sign of the changes increases (or reduces) model interpretability. The results are reported in **Table 1.14**. When we compare the mean value of C&P versus other banks, we find statistically significant differences across the main variables of each business model. Namely:

- **BM1** (*retail focused*): loans to customers (+4.5 pp), customer deposits (+12.3 pp);
- **BM2** (*retail div. funding*): loans to customers (+4.2 pp), wholesale funding (+19.8 pp);
- **BM3** (*retail div. assets*): interbank lending (+24.3 pp), customer deposits (+11.5 pp);
- **BM4** (*large diversified*): trading assets (+5.1 pp), derivatives (+14.4 pp), income diversification (+6.5, HHI), total assets (+0.4, log).

Table 1.14. Composition of business models per sub-sample

	BM1			BM2			BM3			BM4		
	C&P	**Other**	**Diff.**	**C&P**	**Other**	**Diff.**	**C&P**	**Other**	**Diff.**	**C&P**	**Other**	**Diff.**
Number of banks	130	73		22	102		25	84		34	54	
Gross loans to customers	70.0	65.4	4.5**	71.1	66.9	4.2	26.8	38.2	-11.4***	32.8	44.7	-11.9***
Trading assets	1.3	2.7	-1.3***	1.3	2.1	-0.8	0.5	2.4	-1.9*	**14.5**	**9.5**	**5.1*** **
Interbank lending	8.3	7.9	0.4	6.4	9.5	-3.1**	**56.2**	**32.0**	**24.3*** **	18.0	15.9	2.1
Customer deposits	**71.7**	**59.4**	**12.3*** **	27.6	39.7	-12.1***	67.3	55.8	11.5**	**24.5**	**32.3**	**-7.8** **
Interbank borrowing	**9.7**	**14.8**	**-5.1*** **	17.8	22.3	-4.5	22.5	25.1	-2.7	21.7	18.1	3.6
Wholesale funding	5.8	9.7	-3.8***	**41.8**	**22.0**	**19.8*** **	2.6	5.1	-2.5	16.5	23.1	-6.5*
Total derivatives	1.2	1.8	-0.6**	3.5	3.9	-0.3	0.5	1.1	-0.6	**29.2**	**14.7**	**14.4*** **
Income diversification	46.8	47.9	-1.1	35.4	44.9	-9.5***	49.4	45.7	3.7	**59.1**	**52.6**	**6.5*** **
Total assets	6.9	7.1	-0.1***	7.4	7.5	-0.1	6.9	7.0	-0.1	**8.4**	**7.9**	**0.4*** **
Total equity	8.7	9.2	-0.5	4.2	6.4	-2.2***	5.5	7.1	-1.6*	4.0	6.0	-2***

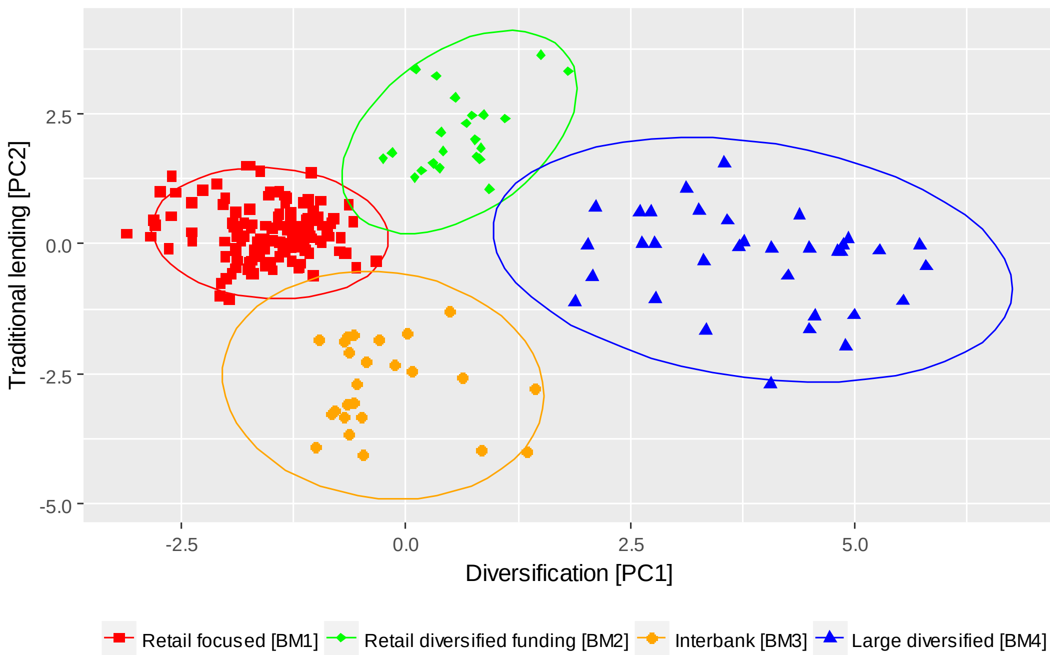
Notes: Mean values, except number of banks (count). Classification obtained via clustering ensemble using PC1 to PC5 as input variables. For each variable and business model, we compute the Tuckey HSD test for comparison of means between the two sub-samples: core and persistent banks (C&P) and other banks (Other). *, ** and *** indicate the statistical significance of the difference of each pairwise comparison at the 10%, 5% and 1% levels, respectively. This table is similar to **Table 1.5** (full sample) but decomposed into two sub-samples, thus both tables are comparable. Values in **bold** indicate the variables, per business model, identified both as (i) statistically different across sub-samples (p-value<5%) and (ii) the highest or lowest across business models. All variables computed as percentage of total assets, except income diversification (HHI) and total assets (log).

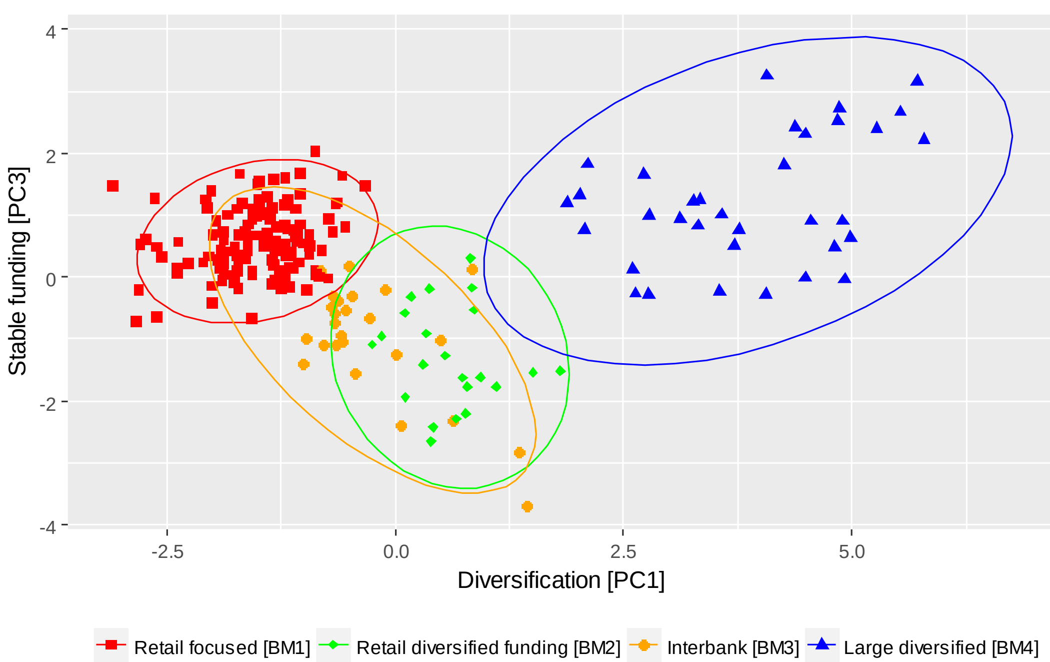
Importantly, the difference between the mean value of C&P and other banks is positive for the variables in which the business model records the highest value compared to other models (*vide* **Table 1.6**). This implies that the differences between business models become accentuated in the C&P sample, apparently conforming more closely to distinctive organizational configurations. **Figure 1.2** shows the graphical representation of the data points labelled as C&P using three of the five retained principal components (PC1, PC2 and PC3), representing a total variation explained of 61.0%. In general, the graphical inspection provides further evidence of a clear separation between models and homogeneity within each model. These results, in our view, sustain the usefulness of using core and persistent banks as a method to increase the robustness of business models analysis.

1.9.5. Out-of-sample examples of banks per business model

In our final check, we assess whether our approach allows the identification of business models for out-of-sample banks. To perform this analysis, we take exemplary banks and re-run our procedure to identify banking business models. More precisely, we begin by adding 25 US and Japanese global banks included in the study by Roengpitya *et al.* (2017) to our original sample (n=549=524+25) and selecting the optimal number of clusters based on the valuation criteria of each clustering method (FCM, SOM, PAM). Untabulated results indicate that the original findings reported in **Table 1.5** (that lead us to identify four business models) remain virtually unchanged. Next, we check whether the composition of business models suffered any significant changes. Using Tuckey HSD tests to compare the mean values for each business model variable between the original sample (n=524) and the new sample (n=549), we were unable to reject the null hypothesis of equality of means – which, again, lends support to the stability of our initial composition. Finally, we report the business model classification of the 'new' banks (for brevity reasons we only report the classification of the US banks):

Figure 1.2. Business model representation





Notes: Sample, 'core and persistent banks'(n=211: BM1 = 130, BM2=22, BM3=25, BM4=34). BM classification obtained from clustering ensemble. For parsimony we plot the top three principal components which explain 61.0% of total variation, as described in **Table 1.3**.

BM1 (*retail focused*)

- Bank of America: gross loans to customers (52.0%), customer deposits (71.1%);
- BB&T: gross loans to customers (66.0%), customer deposits (69.1%);
- Capital One Financial: gross loans to customers (66.0%), customer deposits (63.3%);
- Comerica: gross loans to customers (73.2%), customer deposits (76.6%);
- PNC Financial Serv.: gross loans to customers (58.2%), customer deposits (67.5%);
- SunTrust Banks: gross loans to customers (71.4%), customer deposits (71.3%).

BM2 (*retail diversified funding*)

- Wells Fargo & Comp.: gross loans to customers (62.4%), wholesale funding (15.0%);

BM3 (*retail diversified assets*)

- Bank of New York Mellon: interbank lending (36.9%), customer deposits (66.2%);
- Deutsche Bank Trust Corp.: interbank lending (76.9%), customer deposits (54.2%);
- Northern Trust Corp.: interbank lending (31.2%), customer deposits (78.2%);
- State Street Corp.: interbank lending (29.7%), customer deposits (68.7%);

BM4 (*large diversified*)

- Goldman Sachs: trading assets (30.7%), derivatives (12.7%), income diversification (59.1, HHI), total assets (8.8, log);
- JPMorgan Chase Bank: trading assets (13.9%), derivatives (8.5%), income diversification (68.3, HHI), total assets (9.1, log);
- Morgan Stanley: trading assets (27.5%), derivatives (9.6%), income diversification (53.1, HHI), total assets (8.8, log).

We note that despite the out-of-sample banks only comprising large global banks and size being one of the business model variables used in the clustering process, we are still able to identify at least one bank per banking business model. In our view, such result seems to suggest that our proposed approach is extensible to geographies beyond Europe and, hence, may be actionable for policy and managerial purposes.

1.10. Conclusions

In this paper we propose a clustering ensemble approach to distinguish banks in terms of (i) their long-term similarity with other banks operating with the same business model (core vs non-core) and (ii) their persistency over time (persistent vs non-persistent). In order to frame this approach, we provide a definition of business model which follows the fuzzy approach to strategic groups theory (Reger & Huff, 1993; DeSarbo & Grewal, 2008). The methods included in our ensemble are chosen based on their different strengths, including their ability to perform fuzzy clustering (Fuzzy C-Means), to yield intuitive visualizations of the clusters (Self-Organizing Maps) and to circumvent the presence of data outliers (Partitioning Around Medoid). The consensus reached among the methods that form the ensemble is based on a majority rule which allows us to have an increased level of confidence regarding the accuracy of the classification attributed to the banks that meet the criterion.

We find four business models in the European banking industry (2005-16): retail focused, retail diversified funding, retail diversified assets and large diversified. The banks labelled as core exhibit a significantly higher adherence to their assigned business model (lower fuzziness) than non-core banks. Moreover, the tests for stability of classification show that the ensemble classification is practically immune to disturbances to the sample, the choice of methods and the choice of variables. Also, we detect significant differences in the mean values of the key dimensions of each business model when using the sample of core and persistent banks when compared to the remaining banks. Importantly, in the sample of core and persistent banks the differences between business models become clearer (i.e., more accentuated) when compared to the differences observed among the remaining banks. Finally, we provide evidence that expanding our approach to include banks in the US and Japan yield meaningful results.

Based on our findings, we envision two areas of interest for future research: first, the use of the concepts of core and persistent banks to study topics such as bank performance, riskiness and systemic risk. Namely, by narrowing the analysis of bank performance to a sample of banks which are consistently classified under the same business model, researchers may expect to have a better handle on undesired sources of heterogeneity or endogeneity (e.g., shift in strategic orientation), and hence enjoy a cleaner testing environment to grasp the long-term effects of business models. A second area of interest is related with the study of the effects of business model changes by non-persistent banks on bank performance and riskiness.

CHAPTER 2.

The profitability and distance to distress of European banks: does the business model matter?

2.1 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)? Is it expected that such choices 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?

Our paper addresses these questions by drawing on two conceptual frameworks (strategic groups theory and agency theory) as well as previous studies that apply the notion of business model to explain bank profitability and distance to distress. For instance, Ayadi *et al.* (2015) find that banks operating with retail business models (i.e. with high values of customer deposits and loans to customers) outperformed banks operating with other business models. Hryckiewicz & Kozłowski (2017), on the other hand, find that banks operating with an investment model (i.e., with high values of securities and low customer deposits) contribute more to systemic risk. On the other hand, Köhler (2015) shows that income diversification increases distance to distress for retail-oriented banks and decreases for investment-oriented banks. Similarly, Mergaerts & Vennet (2016) provide a detailed account of the heterogeneity effects of a variety of business choices. For instance, the authors find that loans to customers positively affect the distance to distress only for banks with high retail orientation. Moreover, evidence provided in the Liikanen Report (2012) suggests that the failure of the Royal Bank of Scotland during the global financial crisis may be linked to business model changes that occurred in the years that preceded the crisis, namely related with the bank's funding strategy.

This paper aims to contribute to this strand in several ways. Firstly, we grasp the effects of business model choices on profitability and distance to distress by taking into account three types of business model variables: individual features (e.g., Köhler, 2015), bank orientation (e.g., Mergaerts & Vennet, 2016) and business model classification (e.g., Hryckiewicz & Kozłowski, 2017). 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 in **Chapter 1** to identify discrete banking business models, that 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 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 model decisions on bank profitability and distance to distress by coupling two previously unreconciled methods: rolling regressions with bank orientation as the mediating variable (Mergaerts & Vennet, 2016) and OLS regressions on sub-samples of banking business models (Köhler, 2015). Providing further insight into the heterogeneity of business model effects 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.* (2018) 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. Particularly, 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.* (2018) in two meaningful ways. Firstly, the authors match all banks in the sample (first stage) and analyze the pooled business model changes (second stage); whereas we only match banks with the same *a priori* business models and analyze business model changes within each pair of source-destination business model. The relevance of our approach is backed by our findings, that 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 year to the next, as implicitly assumed by Ayadi *et al.* (2018), 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 model 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 three IVs: proximity to financial centers, Lerner index and non-rural area (dummy); 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 literature.

Our results suggest that the strategies followed by European banks may be mapped using two *continuum* bank orientations (relationship and transactional banking) and four discrete business models (retail focused, retail diversified funding, retail diversified assets, large diversified). 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 model features on profitability and distance to distress. Namely, only banks with high orientation towards relationship banking tend to benefit (i) from income diversification in terms of distance to distress and (ii) from trading assets and derivatives in terms of profitability, (iii) 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 to a better performing business model pays-off in the medium term – hence, lending some support to the adaptation view of management (Child, 1972) and the implementation of forward-looking supervision (BIS, 2018). Our baseline results remain generally unchanged to the robustness checks using IV and GMM regressions.

The paper is structured as follows. **Section 2.2** provides a brief overview of literature on the link between banking business models, profitability and distance to distress. **Section 2.3** presents the methodology. The dataset, variables and descriptive statistics are exposed in **Section 2.4**. **Section 2.5** presents and discusses the results. Robustness checks regarding endogeneity and persistency concerns are performed in **Section 2.6**, before concluding in **Section 2.7**.

2.2. Strategic groups theory, agency theory and banking business models

We frame our analysis using two conceptual frameworks: 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 across 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) (Porter, 1979). In this paper we follow the approach proposed by Mergaerts & Vennet (2016) and equate the term business model to that of strategic group and identify business models based 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.

Moreover, each of the abovementioned business model choices is poised to bear implications in terms of the agency problems typically faced by banks[7] (Diamond, 1984). Particularly, the choices related with the asset and funding structures are likely to affect in several ways the relations between the bank and its stakeholders, both in 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,

[7] Consider two commonly referred bank agency relations: debtholders-bank and bank-borrowers. Regarding the former, the debtholders (including depositors) act as principals by trusting their funds to the bank (agent) that 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).

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 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.*, 2005b). Finally, two well established results in 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 show 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, such 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.

Next, we turn to the empirical literature, where we find an abundant set of works testing the impact of each business model choice on bank profitability and riskiness while holding the remaining choices constant (under the standard OLS assumption). For instance, asset and funding structures (Demirgüç-Kunt & Huizinga, 2010), diversification (Stiroh &

Rumble, 2006), size (Altunbas *et al.*, 2011) and capital (Beltratti & Stulz, 2012). This paper relates to a smaller and more recent strand of studies that has looked specifically into testing the effects of simultaneously determined business model choices provide additional insights into the study of bank profitability and riskiness. Using a large sample of European banks, Ayadi *et al.* (2015) find that banks operating with retail business models (i.e. with high values of customer deposits and loans to customers) tend to record higher ROE and Z-score than other models. 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). Similarly, De Haan & Kakes (2019) 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. Finally, Mergaerts & Vennet (2016) find that long-term retail orientation increases bank profitability and distance to distress.

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 features (Demirgüç-Kunt & Huizinga, 2010), factor analysis (Mergaerts & 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, analyzing the impact of individual features allows us to identify which specific choices are driving the overall results; using dimensionality reduction techniques provides us with valuable visual inspection of the business model choices; and clustering analysis may allow us to perform peer group analysis. In this paper we adopt an agnostic perspective on this methodological issue, and investigate the relationship between business models, profitability and distance to distress using three business model proxies, as described below.

2.3. Methodology

2.3.1. Identification of bank orientation and business models

The method used to identify bank orientation and business models follows the approach developed in **Chapter 1**, which may be summarized in the following way. Firstly, we perform principal components analysis on a selection of business model variables related with the assets and funding structures, diversification, size and capital. This step allows us to (i) identify the bank orientation, i.e. "the choice of relationship-based versus transactional banking" (Degryse & Ongena, 2007: p.399), by retaining the top two components and (ii) 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 model 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. Given the absence of an established taxonomy of discrete banking business models, the use of an ensemble of clustering methods (rather than a single method) is expected to increase the accuracy of the assignment of banks to business models relative to their *true*, unobserved, classification (Kuncheva, 2004).

2.3.2. Impact of business models choices on bank profitability and distance to distress

We begin our analysis by testing the equality of business model choices 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 business model proxies (individual features, 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 models. 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. However, 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:

$$Y_i = \alpha + \boldsymbol{\gamma} BM_i + \boldsymbol{\beta} X_i + \delta Country + \varepsilon_i \tag{2.1}$$

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; BM_i is the mean vector of business model choices recorded by bank i (individual business model features, bank orientation, business model classification); X_{i} is the mean vector of bank-level controls; $Country$ is a vector of dummies identifying the country where the banks' headquarters are located; γ, β, δ are the regression coefficients' vectors; and $\varepsilon_{\mathrm{i,t}}$ is the disturbance term.

2.3.3. Heterogeneous effects of business models 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 of banks, we draw on two testing strategies. First, we perform rolling regressions using the main bank orientation as the mediating variable (Mergaerts & Vennet, 2016). The idea is that, if heterogeneity exists, we may expect the coefficients of the individual business model features 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.

2.3.4. 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.*, 2018). 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.*, 2018). 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 year triennium $t-1$ for bank i:

$$p(X_{i,t-1}) = Pr(\,T_{i,t} = 1 \mid X_{i,t-1}) \tag{2.2}$$

Wherein $T_{i,t}$ is a dummy that states bank i changed business model in triennium i[8]; 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

[8] 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 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 3.3.1**. In this context, we label as business model change a pair of consecutive bank-triennium observations that are assigned to different business models.

matching estimator is chosen that sets the way 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:

$$\tau = E\left(\Delta Y_{i,t}^{1} \,\middle|\, T_{i,t} = 1, p\left(X_{i,t-1}\right)\right) - E\left(\Delta Y_{i,t}^{0} \,\middle|\, T_{i,t} = 0, p\left(X_{i,t-1}\right)\right) \tag{2.3}$$

Where the first component is estimated using the average value of the evolution of profitability of banks that change business model in triennium t; and the second component is estimated using the average value of the evolution of profitability of the matched banks. Moreover, we extend our baseline test to include the evolution of profitability with one and two triennium lags, given that we suspect that the effects of a structural change in business model are likely to exhibit a dynamic pattern.

2.4. Data

2.4.1. Sample selection

Our sample includes 524 European banks, both listed and non-listed, from 2005 to 2016. We collect year-end consolidated data from Bankscope and Orbis Bank Focus. The following criteria are applied: headquarters in 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.

2.4.2. Selection of variables

2.4.2.1. Performance and riskiness variables

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

$$ROAA_{i,t} = \frac{\left(NII_{i,t} + NNII_{i,t} - OE_{i,t} - TIC_{i,t}\right)}{\left[\left(TA_{i,t} + TA_{i,t-1}\right)/2\right]} \tag{2.4}$$

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:

$$Z_{i,t} = \left(\frac{TE_{i,t}}{\left[\left(TA_{i,t} + TA_{i,t-1}\right)/2\right]} + ROAA_{i,t}\right)/SDROAA_i \tag{2.5}$$

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.

2.4.2.2. Business model variables

In this section we identify the set of variables that we use as proxies for banking business models. 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 2.1**.

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, 2013).

Liability structure. The ratio of *customer deposits to total assets* reflects the dependence of banks on the most traditional source of funding, also tipically 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 bank's ability to diversify into fee-based financial services such as bancassurance, investment advice and credit card services (Elsas *et al.*, 2010) which may enable it to improve the screening and monitoring of customers due to access to additional information as well as to diversify risks (Diamond, 1984).

Size. The (log) value of *total assets* may be an important indicator of banking business models in the sense that different banking activities seem to bear different potential for economies of scale (DeYoung, 2000). 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 are 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).

Leverage. The ratio of accounting *equity to total assets* is also expected to vary with the choice of other business model variables, for a variety of reasons. For instance, large banks seem to benefit from too-big-to-fail 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 buybacks and dividends to shareholders (Easterbrook, 1984), hence resulting in higher bank leverage.

Table 2.1. 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 and 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 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

(cont.)

Table 2.1. Variables description (cont.)

	Description	Unit
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)
Acquiror	Dummy 1 if bank is identified as the acquiror entity in M&A operation in EU28.	Dummy
Target	Dummy 1 if bank is identified as the target entity in M&A operation in EU28.	Dummy
Vendor	Dummy 1 if bank is identified as the vendor entity in M&A operation in EU28.	Dummy
State Aid	Dummy 1 if bank is identified as having received state aid between 2005 and 2006 (namely, capital injection, guarantee, asset relief or loan of government bonds).	Dummy
Fuzziness	Difference between the top two membership scores of each bank, obtained by applying Fuzzy C-Means to the business model features.	PCM
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 2.4 of **Section 2.6.1**).	Index (0-100)
Non-urban	Dummy 1 if bank's headquarter is located in a city that belongs to a region (NUT3) where more than 15% of the population live in a rural local administrative units (LAU), as defined by the EU's rural-urban typology.	Dummy

Notes: Financial statement data was obtained from the Bankscope and Orbis databases; M&A data was obtained from Zephyr; State Aid data was collected from the list of State Aid cases issued by the European Commission's DG Competition; stock market data was obtained via Datastream; and the Urban-Rural typology of each city was drawn from Eurostat.

2.4.2.3. Bank controls

According to 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. The risk culture of banks has been seen as a persistent determinant of performance, particularly during financial crises (Fahlenbrach *et al.*, 2012). To try and capture this effect we use two proxies. The first is *excess loans*, which takes on the value 1 if the bank's average growth of gross loans over the full period is greater than 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 proclicality of loan loss provisions may impact loan mispricing (Bouvatier & Lepetit, 2012) and credit rationing (Jiménez *et al.,* 2017).

Management quality. We obtain an estimate of the management quality by computing the *cost-to-income*, which translates the banks' ability to transform inputs (operational costs) into outputs (operational revenues). This measure has the virtue of allowing 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 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 iliquid 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 under consideration the ownership structure of banks using two dummies. The first one is related with the identification of *stakeholder* banks, in particular cooperative and savings banks. 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 their 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).

2.4.3. Descriptive statistics

The descriptive statistics are presented in **Table 2.2**. We start our analysis by checking the mean values of ROA 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 2.1**, 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).

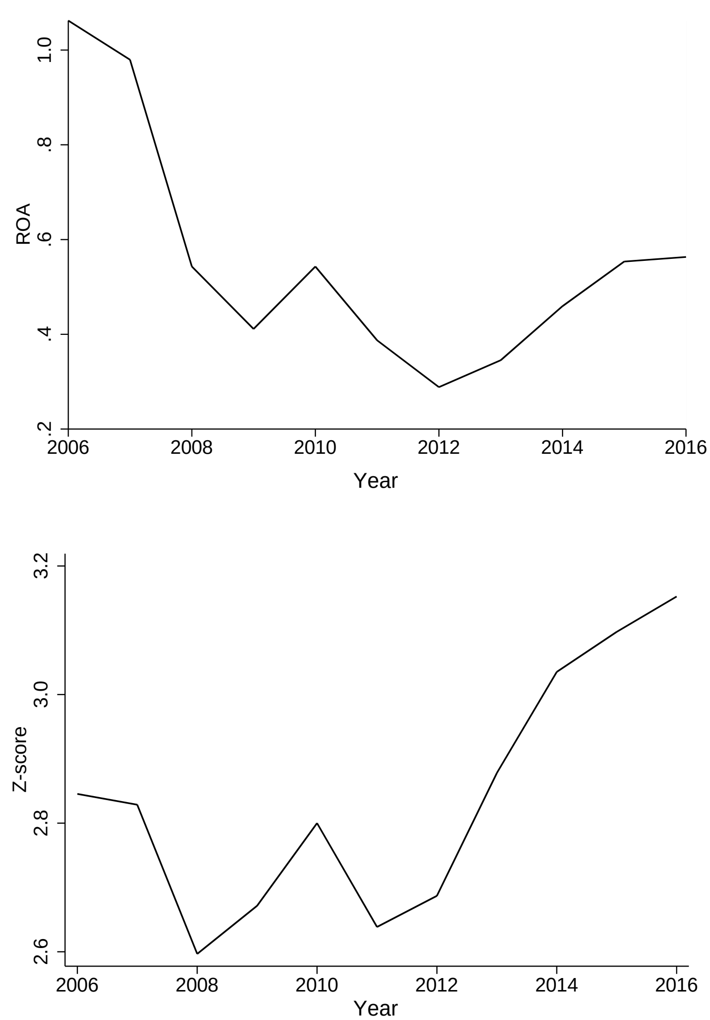
Table 2.2. Descriptive statistics

	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 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.

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. 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 model features exhibit larger between standard deviation than within, which supports the notion that business model features tend to show long-term stability.

Figure 2.1. Evolution of bank profitability and distance to distress



Notes: Mean values per year.

2.5. Results and discussion

2.5.1. Identification of bank orientation and business models

Our first results are related with the identification of bank orientation using principal component analysis. In **Table 2.3**, column (1), the composition of the first retained component (BO1) indicates the presence of large positive loadings by gross loans to customers, customer deposits and total equity, and negative loadings by bank size. Banks that couple high values of gross loans to customers and customer deposits have often been equated to relationship lending, due to their superior ability to provide inter-temporal smoothing of interest rates (Berlin & Mitchell, 1999). For this reason, we label the first component as 'relationship banking'. Regarding the second principal component (BO2), one may observe positive loadings by the variables gross loans to customers, wholesale funding and total assets. Such business strategy is likely to be popular among banks that are focused on providing transactional lending and services, given that hard-information based activities tend to be more scalable than those depending on soft-information (DeYoung & Rice, 2004). In this sense, we label such bank orientation as 'transactional banking'.

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 (Caliński-Harabasz 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 (Roengpitya *et al.*, 2017; Ayadi *et al.*, 2015; Martín-Oliver *et al.*, 2017).

Table 2.3. Identification of bank orientation using principal component analysis

	Relationship banking (BO1)	**Transactional banking (BO2)**
Raw loadings		
Gross loans to customers	0.49	0.72
Interbank lending	-0.57	-0.75
Trading assets		
Customer deposits	0.75	-0.21
Interbank borrowing	-0.30	-0.25
Wholesale funding	-0.44	0.63
Total derivatives	-0.78	
Income diversification	-0.28	-0.27
Total assets	-0.67	0.34
Total equity	0.37	
Variation explained		
Sum of squared loadings	1.64	1.36
Variation explained (VE)	0.27	0.18
Cumulative VE	0.27	0.45

Notes: The results are obtained using the full period average of each input variable for all banks (n=524). We report the raw loadings above the absolute value of 0.2.

The composition and popularity of each business model is presented in **Table 2.4**. 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, and for this reason is described as *retail focused*; **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*.

Table 2.4. 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 (BO1)	1.3 (0.6)$^{+++}$	-0.3 (0.7)$^{+++}$	0.2 (1.0)$^{+++}$	-2.8 (1.2)$^{+++}$
Transactional banking (BO2)	0.2 (0.6)$^{++}$	1.2 (1.0)$^{+++}$	-1.8 (1.0)$^{+++}$	0.0 (1.3)$^{++}$
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 top five principal components for the full period. 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).

2.5.2. Impact of business model choices on bank profitability and distance to distress

2.5.2.1. Individual business model features

Asset structure. Table 2.5 shows that, on average, top performers exhibit significantly lower gross loans to customers than bottom performers. 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 2.5. Top vs bottom profitability: differences in individual business model features

	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 (BO1)	0.54	-0.39	0.93***
Transactional banking (BO2)	-0.55	0.32	-0.88***

Notes: Columns (1) and (2) show the mean values of banks that are 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.

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 steams 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 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 literature, we complement our baseline results with business model specific regressions in **Section 2.5.3**.

Liability structure. The results in **Table 2.5** show that top performing banks rely more on customer deposits than bottom banks do. The regression results in **Table 2.6** 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 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 obtaining in terms of operating expenses. In line with other studies (e.g. Mergaerts & 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 2.5 shows that top performers tend to make less use of derivatives than bottom banks. On the contrary, the regression results in **Table 2.6** 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

Table 2.6. Impact of business model 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 features												
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 (BO1)	0.076***	0.120***	-0.092***	0.166***	0.069***	-0.018**	-0.015	0.062***	0.064***	-0.023**	0.100***	0.738***
Transactional banking (BO2)	-0.077***	0.349***	0.263***	0.037	-0.169***	-0.033***	-0.036*	-0.056***	-0.075***	0.043**	-0.049	-0.704***
Number of observations	524	477	523	524	523	498	510	521	524	469	524	524
R-squared	0.546	0.496	0.338	0.678	0.300	0.270	0.167	0.436	0.450	0.832	0.357	0.357
Adjusted R-squared	0.513	0.456	0.290	0.655	0.250	0.215	0.105	0.396	0.411	0.819	0.311	0.311
	(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.

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 model features.

Regarding income diversification, the mean values are virtually the same for top and bottom performing banks (**Table 2.5**). In the same line, the regressions in **Table 2.6** show that income diversification does not significantly impact ROA or Z-score. Namely, the positive effect beared 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 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 2.5**). In line with this, **Table 2.6** shows that size is negatively associated with ROA and 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 Z-score. These findings are in line with 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 2.5** indicate that top performing banks are significantly better capitalized than bottom banks. Moreover, the OLS estimates in **Table 2.6** 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 (Athanasoglu *et al.*, 2008).

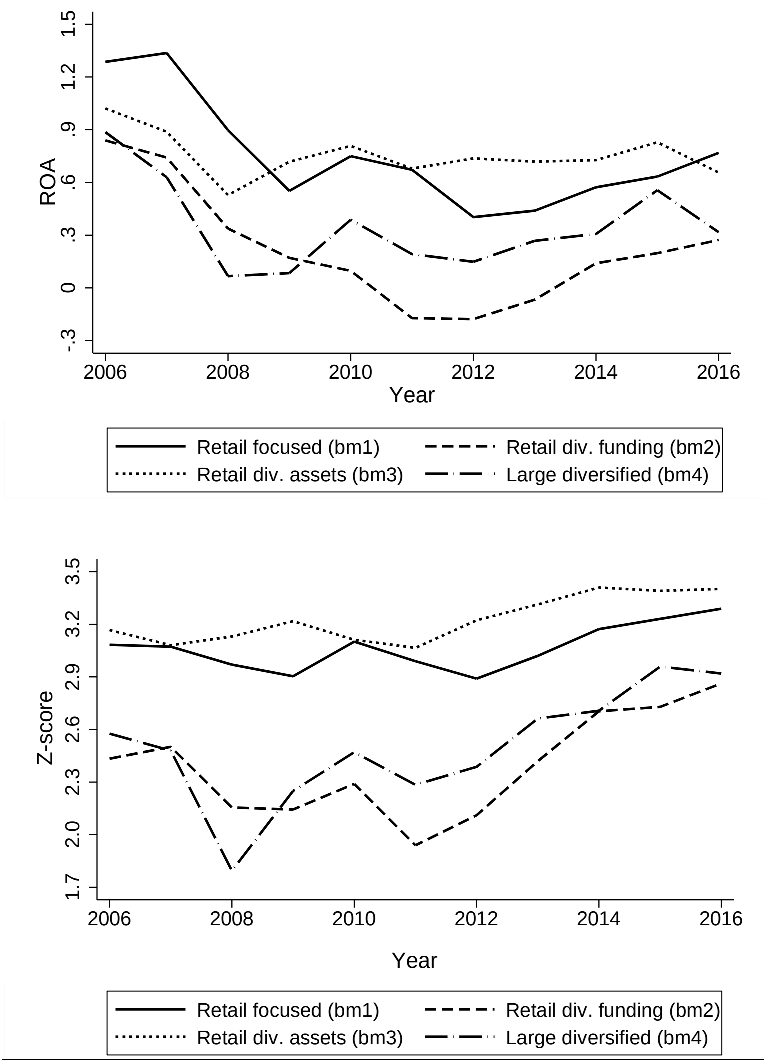
2.5.2.2. Impact of bank orientation on bank profitability and distance to distress

Table 2.5 shows that top performing banks are more oriented to relationship banking and less oriented to transactional banking than bottom banks. Similarly, the coefficients presented in panel B of **Table 2.6** suggest that a long-term orientation towards relationship banking increases ROA and Z-score, whereas the opposite effect is found for transactional banking. Particularly, relationship banking positively affects the ability of banks to generate net interest income and net fees income, as well as to record less impairment charges – which more than offset the higher operating costs and loss of trading income. Also, such banks tend to be better capitalized. As for transactional banking, the negative results seem to be driven by higher interest expenses, higher impairment charges and lower equity. Such combination of effects suggest that a significant share of banks may be adopting a transactional banking orientation as part of a "gamble for resurrection" strategy. Namely, as suggested by Kane (1989) managers of distressed banks may have the incentive to follow risky growth strategies in an attempt to resurrect their bank. If true, such phenomena highlight the importance of running IV regressions – as we do in **Section 2.6.1**. In general, our findings are in line with those reported by Ewijk & Arnold (2014).

2.5.2.3. Impact of business models on bank profitability and distance to distress

The results in **Table 2.4** 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 2.6**, 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 2.2**, which shows the evolution of profitability and distance to distress per business model over the sample period.

Figure 2.2. Evolution of bank profitability and distance to distress per business model



Notes: Mean values per year and business model classification.

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 Z-score (0.621/2.84= 21.9%). The regressions using the sub-components of ROA and 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 caputre fee income – much in line with the results obtained for transactional banking. 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 less effective 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.

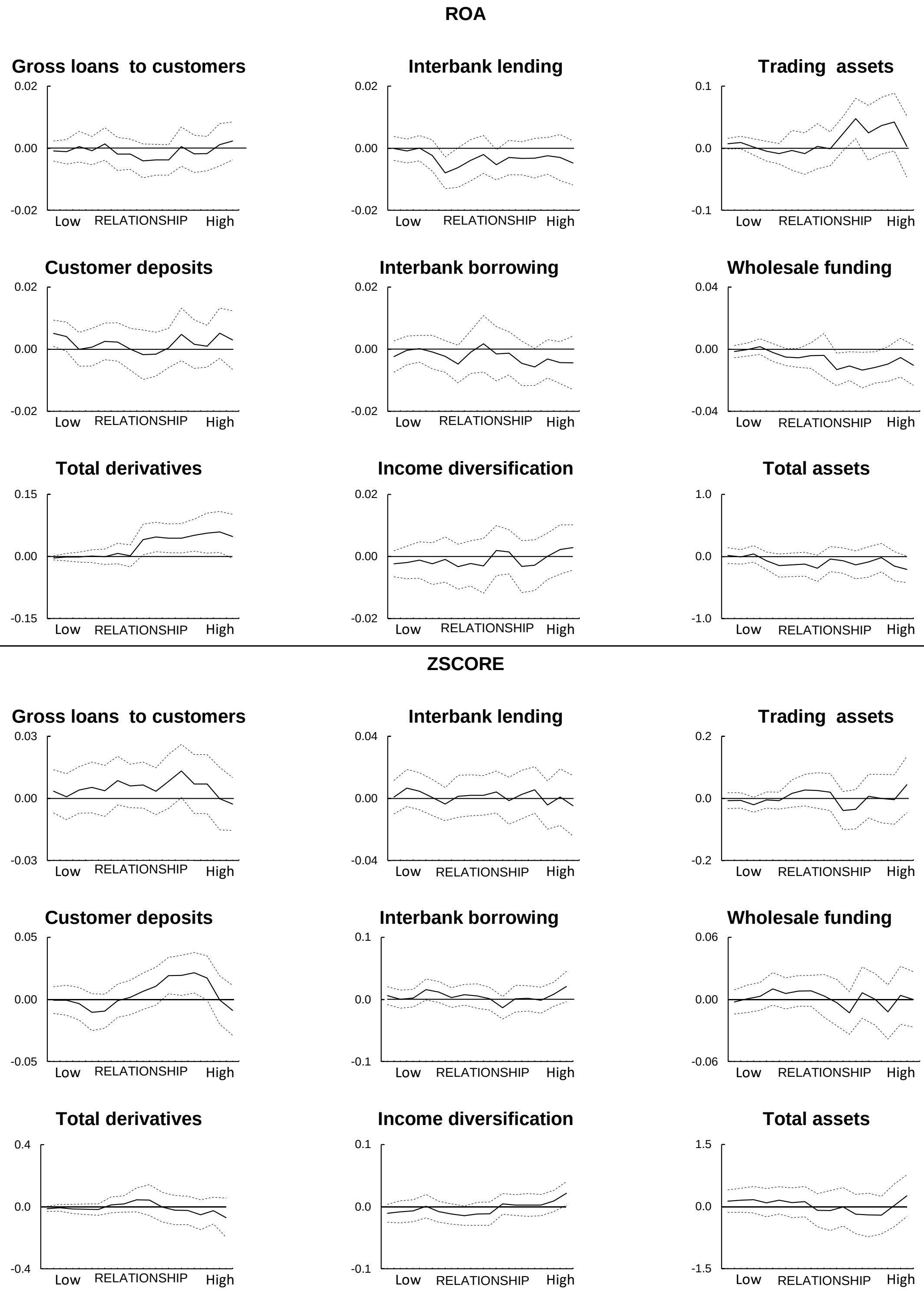
2.5.3. Heterogeneous effects of business models on profitability and distance to distress

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

Regarding trading assets, the rolling regressions in **Figure 2.3** show that the impact on ROA is positive and significant only for banks with a relatively high relationship banking orientation. Such result finds support in the sample split regressions (**Table 2.7**) 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 2.3**). Similarly, the impact of customer deposits on ROA is only positive and significant for large diversified banks (BM4) (**Table 2.7**). As previously commented, results in **Table 2.6** suggest that such 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.

Figure 2.3. Heterogeneity: individual features on profitability and distance to distress



Notes: Rolling regressions using the first retained component (Relationship banking, BO1) as the mediating variable. OLS regressions on 15 sub-samples, 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.

Interestingly, the regressions in **Figure 2.3** suggest that the impact of derivatives on ROA is positive and significant only for banks with a high relationship banking orientation. Also, only retail focused banks (BM1) enjoy a positive relation between derivatives and ROA

Table 2.7. Heterogeneity analysis: individual features, profitability and distance to distress

	All	**BM1**	**BM2**	**BM3**	**BM4**
	(1)	(2)	(3)	(4)	(5)
Panel A: ROA					
Gross loans to customers	-0.001	-0.001	0.005	0.003	-0.001
Interbank lending[a]	-0.003^{**}	0.002	-0.002	-0.004	-0.002
Trading assets[a]	0.000	0.033^{**}_{++}	0.021_{+}	-0.023^{***}_{+++}	0.004_{++}
Customer deposits	0.005^{***}	0.004	0.002_{+}	0.004^{*}_{+}	0.010^{***}_{++}
Interbank borrowing[a]	-0.003^{*}	-0.012^{***}_{+}	0.002_{+++}	-0.006^{***}_{+}	-0.007^{*}_{+}
Wholesale funding[a]	-0.007^{***}	-0.002	-0.000	-0.002	-0.005
Total derivatives	0.004^{*}	0.049^{***}_{+++}	-0.011_{+}	0.008_{+}	-0.002_{+}
Income diversification	0.003	0.011^{**}_{+}	0.007^{*}	0.003	-0.000_{+}
Total assets	-0.118^{***}	-0.199^{**}_{+}	-0.111	-0.040	0.018_{+}
Total equity	0.042^{***}	0.016_{++}	0.041^{**}_{+}	0.049^{***}_{++}	0.090^{***}_{+++}
Number of observations	524	203	124	109	88
R-squared	0.608	0.722	0.520	0.706	0.748
Ajusted R-squared	0.576	0.659	0.385	0.618	0.646
	(6)	(7)	(8)	(9)	(10)
Panel B: Z-score					
Gross loans to customers	0.004	-0.001	0.000	0.004	0.002
Interbank lending[a]	-0.006^{*}	0.020_{+}	0.012	-0.012^{*}_{+}	0.003
Trading assets[a]	-0.013	0.004	0.032	-0.022	-0.010
Customer deposits	-0.001	-0.004	-0.020^{**}_{++}	-0.012^{*}_{+}	0.009_{+}
Interbank borrowing[a]	0.002	0.003	0.013_{+}	0.011	-0.021_{+}
Wholesale funding[a]	-0.007^{**}	0.002	0.014_{+}	0.010_{+}	-0.014_{++}
Total derivatives	0.001	-0.001	-0.005	-0.014	0.004
Income diversification	0.006	0.026^{***}_{+}	0.006_{+}	0.007	0.019
Total assets	-0.231^{**}	-0.192_{+}	0.437_{++}	0.165	-0.216_{+}
Number of observations	524	203	124	109	88
R-squared	0.355	0.597	0.489	0.355	0.582
Adjusted R-squared	0.304	0.510	0.352	0.171	0.423

Notes: Values presented are the coefficient estimates using cross-section OLS regression with bank controls and country fixed effects. 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 2.7**). In our view, both findings are in line with the notion that retail focused banks that contracted interest rate swaps during our sample period (2005-16) are more likely to have successfully mitigated the negative toll that the decline in market interest rates has taken in the ability of banks to generate interest income.

Income diversification, on the other hand, is only positively associated with a higher Z-score at very high values of relationship banking orientation (**Figure 2.1**). Similarly, the positive coefficient of income diversification on Z-score is only statistically significant for retail focused banks (BM1) (**Table 2.7**). 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 retail oriented. These findings may also suggest that, for retail banks an increase in diversification equates mostly to the benign-side of diversification, namely via the provision of basic fee-based services such as account maintenance, safe deposit boxes, and transfers (DeYoung & Torna, 2013).

Finally, we find that the impact of size on ROA is negative only for banks with a very high level of relationship banking (**Figure 2.3**). In a similar vein, only retail focused banks record a negative and significant impact of size on ROA (**Table 2.7**). 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).

2.5.4. Impact of changing business model on bank profitability

The results in **Table 2.8** show that mobility rates vary considerably depending on the source and destination business models, suggesting that some business models may have higher mobility barriers than others. For instance, banks operating under BM4, which tend to be larger than banks with other business models (**Table 2.4**), 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. According to Roengpitya *et al*. (2017: p.17) 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".

Table 2.8. 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).

Bearing this in mind, next we explore the determinants of business model changes (**Table 2.9**). For brevity reasons, we focus on changes from BM2 to BM1 and BM2 to BM4. We find that banks operating with BM2 are more likely to change to BM1 after receiving state aid or divesting. This result is in line with the notion that state aid is often conditional on the approval of a restructuring plan to restore the bank's long-term viability that, in many cases, envisions divestments[9]. Additionally, stakeholder banks are more likely to change from BM2 to BM1, suggesting the return to the traditional way of doing banking that is commonly associated with non-shareholder banks (Cuevas & Fischer, 2006). Moreover, we observe that the likelihood of changing from BM2 to BM4 is positively affected by the Lerner index and size. This finding suggests that BM2 banks with high market power or larger size are in a better position to invest in the specialized resources (human and technological) necessary to operate under the BM4.

[9] For instance, in the context of the state aid measures received by the Österreichische Volksbanken (case: SA.31883), the bank had to significantly reduce the size and complexity of its operations. According to Ayadi *et al.* (2015: p.79): "The bank had to reduce its balance sheet and the complexity of its business model. (...) cease its real estate activities and parts of its corporate financing and investment portfolios (...)."

Finally, the results in **Table 2.10** show that the effects of changing business model on ROA vary depending on the source and destination business models, as well as the time frames considered. Despite the comprehensiveness of our results, we narrow our discussion

Table 2.9. Determinants of business model changes

	BM1 to BM2	**BM1 to BM3**	**BM1 to BM4**	**BM2 to BM1**	**BM2 to BM3**	**BM2 to BM4**
Lerner index	-0.484	-1.210*	-1.390	-1.357*	-0.480	3.037**
Total assets	0.839	-1.175**	0.711	-0.822**	0.127	1.513***
Total equity	-0.123**	-0.061*	0.036	0.031	-0.224	0.002
Net stable funding ratio	-0.005	0.020**	-0.023	0.021**	-0.029	-0.007
Listed	0.685	-1.020	0.328	0.349		-0.146
Stakeholder	-0.157	-0.307	-0.291	0.825**		-0.496
Acquiror	1.033*			0.090	1.367	-0.351
Target	0.867			1.234		
Vendor		1.774		1.066*		0.245
State aid		2.407*		1.553*		
Fuzziness	7.106***	6.955***	2.383	6.624***	10.197*	2.905*
Nbr. of observations (changes)	456(24)	407(35)	398(4)	327(53)	193(7)	306(34)
Likelihood ratio (chi-square test)	35.2***	44.5***	7.6	45.5***	11.9	35.8***
Pseudo R-squared	0.187	0.186	0.17	0.157	0.198	0.168
	BM3 to BM1	**BM3 to BM2**	**BM3 to BM4**	**BM4 to BM1**	**BM4 to BM2**	**BM4 to BM3**
Lerner index	2.490*	-1.290	0.336	-0.237	-0.330	-1.710
Total assets	0.356	0.754	3.685***	-6.347*	-0.454	-1.707*
Total equity	0.041	-0.156	0.073	-0.271	-0.211	-0.034
Net stable funding ratio	-0.002	-0.015	-0.034**	0.024	-0.009	0.029
Listed	1.612***		2.046	0.358	-0.503	
Stakeholder	1.257**		2.035*			
Acquiror	1.080			0.652	0.173	
Target				3.606	2.012**	
Vendor				6.609	1.001	
State aid						
Fuzziness	3.667**	22.694**	9.677***	3.360	6.325***	3.649
Nbr. of observations (changes)	247(27)	114(8)	236(12)	125(5)	184(14)	101(7)
Likelihood ratio (chi-square test)	31.8***	21.3***	40.2***	17.8*	21.1**	14.0*
Pseudo R-squared	0.186	0.368	0.424	0.423	0.213	0.276

Notes: The values reported are the coefficients of logit regressions with triennium fixed effects. 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.

to the changes that occur from the worst performing business model (BM2) to other business models. We find no significant differences in the short-run (i.e. in the triennium that follows the business model change). However, when considering the evolution of the same banks over the two trienniums after the change, the banks that change from BM2 to either of the other business models (BM1, BM3 or BM4) record a significant improvement in profitability relative to their old peers. The interpretation of such results need to be taken with care given the substantial decline in the number of banks that remain in each sub-sample per time frame.

Table 2.10. Impact of changing business model on profitability: propensity score matching

		ATET	**Treated**	**Controls**
BM1 to BM2	ROA_{t-1} - ROA_t	-0.109	24	247
	ROA_t - ROA_{t+1}	-0.403	13	77
	ROA_{t+1} - ROA_{t+2}	-0.757**	9	39
BM1 to BM3	ROA_{t-1} - ROA_t	0.304*	32	309
	ROA_t - ROA_{t+1}	0.288	21	170
	ROA_{t+1} - ROA_{t+2}	0.136	12	54
BM1 to BM4	ROA_{t-1} - ROA_t	-0.299	4	192
	ROA_t - ROA_{t+1}	-0.051	4	184
BM2 to BM1	ROA_{t-1} - ROA_t	-0.243	53	256
	ROA_t - ROA_{t+1}	0.722***	33	154
	ROA_{t+1} - ROA_{t+2}	0.517**	11	41
BM2 to BM3	ROA_{t-1} - ROA_t	-0.162	6	56
	ROA_t - ROA_{t+1}	-0.152	5	32
	ROA_{t+1} - ROA_{t+2}	0.782**	3	7
BM2 to BM4	ROA_{t-1} - ROA_t	0.087	34	201
	ROA_t - ROA_{t+1}	0.440***	10	106
	ROA_{t+1} - ROA_{t+2}	0.534**	5	37
BM3 to BM1	ROA_{t-1} - ROA_t	0.345**	25	182
	ROA_t - ROA_{t+1}	0.460**	12	45
	ROA_{t+1} - ROA_{t+2}	0.930***	9	33
BM3 to BM2	ROA_{t-1} - ROA_t	-0.361	6	32
	ROA_t - ROA_{t+1}	-0.107	3	14
BM3 to BM4	ROA_{t-1} - ROA_t	-0.149	10	94
	ROA_t - ROA_{t+1}	-0.314	2	40
BM4 to BM1	ROA_{t-1} - ROA_t	0.473	4	12
	ROA_t - ROA_{t+1}	1.266***	2	2
BM4 to BM2	ROA_{t-1} - ROA_t	-0.346	11	138
	ROA_t - ROA_{t+1}	0.127	8	66
BM4 to BM3	ROA_{t-1} - ROA_t	0.161	6	28

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.

A possible explanation for our findings is that changing business model requires banks to incur in significant investments in new resources that take their time to yield the expected returns. Additionally, such results may be interpreted as evidence supporting an 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)[10].

2.6. Robustness checks

2.6.1. 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 bank orientation and the level of profitability and distance to distress (Clougherty *et al*., 2016). We address this issue by employing 2SLS using three IV's 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 may be made, however, that the choice of headquarters' location may be, in itself, a function of the proximity of strategic resources. Nonetheless, while to be best of our knowledge there is no work that studies the costs of changing headquarters, anecdotical 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 a

[10] 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).

satisfactory instrument. In order to compute the *proximity to financial center* (PFC_i) we draw on gravitational models literature (Garrett *et al.*, 2005) and use the following specification:

$$PFC_{\boldsymbol{i}} = \frac{1}{T} \times \sum_{t=1}^{T} \sum_{s=1}^{S} \frac{MV_{s,t}}{\left(1 + Dist_{i,s}\right)} \tag{2.6}$$

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 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, 2012). Finally, PFC_i is divided by the maximum value of PFC in the sample and multipled 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, 1956). 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:

$$Lerner_i = \frac{P_i - MC_i}{P_i} \tag{2.7}$$

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 final instrument identifies whether the banks' headquarters are located in a *non-urban area.* We hypothesize that banks located in non-urban areas are more likely to pursue relationship banking, under the assumption that the creditworthiness of borrowers located in such areas is more likely to be assessed using soft information than borrowers located in urban areas. This is in line with the historical evidence collected by Guinnane (2001), suggesting that the success of German rural credit cooperatives may be attributed to their superior ability to process borrowers' private information. We use a dummy variable that identifies whether the bank's headquarter is located in a city that belongs to a region (NUT3) where more than 15% of the population live in a rural local administrative units (LAU), as defined by Eurostat.

The results in **Table 2.11** 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 regressions, we find that the proximity to financial centers decreases both types of bank orientation, but the magnitude of the effect is significantly greater for relationship banking than for transactional banking, as given by the results of a Chow test for the equality of coefficients[11]. Also, our results indicate that banks with lower competition and located in non-urban regions are more likely to pursue relationship banking.

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 Z-score, whereas a negative impact of transactional banking is found for both measures. However, the magnitude of the coefficients are materially different from those obtained in the baseline model, which supports the emerging role of endogeneity mitigation strategies in performance-related studies (Clougherty *et al*., 2016).

[11] A possible explanation for the negative association between proximity to financial center and transactional banking is the fact that transactional banks are likely to face competition from capital market operators which help firms access market debt financing and may be expected to be located in financial centers.

Table 2.11. Endogeneity in the choice of bank orientation: IV regressions

	First stage regressions		Second stage regressions	
	Relationship banking	**Transactional banking**	**ROA**	**Z-score**
	(1)	(2)	(3)	(4)
Instrumental variables				
Proximity to financial center	-0.021***	-0.011***		
Lerner index	1.361*	-1.653***		
Non-urban area	0.533***	0.103		
Instrumented variables				
Relationship banking (BO1)			0.347***	0.243**
Transactional banking (BO2)			-0.887***	-0.465**
Number of observations	524	524	524	524
R-squared	0.365	0.348		
F-test of instruments (p-value)	0.000	0.000		
Stock-Yogo's min. eigenvalue	9.417			
Wald Chi-square test (p-value)			0.000	0.000
Sargan test overid. (p-value)			0.254	0.571

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).

2.6.2. 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 business model proxies: individual features 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).

Table 2.12. Persistency of profitability and distance to distress: System GMM

	ROA	**Z-score**
Panel A: Individual features		
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 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)	0.448***	0.479***
Relationship banking (BO1)	0.266*	0.528*
Transactional banking (BO2)	-0.027	0.558
Number of observations	3993	4517
Number of instruments	21	21
Wald Chi-square test (statistic)	280.1	53.08
Hansen test (p-value)	0.557	0.981
A-B test for AR(1) (p-value)	0.107	0.462
A-B test for AR(2) (p-value)	0.701	0.365

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.

The results in **Table 2.12** 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 coefficient for the lagged dependent variables are positive and statistically significant for all regressions. Regarding the effect of individual business model choices on ROA and Z-score (panel A), we find that the main baseline results remain unchanged, except for size (which becomes statistically insignificant). Such 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 2.12** show that the effect of relationship banking on ROA and Z-score remains positive and significant, while transactional banking becomes non-significant for both measures. The fact that the lagged dependent variables are capturing the effect of transactional banking on ROA and Z-score suggests that the orientation towards transactional banking may be more stable than the orientation towards relationship banking. This result is sustained when comparing the standard deviations of both types of bank orientation for the full sample period (BO1=1.63, BO2=1.32). A explanation for these results emerges from the evidence collected in Panel A. Namely, it is possible that the effects of certain key features of transactional banking (e.g., size) are being captured by the lagged dependent variable because they, too, show significant persistency over time.

2.7. Conclusions and policy implications

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 with size, asset and funding structures, diversification and capital, i.e. their business model. This paper has aimed to contribute to literature on the elusive relationship between business model choices and performance in several ways: (i) by testing a variety of proxies that account for the multidimensional nature of bank business models, (ii) by combining a set of econometric methods to explore the heterogeneity of business model effects, (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 line, 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 model features 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 (i) income diversification in terms of distance to distress and (ii) trading assets and derivatives in terms of profitability, (iii) 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 with size. Additionally, by comparing banks that change business model *vis-à-vis* their old peers, we uncover that on average changing to a better performing business model seems to pay-off 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).

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 heterogeneity of business model effects, 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, under which bank supervisors are expected to anticipate the challenges faced by bank management and promote effective change (BIS, 2018).

CHAPTER 3.

Linking the diversity of business models to the resilience of the banking sector

3.1 Introduction

This paper speaks to the ongoing debate regarding the effects of diversification and diversity on the resilience of the banking sector. In particular, with portfolio selection theory as a key theoretical reference (Markowitz, 1952), it is generally well accepted in literature that banks may be able to reduce total idiosyncratic risk for a given expected level of returns by combining assets from different risk classes in the same portfolio. However, the compound effects of such individual diversification strategies at the aggregate level seem to be less prone to consensus.

On one hand, some authors argue that diversification may be seen as a potential source of distress because as bank holdings expand to different sectors of activity (e.g. real estate) they become less willing to extend loans to firms facing challenges in similar sectors (Wagner, 2008); also, there are a set of other phenomena, such as asset commonality (Allen *et al.*, 2012), collusion (Schaeck *et al.*, 2009) and implicit state guarantee (Acharya & Yorulmazer, 2007) which document the idea that systemic risk in the banking sector may increase as banks become more alike. In line with these findings, some authors have suggested that bank regulators should create incentives for banks to pursue *diverse* diversification strategies (Beale *et al*., 2011), for instance by monitoring the correlation of returns among banks (Goodhart & Wagner, 2012). On the other hand, however, it is also argued that nudging banks to choose *diverse* diversification strategies may push them away from individually optimal risk portfolios, which in turn may increase the likelihood of individual failures and bank contagion, wherein the latter is more likely to occur if failed banks have a larger footprint (Kobayaishi, 2012).

Against this backdrop, empirical findings may prove to be particularly instrumental in helping disentangle the current ‘diversity-diversification’ debate. However, only a reduced number of empirical works has yet to tackle the relationship between diversity and resilience, and those that have done so are mainly focused on measuring diversity from an ownership perspective. For instance, Ayadi *et al.* (2010) find evidence of a positive impact of institutional diversity on the regional growth of seven European countries, wherein the former is measured as the ratio of stakeholder banks' assets to regional GDP. More recently, Baum *et al.* (2020) uncover a positive association between domestic institutional diversity and stability, by measuring diversity as the dispersion of total assets held by banks of different ownership types (commercial, cooperative, savings). The authors also document that more diverse banking systems tend to show smoother earnings during periods of crisis. Finally, Hryckiewicz & Kozłowski (2017) provide evidence that countries where the dominant business model (i.e. the model that represents the highest share of total assets) is the investment model endured a steeper fall of GDP during the 2007-09 crisis, when compared to other countries.

In this paper, we contribute to this strand of literature in several ways. Firstly, we employ a measure of diversity which analytically resembles the approach laid out by Baum *et al.* (2020), in the sense that we also take insights from ecology literature, but we additionally broaden the scope of information by considering different types of business models, rather than ownership types. This methodological decision puts us closer to the approach taken by Hryckiewicz & Kozłowski (2017), although we expand the authors' original range of business model dimensions by including also size, diversification and capital (besides asset and funding structures, as done by the authors). The relevance of measuring business model diversity may be seen in light of the increased interest taken by banking regulators and supervisors regarding the analysis of risks and vulnerabilities that are specific to each type of business model (e.g. EBA, 2014). In order to capture the notion of banking business model we apply a relatively novel clustering approach proposed in **Chapter 1** that 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 just one) is expected to increase the accuracy of the assignment of banks across business models relative to their *true*, unobserved, classification.

Secondly, in our model we explicitly consider the likely interactions of business model diversity with diversification and market power. This is quite relevant given that recent literature has suggested that (i) diversity may be affected by diversification, as diversified banks tend become more similar among each other (Wagner, 2008, 2009, 2010a, 2011; Beale et al., 2011; Goodhart & Wagner, 2012); (ii) diversity may impact resilience directly by reducing the likelihood of joint failures (Acharya & Yorulmazer, 2007; Beale et al., 2011; Haldane & May, 2011; Wagner, 2011); and (iii) diversity may affect market power by deteriorating collusion or enabling strategic interdependence (Porter, 1979). By modelling these relationships explicitly via 3SLS we are able to control endogeneity concerns as well as shed light on the direct and indirect mechanisms via which diversity may affect resilience.

Thirdly, this paper introduces the topic of business model diversity in the longstanding debate regarding the financial stability of market and bank-based systems. This is done by exploring the differences in the relationship between diversity and resilience per type of financial system. The relevance of this contribution seems sustained by the fact that we find consistent differences in the impact of diversity on resilience per type of financial system when adopting alternative methodological approaches (3SLS, rolling regressions, efficient portfolio analysis). In our view such findings provide confidence regarding the importance of diversity in explaining financial stability. We discuss several possible explanations for our findings.

Our fourth and final contribution is to provide an empirical framework to monitor the optimal portfolios of banking business models. This is done by leaning on standard portfolio selection methods, including the computation of a modified Sharpe Ratio (Sharpe, 1966), which accounts for the key elements of Z-score: internal funding and correlations of returns. This contribution answers recent calls by literature (e.g. Goodhart & Wagner, 2012) for macroprudential supervision to monitor the correlation of returns among key market players, for its potential role as an early warning tool of systemic risk in the banking sector.

The main results of the paper may be summarized in the following way. Firstly, using the full sample of 33 countries between 2005 and 2016, we find a positive and significant relationship between business model diversity and resilience. This result is robust to alternative methods (mean comparison, 3SLS, static GMM, dynamic GMM) and proxies for resilience (Z-score, V-lab's systemic risk, regulatory capital ratio, likelihood of systemic bank crisis) and diversity (Shannon diversity, Simpson diversity, Shannon evenness). Secondly, we find evidence of the heterogenous effects of diversity on resilience depending on the type of financial system. Namely, diversity is seen to positively affect the resilience of countries with market-based systems, whereas no significant relationship is found for bank-based systems. This result is robust to alternative methods. In light of the literature review, we interpret such findings as suggesting that the trade-off between the diversity-induced benefits (namely the reduced contagion due to the segregation of market beliefs regarding banks with different business models) and costs (particularly the loss of specialization gains from operating with a single, dominant business model) only pays-off for market-based systems. Our final results indicate that the diversity and business model composition of optimal portfolios are significantly different in market and bank-based structures. Namely, the optimal portfolio of market-based systems is quite diverse and comprised of BM1 (53%), BM2 (35%) and BM3 (12%); whereas the optimal portfolio of bank-based systems is mainly focused on BM1 (87%). Under portfolio selection theory, the result we obtain (i.e. the same level of diversity induces different responses in terms of resilience according to the type of financial system) may be analytically understood under the specific mix of rankings of internal funding, standard deviation and correlation of the banking business models – in other words, it depends on the ecosystem of each financial system.

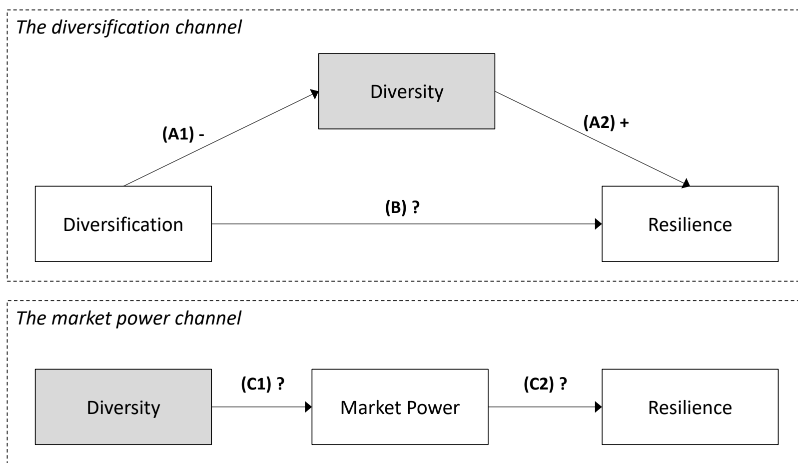
The remaining paper is structured as follows. In **Section 3.2** we provide an overview of literature regarding diversity, resilience and the role of financial systems. In **Section 3.3**, we present the methodologies adopted throughout the study. **Section 3.4** briefly presents the data, as well as the identified banking business models. The results and discussion are shown in **Section 3.5**, before concluding in **Section 3.6**.

3.2. Literature review

3.2.1. The relationship between bank diversity, diversification and resilience

Recent studies have suggested that the link between diversity and resilience may be studied in light of two relatively well covered channels in banking literature: diversification and market power (Baum *et al.*, 2020). As mapped in **Figure 3.1**, the 'diversification-resilience' channel may be seen as comprising two types of effects: an indirect effect (A), whereby diversification is expected to influence diversity (A1) which, in turn, should impact resilience (A2); and a direct effect (B).

Figure 3.1. 'Diversification-resilience' and 'market power-resilience' channels: an overview



Notes: The relationships mapped in this figure steam from the literature review. The codes attributed to each relationship (A1, A2, B, C1, C2) are identified in the main text. The expected sign of each relationship is identified whenever literature offers a clear prediction.

To provide some intuition, consider the following distinction between diversification and diversity. Following literature (e.g. Stiroh, 2004; DeYoung & Torna, 2013), the notion of diversification is typically associated with revenue diversification and is linked to the scope of activities performed within the bank. The notion of diversity, on the other hand, is better viewed at the aggregate level, and corresponds to the variety of bank types or 'species' or, in the case of this paper, business models. In a market with two banks that are both perfectly diversified, there is only one bank type and hence diversity is very low.

Regarding the link between diversification and diversity (A1), a strand of literature has suggested that as banks diversify into new business lines they tend to become more alike, and hence lead to the reduction of diversity in a given banking system (Wagner, 2008, 2009, 2010a, 2011; Beale *et al.*, 2011, Goodhart & Wagner, 2012). According to Wagner (2008) this phenomena may be attributed to two main drivers: (i) deregulation, which allowed banks, particularly in the US[12], to widen the scope of activities; and (ii) financial innovation, for instance via the growth of the derivatives markets, which significantly impacted the ability of banks to share risks with other institutions, hence becoming more similar among themselves. Also, Beale *et al.* (2011) indicate the narrow focus of regulators on individual (rather than systemic) risk as a driver of bank diversification, particularly among large banking conglomerates. Importantly, although all cited works are emphatic (and unanimous) in describing the expected negative relationship between diversification and diversity, to the best of our knowledge no study has yet provided empirical evidence in this regard.

As for the second leg of the indirect effect (A2), literature suggests that the increased bank-level homogeneity that results from the adoption of uniform diversification strategies is expected to increase the likelihood of joint bank failures (Acharya & Yorulmazer, 2007; Beale *et al.*, 2011; Haldane & May, 2011; Wagner, 2011). In particular, according to these works, a banking system that is comprised of banks sharing the same risks is more likely to face contagion whenever a systemic event occurs, such as a large drop in asset market prices or a sudden shortage of liquidity. Hence, according to this strand, policymakers may reduce the likelihood of systemic crises by generating the incentives (e.g. lower capital requirements) for banks to adopt diverse diversification strategies (Beale *et al.*, 2011). This rationale leads us to expect that a positive relationship may be found between the diversity of banking business models and system-wide resilience.

Finally, diversification is also expected to impact resilience directly (B). For instance, one may envision that banks that successfully tap into different revenue streams may, on average, record results that are more stable than their non-diversified peers, assuming that

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[12] An often cited example of bank deregulation in the US is the repeal of the Glass-Steagall Act in 1999. The 'deregulation' driver of diversification is less likely to have had an impact in Europe given the long-standing tradition of universal banking in this region.

the revenue streams are negatively correlated among themselves. In such cases, the aggregate riskiness of a banking sector would, in fact, tend to decrease as banks diversified their asset portfolios. However, literature seems to suggest that seemingly uncorrelated assets may become highly correlated under systemic distress, and especially so trading assets (Jiménez & Mencía, 2009). Also, moving outside the core business lines may significantly increase bank riskiness due to increased moral hazard (Boyd *et al.*, 1998) and lack of expertise and experience (Stiroh, 2004; Goddard *et al.*, 2008). The reasonable plausibility of both intuitions presented above suggests that literature is inconclusive regarding the expected sign of the direct relationship between diversification and resilience. This is backed by the lack of a general consensus in empirical literature regarding the effects of diversification on banking system resilience (e.g. DeYoung & Roland, 2001; Stiroh, 2004; Laeven & Levine, 2007; Mercieca *et al.*, 2007; Blundell-Wignall & Roulet, 2013) – which draws our attention towards providing additional empirical evidence on the relationship between diversification and resilience.

As for the 'market power-resilience' channel, **Figure 3.1** shows that it may be depicted as comprising a single indirect effect (C), wherein diversity is expected to influence market power (C1) which, in turn, is foreseen to impact resilience (C2). In order to grasp the expected relationship between diversity and market power (C1), we draw on Strategic Groups Theory (SGT) (Porter, 1979). According to SGT, banks are likely to make decisions regarding a common set of strategic dimensions (e.g. type of activities, funding sources, diversification, size), which may lead to the formation of groups of banks operating under the same strategic guidelines. In this paper we follow Mergaerts & Vennet (2016) and equate the term 'strategic group' to that of 'business model'. We review SGT and find two opposing mechanisms that may help us shed light on the relationship between diversity and market power.

The first mechanism is related with the occurrence of *collusive agreements*. In particular, the existence of "divergent strategies reduce the ability of oligopolists to coordinate their actions tacitly" (Porter, 1979: p.217). This becomes apparent, for instance, by noting that the composition of the average "price conditions" set by banks (which in general may be seen as including, among others, the contractual interest rate, fees and commissions, and required guarantees) may differ substantially depending on the bank's business model (i.e. the type of activities and services provided, funding sources, and risk appetite), making it harder for banks to set (and monitor) collusive "prices" across business models. Hence, under SGT an 'ecosystem' populated by a diverse set of banking business models seems less likely to originate market power via *collusive agreements*.

The second mechanism concerns the existence of *strategic interdependence*. More specifically, under some circumstances banks may compete "à la Bertrand" (Yanelle, 1997; Smith, 1998), wherein strategic variables such as price (i.e. the lending rate) and the underwritten risks may be viewed as *strategics complements*. For instance, an increase in the average risk premium charged in corporate loans by a given retail bank may interpreted as a signal of increased riskiness of the business cycle, inducing other retail banks to increase the premium charged in SME and retail loans. In such a case, it is well documented that, under the Bertrand model with some degree of product diversification, a price increase in the services provided by one firm tends to be accompanied by an increase in the price charged by the competing firm (and hence increased market power) (Bertrand, 1883). In tune with this view, Porter (1979) acknowledges that the previously noted negative relationship between diversity and market power is likely to be tuned down (and possibly inverted) depending on the level of strategic interdependence between firms. In sum, the two SGT mechanisms used to describe the diversity-market power nexus (collusive agreement and strategic interdependence) offer mixed predictions regarding the expected sign of the relationship between diversity and market power. Critically, in our view such lack of consensus regarding the diversity-market power relationship generates an important research gap that this paper aims to fill.

Finally, several arguments have been presented in literature predicting a positive effect of market power on resilience (C2). Effectively, market power may be expected to positively contribute to the systemic 'buffer' against adverse shocks (via higher profits) as well to the overall bank charter value, mitigating the incentives for owners and managers to take on excessive risk, hence decreasing the likelihood of a systemic banking crisis (Hellman *et al.*, 2000; Allen & Gale, 2000). In the same line, according to Beck *et al.* (2006), it may be argued that it is substantially easier to monitor a few banks in a concentrated banking system. From this perspective, supervision of banks may be more effective (and the risks of contagion be lower) where banks enjoy a higher market power. On the other hand, however, the model proposed by Boyd & De Nicoló (2005) envisions that market power may in fact lead to reduced resilience, given that banks in a monopolistic position will tend to increase interest rates charged to borrowers, which in turn is likely to increase the bankruptcy risk of borrowers and, under moral hazard, generate incentives for them to adopt risky business strategies. Similarly, Mishkin (1999) suggests that systems with high market power are more likely to benefit from 'too-big-to-fail' implicit state guarantees, and hence increase bank *ex-ante* risk-taking incentives, given that policymakers are more concerned about failures when there are few banks. Importantly, as stated by Boyd & De Nicoló (2005), the existing empirical literature focused on the 'market power-resilience' nexus does not offer a clear answer regarding the sign of the relationship, and may be better described as mixed – and hence we also attempt to contribute to this strand of literature.

3.2.2. Types of financial systems, diversity and resilience

Our study is also related to a recent line of literature that analyses the contribution of the type of financial system (market or bank-based) to financial stability – wherein the latter may be seen as encompassing financial systems with a strong orientation towards stock and bond market financing, characterized by the prevalence of arms-length contracts and monitoring via market discipline (Boot & Thakor, 2000); and the former refer to financial systems with a stronger dependence on bank financing and hence a greater orientation towards relationships-contracts, which are mainly monitored via regulation and supervision (Rajan & Zingales, 1998).

In this regard, some studies have documented that financial crises tend to be more severe in bank-based systems (Gambacorta *et al*., 2014). This is seen to occur for a variety of reasons, including (i) the procyclicality of bank lending (Pagano *et al.*, 2014; Langfield & Pagano, 2016), (ii) the high leverage of banks, which makes them prone to runs by depositors and other creditors (Acharya & Thakor, 2016), and (iii) their interconnectedness, which induces contagion via counterparty risk (Drehmann & Tarashev, 2013). Under such context, it may seem reasonable to hypothesize that an increase in the diversity of banking business models should induce resilience in bank-based systems, particularly if the performance of different business models is not positively correlated. This is so because if one business model is particularly affected by a negative shock (e.g. sudden drop in Housing prices) banks operating with less affected business models may be able to continue to provide lending to the economy. However, as suggested by Jiménez & Mencía (2009), seemingly uncorrelated bank assets (and liabilities) may become highly correlated under systemic distress due to the presence of unobserved, latent factors (Duffie *et al*., 2009). Moreover, the financial innovation that implicitly drives business model diversity (Ellis *et al*, 2014) may also impose significant challenges to the effectiveness of bank supervision. To this effect, it may be noteworthy that, according to the Liikanen Report (2012), some of the banks that failed during the 2007-09 crisis did so after changing their business model prior to the crisis (e.g. Royal Bank of Scotland). In our view, such episodes speak to the possibility that the effectiveness of bank supervision may, in fact, be hindered in the presence of novelty in the way that banks run their business. Both arguments (latent bank correlation and challenges to bank supervision) seem to significantly dampen our initial prediction regarding the effects of diversity on the resilience of bank-based systems.

Another strand of literature that may help us shed light on the relationship between financial system, diversity and resilience is focused on the role of information and market discipline in bank contagion. In particular, it is argued that while in normal times market creditors may adequately monitor banks due to their superior experience and access to information (Calomiris, 1999), such market discipline is likely to be less effective (and may even induce bank contagion) in the presence of noisy public signals (Huang & Ratnovski, 2011). More specifically, such contagion may be accelerated by market discipline via the high degree and speed of adjustment at which the beliefs of stakeholders are updated in market-based systems, namely if bank entities are seen as homogenous (Wagner, 2009b). Conversely, in bank-based countries the reaction of market players to signals regarding the banking system will tend to less acute given the greater presence of bank regulation and supervision (e.g. explicit deposit guarantee schemes). Hence, this strand of literature seems to suggest that diversity may play a more significant role in increasing the resilience of market-based systems than in bank-based systems, given the incentives faced by banks to pursue *diverse* diversification strategies (Beale *et al*., 2011) in order to avoid contagion.

3.3. Methodology

3.3.1. Identification of banking business model diversity

The first step in measuring the diversity of banking business models consists in the identification of business models at the bank-level. In this regard we follow the methodology laid out in **Chapter 1**: firstly, we perform principal components analysis on a selection of business model variables related with the assets and funding structures, diversification, size and capital of banks. Among other things, this step ensures that clustering is performed in an orthogonal space (Sharma, 1996); secondly, we run clustering analysis using three alternative methods (Fuzzy C-Means, Self-Organizing Maps, Partitioning Around Medoids) and combine the classification outputs of each algorithm into one single classification, using a majority consensus rule. Using an ensemble of clustering methods (rather than one single method) is expected to increase the accuracy of the assignment of banks to business models relative to their *true*, unobserved, classification (Kuncheva, 2004), which may be seen as particularly valuable given the absence of an established taxonomy of discrete banking business models. To determine the optimal number of clusters we rely on a set of internal selection criteria (Silhouette Width, the Calinski-Harabasz Index, Davies-Bouldin Index, Dunn Index).

The identification of banking business models is performed using the full period mean values of the input variables for each bank, resulting in the allocation of each bank to a unique business model over the entire sample period. Such approach is in line with the notion of business model as a stable, long-term concept (Mergaerts & Vennet, 2016). Also, in order to ensure comparability of results with other studies focused on banking business models, which are mainly addressed at European banks (Ayadi *et al.*, 2015; Mergaerts & Vennet, 2016;

Martín-Oliver *et al.*, 2017) we perform clustering at the regional level. In other words, we run our clustering procedures separately for banks operating in Europe, Asia and America.

Next, we follow a recent strand of studies (Michie & Oughton, 2013; Baum *et al.*, 2020) and draw on ecology literature to compute the country-level diversity of banking business models. Particularly, we use the notion of Shannon diversity to measure the level of banking business model diversity for each country-year ($SHD_{i,t}$) (Maurer & McGill, 2011):

$$SHD_{i,t} = -\sum_{j=1}^{J} p_{i,t}^{j} \times \ln p_{i,t}^{j} \tag{3.1}$$

Wherein $p_{i,t}^{j}$ is the market share of assets held by all banks with headquarters in country i, in year t, operating under business model j (with $j = 1, \ldots, J$). The higher the value of the Shannon diversity, the more evenly distributed across business models the total assets are. Alternative measures of diversity (e.g. Simpson diversity) are used as robustness check.

3.3.2. Impact of business model diversity on resilience

One of the key takeaways from our survey of literature is that the relationship between diversity and resilience seems intertwined with two relatively well-known drivers of resilience: diversification and market power. This means that some of the key variables of interest in our study should be considered on both the left (explained) and right (explanatory) side of the estimated equations. Namely, by observing **Figure 3.1** it becomes apparent that both diversity and market power are expected to simultaneously constitute explained and explanatory variables in a system of equations. Such empirical setting sets up well for the estimation of a three-stage simultaneous equation model (3SLS), which not only allows us to take under consideration the endogenous nature of the relationships between a set of variables, but also ensures a superior use of information in comparison with 2SLS, due to the simultaneous estimation approach (Jacques & Nigro, 1997). For these reasons, in this paper we jointly estimate the following system of equations (wherein the endogenous variables are identified in **bold**; note that the definitions of all variables are provided in **Table 3.1**):

$$\begin{cases} \boldsymbol{SHD_{i,t}} = \alpha_0 + \alpha_1 \boldsymbol{RD_{i,t}} + \alpha_2 ARI_{i,t} + \alpha_3 STK_{i,t} + C_i + Y_t + \varepsilon_{i,t} & (3.2) \\ \boldsymbol{LI_{i,t}} = \beta_0 + \beta_1 \boldsymbol{SHD_{i,t}} + \beta_2 ERI_{i,t} + \beta_3 CON_{i,t} + \beta_4 BCL_{i,t} + C_i + Y_t + \varepsilon_{i,t} & (3.3) \\ \boldsymbol{ZS_{i,t}} = \gamma_0 + \gamma_1 \boldsymbol{SHD_{i,t}} + \gamma_2 \boldsymbol{RD_{i,t}} + \gamma_3 \boldsymbol{LI_{i,t}} + \gamma_4 SIZ_{i,t} + \gamma_5 BCL_{i,t} + PC_{i,t} + C_i + Y_t + \varepsilon_{i,t} & (3.4) \end{cases}$$

Regarding equation (3.2), our main relationship of interest is between revenue diversification (RD) and diversity, proxied by Shannon diversity (SHD) (**Figure 3.1:** A1, a negative association is expected). Despite RD not being defined as an explained variable in any of the other equations, we define it as endogenous because it is likely to be influenced by several variables included in the system (e.g. scope of activities, size). In addition to RD, equation (2) includes two exogenous regressors: activity restriction index (ARI), which depicts the level of restrictions imposed on the ability of banks to perform activities related with securities, insurance, and real estate (Barth *et al.*, 2006) (a negative association with diversity is expected); and the share of total assets held by stakeholder banks (STK). Such banks have often been seen as drivers of diversity in the banking sector (Ayadi *et al.*, 2015), given their propensity to stick to a traditional way of doing business, hence avoiding uniform diversification strategies (Beale *et al*., 2011) (a positive relation with diversity is expected).

As for equation (3.3), we are mainly focused on the relationship between SHD and market power, which is proxied by the Lerner Index (LI) (**Figure 3.1:** C1, no clear sign is expected for this relationship). Literature on market power is quite profuse, hence we include three exogenous variables in the regression: entry restriction index (ERI), which evaluates the number of entry requirements imposed by a country's bank supervisory agencies (Barth *et al.*, 2006), and proxies for the height of barriers faced by new entrants (a positive relationship is expected); the concentration of assets in the 5 largest banks of each country (CON) (the low rivalry implicit in highly concentrated markets induces us to expect a positive relationship); and the business cycle, computed as the annual growth of GDP (BCL) (which may be expected to be positively related with market power, given the expected negative impact on rivalry).

Table 3.1. Variables description

	Description	Source
Resilience		
Z-score (ln)	Natural log of: ROA plus the ratio of total equity to total assets, divided by the standard deviation of ROA, using the full sample period at the bank-level. Aggregation at country level is obtained using the median value.	Bankscope/Orbis authors' calculation
Diversity		
Shannon diversity	Calculated as: $-[\sum p_i * \ln(p_i)] = -[p_1 * \ln(p1) + \ldots + p_j * \ln(p_j)]$, where i is the banking business model, j is the total number of business models, and p_i is the proportion of abundance of business model i in a country, computed as the share of a country's total bank assets run by banks operating with business model i.	authors' calculation
Country controls		
Revenue diversification	For each bank: 1 minus the sum of squared of four components of total operating income (TOR): 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: $[1 - [(NII/TOR)^2 + (NFC/TOR)^2 + (NTI/TOR)^2 + (OTH/TOR)^2]]$. Country-level aggregation using mean value.	authors' calculation
Lerner index	Output prices minus marginal costs, divided by output prices. The prices are proxied by total operating revenues divided by total assets. The marginal costs are obtained using a translog cost function with respect to output (Demirgüç-Kunt & Pería, 2010). A higher value of the Lerner index indicates higher market power.	Global financial development database (World Bank)
Financial system	Calculated as: the ratio between private credit by deposit money banks and the sum of the outstanding domestic and international private debt securities and total stock market capitalization (%). Credit and stock market data is obtained via World bank and debt securities via BIS (Bats & Houben, 2020).	Global financial development database (World Bank), BIS
Concentration	Share of total assets held by 5 largest banks in each country (%).	authors' calculation
Activity restriction index	This index assesses the ability of banks to engage in activities related with securities, insurance, and real estate. The index is built using the World Bank's 'Bank Regulation and Supervision Survey' of 2007, 2011 and 2017. A higher value equates to greater activity restrictions.	Bank Regulation and Supervision Survey (WB), Barth *et al.* (2006)
Stakeholder	Share of a country's total bank assets held by cooperative or savings banks (%).	authors' calculation
Entry requirements index	This index assesses the number of entry requirements imposed by a country's banking supervisory agency. The following 10 requirements are assessed (e.g. including draft inlaws, financial information on main potential shareholders). A higher value equates to greater entry barriers.	Bank Regulation and Supervision Survey (WB)
Business cycle	Annual growth of GDP per capita (%).	Global financial dev. database (WB)
Size of the banking sector	Total assets held by deposit money banks as a share of GDP (%).	Global financial dev. database (WB)
Business model features		
Gross loans to customers	Gross loans and advances to customers.	Bankscope/Orbis
Interbank lending	Net loans and advances to banks, reverse repos, securities borrowed, cash collateral.	Bankscope/Orbis
Trading assets	Financial assets trading and at fair value through profit or loss.	Bankscope/Orbis
Customer deposits	Customer deposits.	Bankscope/Orbis
Interbank borrowing	Bank deposits, repurchase agreements, securities loaned, cash collateral.	Bankscope/Orbis
Wholesale funding	Other deposits, short-term funding and debt securities (maturity < 1 year), long-term borrowings and debt securities at historical cost, subordinated liabilities, other long-term borrowing.	Bankscope/Orbis
Total derivatives	Derivative financial instruments, asset and liability-side.	Bankscope/Orbis
Income diversification	Herfindahl-Hirschman Index (HHI); total operating income (OR) 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: $[1 - [(NII/OR)^2 + (NFC/OR)^2 + (NTI/OR)^2 + (OTH/OR)^2]]$.	Bankscope/Orbis authors' own calculations
Total assets	Log of average assets in thousand euros.	Bankscope/Orbis
Total equity	Total equity.	Bankscope/Orbis

Finally, equation (3.4) models the level of resilience in the banking system, proxied by the median Z-score in each country-year (ZS). The main relationships of interest in this equation are threefold: (i) SHD and ZS (**Figure 3.1:** A2, a positive sign is expected); (ii) DIV and ZS (**Figure 3.1:** B, no clear sign is expected); and (iii) LI and ZS (**Figure 3.1:** C, again the expected sign is unclear). Moreover, three exogenous variables are included: the total size of banking assets in proportion to GDP (SIZ), which may reflect the degree to which the country is 'overbanked', particularly in Europe (ESRB, 2014) (expected sign: negative); the business cycle (BCL) (expected sign: positive); and a set of dummies that account for past financial crises (PC), which may reflect two opposing effects: the persistent nature of bank risk culture (Fahlenbarch *et al.*, 2012); or a learning effect (Yu, 2018) (expected sign: unclear). Equations (3.2, 3.3, 3.4) include country (C_i) and year (Y_t) fixed effects. Importantly, we perform and report the Sargan-Hansen test of validity (exogeneity) of instruments.

3.3.3. Efficient portfolios of banking business models

Our final empirical task is to find the efficient compositions of banking business models, at the aggregate level, and test their relationship with diversity in market and bank-based systems. To do so, we equate our exercise to that of portfolio selection (Markowitz, 1952), but instead of using a conventional risk-return measure such as the Sharpe Ratio (Sharpe, 1966) we employ the Z-score – which allows us to depict the notion of resilience, and is in tune with the rest of the paper, e.g. *vide* equation (3.4). Importantly, applying this method allows us to explore the strategic interdependence between business models by explicitly taking into account the covariates of returns between business models in the determination of optimal composition of portfolios of business models.

In particular, for each type of financial system (market and bank-based), we find the vector of weights of the portfolio (or market shares) of business models ($\vec{\omega}$) which minimize the standard deviation of returns of a given level of internal funding ($\overrightarrow{SDROA}$), by employing linear programing tools to solve the following problem:

$$\min \ f(\omega) = \overrightarrow{SDROA} = \sqrt{\overrightarrow{\omega^T} \times \Omega \times \vec{\omega}}$$

s.t.:

$$\text{(i)} \quad \vec{\rho} = \overrightarrow{\omega^T} \times \left(\overrightarrow{ROA} + \overrightarrow{CAR}\right) = K \tag{3.5}$$

$$\text{(ii)} \quad \vec{\omega} = 1$$

$$\text{(iii)} \quad \omega_j \geq 0$$

Wherein $\vec{\rho}$ is the vector of mean internal funding, comprised of the weighted vector of mean returns on assets ($\overrightarrow{ROA}$) and capital ratio ($\overrightarrow{CAR}$) per business model; $\overrightarrow{\omega^T}$ is the transposed vector of mean weights or market shares of assets held by each business model j; and $\mathbf{\Omega}$ stands for the variance-covariance matrix of returns (ROA), obtained using annual values for the full sample period (2005-16). As for the constraints: (i) holds some parallel with standard portfolio selection studies, in which the minimization of the volatility of returns is performed for a given level of returns. In our study, instead of returns, we pre-set the level of internal funding to K (below we discuss how the values of K are identified); constraint (ii) sets the sum of weights in vector $\vec{\omega}$ to 1, as the sum of the market shares of each business model must comprise the totality of the market; and (iii) determines that all portfolio weights must be non-negative, reflecting the fact that negative market shares hold no economic significance. For each type of financial system, we run (5) for all feasible values of K. In particular, we begin with the lowest value of $\vec{\rho}$ and incrementally add 5 basis-points until we reach the maximum feasible value. Finally, the *efficient* frontier of business model portfolios is obtained by discarding the portfolios with a higher $\overrightarrow{SDROA}$ than the portfolio with the lowest $\overrightarrow{SDROA}$. Our efficiency frontier is measured in terms the Z-score which is computed as:

$$Z = \frac{\vec{\rho}}{\overrightarrow{SDROA}} \tag{3.6}$$

Finally, we check whether the impact of diversity is different for market and bank-based systems for the efficient portfolios. We do this by performing a modified version of the Gibbons-Ross-Shaken Test (Gibbons *et al.*, 1989) wherein the null hypothesis is that the

Z-score of efficient portfolios with a similar level of diversity are not statistically different in market and bank-based systems. The statistic for this test is given by:

$$(G \mid d_i) = \left(\frac{T - J - 1}{J}\right)\left[\frac{(Z_m^2 \mid d_i) - (Z_d^2 \mid d_i)}{1 + (Z_d^2 \mid d_i)}\right] \sim F(J, T - J - 1) \quad (3.7)$$

Wherein, $(G \mid d_i)$ is the Gibbons statistic obtained for a given level of portfolio diversity (d_i), T is the number of yearly observations in the sample ($T = 12$: 2005-16), J refers to the total number of business models potentially included in each portfolio, $(Z_m^2 \mid d_i)$ and $(Z_b^2 \mid d_i)$ are the squared Z-scores of efficient portfolios for market and bank-based conditioned on the level of portfolio diversity (d_i).

3.4. Data

3.4.1. Sample selection

Our sample selection process comprises two steps. In the first step, we identify the bank-level sample using the Bankscope/Orbis dataset and implementing a set of criteria followed in similar studies (Mergaerts & Vennet, 2016), namely: (a) consolidation code (C1, C2, U1); (b) specialization code (commercial bank, savings bank, cooperative bank, real estate and mortgage bank, investment bank, specialized governmental credit institutions); (c) more than 5B euros at least one year in the sample period (2005-16); (d) average customer deposits to total funding and gross loans to customers to total assets greater than 5%; and (e) at least 3 observations in the sample period, with no gaps. By applying these criteria, we avoid the duplication of entities in our sample, and only deal with institutions with some level of bank activity and relatively high quality of data reporting.

The second step consists in applying an additional filter when aggregating data at the country-level. Given the focus of our study on the diversity of business models, we require countries to have (a) at least 10 banks in one year during the sample period (2005-16); and (b) no missing data in the World Bank's Global Financial Database regarding the variables of interest (e.g. size of the banking sector). Moreover, to ensure additional confidence regarding our diversity measures (which are computed based on bank-level information) we place critical importance on the stability of our sample by (c) only using country-year observations for which the number of banks is at least 2/3 of the maximum number of banks recorded for each country during the entire sample period. This leads us to remove a set of years for specific set of countries, while avoiding *gaps* in the sample, yielding an unbalanced panel of 336 country-year observations (instead of 396 = 33 countries*12 years), distributed across 33 countries. As for the underlying bank-level sample, which is used to compute several measures that are aggregated at the country level (e.g. diversity measures), it is comprised of 1268 banks and 12103 bank-year observations (*vide* **Appendix 3.1**).

3.4.2. Banking business models

Table 3.2 shows the results of the selection criteria for each clustering partition. In general, we obtain consistent results across regions and clustering methods, that suggest an optimal partition of four clusters in our sample (J=4). For instance, in Europe, J=4 records the highest value of Calinski-Harabasz Index (CHI) for FCM, SOM and PAM; in Asia, for the SOM algorithm, the four cluster solution records the highest values of Average Silhouette Witdth (ASW), CHI and Dunn Index (DI) and the lowest Davies-Boulding Index (DBI); and, in America, the J=4 solution records the lowest DBI for all algorithms. Such results are consistent with recent literature using clustering to identify banking business models of European (Ayadi *et al.*, 2015) and Global banks (Roengpitya *et al.*, 2017). To the best of our knowledge no literature exists employing clustering methods to identify banking business models in Asia or America.

The next step in our analysis is to interpret the composition of the clusters obtained *within* each region (using the cluster-mean values of each input variable) and match the clusters with similar compositions *between* regions. While performing this step, we find that in Asia and in America the composition of a given cluster (J_α) does not significantly differ from the composition of another cluster present in that region as well as in other regions (J_θ, 'popular cluster'). To solve this issue, we use the clustering results obtained for the three cluster partition for Asia and America, whereas we maintain the four cluster partition for Europe. This situation generates the absence of one cluster from Asia and America *vis-à-vis*

Table 3.2. Number of business models per region: selection criteria

	Europe				**Asia**				**Americas**			
	ASW	**CHI**	**DBI**	**DI**	**ASW**	**CHI**	**DBI**	**DI**	**ASW**	**CHI**	**DBI**	**DI**
FCM												
J=3	**0.175**	117.90	1.70	0.036	**0.238**	**120.12**	1.65	0.026	0.250	93.21	1.57	**0.060**
J=4	0.162	**122.56**	1.53	0.031	0.215	113.57	**1.50**	0.013	**0.274**	**101.45**	**1.22**	0.030
J=5	0.137	110.73	1.62	0.031	0.212	99.24	1.74	0.027	0.171	84.82	1.48	0.010
J=6	0.158	111.16	**1.50**	**0.037**	0.154	84.95	1.79	**0.029**	0.183	82.24	1.38	0.029
SOM												
J=3	0.165	108.51	1.76	0.039	0.170	100.25	1.87	0.027	0.259	**86.45**	1.50	**0.042**
J=4	**0.167**	**117.86**	**1.48**	0.024	**0.214**	**117.32**	**1.48**	**0.031**	**0.260**	78.09	**1.42**	0.040
J=5	0.134	104.34	1.66	**0.050**	0.151	93.72	1.76	0.024	0.197	73.73	1.64	0.026
J=6	0.076	85.25	1.89	0.027	0.101	82.26	1.78	0.018	0.170	61.51	1.59	0.028
PAM												
J=3	**0.225**	121.12	1.53	0.028	0.173	106.25	1.48	0.019	**0.316**	84.73	1.27	0.041
J=4	0.195	**126.29**	1.50	0.030	0.221	113.86	1.46	0.013	0.280	**97.51**	**1.21**	0.040
J=5	0.193	125.23	1.45	0.027	**0.232**	**115.45**	**1.38**	0.021	0.240	89.43	1.35	0.008
J=6	0.194	116.10	**1.37**	**0.046**	0.191	102.36	1.41	**0.023**	0.189	79.62	1.33	**0.046**
Count of #1 rank (considering all criteria, per region)												
J=3	2				2				4			
J=4	**5**				**5**				**7**			
J=5	1				3				0			
J=6	4				2				1			

Notes: Results of running the PAM, SOM and FCM algorithms on the full period average sample, with inputs PC1 to PC5 for different number of clusters (J). Selection criteria: Average Silhouette Width (ASW), Calinski-Harabasz Index (CHI), Davies-Bouldin Index (DBI) and Dunn Index (DI). The partitions with the top values (#1) for each criterion are presented in **bold.** Note that the best partitions minimize SW<0 and DBI and maximize the remaining criteria.

Europe (J_δ, ‘missing cluster’). In order to understand the implications of this methodological decision and identify potential distortions, we perform several analyses.

Firstly, we check whether the affected clusters (J_θ and J_δ) are the same in Asia and America[13], as this could exacerbate any potential distortions. This is not the case as both the ‘popular’ (J_θ) and the ‘missing’ (J_δ) clusters are different in Asia and America: $\theta_{Asia}=3 \neq \theta_{America}=1$, $\delta_{Asia}=4 \neq \delta_{America}=3$. Secondly, we compare the composition of the ‘popular cluster’ (J_θ) for the three and four clusters partition, as a significant change would indicate that J_θ might not be as similar to J_α as initially suspected. We find no significant changes in the composition of J_θ in the distinctive features of each business model for the three and four clusters partition. Thirdly, we test if the banks in Asia and America represent a significant share of total assets of J_θ, as this could signal a potential distortion in the aggregate composition of business models. We find that banks in America only contribute with 18.3% of BM1 total assets. However, banks in the Asian region contribute with 89.1% of the total assets of BM3 – a result which seems to be mainly driven by Chinese banks, that account for 66.7% of the total assets of BM3 (versus 13.0% of other business models). Moreover, due to data availability issues Chinese banks are only present in the sample during the 2012-16 period. This feature of our sample leads us to handle with care the analyses related with the aggregate composition of business models. For instance, (i) we exclude Chinese banks from the analysis of efficient portfolios performed in **Section 3.5.3**, which critically depends on the stability of the sample composition over the sample period (particularly to compute the variance-covariance matrix of portfolio returns) and (ii) as a robustness check, we test whether our baseline results maintain when banks from dominant countries, such as China, are removed from our sample.

Next, we analyze the popularity and composition of each business model. In particular, the results in **Table 3.3** show that:

[13] To facilitate the discussion of the problem at hand, we instantiate the values of θ and δ for Asia and America using the same numbering of business models as the one used in **Table 3**, which will be discussed below. In other words, J_1=BM1, J_2=BM2, J_3=BM3 and J_4=BM4.

Table 3.3. Banking business models: popularity and composition

	BM1	**BM2**	**BM3**	**BM4**
Number of banks	563	283	288	134
Share of total banks	44.4	22.3	22.7	10.6
Share of total assets	10.2	31.7	18.3	39.8
Market-based systems	8.9	23.2	6.4	61.6
Bank-based systems	11.2	38.2	27.3	23.3
excluding *China*	17.1	34.2	9.8	38.9
Gross loans to customers	63.3 (12.8)$^{+++}$	**68.7 (11.9)**$^{+++}$	41.5 (15.4)$^{++}$	41.5 (18.1)$^{++}$
Interbank lending	6.9 (7.3)$^{++}$	5.8 (4.6)$^{++}$	**23.6 (15.2)**$^{+++}$	16.2 (11.1)$^{+++}$
Trading assets	1.2 (2.7)$^{+++}$	2.0 (3.6)$^{++}$	2.8 (5.4)$^{++}$	**11.1 (8.5)**$^{+++}$
Customer deposits	**78.0 (12.2)**$^{+++}$	52.9 (19)$^{+++}$	56.9 (19.5)$^{+++}$	36.5 (20.6)$^{+++}$
Interbank borrowing	5.4 (7.0)$^{+++}$	8.3 (9)$^{+++}$	**21.0 (14.4)**$^{++}$	19.0 (12.5)$^{++}$
Wholesale funding	4.2 (5.1)$^{++}$	**19.6 (15.8)**$^{+++}$	5.9 (9.1)$^{++}$	15.1 (13.6)$^{+++}$
Total derivatives	0.5 (1.4)$^{+++}$	2.0 (2.9)$^{++}$	1.5 (3.9)$^{++}$	**13.1 (12.0)**$^{+++}$
Income diversification	36.9 (13.5)$^{+++}$	46.1 (10.4)$^{+++}$	42.4 (14.2)$^{+++}$	**53.5 (10.2)**$^{+++}$
Total assets	7.0 (0.4)$^{+++}$	7.4 (0.6)$^{+++}$	7.2 (0.5)$^{+++}$	**7.8 (0.8)**$^{+++}$
Total equity	8.1 (3.5)	8.6 (3.6)$^{+}$	8.5 (4.3)$^{+}$	7.3 (4)$^{++}$

Notes: Mean values and standard deviations in parentheses. All variables computed as percentage of total assets, except number of banks (count), income diversification (HHI) and total assets (log). 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 each variable, we compute the Tuckey HSD test for comparison of means per pair of business models. The number of ($^{+}$) indicates the number of pairwise comparisons which are statistically different at the 5% level. Values in **bold** indicate the business models with the highest mean values for each variable, when the number of plus signs is ($^{++}$) or ($^{+++}$). Market (bank) based systems refer to countries which record a financial system index below (above) the cross-section median value of financial system (73.0%).

- **BM1** is the most popular model in terms of number of banks (44.4%) but represents the lowest share of total assets (10.2%), which speaks to the relatively small size of such banks (total assets: 7.0, log); in terms of composition, BM1 couples high values of gross loans to customers (63.3%) and customer deposits (78.0%), and records the lowest income diversification (36.9, HHI), which is in line with a traditional, retail oriented banking model (Chiorazzo *et al*., 2018); hence, BM1 is labelled as *retail focused*;
- **BM2** represents the largest share of total assets in bank-based systems (38.2%); the composition of assets is concentrated in gross loans to customers (65.5%) but the funding side is relatively diversified, mainly due to the significant exposures to wholesale funding (19.6%); BM2 banks also tend to be relatively large (7.3, log); as such, BM2 is termed *retail diversified funding*;

- **BM3** is the second most popular business model in terms of number of banks (22.7%); as previously noted, untabulated results show that Chinese banks account for 66.7% of the total assets of BM3 – which may also be deduced by comparing lines 5 and 6 of **Table 3**, that show the distribution of total assets per business model of bank-based countries with and without China, respectively; BM3 records a diversified asset structure composed of relatively high values of interbank lending (23.6%) and low values of gross loans to customer (41.5%) when compared to the other business models; on the other hand, it relies mostly on traditional customer deposits for its funding (56.9%); given its composition, BM3 is denoted as *retail diversified assets*; *and*
- **BM4** is the least popular in terms of number of banks (10.6%), but represents the largest share of total assets (39.8%), which is mainly driven by its strong presence among market-based systems (61.6%); BM4 exhibits diversified asset and funding structures, as evidenced, for instance, by the relatively high values of trading assets (11.1%) and wholesale funding (15.1%), and the low values of gross loans to customers (41.5%) and customer deposits (36.5%); banks following the BM4 business model, also tend to exhibit high values of derivatives (13.1%), income diversification (53.5, HHI) and size (7.8, log); such description may be seen as resembling the notion of global diversified banks (Akhavein *et al*., 1997; Pilloff & Rhoades, 2000), which leads us to label BM4 as *large diversified*.

Interestingly, the distribution of total assets per business model seems to significantly differ across types of financial systems. Namely, in market-based systems almost two thirds of total assets (61.6%) are concentrated in banks that operate with the large diversified model (BM4). Conversely, bank-based systems tend to exhibit a more evenly distributed 'ecosystem' of business models, as evidenced by the similarity in the share of assets held by each of business model (BM1: 11.2%, BM2: 38.2%, BM3: 27.2%, BM4: 23.3%). Given that the composition of business models lies at the heart of our notion of diversity, we interpret these findings as a clear indication that the levels of diversity are deemed to be significantly different between market and bank-based systems.

3.4.3. Summary statistics

Table 3.4 provides an overview of the descriptive statistics for three samples: all financial systems (Panel A), market-based systems (Panel B) and bank-based systems (Panel C). Countries with a market (bank) based system are below (above) the cross-section median

Table 3.4. Descriptive statistics

	Mean	**SD within**	**SD between**	**Min**	**Max**
Panel A: All financial systems (n=336)					
Z-score (ln)	3.19**	0.13	0.53	1.68	4.42
Shannon diversity	0.65***	0.06	0.32	0.06	1.22
Revenue diversification	1.97	0.13	0.22	1.44	2.93
Lerner index	0.26***	0.05	0.10	-0.07	0.48
Activity restriction index	6.36***	1.12	1.84	3.00	12.00
Business cycle	2.03	2.62	1.77	-7.83	23.94
Concentration	71.92***	3.56	13.51	30.06	98.01
Entry requirements index	7.67**	1.19	0.97	0.00	9.00
Stakeholder	8.54***	2.17	10.81	0.00	37.84
Financial system	92.70***	23.93	78.97	2.06	710.01
Panel B: Market-based systems (n=173)					
Z-score (ln)	3.25	0.14	0.58	1.68	4.42
Shannon diversity	0.56	0.06	0.30	0.06	1.10
Revenue diversification	1.97	0.11	0.18	1.53	2.45
Lerner index	0.24	0.05	0.09	-0.05	0.48
Activity restriction index	5.88	1.04	2.00	3.00	12.00
Business cycle	1.92	2.86	1.32	-7.83	23.94
Concentration	74.75	3.43	10.61	45.73	97.67
Entry requirements index	7.50	1.55	1.29	0.00	9.00
Stakeholder	4.63	1.57	10.46	0.00	34.48
Financial system	50.23	14.35	16.59	2.06	139.45
Panel C: Bank-based system (n=163)					
Z-score (ln)	3.12	0.12	0.42	1.97	3.89
Shannon diversity	0.75	0.06	0.32	0.06	1.22
Revenue diversification	1.97	0.15	0.27	1.44	2.93
Lerner index	0.27	0.05	0.10	-0.07	0.48
Activity restriction index	6.89	1.21	1.53	4.00	11.00
Business cycle	2.14	2.34	2.19	-5.91	9.42
Concentration	68.9	3.70	15.69	30.06	98.01
Entry requirements index	7.85	0.61	0.42	6.00	9.00
Stakeholder	12.68	2.67	10.66	0.00	37.84
Financial system	137.78	31.08	94.78	50.42	710.01

Notes: Countries with a market (bank) based financial system are below (above) the cross-section median value of the financial system index (73.0%). In Panel A, column 'Mean', we report the results of a Tuckey HSD test for comparison of means between market and bank-based systems. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. Variables winsorized at 1 and 99 percentiles.

value of the financial system index (73.0%). In Panel A, in column 'Mean', we report the results of a Tuckey HSD test for the comparison of means between market and bank-based systems.

In general, we note that the mean values of the key variables of interest (resilience, diversity, revenue diversification, and Lerner index) are significantly different between market and bank-based systems. Namely, on average market-based systems are significantly more resilient, less diverse and more competitive than bank-based systems. Moreover, most of our control variables also exhibit significant differences between both types of financial systems. In particular, market-based systems tend to have lower restrictions to the scope of activities, are more concentrated, have lower entry requirements (barriers) and are less populated by stakeholder banks than bank-based systems. Lastly, we observe that the variables preserve some within standard deviation. This is quite relevant given that the specification of our econometric model includes fixed effects for each unit of analysis (i.e. countries). Such specification allows us to eliminate confounding factors but may also significantly reduce the variation in the data. For this reason, when estimating the magnitude of the effects of each variable, we use the within standard deviations of the independent variables as counterfactuals (Mummolo & Peterson, 2018).

3.5. Results and discussion

3.5.1. Impact of business model diversity on resilience

We begin our analysis by observing the results of the comparison of means in **Table 3.5**, which suggest that the countries with the most resilient banking sectors tend to be significantly more diverse, less diversified and hold more market power than those occupying the lower quartile of resilience. Next, we complement the preliminary results with the output of the 3SLS baseline regressions, presented in **Table 3.6**. First, we start by noting that the null hypothesis of exogeneity of instruments (Sargan-Hansen test) is not rejected for any of the specifications and that the R-squares obtained for all regressions are quite high (ranging from 0.75 to 0.96), which gives us some confidence regarding the completeness of our specification. As for the results, Panel A of **Table 3.5** shows that a negative and significant impact of revenue diversification negative on diversity reflecting our literature-based expectation that banks tend to pursue *uniform* diversification strategies (Beale *et al.*, 2011) that, as whole, yield a more homogenous banking sector (Wagner, 2008, 2009, 2010a, 2010b, 2011; Goodhart & Wagner, 2012). Similarly, we also find that a higher Activity Restriction index significantly reduces diversity. Such relationship may be seen as an indication that imposing restrictions on the type of activities performed by banks limits the extent to which they may pursue *diverse* diversification strategies (Beale *et al.*, 2011). Finally, the positive and significant effect of the share of assets held by stakeholder banks on diversity seems to be in tune with the longstanding notion that cooperative and savings banks have a particular way of doing business (Ayadi *et al.*, 2015), and hence are less likely to herd around uniform diversification strategies.

Table 3.5. Top versus bottom resilient systems

	Top	**Bottom**	**Diff.**
	(1)	(2)	(3)
Number of country-year obs.	85	97	
Z-score (ln)	3.74	2.59	1.15***
Shannon diversity	0.63	0.51	0.12**
Revenue diversification	1.92	2.10	-0.17***
Lerner index	0.30	0.24	0.05***

Notes: Country-year observations labelled as 'Top' ('Bottom') refer to observations recorded by countries located in the top (bottom) quarter of cross-section Z-score per type of financial system. In other words, such observations consist in the aggregation of Panels A and B of **Table 3.7** below. In column (1) and (2) we present mean values, 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.

The results for the market power equation are exhibited in Panel B of **Table 3.6**. As for the impact of diversity on market power, we may observe that the estimated coefficient is positive and significant. Such result suggests that the 'collusive agreement hypothesis' (Porter, 1979), according to which diversity would reduce market power by threatening the stability of tacit collusive agreements among competitors, is not observed in our empirical context. It is hence more likely that the alternative mechanism put forward by the Strategic Groups Theory, i.e. strategic interdependence, is igniting our results. More specifically, our results suggest that the choices of different business models may be acting as strategic

Table 3.6. 3SLS regressions: baseline results

	Shanon Div. (1)	Shanon Div. (2)	Shanon Div. (3)
Panel A: Shanon diversity			
Revenue diversification	-0.304**	-0.302**	-0.301**
Activity Restriction index	-0.008**	-0.008**	-0.008**
Stakeholder	0.012***	0.012***	0.012***
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Number of observations	336	336	336
R-squared	0.96	0.95	0.96
	Lerner index (4)	**Lerner index (5)**	**Lerner index (6)**
Panel B: Market power			
Shanon diversity	0.371***	0.378***	0.381***
Entry Requirements index	0.008***	0.008***	0.007**
Concentration	0.002	0.002*	0.002**
Business cycle	0.002*	0.003*	0.003*
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Number of observations	336	336	336
R-squared	0.78	0.78	0.78
	Z-score (ln) (7)	**RACAR (ln) (8)**	**RAROA (ln) (9)**
Panel C: Resilience			
Shannon diversity	1.163***	0.995***	0.474
Revenue diversification	0.061	-0.343	0.462
Market power	-0.748	0.799	-1.136
Size of banking sector	-0.002***	-0.002***	-0.002***
Business cycle	0.014***	0.011***	0.009*
Past crises dummies	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Number of observations	336	336	336
R-squared	0.95	0.96	0.75
Validity of instruments			
Sargan-Hansen test (t stat)	4.0	4.2	3.8
Sargan-Hansen test (p-value)	0.86	0.84	0.88

Notes: Values presented are the coefficient estimates using three-stages least squares (3SLS) using country controls and country and year fixed effects. ***, ** and * indicate statistical significance at the 1%. 5% and 10% level, respectively.

complements, *à la* Bertrand. To further test whether the choices of different banking business models are effectively complementary would require a significant workload and access to micro-level data (e.g. loan agreements and bond issuances) and hence falls outside the scope of this paper. The estimates of the remaining three variables (barriers to entry, concentration, and business cycle) show a positive effect on market power, as expected.

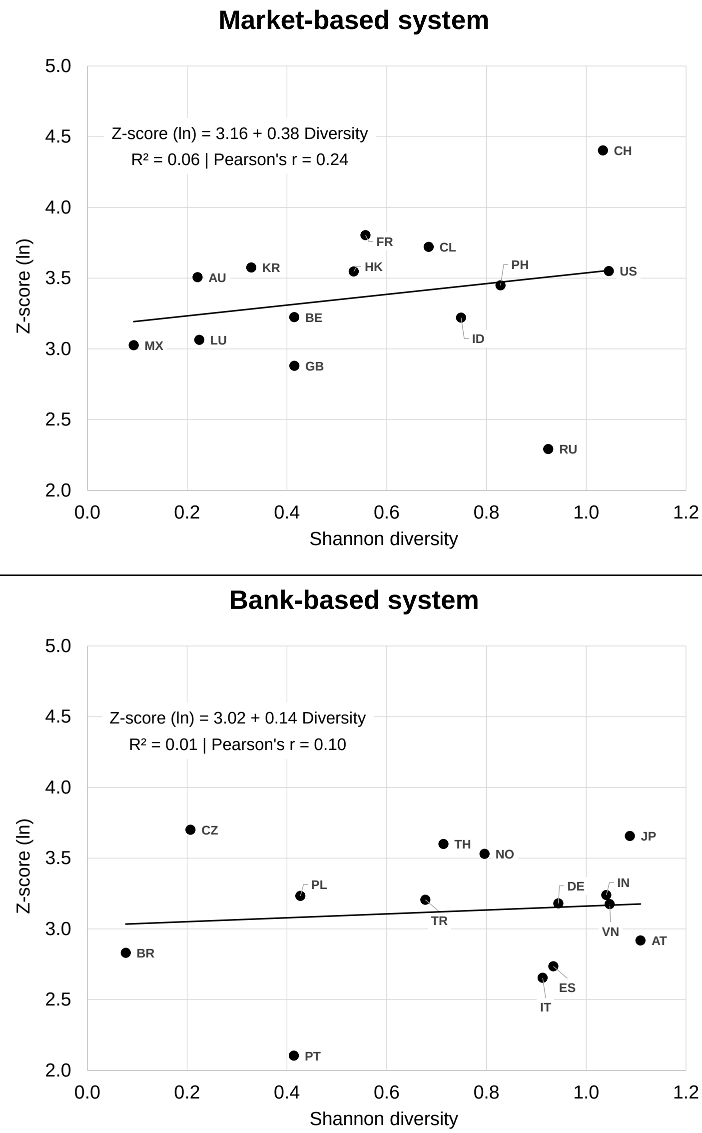
Regarding the results for the determinants of resilience (Panel C), we may see that diversity bears a positive and significant impact on Z-score. This was the expected sign for the relationship and sustains the argument that less homogeneous banking systems are less likely to face systemic distress (Beale *et al.*, 2011; Wagner & Goodhart, 2012). Also, the magnitude of the effect seems economically significant, as we estimate a 7.0% increase in the Z-score of banks as a consequence of a 0.06 increase in the Shannon diversity (which equates to one within standard deviation increase). Moreover, the results suggest that neither revenue diversification nor market power directly affect the distance to distress. Such results are not entirely a surprise, given the mixed evidence in literature, and, coupled with the significant impact of diversity on resilience, seem to suggest that the proper channel via which these drivers impact resilience is in fact diversity – which constitutes a novel and important contribution to literature.

Finally, an apparent inconsistency in the results catches our attention. Namely, **Table 3.4** shows that market-based countries tend to be significantly more resilient than bank-based countries, despite being less diverse, which would indicate a negative relationship between diversity and resilience. However, as noted above, the baseline estimates suggest the opposite sign: a positive association between diversity and resilience. Is it possible to reconcile both results? In the next section we answer this question by looking at whether the relationship between diversity and resilience significantly differs per type of financial system.

3.5.2. Type of financial system, diversity and resilience

In **Figure 3.2** we explore the bivariate relationship between diversity and resilience per type of financial system. Regarding market-based systems, the upper graph suggests the presence of a positive correlation between diversity and resilience (0.24). For instance, we may see that the UK (GB) simultaneously records a lower diversity and Z-score than the US. On the other hand, in the lower panel of **Figure 3.2**, a less clear correlation is found for bank-

Figure 3.2. Business model diversity and resilience per type of financial system



Notes: *Shannon diversity* is computed for each country i as $-[\sum p_j * \ln(p_j)] = -[p_1 * \ln(p_1) + \ldots + p_J * \ln(p_J)]$, where j is the business model, J is the total number of business models present in country i, and p_j is the share of total assets held by banks operating with business model j in country i. *Z-score (ln)* is calculated at the bank level as the natural log of return on assets (ROA) plus capital ratio (CAR) divided by the standard deviation of ROA using the full sample period as window. The method of aggregation is the median value. Due to data issues, the analysis includes only 28 out of the 33 countries present in our panel data: four countries are excluded due to low time-series coverage (present in six or less years) and one country is excluded after performing the Median Absolute Deviation (MAD) test for the detection of outliers in small samples (Iglewicz & Hoaglin, 1993). Visual inspection may suggest that Switzerland, Russia and Portugal could be outliers, but the M-score for these countries is below the test's critical value of 3.5 (respectively: 2.2, 2.8 and 2.1).

based systems. For instance, while Italy, Germany and Japan have a similar level of (high) business model diversity, their distance to distress varies significantly. In both cases, the initial findings are backed by the results presented in panel A and B of **Table 3.7**, which show that only in market-based systems the most resilient banking sectors also tend to exhibit more diversity.

Table 3.7. Top versus bottom resilient systems per type of financial system

	Top	**Bottom**	**Diff.**
	(1)	(2)	(3)
Panel A: Market-based systems			
Number of country-year obs.	39	59	
Z-score (ln)	3.93	2.63	1.29***
Shannon diversity	0.60	0.44	0.15**
Revenue diversification	2.06	2.01	0.04
Lerner index	0.20	0.27	-0.07***
Panel B: Bank-based systems			
Number of country-year obs.	45	38	
Z-score (ln)	3.58	2.52	1.06***
Shannon diversity	0.66	0.60	0.05
Revenue diversification	1.81	2.23	-0.42***
Lerner index	0.38	0.20	0.18***

Notes: Countries with a market (bank) based financial system are below (above) the cross-section median value of financial system (73.0%). Country-year observations labelled as 'Top' ('Bottom') refer to observations recorded by countries located in the top (bottom) quarter of cross-section Z-score per type of financial system. In column (1) and (2) we present mean values, 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.

Two additional analyses are performed: 3SLS regressions using the sub-samples of market and bank-based countries (**Table 3.8**) and rolling regressions using the financial system as the mediating variable (**Figure 3.3**). Regarding the sub-sample regressions, panel A shows that in market-based countries business model diversity positive and significantly impacts resilience (one within standard deviation increase in diversity yields a 10.4% increase in Z-score), whereas no significant effect is detected in the bank-based sample (panel B). This result is corroborated by the rolling regressions. Particularly, by observing **Figure 3.3** we may see that the coefficient of diversity on resilience is only positive and significant when the regressions include a majority of market-based observations (left side of the graph).

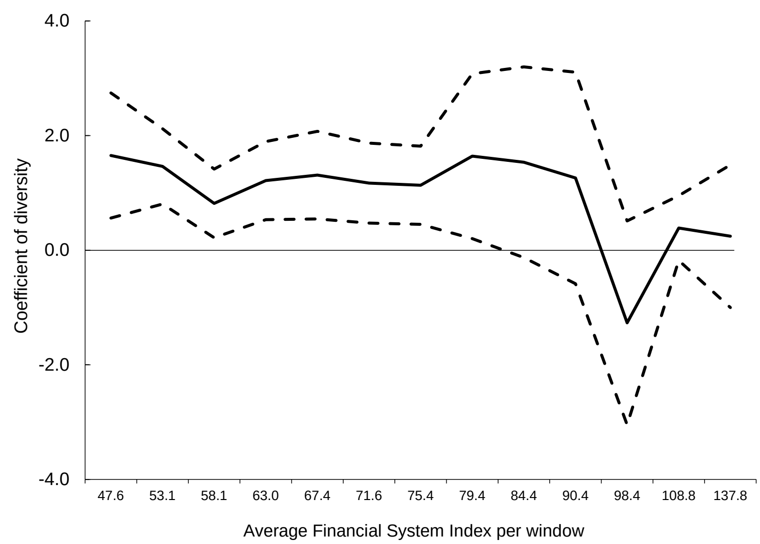
Table 3.8. 3SLS regressions: market versus bank-based systems

	Z-score (ln)	RACAR (ln)	RAROA (ln)
	(1)	**(2)**	**(3)**
Panel A: Market-based systems			
Shanon diversity	1.729***	1.659***	0.450
Revenue diversification	-0.274	-0.105	0.715
Market power	-0.724	-0.869	0.386
Size of banking sector	-0.001	-0.002	-0.003**
Business cycle	0.025***	0.022***	0.008
Number of observations	173	173	173
R-squared	0.96	0.95	0.84
Sargan-Hansen test (t stat)	3.3	3.3	3.3
Sargan-Hansen test (p-value)	0.51	0.51	0.51
	Z-score (ln)	**RACAR (ln)**	**RAROA (ln)**
	(5)	**(6)**	**(7)**
Panel B: Bank-based systems			
Shanon diversity	0.326	0.437	0.080
Revenue diversification	0.344	0.353	0.201
Market power	3.665	4.862	1.092
Size of banking sector	-0.001	-0.001	-0.002
Business cycle	0.001	0.000	0.001
Number of observations	163	163	163
R-squared	0.85	0.75	0.81
Sargan-Hansen test (t stat)	5.1	5.1	5.1
Sargan-Hansen test (p-value)	0.07	0.07	0.07

Notes: Countries with market (bank) oriented financial system are below (above) the median of the Financial system index. Values presented are the coefficient estimates using three-stages least squares (3SLS). For brevity reasons we only report the results of equation (4) in our systems of equations, which also corresponds to Panel C in **Table 3.6**. In order to mitigate endogeneity issues, two changes are made to the baseline specification, (i) the Activity Restriction index is labeled as endogenous, and (ii) Entry Requirement index is added as an instrument for diversity. ***, ** and * indicate statistical significance at the 1%. 5% and 10% level, respectively.

A possible interpretation of the large positive effect of diversity on resilience for market-based systems is that the existence of *diverse* diversification strategies (Beale *et al.*, 2011) within a given banking sector may allow market participants to segregate their beliefs regarding the financial situation of banks operating with different business models – which may be particularly relevant in the presence of noisy public signals (Huang & Ratnovski, 2011). As for the lack of a significant effect of diversity on bank-based systems, we view such result as an indication that mixed effects may be at play: on one hand, it is conceivable that diverse bank-based systems may be more resilient to adverse shocks, given the differences in risk exposure of each business model; on the other hand, bank-based systems may also be more prone to (i) latent factors which, in the face of adverse events, may induce significant return correlations between business models that tend to be uncorrelated in normal times and (ii) less effective monitoring by bank supervisors (due to the additional complexity of monitoring a diverse, rather than an homogenous, set of business models and their inherent risk exposures). Another possible reason for the lack of statistical significance may be linked to the relatively small sample size. To obtain a different perspective on the relationship between diversity and resilience, next we explore the composition of banking business models using portfolio selection analysis – which, although deemed to be sensitive to the length of the time series used to compute the variance-covariance matrix, may be seen as less dependent on the sample size of each type of financial system.

Figure 3.3. Heterogeneity: diversity on resilience per type of financial system



Notes: We report the coefficients of diversity on Z-score obtained for a set of rolling regression using the baseline 3SLS regression specification and the level of financial structure index to construct each rolling window. In the X-axis we report the average value of the financial structure index for each sub-sample. The sub-samples used in the left (right) side of the graph tend to include more observations with market (bank) based systems. A total of 13 sub-samples are used, as a result of a window size of 168 (i.e., 1/2 of full sample size) and step size of 14 [=(336-168)/(13-1)]. The full line represents the coefficient estimates; the bottom and lower dotted lines represent the 10% and 90% confidence intervals, respectively.

3.5.3. Efficient portfolios of banking business models

In order to understand the optimal composition of business models for each level of internal funding, we start by analyzing the input data that goes into the efficiency analysis. Namely, Panel A of **Table 3.9** shows that, for market-based systems, the business model with the highest mean value of internal funding is the retail focused model (BM1), whereas the lowest standard deviation is recorded by the retail diversified funding model (BM2); it also shows that the returns tend to be positive and significantly correlated among business models, wherein the strongest correlation is between BM1 and BM2 (0.86). This result is corroborated

Table 3.9. Mean internal funding, standard deviation and correlations of returns

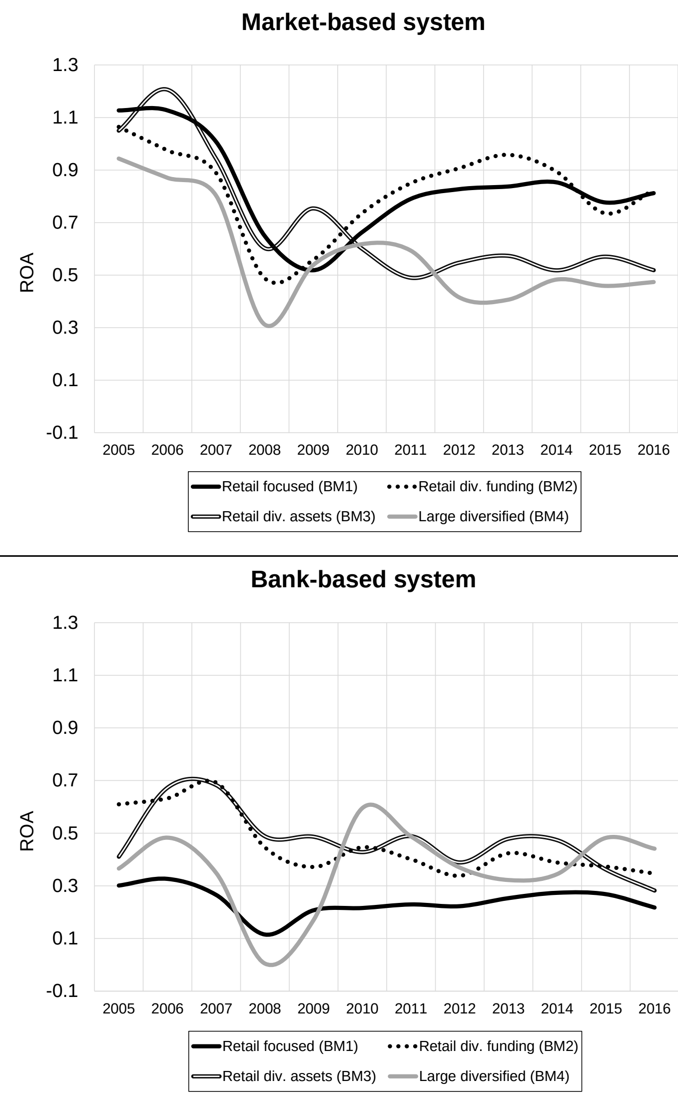
	Mean internal funding	**Standard deviation of returns**	**Z-score**	**Correlations of returns**			
				BM1	**BM2**	**BM3**	**BM4**
Panel A: Market-based system							
Retail focused (BM1)	10.8	0.176	61.5	1.00			
Retail diversified funding (BM2)	9.8	0.162	60.7	0.86***	1.00		
Retail diversified assets (BM3)	9.1	0.228	39.9	0.68**	0.38	1.00	
Large diversified (BM4)	7.5	0.190	39.2	0.73***	0.57*	0.85***	1.00
Panel B: Bank-based system							
Retail focused (BM1)	5.9	0.052	113.3	1.00			
Retail diversified funding (BM2)	7.7	0.115	66.9	0.32	1.00		
Retail diversified assets (BM3)	7.6	0.110	69.1	0.14	0.74***	1.00	
Large diversified (BM4)	5.4	0.151	35.6	0.58**	0.07	0.07	1.00

Notes: *Mean internal funding* is computed in the following way: firstly, we compute the sum of return on assets plus capital ratio at the bank-level for each year; secondly, we identify the median value of internal funding for each combination of financial system-business model-year; finally, we compute the mean value for the full sample period (2005-16). *Standard deviation* is computed using the median annual value of ROA of each combination of financial system-business model. *Z-score* is the ratio between the mean internal funding and the standard deviation of returns. Pearson correlations and t-test computed considering n=12 and df=10, as sample period is 2005-16. ***, ** and * indicate statistical significance at the 1%. 5% and 10% level, respectively.

by the visual inspection of the evolution of returns for market-based countries, in the upper graph of **Figure 3.4**, which shows an almost perfect co-movement of BM1 and BM2 for market-based systems, an exception being the financial crisis period, wherein BM2 recorded the lowest-return in 2008 and BM1 in 2009.

As for bank-based systems, a different picture emerges from **Table 3.9**. Namely, while the highest mean values of internal funding are recorded by the retail diversified models (BM2 and BM3), the retail focused model (BM1) records a significantly greater stability of returns *vis-à-vis* other models. Once more, such findings are echoed by the lower graph of **Figure 3.4**, which show the stable nature of BM1 returns. In sum, the inputs used in the efficiency analysis (internal funding, standard deviation of returns and correlations between the returns of business models) seem to significantly differ across financial systems, which may lead to significant differences in the compositions of the efficient portfolios.

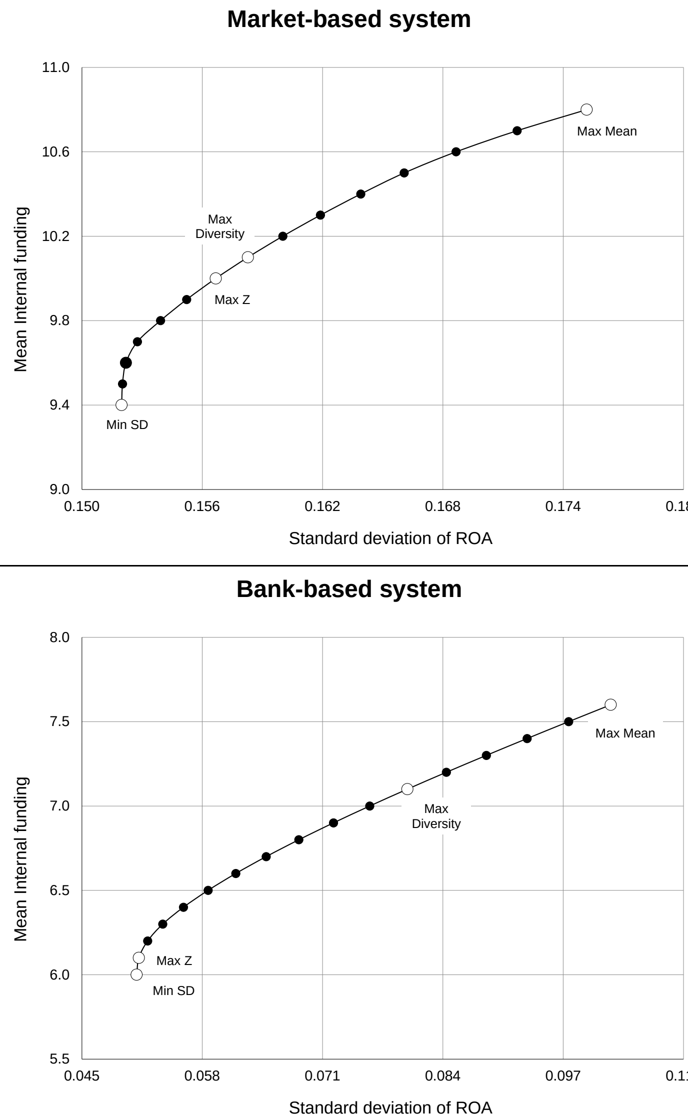
Figure 3.4. Evolution of returns per business model and type of financial system



Notes: ROA is obtained at the bank-level, and consists of the median value per year, business model and type of financial system.

Next, we focus on the efficiency frontiers of market and bank-based systems, presented in **Figure 3.5**. A visual inspection of the graphs shows that the shape of the frontiers is concave, which means that internal funding increases at a diminishing rate with

Figure 3.5. Analysis of efficient frontiers per type of financial system



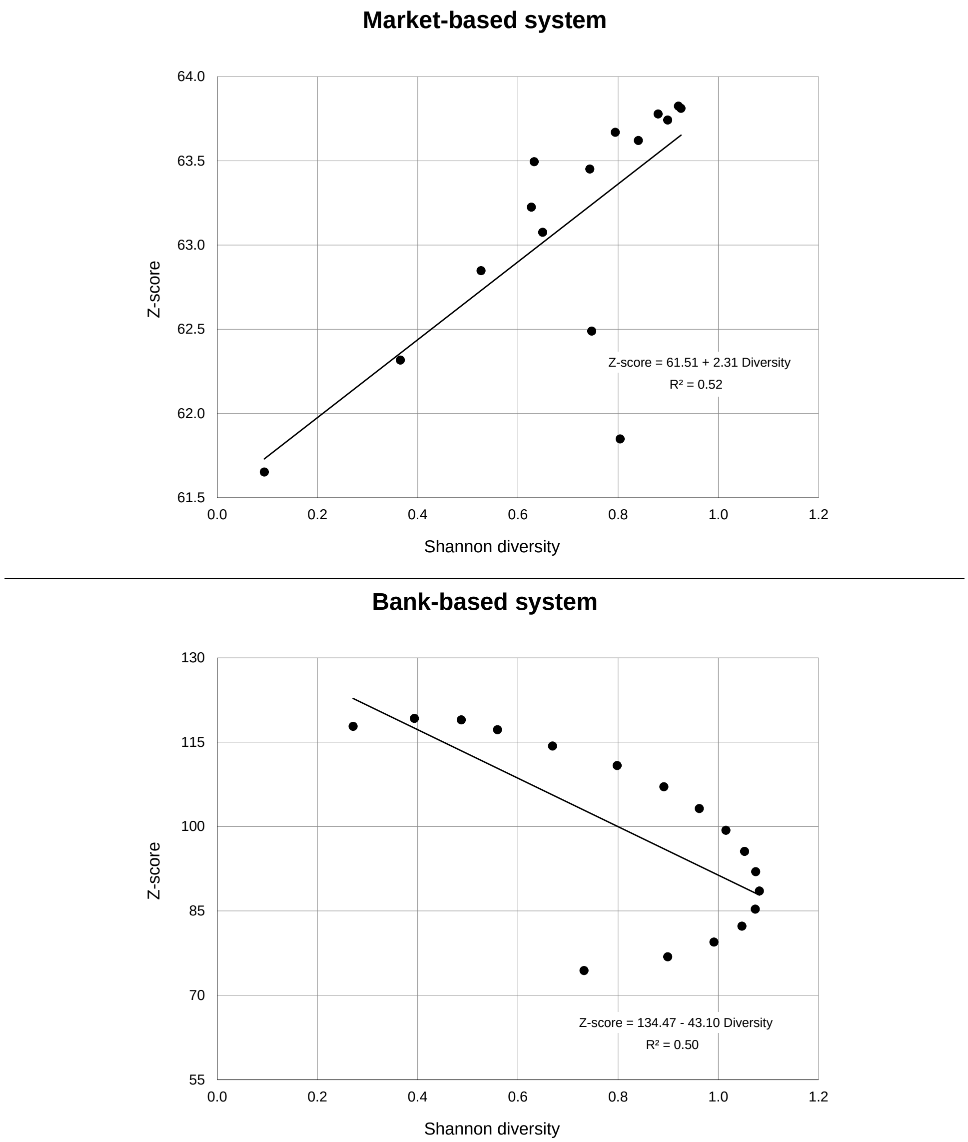
Notes: The efficient frontier is computed using a modified version of the Markowitz Mean-Variance Model (Markowitz, 1952), each point corresponds to a portfolio of business models that minimizes the variance of returns conditional on the level of mean internal funding. Min SD: minimum standard deviation, Max Z: maximum Z-score, Max Diversity: the maximum Shannon diversity of the portfolio weights. Max Mean: maximum mean returns.

increases in the standard deviation of returns (i.e. risk). The figure also allows us to compare the risk profile of the portfolios which maximize the Z-score (Z: Max Z) and the level of diversity (D: Max Diversity). In market-based systems, we may observe that, out of the 15 efficient portfolios mapped, portfolios Z and D rank #7 and #8, respectively, which indicates that both portfolios exhibit a medium risk profile; as for bank-based systems (lower graph), the risk ranking of portfolios Z and D is #2 and #12, respectively, indicating that the maximum Z-score is achieved at significantly lower levels of risk than maximum diversity. This is in line with the previously obtained result for bank-based systems, wherein we identified one business model as recording a very low standard deviation of returns (BM1).

Finally, to complement the initial results, **Figure 3.6** maps the bivariate relationship between the diversity and Z-score of efficient portfolios. For market-based systems, we uncover a positive and significant correlation between diversity and resilience (Pearson's R= 0.72); for bank-based systems, on the other hand, we find that as efficient portfolios become more diverse they tend to yield a lower level of resilience (Pearson's R= -0.71). Both results are consistent with **Figure 3.5** and lead us to look for additional insights by checking the decomposition of Z-score as well as the business model composition of portfolios.

To this effect, **Table 3.10** provides information on the diversity, Z-score, decomposition of Z-score and business model composition of seven selected efficient portfolios per type of financial system. Firstly, we start by looking at the relationship between diversity and Z-score. For market-based systems (Panel A), we may see that when the diversity of portfolios increases the Z-score increases as well; as for bank-based systems, the opposite relationship is uncovered. This confirms our previous finding that diversity seems to be positively (negatively) related with the resilience of market (bank) based systems. Secondly, we analyze the relationship between diversity and the components of Z-score. In this regard, for market-based systems we see that as portfolios become more diverse, the pair 'internal funding-risk' steadily decreases; the opposite relationship is found for bank-based systems. Such finding suggests that diversity impacts the risk profile of portfolios in different ways according to the type of financial system. Thirdly, we look at the business model composition of portfolios with different levels of resilience. For market based systems, we see that for the lowest levels of Z-score (column 1a), the portfolio is mostly comprised of BM1(88%); as the resilience increases, BM1 is progressively replaced by the retail diversified funding model (BM2) and also by the retail

Figure 3.6. Efficient portfolios: relationship between diversity and resilience



Notes: *Z-score* is the ratio between mean internal funding and standard deviation of returns for each efficient portfolio. *Shannon diversity* is calculated as –[∑pi*ln(pi)]= –[p1*ln(p1)+…+ pj*ln(pj)], where i is the banking business model, j is the total number of business models, and pi is the weight of business model i in the portfolio. The equation identified in each graph corresponds to an OLS regression using Shannon diversity as the only explanatory variable (plus an intercept) and Z-score as the explained variable (n_{Market}=15, n_{Bank} =15). Number of efficient portfolios: n_{Market}=15, n_{Bank} =18.

diversified assets model (BM3); this leads to the composition of the portfolio that maximizes the resilience (and stability of returns) for market based systems, which is mostly comprised of BM1 (53%), BM2 (35%) and BM3 (12%). Such ‘stability-diversity’ induced resilience may be understood, from an analytical perspective, as the result of mixed rankings of internal funding, standard deviation and correlations among the different business models[14], which allow the portfolio to record a significantly lower standard deviation of returns and higher mean internal funding than each portfolio taken in isolation.

As for bank-based systems, **Table 3.10** shows that the portfolio with the lowest Z-score (column 7b) is comprised of a diverse set of business models: BM1 (53%), BM3 (35%) and BM2 (12%); as the diversity of portfolios decreases (reading the table from right to left) we see that the exposure to BM2 and BM3 is progressively replaced by a narrower focus on BM1, ultimately resulting in a resilience (and stability) maximizing portfolio that includes 87% of exposure to BM1. Analytically, such 'stability-specialization' channel for bank resilience seems to be a direct consequence of the greater stability of returns recorded by BM1 when compared to other models, which significantly outweighs the differences recorded in internal funding. In fact, the standard deviation of returns of BM1 is less than half of that recorded by the model with the second most stable returns. Such lack of diversity-related gains is also visible in the similarity of standard deviations recorded by the portfolio that maximizes resilience (0.051) and BM1 (0.052). Finally, Panel C summarizes the results for the comparison of the Z-scores of efficient portfolios with similar diversity, per type of financial system. Despite the low number of observations, which hinder the statistical power of the Gibbons-Ross-Shaken Test, we find evidence that the resilience of efficient portfolios is statistically greater in bank-based systems than in market-based systems, except for the portfolio with the highest level of diversity.

In sum, in this section we have applied a 'portfolio selection' approach to study the effects of business model diversity on bank resilience per type of financial system, yielding several new results: (i) we find that efficient portfolios of market-based systems are significantly less resilient than those of bank-based systems; (ii) the evidence suggests

[14] As presented in **Table 3.9**, for market-based structures BM1 records the highest internal funding, BM2 registers the lowest standard deviation of returns, and BM3 shows the lowest correlation with both BM1 and BM2.

Table 3.10. Selected efficient portfolios for given levels of diversity

	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)	(7a)
Panel A: Market-based system							
Shannon diversity	0.37	0.53	0.63	0.74	0.84	0.90	0.93
Z-score	62.3	62.8	63.3	63.5	63.6	63.7	63.8
Mean internal funding	10.7	10.6	10.5	10.4	10.3	10.2	10.1
Standard deviation of returns	0.172	0.169	0.166	0.164	0.162	0.160	0.158
Portfolio weights							
Retail focused (BM1)	0.88	0.78	0.68	0.59	0.51	0.43	0.35
Retail diversified funding (BM2)	0.12	0.22	0.32	0.39	0.45	0.50	0.55
Retail diversified assets (BM3)	0.00	0.00	0.00	0.02	0.04	0.07	0.10
Large diversified (BM4)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)	(7b)
Panel B: Bank-based system							
Shannon diversity	0.39	0.49	0.56	0.67	0.80	0.89	0.96
Z-score	119.2	119.0	117.2	114.3	110.8	107.1	103.2
Mean internal funding	6.1	6.2	6.3	6.4	6.5	6.6	6.7
Standard deviation of returns	0.051	0.052	0.054	0.056	0.059	0.062	0.065
Portfolio weights							
Retail focused (BM1)	0.87	0.81	0.75	0.70	0.64	0.59	0.53
Retail diversified funding (BM2)	0.00	0.00	0.00	0.01	0.05	0.09	0.12
Retail diversified assets (BM3)	0.13	0.19	0.25	0.29	0.31	0.32	0.35
Large diversified (BM4)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(1c)	(2c)	(3c)	(4c)	(5c)	(6c)	(7c)
Panel C: Gibbons-Ross-Shaken Test							
Nbr. of observations	12	12	12	12	12	12	12
Nbr. of possible business models	4	4	4	4	4	4	4
J-statistic	4.66**	4.53**	4.25**	3.92*	3.56*	3.20*	2.83

Notes: The selected efficient portfolios correspond to those with a similar level of diversity in market and bank-based systems. *Mean internal funding* is computed in the following way: firstly, we compute the sum of return on assets plus capital ratio at the bank-level for each year; secondly, we identify the median value of internal funding for each combination of financial system-business model-year; finally, we compute the mean value for the full sample period (2005-16). *Standard deviation* is computed using the median annual value of ROA of each combination of financial system-business model. *Z-score* is the ratio between the mean internal funding and the standard deviation of returns. *Portfolio weights* reflects the weights of each business model in the total assets of each efficient portfolios. The nul hypothesis in the Gibbons-Ross-Shaken Test (Gibbons *et al*., 1989) is that the Z-score of efficient portfolios with similar diversity are not statistically different in market and bank-based systems. ***, ** and * indicate statistical significance at the 1%. 5% and 10% level.

that diversity increases the resilience of market-based systems and reduces that of bank-based systems – by linking (i) and (ii), the diversity of business model may be seen as taken on a particularly relevant role as a mechanism to boost the comparatively low levels of resilience of market-based systems; (iii) in both types of financial systems, the role of the stability of returns (denominator of Z-score) in setting the level of resilience seems to outweigh that of the mean internal funding (numerator of Z-score). Such result suggests that monitoring the correlation of returns among market players may be an effective macroprudential tool to anticipate drops in aggregate resilience (Goodhart & Wagner, 2012), and represents, to the best of our knowledge, a novel result in literature; and (iv) the most resilient portfolios exhibit significant differences in business model composition between types of financial systems, suggesting that 'one size does not fit all' regarding the impact of business model diversity on resilience. In fact, our analysis suggests that the decrease in portfolio riskiness seems to be achieved via two different channels, according to the type of financial system: for market based systems, increasing the diversity of business models tends to reduce riskiness ('diversity-stability' channel), whereas for bank based systems, lower riskiness is obtained via the specialization of countries in business models with the most stable returns ('specialization-stability' channel).

3.6. Robustness checks

3.6.1. Estimation methods

Our first two robustness checks are related with the methods used to estimate the system of simultaneous equations identified in equations (2) to (4). The first issue that we tackle is related to use robust standard deviations. Particularly, the baseline 3SLS results are reported using uncorrected standard deviations. However, when performing the Breusch-Pagan LM test we reject the null hypothesis of no overall system heteroscedasticity. This leads us to estimate the system of equation using the approach of Seemingly Unrelated Regressions (SURE), which allows the computation of Huber-White robust standard errors (White, 1980). More specifically, we implement SURE by applying the conditional mixed-process regression approach, envisioned by Roodman (2011). The results reported in **Table 3.11,** column (1), suggest that the effect of diversity on resilience remains positive and statistically significant. Moreover, untabulated results show that the correlation of the error terms of the three estimated equations are not statistically different from zero, which suggests the absence of overidentification issues.

Table 3.11. Robustness checks

	SURE	**Static GMM**	**Dyn. GMM**	**SYSRISK**	**RCAP**	**NPL (ln)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Shannon diversity	0.273**	0.553***	0.196*	-10.371*	0.980***	-1.613
Past crises dummies	Yes	No	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	303	336	336	336	336	336
Log pseudo-likelihood	1300.7					
Wald Chi-squared (p-value)	0.00					
Hansen's J test (p-value)		0.67	0.91			
AR (1)			0.00			
AR (2)			0.19			
R-squared				0.81	0.22	0.57
Sargan-Hansen test (p-value)				0.87	0.72	0.87
	BCRISIS	**Simpson div.**	**Shan. even.**	**Gov. Qual.**	**Excl. China**	**Excl. US**
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Shannon diversity	-17.363*			1.196***	1.190***	1.701***
Simpson diversity		0.569***				
Shannon evenness			4.144***			
Shannon diversity*Gov. qual.				0.073		
Number of observations	336	336	336	336	331	324
Likelihood ratio (t-stat)	0.00					
R-squared	0.91	0.91	0.92	0.95	0.93	0.93
Sargan-Hansen test (p-value)	0.54	0.54	0.58	0.80	0.86	0.94

Notes: all regressions are estimated using the system of equations (3.2 to 3.4) (**Section 3.3.2**), except for regression (7) for which we only estimate equation (3.4). Regression (1) is estimated using Seemingly Unrelated Regressions (SURE), with Huber-White robust standard errors (1980), following the conditional mixed-process regression approach (Roodman, 2011). To estimate regression (2) we use two-step static GMM with heteroskedasticity and autocorrelation consistent (HAC) weighting matrix, and Bartlett kernel with 2 lags. Regression (3) is obtained by employing dynamic GMM (i.e. the lag dependent variable is included as explanatory variable) with robust standard errors. In regression (4) the explanatory variable is the natural log of V-lab's Systemic Risk measured as "the expected capital shortfall of a financial firm in a systemic crisis where the broad market index falls by more than 40% in a six-month period" (V-lab, n.d.). We compile the value of SYSRISK for all financial firms in a given country-year, including non-bank institutions such as insurance companies. In regression (5) the explanatory variable is the regulatory capital (RCAP) computed as the eligible regulatory capital (Tier 1 + Tier 2) divided by total risk weighted assets, obtained via the World Bank's Global Financial Development Database (GFD). In regression (6) the explanatory variable is non-performing loans to total assets (source: GFDC). In regression (7) the explanatory variable is a dummy which takes one the value 1 if a country experienced a systemic banking crisis (CRISIS) in a given year, as identified by Laeven & Valencia (2018) (full list of crisis identified in **Appendix 3.2)**; we estimate regression (7) using a logit model with year fixed effects. In regression (8) as the diversity measure, we use Simpson diversity which is calculated as the 1 divided by the HHI of total assets' market shares held by each business model. In regression (6) the diversity measure used is Shannon evenness which is computed as the ratio between the Shannon diversity and the number of business models present in each country. In regression (9) we interact diversity with the index of Government quality (Barth *et al.*,2004), computed as the first principal component of six variables obtained from the World Bank's Governance Indicators: control of corruption, rule of law. government effectiveness. political stability and absence of violence/terrorism, regulatory quality, voice and accountability. In regressions (10) to (12) we exclude the most dominant countries in each type of financial system, measured in terms of share of total assets. Namely, China (39.9% of total assets of bank-based systems), France (24.5% of total assets of market-based systems), US (21.1% of total assets of market-based systems) and UK (21.0% of total assets of market-based systems).

Another issue in our baseline regression is related with autocorrelation. In particular, when performing the Harvey LM test we reject the null hypothesis of overall system autocorrelation in our baseline specification. As a way of mitigating such violation of the classical econometric hypothesis of absence of autocorrelation, we apply two alternative methods. First, we run two-step Generalized Method of Moments (GMM) with heteroskedasticity and autocorrelation consistent (HAC) weighting matrix, and Bartlett kernel with 2 lags. Secondly, we employ dynamic GMM (i.e. the lag dependent variable is included as explanatory variable) with robust standard errors, *ala* Arellano & Bover (1995). The results in columns (2) and (3) show that the coefficient of diversity on resilience remains positive and statistically significant using both alternative methods, although at lower levels when compared with the baseline results. Also, for both specifications we do not reject the null hypothesis of instruments' exogeneity, as given by the Hansen test results.

3.6.2. Alternative proxies and disturbances to sample composition

An additional potential concern regarding our results is whether they are robust to changes to the proxy used to measure the resilience of banking sectors. To this effect we change our baseline specification to include as dependent variable (i) the natural log of V-lab's Systemic Risk, measured as "the expected capital shortfall of a financial firm in a systemic crisis where the broad market index falls by more than 40% in a six-month period" (V-lab, n.d.); (ii) the natural log of regulatory capital (Tier 1 plus Tier 2) to risk-weighted assets; and (iii) the ratio of non-performing loans to total gross loans, both (ii) and (iii) obtained via the World Bank's Global Financial Development Database. As reported in columns (4) and (5) of **Table 3.11**, business model diversity is expected to significantly reduce systemic risk and increase regulatory capital, which is in line with our baseline results. As for loan riskiness, the effect of diversity is negative but not statistically significant. This suggests that the role of returns' correlations as driver of the 'diversity-stability' nexus (documented in **Section 3.5.3**) does not seem to occur via correlations of credit risk. For brevity reasons, we refrain from exploring the other potential profit channels (e.g. efficiency, interest income, non-interest income), but flag this as a possible avenue for future research. Finally, we explore the association between business model diversity and the probability of occurring a systemic banking crisis, as surveyed by Laeven & Valencia (2018). We perform this analysis using a logit model with year fixed effects. As expected, the coefficient of diversity is negative and significant, which indicates that more diverse banking systems are less likely to face systemic banking crisis.

Next, we test whether replacing our measure of business model diversity (Shannon diversity) with other measures taken from ecology literature significantly changes the nature of our baseline results (Maurer & McGill, 2011). In particular, we test (i) Simpson's formulation of diversity, which is computed as the inverse of the Herfindhal-Hirshman Index using the total assets' market shares of each business model per country; and (ii) Shannon evenness, measured as the Shannon diversity divided by the natural log of the number of business models identified in each country. The results presented in columns (8) and (9) show a positive and significant impact of the alternative measures of diversity on resilience, which may be seen as an indication of the robustness of the 'diversity-resilience' nexus to potential measurement errors.

We also check whether the impact of diversity on resilience depends on the quality of government. Namely, some studies suggest that country-level quality of government may have a role in terms of banking sector resilience, although not always a positive one (Barth *et al.*, 2004). For instance, Houston *et al.* (2010) find that strong creditor rights tend to be associated with greater risk-taking by banks, whereas information sharing and transparency initiatives tend to potentiate the profitability and resilience of banks. We follow literature (Barth *et al.*, 2004) and build an index of government quality by computing the first principal component of six variables obtained from the World Bank's Governance Indicators (see list of variables in the notes to **Table 3.11**). To assess the impact of the quality of government on our baseline results, we include the government quality index as an interaction term with diversity. The results presented in column (10) show that our main findings remain unchanged and that diversity does not seem to significantly depend on the level of government quality.

In our final inquiry we analyze whether iteratively removing the two largest banking sectors in total assets (US and China) from our sample modifies the baseline results. As may be observed in columns (11) and (12), the impact of diversity on resilience remains positive and significant after removing the US and China, respectively, which suggests that in general our results may be deemed robust to disturbances to the sample composition.

3.7. Conclusions and policy implications

There is an open debate in literature regarding the relative merits of diversification and diversity on the resilience of banking sectors. While one strand of literature puts emphasis on the additional risks that increased diversification/homogenization may bear (for instance, in terms of loan rationing, asset commonality, collusive behavior and risk-induced by implicit state guarantees), another strand suggests that not allowing banks to choose the risk diversification strategies that are individually optimal, may be a 'worse remedy than the disease itself'. This paper has aimed to provide several contributions to this discussion, including (i) the development of a new measure of bank diversity which takes into account recent developments in business model analysis, (ii) the specification of an econometric model that explicitly takes into account the interactions of business model diversity with diversification and market power, (iii) the analysis of heterogeneity in the 'diversity-resilience' nexus according to the type of financial system, and (iv) the application of portfolio selection methods to uncover the diversity and composition of optimal portfolios of business models.

Our results suggest that revenue diversification reduces business model diversity, which, in turn, increases both market power and resilience; whereas diversification and market power are found to have no significant direct impact on resilience. When breaking down the analysis per type of financial system, we may observe that the relationship between diversity and resilience is, in fact, driven mostly by market-based systems. We attribute this novel and interesting finding to the trade-off between diversity induced benefits (mainly reduced contagion) and costs (loss of specialization gains), which seems to be more favorable for market-based systems. The results of our efficiency frontier analysis complement the baseline findings in the sense that they seem to suggest that a similar level of diversity may in fact induce different resilience responses according to the type of financial system. In light of standard portfolio selection theory, such conclusion may be seen as a direct result of the specific mix of rankings of internal funding, standard deviation and correlation of the banking business models – in other words, it depends on the 'ecosystem' of each type of financial system.

The results in this paper bear potential contributions to both micro and macro-prudential policies. Firstly, the heterogeneous effects observed in the 'diversity-resilience' nexus suggest that the type of financial system should be taken into account when defining microprudential policies that may affect the business model appetite of supervised entities. For instance, policies related with restrictions to the type of activities, funding sources or size increase. Secondly, the results of the efficiency frontier analysis suggest that monitoring the correlation of returns among market players may provide relevant insights regarding the concentration of risk in some areas of the banking sector. This suggests that such monitoring of correlations may indeed play a role as an early warning tool of systemic risk, as suggested by Goodhart & Wagner (2012). We must state, however, that testing the efficacy of such tool has fallen outside the scope of this paper, and hence further investigation is needed in the future.

CONCLUSIONS

In this thesis we have presented three empirical papers focused on testing the link between banking business models, bank profitability and riskiness.

In the first paper, included in **Chapter 1**, we provided an expansion of the definition of banking business model used in literature, established a new method to identify banking business models, identified the number of banking business models in Europe, and described their distinctive features, level of fuzziness and stability over time. More specifically:

1.1. The proposed definition of banking business models provided a framework to accommodate two empirical observations: (i) under some circumstances, banks may have some affinity with more than one business model, e.g. following a merger or acquisition, or a change in business policy; and, relatedly, (ii) banks may change their business model over time, particularly in reaction to changes in their environment.

1.2. The proposed method to identify business models was conceived in order to handle fuzzy data (FCM), yield intuitive visualizations of the models (SOM) and circumvent the presence of data outliers (PAM).

1.3. The tests regarding the stability of classification showed that the proposed method bears high immunity to disturbances to the sample, methods and variables used – a result which we attributed to the robustness of the ensemble approach (Kuncheva, 2004).

1.4. By applying the method to a sample of 524 European banks between 2005 and 2016, at the consolidated level, we found evidence of four banking business models: the retail focused model, the retail diversified funding model, the retail diversified assets model, and the large diversified model.

1.5. The *retail focused model*, the most popular banking configuration, was found to record high values of loans to customers, customer deposits and total equity, as well as a relatively small size. As such, the model may be seen as akin to a traditional way of doing banking, and is expected to be mostly exposed to credit risk via its banking book.

1.6. The *retail diversified funding model* was shown to couple customer lending with a high exposure to wholesale funding, and a relatively large size. Given the potential lack of stability of short-term wholesale markets and the general illiquidity of the banking book, such configuration may be expected to be mainly exposed to liquidity and funding risks.

1.7. The *retail diversified assets model* was demonstrated to be followed by relatively small banks, with a significant exposure to interbank lending, which is funded via customers deposits. Such configuration was seen as potentially generating significant counterparty risk. In some cases, such risk was found to be mitigated by the fact that the counterparts belong to the same network of cooperative or savings banks.

1.8. The *large diversified model* was found to be significantly diversified in both sides of the balance sheet. The left side showed a sizeable trading book, whereas the right side exhibited a mix of funding sources. On average, banks operating with this model were also found to be large, with a diversified income structure and significantly exposed to the derivatives market. The banks following such model, which include large investment banks, are expected to be particularly exposed to market risks originated in the trading book, and may be seen as a significant source of systemic risk due to the size and complexity of their operations.

1.9. Additionally, it was found that the level of affinity of banks with their allocated model differs according to the business model. Namely, banks operating with a retail diversified (assets or funding) model tend to operate less closely to the group's typical business strategy. This result was seen a potential early signal for bank supervisors to the fact that the analysis of the business model of retail diversified banks may require additional insights from a qualitative perspective in order to adequately grasp the risk exposures of these banks.

1.10. Finally, our analysis suggested that the height of mobility barriers vary significantly across business models. Namely, we found that customer deposits hinder banks from moving from the retail focused model to other models; size constraints the mobility of banks with a retail diversified funding or a large diversified models; and the exposure to interbank lending limits the ability of banks to change from the retail diversified assets model to other models.

In the second paper, featured in **Chapter 2**, we examined which business model choices are more likely to increase the profitability and distance to distress of banks, whether the effects of business choices are heterogeneous, and if changing business model pays-off.

2.1. We found evidence that profitability and distance to distress tend to be higher for relationship-oriented banks and banks following a retail focused business model. On the other hand, banks with a transactional-orientation and banks operating with the retail diversified funding model and the large diversified model, were found to be significantly less profitable and with a lower distance to default, than other types.

2.2. Additionally, by analyzing the individual business features we found that such results are significantly driven by the choices related with size, customer deposits, and capital.

2.3. The size of banks was found to negatively impact bank profitability and distance to distress. Such result was interpreted as suggesting that increases in bank size seem to bear a greater impact on agency costs (Jensen & Meckling, 1976) than on efficiency gains (Scholes *et al.*, 1976). This finding seems to have implications, for instance, in the context of the current wave of acquisitions in the banking sector. More specifically it suggests that bank synergies may easily be overestimated if agency costs and, relatedly, the efficacy of the governance mechanisms, are not explicitly considered.

2.4. The level of customer deposits was shown to positively impact bank profitability, wherein such effect was found to occur mainly via reduced funding costs. Such outcome was seen to validate the notion that customer deposits constitute a stable source of funding, likely due to the presence of deposit guarantee schemes (Rajan, 1992).

2.5. The level of bank capital was found to positively affect bank profitability. Namely, by contributing to the reduction of funding costs and to the increase in non-interest income. This result was interpreted as supporting the view that well capitalized banks are in a better position to pursue business opportunities (Athanasoglu *et al.*, 2008), and as such corroborate the recent to strengthen the capital position of European banks.

2.6. Concerning the heterogeneous effects of business model choices, it was found that the benefits of asset and income diversification (in terms of profitability and distance to distress, respectively) only show up for banks with a high relationship orientation – a result which we associated to the benign-side of diversification, i.e. the benefits of retail banks investing a small portion of their assets in low-risk fixed income instruments, such as sovereign debt, and by providing standard fee-based services to customers, such as insurance sales, money transfers, and safe deposit boxes (DeYoung & Torna, 2013).

2.7. Additionally, size was found to negatively impact profitability only for banks with a high relationship orientation. Such result was deemed to be in line with relationship lending literature, according to which larger organizations tend to be less effective in handling soft information (Liberti & Mian, 2008) – a feature that has often been identified as a key success factor for relationship banking (Petersen & Rajan, 1995).

2.8. Moreover, it was found that the benefits of customer deposits in terms of profitability only occur for banks with a low relationship orientation, which may be seen as evidence of the stabilizing effects of customer deposits on non-retail banks (Huang & Ratnovski, 2011) and seem to provide some support for the implementation of liquidity-specific regulatory requirements, such as the Net Stable Funding Ratio.

2.9. As for the innovative study of the effects of business model changes on profitability, it was found that a significant share of banks operating with a retail *diversified* model changed to the retail *focused* model between 2005 and 2016.

2.10. It was also shown that banks that received state aid during the GFC were significantly more likely to change to the retail focused model. Such result may be seen as evidence that the restructuring plans that underly state aid programs have effectively lead banks to adopt simpler, more traditional business models.

2.11. Lastly, it was found that on average changing from the worst performing business model (BM2) to other models tends to pay-off in the medium term (i.e. two trienniums after the change). Within management literature, this finding seems to support the view that managerial decisions may positively influence the performance of firms as response to changes in the competitive landscape (Child, 1972), in contrast to the ecological perspective, according to which firms should not, under any circumstance, deviate from their long-term strategy, given the substantial costs and added risks for survival (Haveman, 1992).

2.12. An important contribution of the second paper was to establish two testing strategies to mitigate endogeneity concerns. The implementation of 2SLS regressions required the development and thorough analysis of candidate instruments to proxy for bank orientation, wherein the final choice of instruments included the proximity to financial centers, the Lerner index, and the non-rural area dummy. A discussion on the merits and handicaps of each instrument was performed, and their exogeneity tested. The implementation of system GMM, too, involved many tests in search for a specification that yielded stable and robust results. Importantly, in both cases the exogeneity of instruments was ensured and the direction of the baseline results remained unchanged.

The third and final paper, presented in **Chapter 3**, tested the simultaneous relationship between business model diversity, diversification, market power and resilience, it checks whether the 'diversity- resilience' nexus differs for market and bank-based systems, and it studies the diversity and composition of efficient portfolios of banking business models.

3.1. It was found that revenue diversification significantly reduces business model diversity, in tune with the view that banks tend to pursue *uniform* diversification strategies (Beale *et al.*, 2011) that, as whole, yield a more homogenous banking sector (Wagner, 2008).

3.2. The evidence also uncovered a positive relationship between business model diversity and market power. Such result is viewed as evidence in support of the 'strategic interdependence' narrative put forward by Strategic Groups Theory (Porter, 1979), according to which the choices of different business models may be seen as strategic complements, *à la* the Bertrand model with differentiation (1883).

3.3. Importantly, business model diversity is found to bear a positive and significant impact on resilience. This finding suggests that less homogeneous banking systems are less likely to face systemic distress (Wagner & Goodhart, 2012). More specifically, by using the coefficients of the 3SLS regressions, we estimated a 7.0% increase in the Z-score of banks as a consequence of a one (within) standard deviation increase in business model diversity.

3.4. Neither revenue diversification nor market power were found to directly affect the resilience of the banking sector. This result is not entirely a surprise, given the mixed evidence in literature, and coupled with the previous finding suggests that business model diversity plays a central role in explaining banking resilience.

3.5. Regarding the sensitive to the baseline results to the type of financial system, we found that the positive relationship between business model diversity and resilience only holds for market-based systems. We interpreted such findings as evidence of the stabilizing effects of diversity on market-based systems, which tend to be more prone to bank contagion, for instance via the wholesale markets (Huang & Ratnovski, 2011) – an intuition which draws some parallel with the stabilizing role of customer deposits for non-retail banks (*vide* finding **2.8** in this section).

3.6. By analyzing the efficient portfolios of market and bank-based systems, we found that (i) efficient portfolios of market-based systems are significantly less resilient than those of bank-based systems and (ii) diversity increases (reduces) the resilience for market (bank) systems. The joint consideration of both results seems to suggest that the effects of diversity on resilience may be in fact heterogenous, i.e. conditional on the level of resilience.

3.7. Additionally, evidence was collected suggesting that, in both types of financial systems, the role of the stability of returns (denominator of Z-score) in setting the level of resilience seems to outweigh that of the mean internal funding (numerator of Z-score). Such result is interpreted as an indication that monitoring the correlation of returns among market players may be an effective macroprudential tool to anticipate drops in aggregate resilience (Goodhart & Wagner, 2012), and represents, to the best of our knowledge, a novel result in literature

3.8. Finally, it was found that the most resilient portfolios exhibit significant differences in business model composition between types of financial system. Particularly, the results suggest that, depending on the type of financial system, a decrease in portfolio riskiness may be achieved via two alternative channels: for market based systems, reduced riskiness is achieved via an increase in the diversity of business models ('diversity-stability' channel); whereas for bank based systems, lower riskiness is obtained via the specialization in the business model with the most stable returns ('specialization-stability' channel). In line with management literature that places particular relevance on the competitive landscape (e.g. Zúñiga-Vicente & Vicente-Lorente, 2006), this finding suggests that 'banking ecosystems' matter for the study of banking resilience.

In summary, this thesis advocates that (i) banking business models are diverse, and subject to specific risks and vulnerabilities, and hence their measurement and monitoring is informative as a unit of analysis for management literature and practitioners; (ii) the last decade has seen the return to (and the relative prosperity of) a traditional way of doing banking, which is in tune with the current regulatory trends; (iii) literature on business model analysis should continue to carefully account for the heterogeneous effects of business model choices; (iv) the effects of the diversity of business models on the resilience of banking sectors are sensitive to the type of 'banking ecosystem'; and (v) more broadly, the DNA of the field of banking business models analysis may be summarized in the following *motto*: 'one size does *not* fit all'.

REFERENCES

Abellán, J., & Castellano, J. G. (2017). A comparative study on base classifiers in ensemble methods for credit scoring. *Expert Systems with Applications, 73*(1), 1-10.

Acharya, V. V., Gale, D., & Yorulmazer, T. (2011). Rollover risk and market freezes. The *Journal of Finance, 66*(4), 1177-1209.

Acharya, V. V., & Thakor, A. V. (2016). The dark side of liquidity creation: Leverage and systemic risk. *Journal of Financial Intermediation, 28*(1), 4-21.

Acharya, V. V., & Yorulmazer, T. (2007). Too many to fail—An analysis of time-inconsistency in bank closure policies. *Journal of Financial Intermediation, 16*(1), 1-31.

Akhavein, J. D., Berger, A. N., & Humphrey, D. B. (1997). The effects of megamergers on efficiency and prices: Evidence from a bank profit function. *Review of Industrial Organization, 12*(1), 95-139.

Ala'raj, M., & Abbod, M. F. (2016). A new hybrid ensemble credit scoring model based on classifiers consensus system approach. *Expert Systems with Applications, 64*(1), 36-55.

Alam, P., Booth, D., Lee, K., & Thordarson, T. (2000). The use of fuzzy clustering algorithm and self-organizing neural networks for identifying potentially failing banks: an experimental study. *Expert Systems with Applications, 18*(3), 185-199.

Allen, F., & Gale, D. (2000). Financial contagion. *Journal of Political Economy, 108*(1), 1-33.

Allen, F., Babus, A., & Carletti, E. (2012). Asset commonality, debt maturity and systemic risk. *Journal of Financial Economics, 104*(3), 519–534.

Altunbas, Y., Marqués-Ibáñez, D., & Manganelli, S. (2011). *Bank risk during the financial crisis: do business models matter?* ECB Working Paper Series, Macroprudential Research Network, no. 1394, November 2011, 1–53.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics, 68*(1), 29-51.

Aryuni, M., Madyatmadja, E. D., & Miranda, E. (2018). Customer Segmentation in XYZ Bank Using K-Means and K-Medoids Clustering. *Proceedings of the 2018 International Conference on Information Management and Technology*, 412-416.

Ayadi, R., Arbak, E., & Pieter De Groen, W. (2011). *Business Models in European Banking: A pre-and post-crisis screening*. Center for European Policy Studies, Brussels.

Ayadi, R., De Groen, W. (2015). *Banking business models monitor 2014: Europe*. Center for European Policy Studies, Brussels.

Ayadi, R., De Groen, W., Sassi, I., Mathlouthi, W., Rey, H., & Aubry, O. (2016). *Banking business models monitor 2015: Europe*. Center for European Policy Studies, Brussels.

Ayadi, R., Bongini, P., Casu, B., & Cucinelli, D. (2018). *Bank business models' migrations in Europe: Determinants and effects*. Working Paper, Centre for Banking Research, Cass Business School.

Azadeh, A., Javanmardi, L., & Saberi, M. (2010). The impact of decision-making units features on efficiency by integration of data envelopment analysis, artificial neural network, fuzzy C-means and analysis of variance. *International Journal of Operational Research, 7*(3), 387-411.

Back, B., Oosterom, G., Sere, K., & Van Wezel, M. (1995). *Intelligent information systems within business bankruptcy predictions using neural networks*. In 3rd European Conference on Information Systems, 1-3.

Bain, J. S. (1956). *Barriers to New Competition*. Cambridge: Harvard University Press.

Baltagi, B. H., & Griffin, J. M. (1984). Short and long run effects in pooled models. *International Economic Review, 25*(3), 631-645.

Barth, J. R., Caprio, G., & Levine, R. (2004). Bank regulation and supervision: what works best?. *Journal of Financial Intermediation, 13,* 205–248.

Barth, J. R., Caprio, G., & Levine, R. (2006). *Rethinking bank regulation: Till angels govern*. Cambridge: Cambridge University Press.

Basile, R., Capello, R., & Caragliu, A. (2012). Technological interdependence and regional growth in Europe: Proximity and synergy in knowledge spillovers. *Papers in Regional Science, 91*(4), 697-722.

Bats, J. V., & Houben, A. C. (2020). Bank-based versus market-based financing: implications for systemic risk. *Journal of Banking & Finance, 114*, 1-13.

Baum, C. F., Grazzini, C. F., & Schäfer, D. (2020). *Institutional diversity in domestic banking sectors and bank stability: A cross-country study*. DIW Berlin Discussion Paper No. 1869.

BCBS. (2011). *Basel III: A global regulatory framework for more resilient banks and banking systems*. Basel Committee on Banking Supervision. June 2011, Basel.

Beale, N., Rand, D. G., Battey, H., Croxson, K., May, R. M., & Nowak, M. A. (2011). Individual versus systemic risk and the regulator's dilemma. *Proceedings of the National Academy of Sciences, 108*(31), 12647-12652.

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2006). Bank concentration, competition, and crises: First results. *Journal of Banking & Finance, 30*(5), 1581-1603.

Beck, T., De Jonghe, O., & Schepens, G. (2013). Bank competition and stability: Cross-country heterogeneity. *Journal of Financial Intermediation*, *22*(2), 218-244.

Becker, S. O., & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal*, *2*(4), 358-377.

Beltratti, A., & Stulz, R. (2012). The credit crisis around the globe: Why did some banks perform better?. *Journal of Financial Economics*, *105*(1), 1-17.

Ben-Bassat, A. (1980). The optimal composition of foreign exchange reserves. *Journal of International Economics*, *10*(2), 285-295.

Bencivenga, V. R., & Smith, B. D. (1991). Financial intermediation and endogenous growth. *The Review of Economic Studies*, *58*(2), 195-209.

Berger, A., Clarke, G., Cull, R., Klapper, L., & Udell, G. (2005a). Corporate governance and bank performance: A joint analysis of the static, selection, and dynamic effects of domestic, foreign, and state ownership. *Journal of Banking & Finance, 29*(8), 2179-2221.

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005b). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics, 76*(2), 237-269.

Berger, A. N., Klapper, L. F., & Turk-Ariss, R. (2009). Bank competition and financial stability. *Journal of Financial Services Research*, *35*(2), 99-118.

Bertrand, J. (1883). Théorie mathématique de la richesse sociale. *Journal des Savants, 67*(1883), 499-508.

Bezdek, J., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. *Computers & Geosciences, 10*(2-3), 191-203.

BIS. (2018). *Structural changes in banking after the crisis*. Bank for International Settlements, Committee on the Global Financial System. CGFS Papers, No 60. Basel.

Blundell-Wignall, A., & Roulet, C. (2013). Business models of banks, leverage and the distance-to-default. *OECD Journal: Financial Market Trends, 2012*(2), 7-34.

Blundell-Wignall, A., Atkinson, P., & Roulet, C. (2014). *Bank business models and the Basel system: Complexity and interconnectedness.* OECD Journal: Financial Market Trends 2013, 2, 43-68.

Boot, A. W., & Thakor, A. V. (2000). Can relationship banking survive competition?. *The Journal of Finance*, *55*(2), 679-713.

Bouvatier, V., & Lepetit, L. (2012). Provisioning rules and bank lending: A theoretical model. *Journal of Financial Stability, 8*(1), 25-31.

Boyd, J., Chang, C., & Smith, D. (1998). Moral hazard under commercial and universal banking. *Journal of Money, Credit and Banking, 30*(3), 426-468.

Boyd, J. H., & De Nicolo, G. (2005). The theory of bank risk taking and competition revisited. *The Journal of Finance, 60*(3), 1329-1343.

Budayan, C., Dikmen, I., & Birgonul, M. T. (2011). Hybrid strategic groups in construction. *Engineering Project Organization Journal, 1*(3), 183-196.

Caliński, T., & Harabasz, J. (1974). A dendrite method for cluster analysis. *Communications in Statistics: Theory and Methods, 3*(1), 1-27.

Calomiris, C. (1999). Building an incentive-compatible safety net. *Journal of Banking & Finance, 23*, 1499–1519.

Casu, B., Clare, A., Sarkisyan, A., & Thomas, S. (2013). Securitization and bank performance. *Journal of Money, Credit and Banking*, *45*(8), 1617-1658.

Cavelaars, P., & Passenier, J. (2012). Follow the money: What does the literature on banking tell prudential supervisors about bank business models?. *Journal of Financial Regulation and Compliance*, *20*(4), 402-416.

Cebeci, Z., Yildiz, F., Kavlak, A., Cebeci, C., & Onder, H. (2019). *ppclust: Probabilistic and Possibilistic Cluster Analysis*. R package version 0.1.2.

Cernov, M., & Urbano, T. (2018). *Identification of EU bank business models: a novel approach to classifying banks in the EU regulatory framework.* EBA Staff Paper Series 2/2018. London.

Chair, S., & Charrad, M. (2017). *multisom: Clustering a Data Set using Multi-SOM Algorithm*. R package version 1.3.

Chang, F., Qiu, W., Carey, V., Zamar, R., Lazarus, R. Wang, X. (2019). *clues: Clustering Method Based on Local.* R package version 0.6.2.2.

Child, J. (1972). Organizational structure, environment and performance. *Sociology, 6*, 1,1-22.

Chiorazzo, V., Milani, C., & Salvini, F. (2008). Income diversification and bank performance: Evidence from Italian banks. *Journal of Financial Services Research, 33*(3), 181-203.

Chiorazzo, V., D'Apice, V., DeYoung, R., & Morelli, P. (2018). Is the traditional banking model a survivor?. *Journal of Banking & Finance, 97*, 238-256.

Clougherty, J. A., Duso, T., & Muck, J. (2016). Correcting for self-selection based endogeneity in management research: Review, recommendations and simulations. *Organizational Research Methods, 19*(2), 286-347.

Cosma, S., Ferretti, R., Gualandri, E., Landi, A., & Venturelli, V. (2017). The business model of banks: A review of the theoretical and empirical literature. In G. Chesini *et al.* (Eds.), *The Business of Banking* (pp. 131-167). London, UK: Palgrave Macmillan.

Cuevas, C. & K. Fischer. (2006). *Cooperative Financial Institutions: Issues in Governance, Regulation, and Supervision.* World Bank Working Paper No. 82, Washington, D.C., USA.

Curi, C., Lozano-Vivas, A., & Zelenyuk, V. (2015). Foreign bank diversification and efficiency prior to and during the financial crisis: Does one business model fit all?. *Journal of Banking & Finance, 61*, S22-S35.

Curry, B., Davies, F., Phillips, P., Evans, M., & Moutinho, L. (2001). The Kohonen self-organizing map: an application to the study of strategic groups in the UK hotel industry. *Expert systems, 18*(1), 19-31.

Davalos, S., Leng, F., Feroz, E. H., & Cao, Z. (2014). Designing an if–then rules-based ensemble of heterogeneous bankruptcy classifiers: a genetic algorithm approach. *Intelligent Systems in Accounting, Finance and Management, 21*(3), 129-153.

Davies, D. L., & Bouldin, D. W. (1979). A cluster separation measure. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 1*(2), 224-227.

De Andrés, J., Lorca, P., Javier de Cos Juez, F., & Sánchez-Lasheras, F. (2011). Bankruptcy forecasting: A hybrid approach using Fuzzy c-means clustering and Multivariate Adaptive Regression Splines (MARS). *Expert Systems with Applications, 38*(3), 1866-1875.

De Haan, L., & Kakes, J. (2019). European banks after the global financial crisis: Peak accumulated losses, twin crises and business models. *Journal of Banking Regulation, forthcoming*.

De Haas, R., & Van Lelyveld, I. (2010). Internal capital markets and lending by multinational bank subsidiaries. *Journal of Financial Intermediation, 19*(1), 1-25.

Degryse, H., & Ongena, S. (2007). The impact of competition on bank orientation. *Journal of Financial Intermediation*, *16*(3), 399-424.

Deboeck, G. J. (1998). Financial applications of self-organizing maps. *Neural Network World, 8*(2), 213-241.

Demirguc-Kunt, A., & Huizinga, H. (2010). Bank activity and funding strategies : The impact on risk and returns. *Journal of Financial Economics, 98,* 626–650.

Demirguc-Kunt, A., & Pería, M. S. (2010). *A framework for analyzing competition in the banking sector: an application to the case of Jordan*. The World Bank, Policy Research Working Paper WPS no. 5499, December 2010.

DeSarbo, W. S., & Grewal, R. (2008). Hybrid strategic groups. *Strategic Management Journal*, *29*(3), 293-317.

Desgraupes, B. (2016). *clustercrit: Clustering Indices*. R package version 1.2.7.

DeYoung, R. (2010). Scale economies are a distraction. *The Region, 10*(3), 7.

DeYoung, R., & Rice, T. (2004). How do banks make money? A variety of business strategies. *Economic Perspectives, 28*(4), 52.

DeYoung, R., & Roland, K. P. (2001). Product mix and earnings volatility at commercial banks: Evidence from a degree of total leverage model. *Journal of Financial Intermediation, 10*(1), 54-84.

DeYoung, R., & Torna, G. (2013). Nontraditional banking activities and bank failures during the financial crisis. *Journal of Financial Intermediation, 22*(3), 397-421.

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy, 91*(3), 401-419.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *Review of Economic Studies, 51*(3), 393-414.

Diamond, D. W., & Rajan, R. G. (2001). Liquidity risk, liquidity creation, and financial fragility: A theory of banking. *Journal of Political Economy, 109*(2), 287-327.

Drehmann, M., & Tarashev, N. (2013). Measuring the systemic importance of interconnected banks. *Journal of Financial Intermediation, 22*(4), 586-607.

Duffie, D., Eckner, A., Horel, G., & Saita, L. (2009). Frailty correlated default. *The Journal of Finance, 64*(5), 2089-2123.

Dunn, J. C. (1974). Well-separated clusters and optimal fuzzy partitions. *Journal of Cybernetics*, *4*(1), 95-104.

Easterbrook, F. H. (1984). Two agency-cost explanations of dividends. *American Economic Review, 74*(4), 650-659.

EBA. (2013). *EBA report on impact assessment for liquidity measures under Article 509(1) of the CRR*. European Banking Authority. 20 December 2013, London.

EBA. (2014). *Guidelines on on common procedures and methodologies for the supervisory review and evaluation process*. European Banking Authority. EBA/GL/2014/13. 19 December 2014, London.

EBA. (2015). *EBA report on net stable funding requirements under Article 510 of the CRR*. European Banking Authority. EBA/Op/2015/22. 15 December 2015, London.

EBA. (2016). *EBA report on the leverage ratio requirements under Article 511 of the CRR.*European Banking Authority. EBA/Op/2016/13. 15 December 2015, London.

ECB. (2018). *SSM thematic review on profitability and business models: report on the outcome of the assessment*. European Central Bank, September 2018, Frankfurt.

Ellis, L., Haldane, A., & Moshirian, F. (2014). Systemic risk, governance and global financial stability. *Journal of Banking & Finance, 45*, 175-181.

Elsas, R., Hackethal, A., & Holzhäuser, M. (2010). The anatomy of bank diversification. *Journal of Banking & Finance, 34*(6), 1274-1287.

Ewijk, S., & Arnold, I. (2014). How bank business models drive interest margins: Evidence from US bank-level data. *The European Journal of Finance, 20*(10), 850-873.

Fahlenbrach, R., Prilmeier, R., & Stulz, R. M. (2012). This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis. *The Journal of Finance, 67*(6), 2139-2185.

Fonteyne, W. (2007). *Cooperative Banks in Europe: Policy Issues*. International Monetary Fund Working Paper, WP/07/159.

Galbraith, C., & Schendel, D. (1983). An empirical analysis of strategy types. *Strategic Management Journal*, *4*(2), 153-173.

Gambacorta, L., Yang, J., & Tsatsaronis, K. (2014). *Financial structure and growth*. BIS Quarterly Review March 2014.

Garrett, T. A., Wagner, G. A., & Wheelock, D. C. (2005). A spatial analysis of state banking regulation. *Papers in Regional Science, 84*(4), 575-595.

Gates, A. J., Wood, I. B., Hetrick, W. P., & Ahn, Y. Y. (2019). Element-centric clustering comparison unifies overlaps and hierarchy. *Scientific Reports, 9*(1), 8574.

Gelman, A., & Su, Y. (2018). *arm: Data Analysis Using Regression and Multilevel/ Hierarchical Models.* R package version 1.10-1.

Gennaioli, N., Shleifer, A., & Vishny, R. (2012). Neglected risks, financial innovation, and financial fragility. *Journal of Financial Economics, 104*, 452–468

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica, 57*(5), 1121-1152.

Goddard, J., Liu, H., Molyneux, P., & Wilson, J. O. (2011). The persistence of bank profit. *Journal of Banking & Finance, 35*(11), 2881-2890.

Goddard, J., McKillop, D. & Wilson, J. (2008). The diversification and financial performance of US credit unions. *Journal of Banking & Finance, 32*(9), 1836–1849

Goddard, J., McKillop, D. & Wilson, J. (2016). Ownership in European Banking. In: Beck, T., & Casu, B. (Eds.). *The Palgrave Handbook of European Banking*. London, 2016, 103-134.

Goodhart, C., & Wagner, W. (2012). *Regulators should encourage more diversity in the financial system*. VOX, CEPR's Policy Portal, 12 April.

Gorton, G., & Metrick, A. (2012). Securitized banking and the run on repo. *Journal of Financial Economics, 104*(3), 425-451.

Grossman, S. J., & Hart, O. D. (1988). One share-one vote and the market for corporate control. *Journal of Financial Economics, 20*, 175-202.

Guinnane, T. W. (2001). Cooperatives as information machines: German rural credit cooperatives, 1883–1914. *The Journal of Economic History, 61*(2), 366-389.

Halaj, G., & Zochowski, D. (2009). Strategic groups and banks' performance. *Financial Theory and Practice, 33*(2), 153-186.

Haldane, A., Alessandri, P. (2009). *Banking on the State*. Federal Reserve Bank of Chicago, 12th annual International Banking Conference on "The International Financial Crisis: Have the Rules of Finance Changed?", Chicago, 25 September 2009.

Haldane, A.,& May, R.(2011). Systemic risk in banking ecosystems. *Nature, 469*(7330), 351–5.

Houston, J. F., Lin, C., Lin, P., & Ma, Y. (2010). Creditor rights, information sharing, and bank risk taking. *Journal of Financial Economics, 96*(3), 485-512.

Hryckiewicz, A., & Kozłowski, Ł. (2017). Banking business models and the nature of financial crisis. *Journal of International Money and Finance, 71*, 1-24.

Hsu, T. (2000). An application of fuzzy clustering in group-positioning analysis. *Proceedings National Science Council of the Republic of China, 10*(2), 157-167.

Huang, R., & Ratnovski, L. (2011). The dark side of bank wholesale funding. *Journal of Financial Intermediation, 20*(2), 248-263.

Hubert, L., & Arabie, P. (1985). Comparing partitions. *Journal of Classification*, 2(1), 193-218.

Huizinga, H., & Laeven, L. (2019). The procyclicality of banking: evidence from the euro area. *IMF Economic Review, 67*(3), 496-527.

Hunter, W. C., & Timme, S. G. (1986). Technical change, organizational form, and the structure of bank production. *Journal of Money, Credit and Banking, 18*(2), 152-166.

Iglewicz, B. & Hoaglin, D.C. (1993). *How to detect and handle outliers*. Milwaukee: ASQC Quality Press.

Jaccard, P. (1901). Étude comparative de la distribution florale dans une portion des Alpes et du Jura. *Bulletin de la Societé Vaudoise de la Science Naturelle, 37*, 547-579.

Jacques, K., & Nigro, P. (1997). Risk-based capital, portfolio risk, and bank capital: A simultaneous equations approach. Journal of Economics and Business, 49(6), 533-547.

Jackman, S. (2017). *pscl: Political Science Computational Laboratory*. R package version 1.5.2.

Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters, 31*(8), 651-666.

Jensen, M., & Meckling, W. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305-360.

Jensen, M. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review, 76*(2), 323-329.

Jiménez, G., & Mencía, J. (2009). Modelling the distribution of credit losses with observable and latent factors. *Journal of Empirical Finance, 16*(2), 235-253.

Jiménez, G., Ongena, S., Peydró, J. L., & Saurina, J. (2017). Macroprudential policy, countercyclical bank capital buffers, and credit supply: evidence from the Spanish dynamic provisioning experiments. *Journal of Political Economy, 125*(6), 2126-2177.

Kane, E. (1989). *The S&L insurance mess: How did it happen?*. The Urban Insitute, Washington DC.

Kaufman, L., & Rousseeuw, P. J. (1990). *Finding groups in data*. Hoboken; New Jersey: John Wiley & Sons.

Kiviluoto, K., & Bergius, P. (1998). *Two-level self-organizing maps for analysis of financial statements*. In IEEE International Joint Conference on Neural Networks Proceedings. IEEE World Congress on Computational Intelligence, 1, 189-192.

Kobayashi, T. (2012) *Diversity among banks may increase systemic risk*. Kobe University Discussion Paper No. 1213, August 2012.

Köhler, M. (2015). Which banks are more risky? The impact of business models on bank stability. *Journal of Financial Stability, 16*, 195-212.

Kohonen, T. (1997). Exploration of very large databases by self-organizing maps. *Proceedings of International Conference on Neural Networks, 1*, PL1-PL6.

Kuncheva, L. (2004). *Combining pattern classifiers: methods and algorithms*. New Jersey: John Wiley & Sons.

Laeven, L., & Levine, R. (2007). Is there a diversication discount in financial conglomerates?. *Journal of Financial Economics, 85*(2), 331–367.

Laeven, M. L., & Valencia, M. F. (2018). *Systemic Banking Crises Revisited*. International Monetary Fund Working Paper, WP/18/206, September 2018.

Langfield, S., & Pagano, M. (2016). Bank bias in Europe: effects on systemic risk and growth. *Economic Policy, 31*(85), 51-106.

Liberti, J. M., & Mian, A. R. (2008). Estimating the effect of hierarchies on information use. *Review of Financial Studies, 22*(10), 4057-4090.

Liikanen, E. (2012). *Reforming the structure of the EU banking sector.* Report of the High Level Expert Group, chaired by Erkki Liikanen, European Commision. October 2012, Brussels.

Liu, Y., Wang, X., & Zhai, D. (2010). Commercial banks exceptional client distinguish based on data mining. *Proceedings of the 2010 International Forum on Information Technology and Applications*, 1, 164-166.

Maechler, M. (2018). c*luster: "Finding Groups in Data": Cluster Analysis Extended Rousseeuw et al*. R package version 2.0.7-1.

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability,1*(14), 281-297.

Marghescu, D., Sarlin, P., & Liu, S. (2010). Early-warning analysis for currency crises in emerging markets: A revisit with fuzzy clustering. *Intelligent Systems in Accounting, Finance & Management, 17*(3-4), 143-165.

Markowitz, H. (1952). Portfolio Selection. *Journal of Finance, 7*(1), 77-91.

Marques, B., & Alves, C. (2020). Using clustering ensemble to identify banking business models. *Intelligent Systems in Accounting, Finance and Management, 27*(2), 66-94.

Martin, A., Gayathri, V., Saranya, G., Gayathri, P., & Venkatesan, P. (2011). A hybrid model for bankruptcy prediction using genetic algorithm, fuzzy c-means and MARS. *International Journal on Soft Computing, 2*(1), 12-24.

Martín-Oliver, A., Ruano, S., & Salas-Fumás, V. (2017). The fall of Spanish cajas: Lessons of ownership and governance for banks. *Journal of Financial Stability, 33*, 244-260.

Maurer, B. A., & McGill, B. J. (2011). Measurement of species diversity. In A. E. Magurran, & B. J. McGill (Eds.), *Biological diversity: frontiers in measurement and assessment* (pp. 55-65). Oxford: Oxford University Press.

Mercieca, S., Schaeck, K., & Wolfe, S. (2007). Small European banks: Benefits from diversification?. *Journal of Banking & Finance, 31*(7), 1975-1998.

Mergaerts, F., & Vander Vennet, R. (2016). Business models and bank performance: A long-term perspective. *Journal of Financial Stability, 22*, 57-75.

Michalopoulos, M., Dounias, G., Hatas, D., & Zopounidis, C. (2002). On the use of a combination approach to automated knowledge acquisition based on neural networks and fuzzy logic with regard to credit scoring problems. In Zapounidis, C. (Ed.), *New Trends in Banking Management* (pp. 87-101). Heidelber; New York: Physica.

Michie, J., & Oughton, C. (2013). *Measuring diversity in financial services markets: A diversity index*. Centre for Financial and Management Studies Discussion Paper Series, No. 113, April 2013.

Miles, D., Yang, J., & Marcheggiano, G. (2013). Optimal bank capital. *The Economic Journal, 123*(567), 1-37.

Miller, D. (1986). Configurations of strategy and structure: Towards a synthesis. *Strategic Management Journal*, *7*(3), 233-249.

Milligan, G. W., & Cooper, M. C. (1986). A study of the comparability of external criteria for hierarchical cluster analysis. *Multivariate Behavioral Research, 21*(4), 441-458.

Mishkin, F. S. (1999). Financial consolidation: Dangers and opportunities. *Journal of Banking & Finance, 23*(2-4), 675-691.

Modigliani, F., & Miller, M. (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review, 48*(3), 261-297.

Mummolo, J., & Peterson, E. (2018). Improving the interpretation of fixed effects regression results. *Political Science Research and Methods, 6*(4), 829-835.

O'Hara, M., & Shaw, W. (1990). Deposit insurance and wealth effects: the value of being “too big to fail”. *Journal of Finance*, *45*(5), 1587-1600.

Onan, A. (2019). Consensu clustering-based undersampling approach to imbalanced learning. *Scientific Programming, 2019,* 1-14.

Pagano, M., Langfield, S., Acharya, V., Boot, A., Brunnermeier, M., Buch, C., Hellwig, M., Sapir, A., van den Burg, I. (2014). *Is Europe Overbanked?* The European Systemic Risk Board's Advisory Scientific Committee, Report No 4.

Petersen, M. A., & Rajan, R. G. (1995). The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics, 110*(2), 407-443.

Pilloff, S. J., & Rhoades, S. A. (2000). Do Large, Diversified Banking Organizations Have Competitive Advantages?. *Review of Industrial Organization*, *16*(3), 287-302.

Popović, D., & Bašić, B. (2009). Churn prediction model in retail banking using fuzzy C-means algorithm. *Informatica*, *33*(2), 243-248.

Porter, M. E. (1979). The structure within industries and companies' performance. *Review of Economics and Statistics*, *61*(2), 214-227.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's length debt. *The Journal of Finance*, *47*(4), 1367-1400.

Rand, W. M. (1971). Objective criteria for the evaluation of clustering methods. *Journal of the American Statistical Association*, *66*(336), 846-850.

Ravikumar, P., & Ravi, V. (2006). Bankruptcy prediction in banks by an ensemble classifier. *Proceedings of the 2006 IEEE International Conference on Industrial Technology*, 2032-2036.

Reger, R. K., & Huff, A. S. (1993). Strategic groups: A cognitive perspective. *Strategic Management Journal*, *14*(2), 103-123.

Roengpitya, R., Tarashev, N. A., & Tsatsaronis, K. (2014). *Bank business models*. BIS Quarterly Review December 2014, 55-65.

Roengpitya, R., Tarashev, N., Tsatsaronis, K., & Villegas, A. (2017). *Bank business models: popularity and performance.* BIS Working Papers n. 682.

Roodman, D. (2011). Fitting fully observed recursive mixed-process models with cmp. *The Stata Journal*, *11*(2), 159-206.

Rousseeuw, P. J. (1987). Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics, 20*, 53-65.

Sarlin, P., & Marghescu, D. (2011). Visual predictions of currency crises using self-organizing maps. *Intelligent Systems in Accounting, Finance and Management, 18*(1), 15-38.

Sarlin, P. (2016). Visual Macroprudential Surveillance of Banks. *Intelligent Systems in Accounting, Finance and Management, 23*(4), 257-264.

Schaeck, K., Cihak, M., & Wolfe, S. (2009). Are competitive banking systems more stable?. *Journal of Money, Credit & Banking, 41*(4), 711-734.

Scholes, M., Benston, G., & Smith, C. (1976). A transactions cost approach to the theory of financial intermediation. *The Journal of Finance, 31*(2), 215-231.

Serrano-Cinca, C. (1996). Self organizing neural networks for financial diagnosis. *Decision Support Systems, 17*(3), 227-238.

Sharma, S. (1996). *Applied Multivariate Techniques*. John Wiley & Sons.

Sharpe, W. (1966). Mutual fund performance. *The Journal of Business, 39*(1), 119-138.

Smith, R. T. (1998). Banking competition and macroeconomic performance. *Journal of Money, Credit and Banking, 30*(4), 793-815.

Stiroh, K. J. (2004). Diversification in banking: Is noninterest income the answer?. *Journal of Money, Credit, and Banking, 36*(5), 853-882.

Taylor, J. B., & Williams, J. C. (2009). A black swan in the money market. *American Economic Journal: Macroeconomics, 1*(1), 58-83.

V-lab (n.d.). *Systemic Risk GMES Analysis Page*. New York University, Volatility Laboratory. Retrieved September 16, 2020, from: https://vlab.stern.nyu.edu/

Van Ewijk, S., & Arnold, I. (2014). How bank business models drive interest margins: Evidence from US bank-level data. *The European Journal of Finance, 20*(10), 850-873.

Wagner, W. (2008). The homogenization of the financial system and financial crises. *Journal of Financial Intermediation, 17*(3), 330–356.

Wagner, W. (2009). Efficient asset allocation in the banking sector and financial regulation. *International Journal of Central Banking, 5*(1), 75–95.

Wagner, W. (2010a). Diversification at financial institutions and systemic crises. *Journal of Financial Intermediation, 19*(3), 373-386.

Wagner, W. (2010b). In the quest of systemic externalities: A review of the literature. *CESifo Economic Studies, 56*(1), 96-111.

Wagner, W. (2011). Systemic liquidation risk and the diversity–diversification trade-off. *The Journal of Finance, 66*(4), 1141-1175.

Warnes, G. R., Bolker, B., Lumley, T., & Johnson, R. C. (2018). *gmodels: Various R Programming Tools for Model Fitting*. R package version 2.18.1.

Weber, S., & Péclat, M. (2017). A simple command to calculate travel distance and travel time. *The Stata Journal*, *17*(4), 962-971.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica, 48*(4), 817-838.

Yanelle, M. O. (1997). Banking competition and market efficiency. *The Review of Economic Studies*, *64*(2), 215-239.

Yu, Y. (2018). *Is this Time Different? Do Bank CEOs Learn from Crises?*. INSEAD Working paper, Department of Finance, Fontainebleau.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338-353.

Zott, C., Amit, R., & Massa, L. (2011). The business model: recent developments and future research. *Journal of Management, 37*(4), 1019-1042.

Zúñiga-Vicente, J. Á., & Vicente-Lorente, J. D. (2006). Strategic moves and organizational survival in turbulent environments: The case of Spanish banks (1983–97). *Journal of Management Studies, 43*(3), 485-519.

APPENDICES

Appendix 1.1. Clustering algorithms

Fuzzy C-Means. The following algorithm was run (Cebeci *et al.*, 2019):

1. Randomly initialize the membership matrix ($\boldsymbol{U_{i \times j}}$), where i are the data points and j are the clusters ($j = 1, \ldots, J$, with pre-defined J). The following constraints must be satisfied:

$$\mu_{i,j} = [0,1] \;\; ; \;\; 1 \leq i \leq n \,, 1 \leq j \leq J$$

$$0 \leq \sum_{i=1}^{n} \mu_{i,j} \leq n \;\; ; \;\; 1 \leq j \leq J$$

$$\sum_{j=1}^{J} \mu_{i,j} = 1 \;\; ; \;\; 1 \leq i \leq n$$

   where i are the observations ($i = 1, \ldots, n$), j are the clusters ($j = 1, \ldots, J$) and J is pre-determined.

2. Calculate the prototype cluster centres ($\vec{v}_j$, $1 \leq j \leq J$) using a pre-determined measure of fuzziness ($1 \leq m < \infty$):

$$\vec{v}_j = \frac{\sum_{i=1}^{n} \mu_{i,j}^{m} \, \vec{x}_i}{\sum_{i=1}^{n} \mu_{i,j}^{m}}$$

3. Compute the dissimilarity matrix (d^2), i.e. the squared Euclidean distance, between the data points ($\vec{x}_i$) and each cluster centre $\vec{v}_j$:

$$d^2(\vec{x}_i, \vec{v}_j) = \left\| \vec{x}_i - \vec{v}_j \right\|^2$$

4. Update the previous version of $\mu_{i,j}$:

$$\mu_{i,j} = \frac{\left({}^{1}\!/_{d^2(\vec{x}_i, \vec{v}_j)} \right)^{1/(m-1)}}{\sum_{l=1}^{k} \left({}^{1}\!/_{d^2(\vec{x}_i, \vec{v}_l)} \right)^{1/(m-1)}}$$

   where the denominator is the sum of all weights and is used to normalize the membership scores.

5. Repeat steps 2 to 4 until the objective function cannot be improved:

$$\min J = \sum_{i=1}^{n} \sum_{i=1}^{n} \mu_{i,j}^{m} d^2(\vec{x}_{i,}, \vec{v}_j)$$

Self-Organizing Maps. Chair & Charrad (2017) implement a batch version of the following algorithm:

1. Initialize the 'neurons' weights matrix ($\boldsymbol{W_{j \times p}}$) based on the linear grids upon the first two principle components direction, where j are the 'neurons' ($j = 1, \dots, J$, with pre-defined J) and p are the input variables.
2. Draw a sample training input vector $\vec{x}_i$.
3. Find the winning neuron $I(\vec{x}_i)$ so that:
$$\min d^2(\vec{x}_i, \vec{w}_j) = \|\vec{x}_i - \vec{w}_j\|^2 = d^2(\vec{x}_i, I(\vec{x}_i))$$
4. Compute weight update equation:
$$\Delta w_{ji} = \rho(t)\, T_{j,I(\vec{x}_i)}(t)\left(\vec{x}_i - \vec{w}_j\right)$$
where $\mathrm{T}_{\mathrm{j,I}(\vec{\mathrm{x}}_\mathrm{i})}$ is the Gaussian neighbourhood and $\rho(t)$ is the learning rate.
5. Repeat steps 2 to 4 until $\rho(t)$ cannot be improved.

Partitioning Around Medoids. The algorithm takes the following steps (Maechler, 2018):

1. Randomly select J prototype 'representative data points' or medoids ($\vec{c}_j$), where j are the clusters ($j = 1, \dots, J$, with pre-defined J).
2. Based on the dissimilarity matrix, assign each data point to the nearest medoid and compute the sum of all distances to their medoids ('cost') and to other points in the same cluster.
3. Find a new prototype medoid, by taking the point with the lowest sum of distances to the other points in the same cluster.
4. Re-run step 2 (update of assignment and cost) with new prototype medoid.
5. Compute total swapping cost, by comparing the 'cost' of the new prototype with the previous.
6. Repeat steps 3 to 5 until total swapping cost becomes zero or negative.

Appendix 1.2. List of R packages used in the paper

- ‘arm: Data Analysis Using Regression and Multilevel/Hierarchical Models’, version 1.10-1 (Gelman & Su, 2018) – applied in the Bayesian logistic regression to capture differences in the observed variables between persistent and non-persistent banks.
- ‘clues: Clustering Method Based on Local’, version 0.6.2.2, (Chang *et al.*, 2019) – used to compute the cluster similarities measures, namely the Rand Index, the Adjusted Rand Index and the Jaccard Index.
- ‘cluster: “Finding Groups in Data”: Cluster Analysis Extended Rousseeuw et al.’, version 2.0.7-1 (Maechler, 2018) – used to employ the Partitioning Around Medoids algorithm;
- ‘clusterCrit: Clustering Indices’, version 1.2.7 (Desgraupes, 2016) – employed to examine the quality of the clustering outputs, i.e. to obtain the Silhouette Width, the Caliński-Harabasz Index, the Davies-Bouldin Index, and the Dunn Index;
- ‘ggplot2: Create Elegant Data Visualisations Using the Grammar of Graphics’, version 2.2.1 (Wickham & Chang, 2019) – used to build 2d plots of business models;
- ‘gmodels: Various R Programming Tools for Model Fitting’, version 2.18.1 (Warnes *et al.,* 2018) – implemented to perform the Chi-Square Independence Test;
- ‘multisom: Clustering a Data Set using Multi-SOM Algorithm’, version 1.3 (Chair & Charrad, 2017) – used to compute the Self-Organizing Maps;
- ‘ppclust: Probabilistic and Possibilistic Cluster Analysis’, version 0.1.2 (Cebeci *et al.*, 2019) – used to compute the Fuzzy C-Means algorithm;
- ‘pscl: Political Science Computational Laboratory’, version 1.5.2 (Jackman, 2017) – applied to obtain the McFadden’s pseudo R^2 in the logistic regression.
- ‘stats: The R Stats Package’, version 3.4.4 (this package is maintained by the R Core Team) – employed to obtain descriptive statistics as well as to compute the ex-post Tuckey HSD test for comparison of means across clusters.

Appendix 1.3. Valuation criteria

The *Silhouette Width* for each observation (SW_i) is computed as the difference between the average distance of observation i to other observations in the nearest cluster (b_i) and the average distance between observation i and observations in its assigned cluster (a_i). Hence, the average silhouette width (SW) is given by (Rousseeuw, 1987):

$$SW = \frac{1}{n} \times \sum_{i=1}^{n} SW_i = \frac{1}{n} \times \sum_{i=1}^{n} \frac{b_i - a_i}{\max(a_i, b_i)}$$

The value of SW is positively related with cluster quality.

The *Caliński-Harabasz index* (CHI) is computed as the ratio of between-groups sum of squares ($BGSS$) to within-group sum of squares ($WGSS$), for a given partition of J clusters (Caliński & Harabasz, 1974):

$$CHI = \frac{n - J}{J - 1} \times \frac{BGSS}{WGSS}$$

A higher value CHI is an indication of good cluster quality.

The *Davies-Bouldin index* (DBI) is the average value of the largest within dispersion-to-between separation of each cluster (M_J) (Davies & Bouldin, 1974):

$$DBI = \frac{1}{J} \times \sum_{J=1}^{J} M_J$$

The value of DBI is negatively related with cluster quality.

The *Dunn index* (DI) measures the ratio between the minimum distance between observations in different clusters (d_{min}) and the maximum distance between observations in the same cluster (d_{max}) (Dunn, 1974):

$$DI = \frac{d_{min}}{d_{max}}$$

A higher value of DI values indicate better clustering output.

Appendix 1.4. Composition of business models per clustering method

	BM1	BM2	BM3	BM4
FCM				
Number of banks	185	134	115	90
Gross loans to customers	68.0 (12.8)$^{++}$	69.5 (11.9)$^{++}$	35.7 (16.1)$^{++}$	40.8 (18.6)$^{++}$
Trading assets	1.8 (3.5)$^{+}$	2.0 (2.5)$^{+}$	2.0 (4.8)$^{+}$	**11.2 (9)**$^{+++}$
Interbank lending	8.2 (5.5)$^{++}$	8.2 (5.8)$^{++}$	**36.6 (19.1)**$^{+++}$	16.5 (12.6)$^{+++}$
Customer deposits	**69.0 (12.5)**$^{+++}$	40.6 (15.7)$^{+++}$	56.3 (23.9)$^{+++}$	**28.8 (16.1)**$^{+++}$
Interbank borrowing	**10.2 (7.4)**$^{+++}$	21.1 (15.2)$^{++}$	**25.8 (19.8)**$^{+++}$	19.1 (10.5)$^{++}$
Wholesale funding	6.9 (6.2)$^{++}$	23.4 (16.3)$^{++}$	5.0 (9.2)$^{++}$	21.5 (16.6)$^{++}$
Total derivatives	1.4 (2.1)$^{+}$	3.2 (3.2)$^{+}$	1.2 (3.0)$^{+}$	**20.3 (14.3)**$^{+++}$
Income diversification	46.9 (11.3)$^{+}$	44.4 (12.4)$^{+}$	46.6 (12.4)$^{+}$	54.3 (10.6)$^{+++}$
Total assets	7.0 (0.3)$^{++}$	7.5 (0.5)$^{+++}$	7.0 (0.4)$^{++}$	**8.1 (0.7)**$^{+++}$
Total equity	**9.0 (4.4)**$^{+++}$	6.2 (3.2)$^{+}$	6.9 (4.7)$^{++}$	5.2 (3.0)$^{++}$
SOM				
Number of banks	199	105	106	114
Gross loans to customers	69.1 (11.4)$^{++}$	71.1 (11.3)$^{++}$	**35.2 (15.7)**$^{+++}$	41.4 (17.6)$^{+++}$
Trading assets	1.7 (3.2)$^{+}$	1.6 (2.3)$^{+}$	2.2 (4.9)$^{+}$	**9.6 (8.8)**$^{+++}$
Interbank lending	8.2 (5.5)$^{++}$	7.7 (5.3)$^{++}$	**36.4 (19.6)**$^{+++}$	17.8 (13.5)$^{+++}$
Customer deposits	**67.5 (13.2)**$^{+++}$	37.4 (16.6)$^{+++}$	61.2 (20.6)$^{+++}$	**30. (16.1)**$^{+++}$
Interbank borrowing	**11.6 (8.7)**$^{+++}$	21.4 (17.7)$^{+}$	21.9 (18)$^{+}$	22.0 (13.6)$^{+}$
Wholesale funding	7.3 (6.6)$^{++}$	**26.4 (18)**$^{+++}$	3.8 (6.7)$^{++}$	20.2 (14.8)$^{+++}$
Total derivatives	1.3 (1.7)$^{+}$	3.4 (3.9)$^{+}$	1.2 (3.4)$^{+}$	**16.7 (14.4)**$^{+++}$
Income diversification	47.2 (11)$^{++}$	41.8 (13.1)$^{+++}$	47.1 (12.3)$^{++}$	53.5 (10.4)$^{+++}$
Total assets	7.0 (0.3)$^{++}$	7.5 (0.5)$^{+++}$	7.0 (0.4)$^{++}$	**8.0 (0.7)**$^{+++}$
Total equity	**8.8 (4.5)**$^{+++}$	6.0 (3.4)$^{+}$	7.1 (4.6)$^{++}$	5.3 (2.9)$^{++}$
PAM				
Number of banks	230	143	103	48
Gross loans to customers	**69.1 (13)**$^{+++}$	61.3 (15.2)$^{+++}$	35.1 (15.9)$^{++}$	29.5 (14)$^{++}$
Trading assets	1.7 (3.2)$^{++}$	3.4 (4.3)$^{++}$	2.0 (5.1)$^{+}$	**15.5 (9.1)**$^{+++}$
Interbank lending	8.3 (5.6)$^{++}$	11.0 (9.8)$^{++}$	**38.0 (19.2)**$^{+++}$	19.3 (13.1)$^{+++}$
Customer deposits	**65.0 (14.7)**$^{+++}$	34.8 (16.2)$^{+++}$	59.3 (23)$^{+++}$	**25.9 (15.3)**$^{+++}$
Interbank borrowing	**13.2 (10.8)**$^{+++}$	19.7 (14.8)$^{++}$	24.9 (20.2)$^{++}$	20.3 (10.2)$^{+}$
Wholesale funding	7.9 (7.1)$^{+++}$	**28.1 (16.9)**$^{+++}$	**3.7 (7)**$^{+++}$	14.9 (12.4)$^{+++}$
Total derivatives	1.5 (2.2)$^{++}$	6.3 (5.7)$^{+++}$	0.8 (2.8)$^{++}$	**27.6 (15.6)**$^{+++}$
Income diversification	47.4 (10.8)$^{+}$	44.7 (12.7)$^{+}$	46.6 (12.7)$^{+}$	58.1 (9.5)$^{+++}$
Total assets	7.0 (0.4)$^{++}$	7.7 (0.6)$^{+++}$	7.0 (0.4)$^{++}$	**8.0 (0.8)**$^{+++}$
Total equity	**8.8 (4.6)**$^{+++}$	5.7 (3)$^{+}$	6.5 (3.9)$^{+}$	5.1 (3.5)$^{+}$

Notes: Mean values and standard deviation in brackets, except number of banks (count). Classification obtained using PC1 to PC5 as input variables. 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.

Appendix 3.1. Sample composition: number of observations per country and region

	Banks	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Bank-year obs.	Country-year obs.
Europe (N=17)															
Austria	38	27	33	34	34	34	33	34	35	36	37	37	37	411	12
Belgium	12		9	9	9	9	9	11	11	12	12	12	12	115	11
Czech Republic	10	7	7	7	8	8	8	8	8	9	10	10	10	100	12
France	58						46	49	50	52	58	58	58	371	12
Germany	76	54	65	65	69	70	71	71	73	75	76	75	75	839	12
Ireland	10	8	8	8	8	8	9	9	9	10	10	10	10	107	12
Italy	51	41	45	46	49	49	49	51	51	51	51	51	51	585	12
Luxembourg	24	17	17	21	22	22	22	23	23	24	24	23	23	261	12
Netherlands	19								17	18	19	18	17	89	5
Norway	16		12	13	14	15	15	15	15	16	16	16	16	163	11
Poland	13	10	11	11	11	12	12	13	13	13	13	13	12	144	12
Portugal	10	8	9	9	9	9	9	9	9	9	10	10	10	110	12
Russia	31		22	22	25	27	29	31	31	31	31	31	31	311	11
Spain	25						21	23	23	25	25	25	25	167	7
Switzerland	34	30	30	30	30	30	32	32	33	34	34	34	33	382	12
Turkey	14			13	13	13	13	13	14	14	14	14	14	135	10
United Kingdom	44	35	37	37	38	37	37	42	43	43	43	43	43	478	12
Europe total	**485**													**4768**	**182**
Asia (N=11)															
Australia	18		18	18	18	18	18	18	18	18	18	18	18	198	11
China	157								121	153	157	157	157	745	5
Hong Kong	21	19	19	19	19	19	19	19	19	20	21	21	21	235	12
India	43	35	37	38	40	40	41	41	42	43	43	43	43	486	12
Indonesia	20	15	16	16	16	17	17	18	19	20	20	20	19	213	12
Japan	182	166	167	169	171	172	176	179	180	180	182	182	181	2105	12
Korea	17						13	15	14	15	16	16	16	105	7
Malaysia	17							17	17	17	17	17	17	102	6
Philippines	12	11	11	11	11	11	11	12	12	12	12	12	12	138	12
Thailand	19			15	15	16	18	19	19	19	19	19	18	177	10
Vietnam	13		10	11	12	12	12	12	13	13	13	13	13	134	11
Asia total	**519**													**4638**	**110**
Americas (N=5)															
Brazil	28						23	27	27	28	27	27	27	186	7
Chile	10						10	10	10	10	10	10	10	70	7
Colombia	10							10	10	10	10	10	10	60	6
Mexico	15	14	15	15	15	15	15	15	15	15	15	15	15	179	12
United States	201	164	165	165	166	169	170	198	201	201	201	201	201	2202	12
Americas total	**264**													**2697**	**44**
Total (N=33)	**1268**													**12103**	**336**

Appendix 3.2. Systemic banking crises: do countries learn from prior crises?

	Countries *with* banking crisis in 2007-08	**Countries *without* banking crisis in 2007-08**
Countries ***with*** banking crises prior to 2005	Russia (1998, 2008) Spain (1977, 2008) United States (1988, 2008)	Brazil (1990, 1994) Chile (1976, 1981) China (1998) Colombia (1982, 1998) Czech Republic (1996) India (1993) Indonesia (1997) Japan (1997) Korea (1997) Malaysia (1997) Mexico (1981, 1994) Norway (1991) Philippines (1983, 1997) Poland (1992) Thailand (1983, 1997) Turkey (1982, 2000) Vietnam (1997)
Countries ***without*** banking crises prior to 2005	Austria (2008) Belgium (2008) France (2008) Germany (2008) Ireland (2008) Italy (2008) Luxembourg (2008) Netherlands (2008) Portugal (2008) Switzerland (2008)	Australia Hong Kong

Notes: The data on systemic banking crises obtained from Laeven & Valencia (2018).