Banks’ Business Model Migrations in Europe: Determinants and Effects

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Abstract

This study investigates the determinants of business model changes for European banks and the effects of such migrations on bank performance. Based on a sample of over 3,000 banks from 32 European countries, we define business models and migrations following Ayadi and de Groen (2014). We consider the period 2006 -2016; univariate analysis shows that, post-crisis banks, moved to more traditional business models thus decreasing diversity in the banking system. We find that banks with higher risk, lower profitability and that received state aid during the crisis period are more likely to change business model. Another important driver of business model migration are merger and acquisition (M&A) operations. Employing a propensity score matching approach, we investigate the effect of migration on bank performance and we find that it affects banks negatively in the year of migration, whereas the effect is positive in the subsequent years.

Keywords: *banks; business model; banking strategy; propensity score matching; treatment effects*

JEL codes: G21; G28; L21; L25

1. Introduction

Since the global financial crisis, the European banking sector has undergone fundamental changes. In this context, an analysis of banks' business models (BM) is crucial to better understand the nature of banking risks and their contribution to systemic risk throughout the economic cycle (Ayadi et al., 2016). The importance of business models was recognized in the regulatory framework Europe implemented in 2013.[1] A central component of the Supervisory Review and Evaluation Process[2] (SREP) is the requirement that the competent supervisory authorities integrate bank business models into the supervisory framework. This has prompted supervisors to take quantitative and qualitative approaches to understanding the business models of European banks. Analyzing banks' business models allows for an understanding of banking activities, customer groups, distribution channels, and sources of profits, thereby overcoming the traditional approach to prudential supervision which is mainly focused on the adequacy of bank capital and the management of liquidity risk (Cavelaars and Passenier, 2012).

The literature on business models has a long tradition, particularly in the field of management studies (Zott and Amit, 2011). In general, a business model is interpreted from a strategic view that is translated into balance sheet and income statement results. Studies on business models with specific reference to the banking industry are more recent. With the exception of the early work of Amel and Rhoades (1988), only in the last two decades have both regulators and academics focused their attention on the definition of banks' business models. In fact, in light of the recent financial crisis and the banking system turmoil, several authors have emphasized that not all banks faced the same challenges or responded in the same way. In this sense, the business models' analysis, as first introduced by Ayadi et al. (2011), is essential to better understand the contribution of each type to systemic risk (De Meo et al., 2018; Cernov and Urbano, 2018).

Our study contributes to the ongoing debate on bank business models by first assessing the determinants behind the decision to migrate from one business model to another and second by gauging whether migrating banks improved their performance as a result of making this decision. Defining the bank business model has always been difficult and many authors have tried to offer an acceptable definition using balance sheet data—quantitative and

[1] The Capital Requirements Directive (CRDIV) found in and the Capital Requirements Regulation (CRR) http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2013:321:0006:0342:EN:PDF

[2] The guidelines regarding the application of common supervisory procedures and methodologies by all the supervisory authorities in the EU are set in the Supervisory Review and Evaluation Process (SREP) guidelines: https://www.eba.europa.eu/documents/10180/935249/EBA-GL-2014-13+(Guidelines+on+SREP+methodologies+and+processes).pdf

qualitative-based approaches. Ayadi et al. (2011) propose an asset/liability approach using activity and funding indicators to define bank business models and applied a clustering approach to identify them. In their seminal study, they analyze a sample of 26 major European banks and identify three different business models: retail banks, investment banks, and wholesale banks. The authors underline that during the period observed most banks reverted to more traditional business models, focusing their activity using more stable retail funding and becoming more liquid. In addition, they suggest that greater pressure on the banking system pushed banks to search for a less complex business structure. In sum, they show that banks with a retail business model fared better throughout the crisis as compared to the other business models analyzed, and a retail business model in particular leads banks to a lower risk-taking, particularly if these banks are adequately capitalized.

Similar approaches are used in Farnè and Vouldis (2017) and Roengpitya et al. (2017). In particular, these authors consider both the banks' activities, such as interbank lending and gross loans, and the liability side, such as interbank borrowing and wholesale debt. They do not use income statement variables to define the business model, since financial and economic results depend upon the strategy adopted. Unlike in management studies, in the majority of studies on banks' business models, data-driven methodologies are adopted in order "to minimize the importance of expert judgment in the choice of clustering variables and method" (Farnè and Vouldis, 2017, p. 6). A more recent study by Cernov and Urbano (2018) proposes a mixed approach to business models classification, combining both qualitative and a quantitative component. This represents a new approach in the literature on business model identification and classification, and was made possible thanks to a rich and unique bank-level dataset collected for the first time for the full population of EU banks. In particular, the qualitative component is based on the expert knowledge of the supervisory authority, which is then either confirmed or challenged by quantitative indicators.

A further strand of literature investigates the relationship between banks' business models and banks' characteristics, such as size, capitalization, risk, performance, operating efficiency, and ownership (Altunbas et al., 2011; Ayadi et al., 2014; Kohler, 2015; Mergaerts and Vander Vennet, 2016; Ayadi et al., 2016, De Meo et al., 2018). The main findings suggest that investment and wholesale banks are more oriented to deliver high financial performance and they accumulate more risk, while retail-oriented banks are those that actually support the real economy. In addition, findings suggest that retail banks show better profitability and higher stability, but also a lower default risk, at least prior to the GFC. Finally, banks with investment and wholesale business models that tend to display higher risk have lower capital, larger size, greater reliance on short-term market funding, and aggressive credit growth. By contrast, banks with lower risk follow a business model characterized by a strong deposit base and greater income diversification (Altunbas et al., 2011).

In addition to the definition of banks' business models, analyzing changes in these models is crucial since these migrations generate changes in the market structure. In fact, if the majority of banks move to one specific business model, then within this group of banks the competition might increase (or by contrast decrease), while competition might decrease (or increase) in other business models. Understanding whether banks shift to riskier business models or less risky ones is important in order to manage the stability of the banking system (Baravelli, 2015).

Some contributions speculate on the possible drivers that may push banks to change their business strategy. Roengpitya et al. (2017) investigate whether the switch to a different model could be explained by poor pre-switch performance. However, their results suggest that there is no evidence that poor performance leads banks to reassess their business strategy. In addition, in the pre-crisis period, retail banks and universal banks tended to move to wholesale models, while during the 2009 to 2015 period, as result of the crisis and the re-regulation, wholesale and universal banks moved to retail-focused models. This confirms Roengpitya et al.'s (2014) previous findings that the direction of change in banks' business models is very different in the post-crisis period than it was in the pre-crisis period. Gambacorta et al. (2017) also underline that banks change their business models in response to the financial crisis and re-regulation that push them to change the composition of their funding mix.

In a recent study, Ayadi et al. (2016) list the most important reasons leading banks to change their business models. In particular, *"banks adapt their business models for the following reasons: a) to respond to market forces and competitive pressures (i.e. mergers and acquisitions, overall sector's restructuring movement); b) to respond to regulatory and government led decisions (i.e. increase of capital, changes in monetary policy, State aid decisions with a restructuring plan requirement, others); c) other non-obvious reasons (i.e. political or other excessive risk taking activities) which could be essential to understand banks' behaviors"*.

In addition, mergers and acquisitions (M&A) operations are a further potential cause of BM migrations. In fact, the drivers of M&A are usually identified in: i) the creation of value, such as to obtain major market power or a higher level of efficiency; ii) managerial self-interest (i.e., value destruction), such as compensation or target defense tactics; iii) environmental factors, such as regulation, networks ties, or environmental uncertainty; and finally, iv) firm characteristics, such as the acquisition of experience and firm strategy and position (Haleblian et al., 2009). As a consequence of the decision to embark on an M&A operation, the BM could be changed to evolve the BM into a model able to better support the new bank's strategy.

The drivers that push banks to migrate from one BM to another may be distinguished according to endogenous and exogenous factors. Business models change not just for cost reasons, but also as a consequence of changes in demand for banking services, particularly during a period characterized by a deep recession (2008–2015) (Baravelli, 2015). In light of this evidence, bank business models are intended to further evolve in order to provide adequate support for eventual economic recovery.

All the studies mentioned above focus on the definition of banks' business models and the migration from one model to another. However, they are focused on the descriptive analysis of bank characteristics related to each BM identified, or, in a few cases, on the relationship between business models and both risk and performance. To the best of our knowledge, there are no studies that investigate the drivers of the migration from one business model to another. We aim to contribute to the current literature with an analysis of the determinants of the migration of banks among different business models, distinguishing between bank-specific variables, strategic choices, and crisis-related interventions. Subsequently, we investigate the effects of the decision to migrate on bank performance. In light of the evidence, our testable hypotheses are the following:

i) banks showing higher risk and lower performance are more likely to change their BM;

ii) banks involved in an M&A operation are more likely to change their BM;

iv) banks that received state aids during the crisis are more likely to change their BM;

v) after migration, migrating banks improve their performance more than non-migrating banks.

The contribution of our paper is threefold. First, we analyze banks' characteristics, distinguishing between migrating and non-migrating banks in order to investigate the features of banks that decide to change their structure in terms of their asset composition and/or liabilities. Second, we focus on the determinants of migration, whereas previous studies have usually focused on the definition of BM and on the analysis of the relationship between business models and some accounting measure, such as performance or risk. The novel contribution of this analysis is helpful to better understand the drivers of these strategic choices. Finally, we investigate the effects of bank migration in order to understand if a bank may improve its performance by changing its business model.

The remainder of the paper is organized as follows: Section 2 presents the preliminary univariate analysis of the data; Section 3 discusses the methodology adopted to estimate the drivers of migration and their effects on bank performance; Section 4 presents the results of our analysis, which are subsequently subjected to robustness tests in Section 5; and Section 6 concludes.

2. Sample and descriptive analysis

Our initial sample is composed of 3,287 banks from 32 European Economic Area (EEA) countries and Switzerland.[3] More specifically, in the 19 countries in the Euro-zone, 2,672 institutions are considered, whereas in the nine non-Euro-zone countries we observe 357 banking institutions. Finally, from the four EFTA countries (Switzerland, Iceland, Norway, and Liechtenstein), 258 banking groups and subsidiaries are included in total. The sample covers more than 95% of the banking assets in the EEA. The sample includes 22,787 bank-year observations spanning 2005 to 2016, covering before and during the financial crisis, along with the recovery period. Our sample includes 815 commercial banks, 692 savings and loans banks, 1,702 cooperative banks, and 78 public banks. We separately considered nationalized banks, i.e., banks that transferred their ownership to the government during the great financial crisis (GFC), for one main reason: the nationalization was in fact triggered by the insolvency of financial institutions during the GFC. Since we consider state aid a specific driver for migration from one BM to another, we need to distinguish between truly public banks (i.e., those with a relevant government stake before the onset of the GFC) and those that went under the public umbrella during the crisis. Typically, these nationalizations were meant to be temporary solutions to the looming crisis with the government acting as a trustee in the bank receivership, anticipating that the bank would privatize as soon as its financial, economic, and capital position improved. Our sample includes 32 nationalized banks.

Data are collected from several data sources: bank-specific variables from SNL (S&P Global Market Intelligence); macroeconomic variables from the World Bank; state aid

[3] The distribution of banks by country and year is reported in the Appendix (Table A).

information from the ECB and the European Commission database; and corporate operations data (M&A) are collected from the Zephyr database.

We identify five business models on the basis of the definition and methodology implemented by Ayadi and de Groen (2014) and Ayadi et al. (2016). Banks are clustered as follows:

i) **focused retail**, in which banks use customer deposits as the primary means of funding loans and maintain a relatively high level of loss-absorbing capital;

ii) **diversified retail (type 1)** that groups retail-oriented banks, which use relatively non-traditional funding sources but show a relatively high dependence on customer deposits and limited reliance on both bank deposits and debt liabilities to fund retail and investment activities;

iii) **diversified retail (type 2)** includes banks that have more diverse assets and liabilities than other retail-oriented models. They have significantly more trading assets than focused retail banks, but the main difference with the other retail-oriented models is their funding. Among the different business models, diversified retail (type 2) relies most on debt liabilities;

iv) **wholesale**, which groups together banks that are heavily wholesale oriented and largely active in the interbank markets;

v) **investment**, which includes the largest banks, both in terms of their total and average assets, and this cluster groups together banks that have a tendency to engage predominantly in investment activities.[4]

Business models are identified by means of cluster analysis; specifically, Ward's method, which is a criterion applied in the hierarchical cluster analysis that groups together individuals with similar characteristics, particularly individuals that show the minimum variance criterion.[5] Assuming that banks choose their business model, the instrumental variables adopted to define the BM are based on the variables over which banks have control and can somehow manage. For example, Ayadi et al. (2015) explain: "*a bank is likely to have a great degree of choice over its general organizational structure, balance sheet and financial position and some of the risk indicators; in turn, most of the performance indicators are related to instruments that are beyond the bank's control, such as market conditions, systemic risks, customer demand*." For this reason, in the cluster analysis, variables such as customer behavior and income sources are excluded. Therefore, the adoption of one business

[4] The distribution by banks' business models and year are reported in Appendix (Table D).
[5] More specific information about the methodology can be found in the study of Ayadi et al. (2016).

model as opposed to another is a strategic choice which may depend on both internal and external factors.

As a preliminary step, we begin with an analysis of the distribution of migrating banks as opposed to non-migrating banks, considering the timing of the migration, the size of the banks, their ownership structure, and their geographic location. The results of the comparisons are reported in Tables 1 and 2. From a total of 19,500 observations available[6] in the period under investigation (2005–2016), there are 2,571 migrations, corresponding to about 13% of the sample. This means that in general banks had a stable business model during the investigated period. From a total of 3,287 banks, 1,543 banks changed their BM at least once. On average, migrating banks move 1.66 times during the period under investigation, meaning that some banks move more than once during our sample period.

In Table 1, Panel A, the sample period is divided into three subperiods: pre-crisis (2005–2007), financial crisis (2008–2012), and recovery (2013–2016). Looking at the migrations that occurred during these three periods, it is possible to observe that 13.32% and 13.80% of the total banks observed tended to move more before and after the crisis, respectively.

[Table 1. approximately here]

With regard to bank size, we identify three groups based on the bank's total assets: i) small banks are banks in the first tercile of the distribution; ii) medium banks are those in the second tercile; and iii) large banks are banks with total assets greater than those in the second tercile of the distribution. Table 1, Panel B shows the distribution of small, medium, and large bank migrations and demonstrates that the migrations are distributed in a similar way across the three clusters, while noting a slightly higher percentage of migrations in the group of medium banks.[7]

With respect to the banks' ownership structure (Table 1, Panel C), migrations are evenly distributed, although a higher percentage of migrations is present among nationalized and commercial banks – 22.48% and 17.79%, respectively.

Finally, we investigate the distribution of migrations by distinguishing between Euro- and non-Euro-zone. Panel D (Table 1) shows a similar distribution of migrating banks in the

[6] Of the 22,787 total observations, we do not consider the first year in which the bank is observed because it is not possible to determine whether the bank has migrated. Therefore, the observations decrease to 19,500.
[7] Appendix (Figure B) reports the progressive distribution of migration by bank size.

two zones, with a percentage of about 13%. Also in this case, these findings suggest that banks move among different business models regardless of their geographic area.

The analysis of the banks' migrations among the different clusters demonstrates that:

i) Banks change their business models more after a financial crisis. However, this may depend on their willingness to reset their business models after a period of financial turmoil, embracing the signs of economic recovery as a driving force for change.

ii) Banks' business model migrations are observed in banks of all sizes and in all geographic areas. Banks change their business models whether they are small, medium, or large and whether they operate in the Euro-zone or outside of it.

iii) With regard to specialization, commercial and nationalized banks migrate more than others; however, we also observe migrations among savings and cooperative banks, albeit with less frequency. The migration of nationalized banks may be due to government intervention since they obtained government support during the financial crisis in the form of recapitalizations, asset relief measures, loans, and guarantees, and the governments received shares in return (in this case, more than 50% of the shares). After nationalization, these banks are either prepared to become commercial banks or are being liquidated (Ayadi et al., 2015).

We can now move forward and connect the migrations with the different types of business models previously introduced. As Figure 1 highlights, banks assigned to the "focused retail" model show the highest persistence in preserving the chosen business model: 90% of these banks retained the same business model from one year to the next. Also, the majority of "diversified retail (type 1)" banks preserve the same business model (88%), whereas the percentage is slightly lower for the other three business models: lower than 85% in the case of "diversified retail (type 2)" and "wholesale" banks and lower than 80% for "investment" banks. Considering both inflows and outflows from one business model to another, "focused retail" banks are net acquires (+10%) along with "diversified retail (type 1)" (+22%). By contrast, all other models lose more banks than they acquire.

In the Appendix (Table B), we report the migrations among different business models in the three subperiods investigated. In this case, our results confirm that during the pre-crisis period— except for banks that adopt the diversified retail (type 1) business model that migrate mainly to a focused retail model—banks move to diversified retail (type 2), looking for a more diversified business model, which, even if retail-oriented, stands out because of its different funding structure. Conversely, during the financial crisis, diversified banks tend to return to more focused retail-oriented models and investment banks migrate to more diversified business models (both type 1 and type 2). However, during this period the most important change in the business models is the drastic increase in the number of banks that adopt the diversified (type 1) business model at the expense of the diversified (type 2) business model, suggesting that banks, during the financial crisis, refocused on their core activity. Finally, in the recovery period, we observe migrations to the diversified retail (type 1) model that stand out from the other diversified models because they have more trading assets and bank loans.

[Figure 1. approximately here]

In terms of total assets, the evidence is reversed (Table 2). In this case, "diversified retail (type 2)" and "investment" are the models with the highest percentage of perseverance in the same clusters (92% and 91%, respectively). As shown in Figure 1 and in Table 2, the dominance of the focused retail banks is only in terms of their numbers (36.46%), while in terms of assets, they represent only 8%. We observe the same situation with regard to the diversified retail (type 1) model, with 35.84% in terms of their numbers and only 18% in terms of their assets. Contrarily, the investment and the diversified retail (type 2) models account for 6.69% and 14.13% in terms of their numbers and 36% and 37% of total assets, respectively.

The remainder of the migration was primarily directed to the investment bank model, with flows ranging from 14% from wholesale and 15% from diversified (type 1) banks. The other large transition flows are between diversified retail banks. Indeed, a large share of the migration is directed to the diversified retail (type 2) model (3% from investment banks and 6% from focused retail banks). With regard to the diversified retail (type 1) model, the incoming flows span from 5% of investment and diversified retail (type 2) banks to 8% of wholesale banks.

However, observing the weight of banks' total assets for each business model in the three subperiods (pre-crisis, crisis, and recovery), we note that the weight of both investment and diversified retail (type 2) models in the banking sector decreases during both the financial crisis and the recovery period, from 40.30% to 33.48% and from 41.69% to 32.87%, respectively. Conversely, both focused retail and diversified retail (type 1) increase their weight during both the financial crisis and the recovery period, from 4.06% to 10.72% and from 10.77% to 21.32%, respectively. Despite this change, investment and diversified retail (type 2) remain the business models that include the bigger banks (Table 2).[8]

Our hypothesis that banks have recently moved to more traditional business models is confirmed only in terms of numerosity. We observe greater transition flows to focused retail and diversified retail (type 1) models than to the others. However, in terms of total assets, the traditional retail-oriented business models represent only a small part of the European banking system. Indeed, the investment and diversified retail (type 2) models are those clusters which encompass the largest banks.

[Table 2. approximately here]

In addition, we add a cross-sectional analysis of the full sample comparing the characteristics of banks that migrate with those that do not (Table 3). These characteristics pertain to financial statement information, ownership structure, participation in M&A deals, and finally any state aid received during the GFC. We also test the hypothesis that migrating and non-migrating banks are independent samples from a population with the same distribution (t-test).

Our findings emphasize that, on average, migrating banks show lower profitability, lower cost efficiency, higher capitalization, and higher risk appetite. These banks also display a lower credit portfolio quality, showing a higher loan loss provision ratio than non-migrating banks. Furthermore, migrating banks are more involved in M&A operations and they benefit more from ad hoc state aid than their non-migrating counterparties. With regard to the ownership structure, commercial and nationalized banks are more willing to change their business model. Finally, looking at their balance sheet compositions, our findings suggest that migrating banks have in their balance sheet less loans to customers and more trading activities than non-migrating banks, while in regard to their funding strategy, migrating banks show a lower weight of customer deposits over total assets than non-migrating banks, suggesting that the former have a more diversified funding structure.

[Table 3. approximately here]

[8] In Appendix (Table C), we report the transition matrix in terms of total assets among the different business models in the three subperiods analyzed.

3. Empirical design

3.1 The determinants of business model migration

The first step in our empirical analysis involves investigating the drivers of the decision to migrate. For this reason, we apply binomial logistic regression to the entire sample model to assess the determinants of the occurrence of bank migration:

$$P\ (w_{it} = 1) \approx P\ (\alpha_0 + \sum_{k=1}^{K} \alpha_k X_{kit-1} + S_{ki} + Y_{kt} + \varepsilon_{it} > 0), \qquad (1)$$

where α_0 is a constant, K denotes the number of explanatory variables $X_{k,it-1}$ in the selection equation, S_i are country dummies, Y_t are year dummies, and ε_{it} is an identically and independently distributed error term. Explanatory variables are those bank characteristics analyzed in the previous section: relevant financial statement data, ownership and institutional type information, involvement in M&A operations (distinguishing between the role of bidder and that of target), and finally, any state intervention during the GFC (from nationalization to a simple state scheme provided to the entire banking system). Variable descriptions are reported in Table E in the Appendix. All bank-specific variables are included at time t-1. On the left-hand side, the dependent variable w_{it} is set to 1 in the year t in which bank *i* migrates to another bank's business model, measuring the probability of switching, and 0 otherwise.

3.2. The effects of business model migration on bank performance

The second step in the analysis involves determining the effects of migration. In this case, as migrating banks are a heterogeneous group with respect to their size, ownership, and geographical location, we apply the propensity score matching methodology (PSM) (Rosembaum and Rubin, 1983). PSM could be a useful methodology to gauge the casual effects of migration on bank performance. In fact, PSM can be applied in any study where one can identify: i) a treatment; ii) a group of treated subjects; and iii) a control sample of untreated subjects. In our study, the decision to migrate is considered as the treatment. Indeed, the analysis of the effect of migration on bank performance gives rise to several methodological issues, particularly self-selection concerns with regard to the endogeneity of the strategic decision itself, i.e., the decision to migrate.[9] First, the comparison of migrating

[9] These methodological issues are present in any study aimed at estimating the effect of a specific strategic decision on bank performance. Casu et al. (2013) and Barba Navaretti and Castellani (2008) discuss similar issues in estimating the impact of the choice between securitizing and foreign investing.

banks to non-migrating banks might yield biased estimates of the migration effect because the performance of non-migrating banks may differ systematically from the performance of migrating banks in the absence of migration. Therefore, if migrating banks are found to perform better, on average, than non-migrating banks, the difference may be due to the effect of having decided to change BM or to differences existing in the banks' characteristics prior to that decision. Second, considering only migrating banks eliminates the possibility of benchmarking with the hypothetical performance that the bank would have had in the event that it did not change BM. Finally, the observed change in performance might be due to shocks affecting all banks equally (like the GFC).

To ensure that the comparison between migrating and non-migrating banks does not suffer from the above-mentioned methodological issues, matching approaches appears to be a reliable method to apply. Matching is a popular non-parametric approach to estimating causal effects. For this reason, it is largely adopted in policy impact analysis (Essama-Nssah, 2006) and has been recently adopted in the finance literature to gauge the impact of diverse strategic choices (Villalonga, 2004; Casu et al., 2013; Palvia et al., 2015). In our study, to estimate the causal effect of migration on a series of performance outcomes, we define the average treatment effect on the treated (ATET) using Equation (2):

$$ATET = E(\Delta y^1_{it+1} \mid w_{it} = 1) - E(\Delta y^0_{it+1} \mid w_{it} = 1) \qquad (2)$$

Definition (2) relies on what is called the counterfactual framework, or potential outcomes model (Splawa-Neyman et al., 1990; Rubin, 1973). In this framework, w_{it} is the variable that indicates the migration activity and takes the value 1 if banks migrate at time *t* and 0 otherwise. Looking at the other components, Δy^1_{it+1} is the performance change of bank *i* at time *t+1* after having migrated in the period *t* and Δy^0_{it+1} represents the hypothetical performance that the same bank *i* at the same time *t+1* obtains if at time t it has not migrated. As is well known, the Δy^0_{it+1} is only hypothetical, and we cannot estimate it. It represents the counterfactual, and thus, in order to compute ATET, we need to state an identifying assumption that allows for assessing this term (Egger and Hahn, 2010). To overcome this problem, we need to find a proxy for this counterfactual mean and Equation (2) becomes:

$$ATET = E(\Delta y^1_{it+1} \mid w_{it} = 1) - E(\Delta y^0_{it+1} \mid w_{it} = 0)$$

(3)

If this condition holds, the non-migrating banks can serve as an adequate control group. Experimental studies deal with the selection problem using a random assignment of treatment. This ensures that every individual has the same probability of receiving a treatment (Jyotsna and Ravallion, 2003). This is not possible in non-experimental studies such as ours. In order to manage this problem and eliminate the selection bias, in non-experimental studies the most common approaches are the instrumental variables (IVs) and Heckman selection estimators, but both approaches suffer from a number of biases. For this reason, we prefer to adopt the PSM to deal with the selection bias (Casu et al., 2013). This approach allows us to measure the effect of the treatment on a series of outcomes, considering unconfoundedness and common support assumptions.

$$ATET = E(\Delta y_{it+1}^{1} \mid w_{it} = 1, X_{it-1}) - E(\Delta y_{it+1}^{0} \mid w_{it} = 0, X_{it-1}) \tag{4}$$

Where $E(\Delta y_{it+1}^{1} \mid w_{it} = 1, X_{it-1})$ represents the mean performance change of migrating banks at time t+1 after the migration and $E(\Delta y_{it+1}^{0} \mid w_{it} = 0, X_{it-1})$ represents the mean performance change of non-migrating banks (the control group) at time t+1. Finally, X_{it-1} is a vector of conditioning covariates observed at time t-1.

As suggested by Rosenbaum and Rubin (1983), we implement propensity score matching in order to cope with the high dimensionality of the covariate vector X_{it-1}. In fact, the authors underlined the difficulty of implementing the directly matching covariates when the vector X_{it-1} is highly dimensional. At the base of this technique there is the idea that the function $b(X_{it-1})$—called balancing scores—is independent of the assignment into treatment of firm *i* in year *t* on average. The probability of receiving treatment in year *t* given the observed characteristics X_{it-1} is defined as the propensity score $P(X_{it-1})$.

$$\Delta_{ATET,t}^{PSM} = E_{P(X_{it-1}|w_{it}=1)}\,[E(\Delta y_{it+1}^{1} \mid w_{it} = 1, P(X_{it-1})) - E(\Delta y_{it+1}^{0} \mid w_{it} = 0, P(X_{it-1}))] \tag{5}$$

Since migrations are captured by a binary, time-variant variable, the propensity score $P(X_{it-1})$ can be estimated on the basis of a logit model. As a matching algorithm based on the same propensity score estimated, we use the nearest neighbor procedure (Caliendo and Kopeinig, 2005; Casu et al., 2013).

4. Results

4.1 The drivers of the decision to migrate

To estimate the drivers of the decision to migrate, we start estimating a logit regression of a dummy variable that has value 1 for any migrating banks and 0 otherwise. The regressors included in the models reflect both the institutional characteristics of banks and the most likely determinants of a bank's decision to migrate, as highlighted by the empirical literature (Altunbas et al., 2011; Kohler, 2015; Mergaerts and Vander Vennet, 2016).

In particular, we consider three sets of bank-specific variables. The first set reflects the size, risk profile, efficiency, and profitability of our sample banks plus their ownership structure. We consider size as proxied by the natural logarithm of total assets. The risk profile is captured by leverage (the ratio of equity over total assets, E_TA) and a measure of risk appetite, i.e., the ratio of risk weighted assets (RWA) over total assets, respectively. Operating efficiency and profitability are described by the cost to income ratio (C_I) and the return on average assets (ROA), respectively. We also add a proxy for investments in financial technologies (INTANGIBLE_TA), measured by the ratio of intangible assets over total assets, to control for the possibility that the change in business model is driven by the strategic choice of positively answering to the fintech revolution and the related changes in demand for banking services. Finally, we add three different dummies to control for the ownership form of our sample banks: a dummy COMMERCIAL, equal to 1 if the bank is a commercial bank and 0 otherwise; a dummy COOPERATIVE, equal to 1 if the bank is a cooperative and 0 otherwise; and a dummy SAVINGS, equal to 1 if the bank is a savings and loan institution and 0 otherwise.[10]

A second set of information refers to the fact that a change in business model could be driven by the need to adjust the whole banking organization to better support a previously undertaken strategic decision that of pursuing a process of consolidation. We include a dummy variable that equals 1 if the bank is involved in an M&A operation and 0 otherwise (M&A).

The third set of variables controls for the potential assistance received during the financial crisis and includes: a dummy variable that equals 1 if the bank was nationalized and 0 otherwise (NATIONALIZED); a dummy variable that equals 1 if the bank received an ad hoc, specific form of state aid from the government and 0 otherwise (AD_HOC); and a

[10] When the four variables are 0 in all cases, the bank is a public or a nationalized bank.

dummy variable that equals 1 if the bank operates in a country where a general scheme for aiding the financial sector was approved and 0 otherwise (SCHEME).[11] Typically, state aid decisions come with covenants, taking for instance the form of restructuring plan requirements that in turn may trigger the decision to change the bank's business model. Finally, to control for other institutional differences among countries and years, we introduce country and time dummies.

The results of the logistic regressions are reported in Table 4. The second column reports the estimates of a model that includes financial statement and ownership information, the third column shows the results of a specification that adds M&A information, and finally the fourth column includes the whole set of covariates.

The larger the bank's size, the lower its profitability and its leverage and the higher the probability of its migration from one business model to another. Additional bank-specific factors play a crucial role in increasing of the probability of migration: the bank's risk appetite and ownership form. First of all, the bank's risk profile proxied by the RWA density is positively and significantly linked to the probability of migration. Together, these results seem to suggest that those banks with a higher propensity for risky activities and an adequate level of capital are more willing to change their business model, possibly in search for profitability.

With regard to the ownership structure, our findings underscore a positive and significant relationship between migration and shareholder-owned financial institutions: commercial banks are more willing to change their business model during the period under investigation than banks under other ownership forms, all of which are attributable to the stakeholder-oriented model of ownership. As commercial banks are typically profit maximizers, they are better equipped to quickly respond to changes in the competitive environment that might require an adjustment in the adopted business model.

In line with our expectations, M&A operations positively drive the decision to migrate from one business model to another. The complexity of the implementation of a consolidation process can suggest the need and the desire to undergo a simplification of the organizational structure through a related change in the model of business.

[11] Ad hoc state aids are individual interventions into the specific bank, most of which give rise to the signing of hybrid instruments or the purchase of shares and are therefore aimed at the recapitalization of banks in solvency crises. State aid schemes are provided to support the entire banking system of a country or a specific sector within it (for example, to assist cooperative banks) and are therefore accessible to a plurality of banks of the same nationality.

Finally, state aid granted during the GFC and the decision to nationalize a bank significantly and positively impact the probability of migration. With regard to state aid, we observe that only the specific assistance granted to a single bank has a positive and significant relationship to the probability of migrating, while schemes, i.e., assistance granted to an entire country's banking system, do not have any influence on the decision to move from one business model to another. In fact, only nationalization, with its change in the governance structure of troubled banks, and ad hoc government intervention, with its accompanying restructuring plans, had the possibility of profoundly affecting and incentivizing rescued banks to change their business strategy and focus.

In sum, in the last decade, migrations among the different bank business models have been mainly determined by bank-specific variables, such as profitability, capitalization, and riskiness, but also by M&A operations that may push banks to change their BM to become able to better support the new bank's strategy. Finally, government support provided during periods of financial turmoil plays a crucial role in the decision to change banks' business models.

[Table 4. approximately here]

4.2 The impact of business model migration on bank performance

The implementation of propensity score matching can be broken down into three different phases: i) estimating the propensity score; ii) matching migrating banks with non-migrating banks, and iii) estimating the effect of migration on the bank's performance. The propensity score was estimated starting with the full model presented in Table 4 (column 4). This was made possible due to the fact that we included in the first step of the analysis all variables that do not depend on the treatment, i.e., the decision to migrate (Caliendo and Kopeinig, 2005).

Having estimated the propensity scores, we proceed to match migrating banks with non-migrating banks. We employ nearest neighbor matching with replacement. Matching with replacement involves a trade-off between bias and variance. Choosing replacement allows us to increase the average quality of the matching and to decrease the bias. This is important when the propensity score distribution is very different in the treatment and the control group (Caliendo and Kopeinig, 2005). Moreover, Caliendo and Kopeinig (2005) underline the importance of using more than one nearest neighbor (i.e., oversampling). Also in this case, we observe a trade-off between variance and bias. In fact, this implementation allows us to reduce variance, resulting from using more information to construct the counterfactual for each participant, with increased bias that results from, on average, poorer matches.

However, Abadie and Imbens (2002) highlight that the efficiency loss disappears as one increases the number of matches. In practice, the efficiency loss from using more than one match is negligible. In light of this evidence, in our analysis we use four matches as this procedure offers the benefit of not relying on too little information without incorporating observations that are not sufficiently similar (Abadie and Imbens, 2002; Abadie et al., 2004). In addition, in line with the decision to allow for replacement, to avoid the risk of bad matches and increase the matching quality, we impose a caliper of 1%, which means that the tolerance level of the maximum propensity score distance between migrating and non-migrating banks must be at least equal to 1%. This way, the individual from the comparison group is chosen as a matching partner for a treated individual that lies within the caliper (the propensity range) and is the closest in terms of its propensity score (Caliendo and Kopeinig, 2005).

To verify the matching quality, we plot the distribution of the two samples: the pre-matching sample and the post-matching sample. Figure 2, Panel A shows the percentage bias for each explanatory variable both in the unmatched and matched samples, while Figure 2, Panel B depicts the distribution of the propensity scores for the migrating and non-migrating banks, revealing that post-matching these two groups of banks greatly overlap. Migrating banks with appropriate matches from among the non-migrating banks are shown on the graph as "treated on support." Finally, as a robustness check, we also graph the distribution of the propensity score before and after the matching procedure, observing that in the unmatched sample, the propensity score distribution of non-migrating (untreated) banks is skewed to the left, whereas in the matched sample it is very close to that of the migrating (treated) banks (Figure 3). It is clear that the matching procedure has produced a substantially more balanced comparison between the treatment and control groups, as compared to the unmatched sample.

[Figure 2 approximately here]

Finally, to check whether the two samples are balanced, we compare the differences in the means of the covariates of migrating and non-migrating banks, before and after the matching. The results of the test are reported in Table 5 and demonstrate that before the matching the differences are significant, whereas after the matching, the significance of the differences drastically decreases in all covariates and becomes not statistically significant. Thus, we observe that the covariates are balanced in both groups, suggesting successful matching.

[Table 5. approximately here]

We use the matched samples to estimate the effects of migration on a set of bank performance measures: profitability, proxied by ROA; bank soundness, proxied by its distance to default (Z-score)[12]; cost efficiency (measured by the cost to income ratio); and finally, risk appetite (measured by RWA density).

To detect the treatment effect on different years, for each outcome we consider three different windows of time: i) in the year after migration (i.e., $\Delta y_{it+1}^{a}= y_{it+1} - y_{it}$); ii) in the year of treatment (i.e., $\Delta y_{it} = y_{it} - y_{it-1}$); and iii) in the long-term (i.e., $\Delta y_{it+2}^{a}= y_{it+2} - y_{it-1}$) with a three-year window around the time of migration.

Table 6 reports the results of different windows and outcomes. Our findings suggest that the migration has a negative effect on bank profitability only in the year of migration, when we expect the higher incidence of the costs of migration to take place, whereas in the subsequent year (from t to t+1), migrating banks perform better than non-migrating banks. Looking at the coefficients of the Z-score, we observe the opposite result: a negative relationship between the migration and the bank's soundness in the year of migration and a positive and significant relationship between the Z-score and migration in the year after migration. In line with Ayadi et al. (2018), these results suggest that in the year of migration, the decision to change the business model decreases the bank's soundness, leading it closer to default. However, in the year after the migration, the opposite is observed: banks that migrated in the previous year improve their stability in the subsequent period. Moreover, a negative relationship between the cost to income ratio and the migration is detected. It seems that migrating banks improve their cost efficiency after the migration when compared to non-migrating banks. Finally, our findings show a negative relationship between bank risk appetite and migration over a longer period of three years, suggesting that after a change in business model, banks reduce their risk appetite.

To summarize, our results shed light on the effects of bank migration on bank performance, underlining that after the first year in which migrating banks show a worsened

[12] The Z-score, defined as the number of standard deviations by which bank returns have to fall to exhaust bank equity, is considered a proxy for bank soundness.

performance with respect to their non-migrating peers, both in terms of profitability and stability, an improvement in performance and cost efficiency can be expected in the years following the migration.

[Table 6. approximately here]

5. Robustness tests

To validate our findings, we implemented three robustness checks considering: i) alternative time windows; ii) alternative neighbor match techniques; and iii) subsamples of banks with specific characteristics (i.e., those involved in an M&A operation or involved in some rescue package).

5.1 Alternative windows

First of all, we consider the following alternative windows to check the effects of the migration: i) the effect in the two years after migration (i.e., $\Delta y^{b}_{it+2}= y_{it+2} - y_{it}$); ii) the effect two years after migration (i.e., $\Delta y^{c}_{it+2}= y_{it+2} - y_{it+1}$); and iii) the effect around the time of migration (i.e., $\Delta y^{b}_{it+1}= y_{it+1} - y_{it-1}$).

The results are reported in Table 7 and confirm the previous main findings. We still observe a significant positive relationship between profitability and migration in the window from t to t+2, suggesting that migrating banks perform better than non-migrating ones even in the longer term. In the same time frame, our findings emphasize a negative and significant relationship between migration and the cost to income ratio, underling a better cost efficiency in migrating banks than in non-migrating banks. Finally, looking at the Z-score, the results highlight a significant and positive relationship between migration and a bank’s stability, strengthening the results obtained in the main analysis, that after the change of business model banks improve their stability in terms of their lower probability of insolvency.

[Table 7. approximately here]

5.2 Nearest neighbor match

As a second robustness check, we run the propensity score matching estimator using a different nearest neighbor match, as suggested by Abadie and Imbens (2002). We use the nearest neighbor with two matches and the results are reported in Table 8. Our findings substantially confirm those obtained in the main analysis. In general, migrating banks are more profitable, stable, and cost-efficient than non-migrating banks starting in the year following the migration.

[Table 8. approximately here]

5.3 Mergers and Acquisition (M&A) Operations and State Aid

Our third robustness test investigates the effects of migration on bank performance for two subsamples of banks, those that have been involved in M&A operations and those that received an ad hoc state aid. The underlying idea is to focus on the effects of those migrations clearly not driven by exogenous factors like a consolidation process or a state-aid. Thus, in our subsamples we respectively have: a) migrating banks and non-migrating banks that have been involved in a M&A operation; b) migrating banks and non-migrating banks that received an ad hoc state aid. In fact, M&As or state aids are drivers of business model migrations but also have an impact on bank performance on their own (per sè).

Comparing banks that after an M&A (state aid) do migrate with banks that after an M&A (state aid) do not change business model, we are able to isolate the effects of migrations on bank performance from the effects of mergers and acquisitions (rescue packages) on bank performance. Table 9 reports the estimates of the effects of migrations controlling for: *i)* the effects of M&As (Panel A) for both target and bidder banks; ii) the effects of M&As for only bidder banks (Panel B); *iii*) the effects of state interventions into troubled banks.

The first results (Panel A), referring to those banks that have been involved in a M&A operation, are in line with those obtained in the main analysis. Migrating banks have a higher return on assets in the year after the migration, although the magnitude of the effect is negligible. Moreover, migrating banks show a decrease in the cost to income ratio, underlining an improvement in the cost efficiency greater than that obtained by non-migrating banks also involved in a M&A operation. These findings suggest that the effects both on profitability and cost efficiency mainly depend on the decision to migrate and are not necessarily an outcome of the M&A operation. Restricting the subsample to the banks that have been involved in a M&A operation as acquirors (Panel B), our results underline the absence of a statistical significance of the effects of migration on bank performance. This findings may suggest that, contrary to what is highlighted in the Panel A, the effects on bank performance depend on being an acquiror in a M&A operation. In fact, in this subsample we isolate the effect of migration on bank performance from the effect of M&A operations in which the bank is the acquiror and in this case, any significant effect is observed.

Looking at the third subsample, our findings show that the effect of migrations on banks that received an ad hoc state aid is significant only with regard to the Z-score, and, in particular, the findings suggest that in the year of migration, these banks increase the Z-score – reducing their probability of default – while in the subsequent year, their probability of default increases. These results are in contrast with those obtained in the main analysis, in which we observed a deterioration in the Z-score in the year of migration and an improvement in the first year after the migration. This suggests that the positive effect on the bank soundness depends mainly on the receipt of the ad hoc state aid, more than the migration itself.

[Table 9. approximately here]

6. Conclusions

This study aims to detect the differences between banks that change their business model (migrating banks) and those that maintain the same BM (non-migrating banks). Moreover, the paper examines the drivers of bank migration among the different business models during the period under investigation (2005–2016). Finally, we test the effects of migration on bank performance.

With the objective of covering the entire European banking sector, our sample includes 3,287 European banking groups and subsidiaries of non-European banks. We adopt a unique definition and a novel clustering model (see Ayadi and Groen, 2015). For the analysis, 22,787 bank-year observations have been clustered into five broad categories: focused retail, diversified retail (type 1), diversified retail (type 2), wholesale, and investment.

Our results provide new evidence about the drivers that lead banks to change their business models, highlighting that the change depends mainly on low profitability, high levels of risk, and capitalization. Moreover, our findings suggest that banks that decide to change their business models during a period of financial crisis are usually smaller, involved in an M&A operation, and have received ad hoc state aid or have been nationalized.

Furthermore, by employing propensity score matching, we detect the effect of migration on bank performance. Our findings suggest that in the year of migration, migrating banks lower their performance—both in terms of profitability and stability—as compared to non-migrating banks, but in the subsequent year, the performance of migrating banks increases and these banks show higher profitability, cost efficiency and stability and lower risk appetite than the others. These results shed light on the ability of banks to improve their performance after a change in business model. In particular, even if in the year of migration banks undertake more risk than other banks and their performances worsen, in the years after migration, these banks are able to manage their risk and achieve better performance than non-migrating banks, underscoring that the migration from one business model to another may have a positive impact on bank performance and stability.

Considering that the business model analysis can prove insightful in the current debate on proportionality in the regulation and structural reform of the EU banking sector (Ayadi et al., 2016) and that a diverse banking system is seemingly more resilient than a system that tends to coverage toward one business model, our findings may be helpful for regulators and authorities to both better comprehend the drivers of the migration among the different banks' business models and to exploit these variables to address, in case, the banks to specific business models.

To the best of our knowledge, no empirical research exists addressing the question of why banks change their business models and the effects of this decision. Previous analyses have only focused on the definition of banking business models and on the descriptive analysis of bank characteristics related to each BM identified. Therefore, our study offers unique insight for future analyses of the determinants of migration among the different banking business models. The present study has only examined the drivers of bank migration; however, further work will concentrate on the factors driving bank migration by considering both from where and to which business models banks migrate.

It is well known that the business model analysis has a predictive power that is essential for regulators and supervisors to investigate the level of risk accumulation at a systems level over a period of time (Ayadi et al., 2016). In light of this, understanding where banks effectively migrate and which are the drivers and the effects of this decision may be crucial to controlling the level of risk in the banking sector.

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Appendix

Table A Distribution of banks by countries and years

Country/Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Total
AT	9	12	16	16	16	245	245	246	246	245	241	82	1619
BE	4	4	6	6	6	22	22	22	22	21	21	21	177
BG	3	3	4	4	4	9	9	9	9	9	8	8	79
CH	16	20	27	27	27	118	135	139	137	132	126	114	1,018
CY	4	5	5	5	5	10	12	13	13	13	13	12	110
CZ	-	-	-	-	-	8	8	8	8	8	8	7	55
DE	38	43	55	56	58	1,554	1,562	1,568	1,562	1,551	1,484	1,356	10,887
DK	29	30	33	33	32	71	71	69	67	66	64	62	627
EE	-	-	-	-	-	5	5	5	6	6	6	6	39
ES	24	28	36	36	37	58	67	62	65	63	60	60	596
FI	2	2	3	3	3	20	20	22	22	23	23	21	164
FR	6	6	6	6	6	62	67	70	70	70	68	63	500
GB	16	20	21	21	21	143	152	158	155	157	155	144	1,163
GR	10	10	10	10	10	19	15	15	14	13	12	12	150
HR	3	5	7	7	7	14	14	14	14	13	13	13	124
HU	3	3	3	3	3	9	9	9	9	9	6	6	72
IE	6	6	6	6	6	13	12	12	12	12	12	10	113
IS	-	-	-	3	3	6	6	6	6	4	4	4	42
IT	20	26	30	29	29	337	361	391	429	421	408	368	2,849
LI	-	-	1	1	1	6	7	7	7	6	6	6	48
LT	1	1	3	3	3	5	4	3	3	3	2	2	33
LU	1	3	3	3	3	33	33	34	36	33	33	29	244
LV	-	-	-	-	-	4	5	6	14	13	13	12	67
MT	1	1	3	3	3	9	9	10	9	9	9	9	75
NL	7	7	8	9	10	31	32	33	32	32	31	30	262
NO	16	17	25	26	26	99	99	100	97	96	96	90	787
PL	3	4	5	6	7	12	13	12	12	12	11	9	106
PT	4	6	6	6	6	24	24	24	24	25	23	22	194
RO	1	1	2	2	2	5	6	7	7	7	7	7	54
SE	5	5	5	6	6	55	55	57	56	55	55	56	416
SI	-	3	3	3	2	11	11	11	11	11	9	7	82
SK	-	-	1	1	1	5	5	5	5	4	4	4	35
Total	**232**	**271**	**333**	**340**	**343**	**3,022**	**3,095**	**3,147**	**3,179**	**3,142**	**3,031**	**2,652**	**22,787**

Figure A Distribution of banks for years and business models

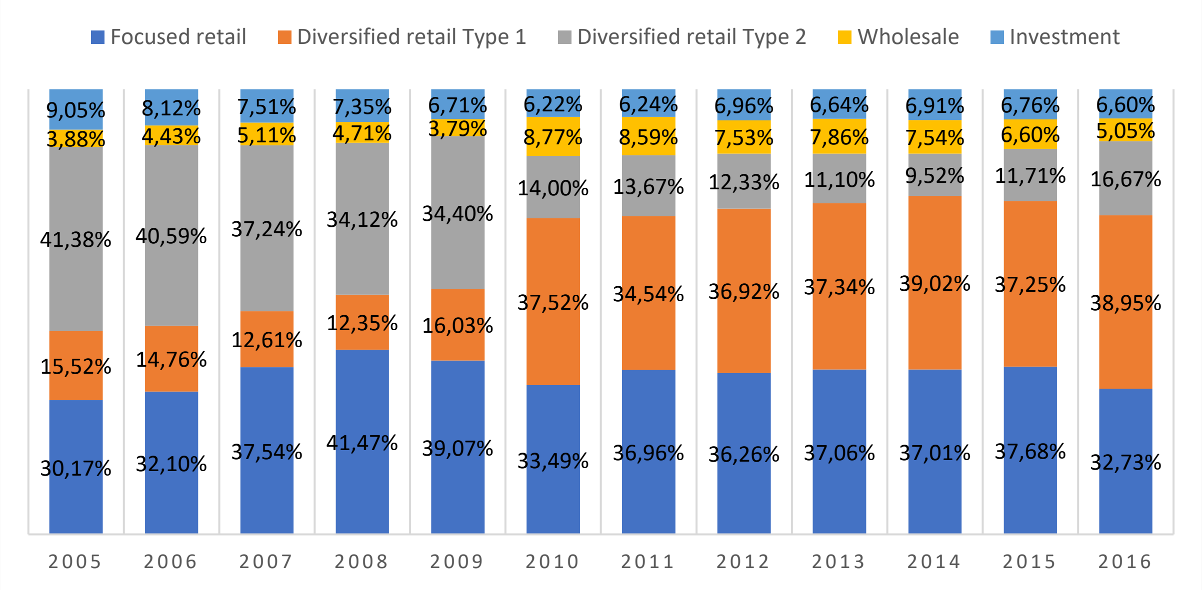


Table B Distribution of migrations among different business models (number of banks)

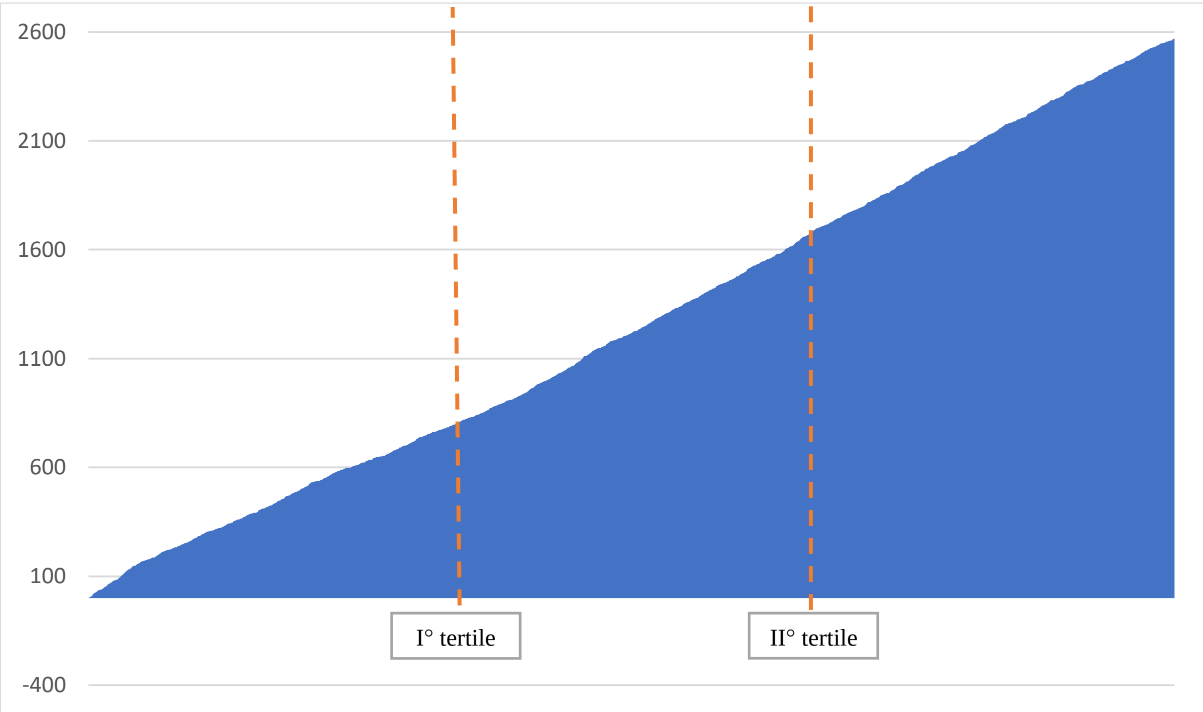
	Focsed (1)	Div type 1 (2)	Div type 2 (2)	Wholesale	Investment	Total
Pre_crisis	**282**	**118**	**330**	**38**	**68**	**836**
%	*33.73%*	*14.11%*	*39.47%*	*4.55%*	*8.13%*	*100.00%*
Focsed (1)	141	5	10	1		157
%	*89.81%*	*3.18%*	*6.37%*	*0.64%*	*0.00%*	*100.00%*
Div type 1 (2)	16	52	1	2	5	76
%	*21.05%*	*68.42%*	*1.32%*	*2.63%*	*6.58%*	*100.00%*
Div type 2 (2)	8	5	192	1		206
%	*3.88%*	*2.43%*	*93.20%*	*0.49%*	*0.00%*	*100.00%*
Wholesale	1	2	1	16	1	21
%	*4.76%*	*9.52%*	*4.76%*	*76.19%*	*4.76%*	*100.00%*
Investment		5	2	1	35	43
%	*0.00%*	*11.63%*	*4.65%*	*2.33%*	*81.40%*	*100.00%*
Empty	116	49	124	17	27	333
%	*34.83%*	*14.71%*	*37.24%*	*5.11%*	*8.11%*	*100.00%*
Crisis	**3572**	**3462**	**1468**	**797**	**648**	**9947**
%	*35.91%*	*34.80%*	*14.76%*	*8.01%*	*6.51%*	*100.00%*
Focsed (1)	2,297	170	42	8	4	2521
%	*91.11%*	*6.74%*	*1.67%*	*0.32%*	*0.16%*	*100.00%*
Div type 1 (2)	201	2,044	13	38	35	2331
%	*8.62%*	*87.69%*	*0.56%*	*1.63%*	*1.50%*	*100.00%*
Div type 2 (2)	74	54	1,047	4	13	1192
%	*6.21%*	*4.53%*	*87.84%*	*0.34%*	*1.09%*	*100.00%*
Wholesale	33	58	4	444	33	572
%	*5.77%*	*10.14%*	*0.70%*	*77.62%*	*5.77%*	*100.00%*
Investment	2	38	8	26	377	451
%	*0.44%*	*8.43%*	*1.77%*	*5.76%*	*83.59%*	*100.00%*
Empty	965	1098	354	277	186	2880
%	*33.51%*	*38.13%*	*12.29%*	*9.62%*	*6.46%*	*100.00%*
Recovery	**4,351**	**4,575**	**1,449**	**821**	**808**	**12004**
%	*36.25%*	*38.11%*	*12.07%*	*6.84%*	*6.73%*	*100.00%*
Focsed (1)	3,905	226	245	30	3	4409
%	*88.57%*	*5.13%*	*5.56%*	*0.68%*	*0.07%*	*100.00%*
Div type 1 (2)	286	3987	130	54	78	4535
%	*6.31%*	*87.92%*	*2.87%*	*1.19%*	*1.72%*	*100.00%*
Div type 2 (2)	103	170	1,044	3	11	1331
%	*7.74%*	*12.77%*	*78.44%*	*0.23%*	*0.83%*	*100.00%*
Wholesale	33	96	2	675	37	843
%	*3.91%*	*11.39%*	*0.24%*	*80.07%*	*4.39%*	*100.00%*
Investment	9	76	14	40	673	812
%	*1.11%*	*9.36%*	*1.72%*	*4.93%*	*82.88%*	*100.00%*
Empty	15	20	14	19	6	74
%	*20.27%*	*27.03%*	*18.92%*	*25.68%*	*8.11%*	*100.00%*
Total	**8,205**	**8,155**	**3,247**	**1,656**	**1,524**	**22,787**
%	*36.01%*	*35.79%*	*14.25%*	*7.27%*	*6.69%*	*100.00%*

Note: Pre-crisis period refers to 2005-2007; Crisis refers to 2008-2012 and finally, Recovery period refers to 2013-2016.

Table C Distribution of migrations among different business models (% of total assets)

Etichette di riga	Focsed (1)	Div type 1	Div type 2	Wholesale	Investment	Total
Pre_crisis	**4.06%**	**10.77%**	**41.69%**	**3.17%**	**40.30%**	**100.00%**
Focused (1)	88.97%	2.68%	7.91%	0.44%	0.00%	100.00%
Div. Type 1 (2)	3.60%	83.37%	0.02%	5.45%	7.56%	100.00%
Div. Type 2 (3)	0.62%	11.55%	87.76%	0.07%	0.00%	100.00%
Wholesale (4)	0.03%	13.48%	17.25%	65.18%	4.07%	100.00%
Investment (5)	0.00%	1.62%	6.14%	0.04%	92.21%	100.00%
Crisis	**7.52%**	**17.40%**	**37.72%**	**1.24%**	**36.12%**	**100.00%**
Focused (1)	90.88%	5.29%	2.59%	0.21%	1.03%	100.00%
Div. Type 1 (2)	1.45%	75.36%	1.92%	0.25%	21.02%	100.00%
Div. Type 2 (3)	1.57%	3.98%	93.14%	0.17%	1.14%	100.00%
Wholesale (4)	3.14%	4.44%	1.60%	61.88%	28.95%	100.00%
Investment (5)	0.05%	8.76%	1.55%	0.45%	89.19%	100.00%
Recovery	**10.72%**	**21.32%**	**32.87%**	**1.61%**	**33.48%**	**100.00%**
Focused (1)	84.46%	6.87%	8.47%	0.20%	0.00%	100.00%
Div. Type 1 (2)	2.92%	80.42%	5.95%	0.40%	10.31%	100.00%
Div. Type 2 (3)	3.49%	4.51%	91.85%	0.00%	0.15%	100.00%
Wholesale (4)	0.96%	7.21%	0.00%	84.92%	6.90%	100.00%
Investment (5)	0.14%	2.99%	3.86%	0.50%	92.50%	100.00%
Total	**8.06%**	**17.61%**	**36.67%**	**1.74%**	**35.93%**	**100.00%**

Figure B The progressive number of migrations by banks' total assets



Note: The Figure underlines that the migrations take place in a linear way, without jumps corresponding to specific banks' size.

Table D Migrating and Non-migrating banks during the period observed

Year	Non-migrating banks	Migrating banks	Total
2006	195	37	232
%	*84.05*	*15.95*	*100.00*
2007	241	30	271
%	*88.93*	*11.07*	*100.00*
2008	278	54	332
%	*83.73*	*16.27*	*100.00*
2009	289	47	336
%	*86.01*	*13.99*	*100.00*
2010	281	44	325
%	*86.46*	*13.54*	*100.00*
2011	2,662	341	3,003
%	*88.64*	*11.36*	*100.00*
2012	2,699	372	3,071
%	*87.89*	*12.11*	*100.00*
2013	2,744	372	3,116
%	*88.06*	*11.94*	*100.00*
2014	2,798	333	3,131
%	*89.36*	*10.64*	*100.00*
2015	2,602	429	3,031
%	*85.85*	*14.15*	*100.00*
2016	2,140	512	2,652
%	*80.69*	*19.31*	*100.00*
Total	16,929	2,571	19,500
%	*86.82*	*13.18*	*100.00*

Table E Variables definition

Variables	Definition	Source
Bank specific variables		
ROA	Return on total assets as measure of banks' profitability	SNL Unlimited
EQ_TA	Equity on total assets as measure of capitalization	SNL Unlimited
INTANGIBLE_TA	Intangible assets over total assets ratio	SNL Unlimited
C_I	Cost to income ratio as measure of operating efficiency	SNL Unlimited
SIZE	Natural logarithm of total assets as measure of dimension	SNL Unlimited
Z	The Z-score measured as [(equity over total assets + the mean of bank's ROA)/the standard deviation of bank's ROA)]	SNL Unlimited
RWA	Risk weighted assets over total assets as measure of regulatory risk requirement	SNL Unlimited
COMMERCIAL	A dummy variable equals 1 if the bank is a commercial bank, 0 otherwise	SNL Unlimited
COOPERATIVE	A dummy variable equals 1 if the bank is a cooperative bank, 0 otherwise	SNL Unlimited
SAVINGS	A dummy variable equals 1 if the bank is a saving bank, 0 otherwise	SNL Unlimited
M&A	A dummy variable equals 1 if bank is involved in a mergers and acquisitions, 0 otherwise	Zephyr Database
ACQUIROR	A dummy variable equals 1 if bank is the acquiror of a mergers and acquisitions, 0 otherwise	Zephyr Database
VENDOR	A dummy variable equals 1 if bank is the vendor of a mergers and acquisitions, 0 otherwise	Zephyr Database
TARGET	A dummy variable equals 1 if bank is the target of a mergers and acquisitions, 0 otherwise	Zephyr Database
Crisis variables		
ADHOC	A dummy variable equals 1 if bank received an ad hoc state aid, 0 otherwise	European Commission
SCHEME	A dummy variable equals 1 if bank is located in a country in which there was a State aid in the form of scheme, 0 otherwise	European Commission
NATIONALIZED	A dummy variable equals 1 if the bank is a nationalized bank, 0 otherwise	SNL Unlimited

List of Tables

Table 1 Distribution of Migrating and Non-migrating banks

Cluster	Migrating banks	Non-migrating banks	Total
Panel A By period investigated			
Pre_crisis	67	436	503
%	*13.32%*	*86.68%*	*100.00%*
Crisis	858	6,209	7,067
%	*12.14%*	*87.86%*	*100.00%*
Recovery	1,646	10,284	11,930
%	*13.80%*	*86.20%*	*100.00%*
Panel B By bank's size			
SMALL	790	5,486	6,276
	12.59%	*87.41%*	*100.00%*
MEDIUM	893	5,634	6,527
	13.68%	*86.32%*	*100.00%*
LARGE	888	5,809	6,697
	13.26%	*86.74%*	*100.00%*
Panel C By Banks' ownership structure			
Commercial	861	3,978	4,839
%	*17.79%*	*82.21%*	*100.00%*
Savings	481	3,746	4,227
%	*11.38%*	*88.62%*	*100.00%*
Cooperative	1,120	8,532	9,652
%	*11.60%*	*88.40%*	*100.00%*
Nationalized	58	200	258
%	*22.48%*	*77.52%*	*100.00%*
Public	51	473	524
%	*9.73%*	*90.27%*	*100.00%*
Panel D By geographical area			
Euro_zone	2,043	13,481	15,524
%	*13.16%*	*86.84%*	*100.00%*
Non_Euro_zone	528	3,448	3,976
%	*13.28%*	*86.72%*	*100.00%*
Total	**2,571**	**16,929**	**19,500**
%	***13.18%***	***86.82%***	***100.00%***

Note: Panel A shows the distribution of migrating and non-migrating banks in three different subperiods: pre-crisis (2005-2007), crisis (2008-2012) and recovery (2013-2016). Panel B underlines the distribution of migrating and non-migrating banks among different bank size: large, medium and small. The size is defined using the tercile distribution. Panel C shows the distribution of migrating and non-migrating banks considering the bank's specialization: cooperative, commercial, savings and nationalized banks. Finally, Panel D shows the distribution of migrating and non-migrating banks in the Euro and Non-Euro zone.

Table 2. Migration in term of total assets of the whole period (%)

t-1↓ / t→	Focused retail	Diversified type 1	Diversified type 2	Wholesale	Investment	Tot
Focused retail	87%	6%	6%	0%	0%	100%
Diversified type 1	2%	78%	4%	1%	15%	100%
Diversified type 2	2%	5%	92%	0%	1%	100%
Wholesale	1%	8%	5%	71%	14%	100%
Investment	0%	5%	3%	0%	91%	100%
Total	**8.06%**	**17.61%**	**36.67%**	**1.74%**	**35.93%**	**100.00%**
Pre_crisis	4.06%	10.77%	41.69%	3.17%	40.30%	100.00%
Crisis	7.52%	17.40%	37.72%	1.24%	36.12%	100.00%
Recovery	10.72%	21.32%	32.87%	1.61%	33.48%	100.00%

Table 3 Summary statistics for all sample banks and univariate tests of differences in characteristics

	Total sample			*Migrating Banks*			*Non-migrating Banks*			*Difference in means*		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Abs	%	P-value ttest
panel A Balance sheet structure												
Customer deposits over total assets	16904	0.653	0.218	2561	0.638	0.266	22744	0.6491	0.2257	-0.011	-2%	0.0014
Customer loans over total assets	16907	0.575	0.204	2564	0.536	0.184	22750	0.5682	0.2039	-0.032	-6%	0.0000
Trading assets over total assets	16580	0.274	0.168	2497	0.287	0.136	22294	0.274	0.1641	0.013	5%	0.0002
Size	16929	6.912	2.014	2571	6.87	1.997	22787	6.8453	2.0007	0.024	0%	0.3268
Intangible assets over total assets	16929	0.002	0.007	2571	0.002	0.009	22787	0.0018	0.0091	0.000	10%	0.0018
Equity over total assets	16884	0.101	0.089	2550	0.115	0.122	22715	0.1029	0.0976	0.012	11%	0.0000
RWA density	14715	0.597	1.24	2228	0.644	1.936	19284	0.6069	1.3379	0.037	6%	0.1189
panel B Income statement												
Return on assets	16807	0.005	0.053	2534	0.001	0.084	22597	0.0047	0.0576	-0.003	-370%	0.0015
Return on equity	16787	0.053	0.707	2528	-0.01	2.209	22563	0.0471	1.0027	-0.057	571%	0.0045
Interest income ratio	16771	0.681	1.786	2521	0.658	0.738	22536	0.6769	1.5661	-0.018	-3%	0.5150
Operating income over total assets	16799	0.037	0.084	2527	0.044	0.171	22582	0.0381	0.0971	0.005	13%	0.0016
Cost to income	16793	0.706	1.594	2527	1.005	7.535	22566	0.7441	3.4005	0.260	26%	0.0000
Loan loss provision over gross loans	14258	0.005	0.084	2175	0.008	0.039	18453	0.0061	0.1137	0.001	24%	0.1260
panel C Ownership form												
Commercial banks	16929	0.235	0.424	2571	0.335	0.472	22787	0.2469	0.4312	0.088	26%	0.0000
Cooperative banks	16929	0.504	0.5	2571	0.436	0.496	22787	0.4982	0.5	-0.062	-14%	0.0000
Savings banks	16929	0.221	0.415	2571	0.187	0.39	22787	0.2159	0.4114	-0.028	-15%	0.0001
Public banks	16929	0.028	0.165	2571	0.02	0.139	22787	0.0263	0.16	-0.006	-32%	0.0179
panel D M&A operations												
M&A dummy	16929	0.061	0.239	2571	0.079	0.27	22787	0.0605	0.2384	0.018	23%	0.0004
M&A acquiror	16929	0.035	0.001	2571	0.045	0.004	22787	0.0347	0.1831	0.010	23%	0.0104
M&A target	16929	0.028	0.001	2571	0.034	0.003	22787	0.0277	0.1643	0.006	19%	0.0787
M&A vendor	16929	0.021	0.001	2571	0.026	0.003	22787	0.0208	0.1427	0.005	20%	0.0951
panel E State aids												
Nationalized banks	16929	0.012	0.108	2571	0.023	0.149	22787	0.0127	0.1121	0.010	45%	0.0000
Ad hoc state aid	16929	0.006	0.075	2571	0.011	0.106	22787	0.0056	0.0744	0.005	49%	0.0011
Scheme state aid	16929	0.303	0.459	2571	0.295	0.456	22787	0.3545	0.4784	-0.059	-20%	0.4226

Table 4. Determinants of Banks' propensity to migrate (odds ratio)

VARIABLES	Mod1	Mod2	Mod3
Constant	-0.370	-0.284	-0.543
	(0.515)	(0.515)	(0.524)
EQ_TA_{t-1}	0.588*	0.583*	0.599*
	(0.314)	(0.314)	(0.314)
$INTANGIBLE\_TA_{t-1}$	-2.207	-2.913	-2.202
	(3.164)	(3.252)	(3.264)
$SIZE_{t-1}$	-0.0603***	-0.0724***	-0.0819***
	(0.0162)	(0.0169)	(0.0170)
ROA_{t-1}	-3.564***	-3.437***	-3.282***
	(1.003)	(1.001)	(0.999)
$COST\_INCOME_{t-1}$	0.00674	0.00694	0.00678
	(0.00634)	(0.00636)	(0.00628)
RWA_{t-1}	0.0278**	0.0272**	0.0272**
	(0.0130)	(0.0130)	(0.0129)
COMMERCIAL	0.342*	0.322*	0.314*
	(0.1705)	(0.1707)	(0.179)
COOPERATIVE	-0.255	-0.2727	-0.271
	(0.1794)	(0.145)	(0.187)
SAVINGS	-0.0270	-0.019	0.0344
	(0.1807)	(0.1809)	(0.188)
$DUMMY\_M\&A_{t-1}$	-	0.1011**	0.204**
	-	(0.101)	(0.103)
NATIONALIZED	-	-	0.469***
			(0.260)
AD_HOC_{t-1}	-	-	0.469**
			(0.236)
$SCHEME_{t-1}$	-	-	0.0001
			(0.0811)
Year dummies	YES	YES	YES
Country dummies	YES	YES	YES
Observations	16,215	16,215	16,215
Log Likelihood	-6072.4484	-6069.3999	-6061.3755
Log-R squared	0.0305	0.0317	0.03378

Note: The table reports the logit regression estimates of banks' propensity to migrate. The dependent variable is equal to 1 if bank changes its business model and 0 otherwise. All explanatory variables, with exception for ownership structure, are lagged 1 year. *, **, *** stand for statistical significance at the 10%, 5%, 1% levels, respectively.

Table 5 t-Test for Equality of Means of Covariates before and after matching

Variable	Matched	Migrating Banks	Non-migrating Banks	T	p>t
EQ_TA_{t-1}	U	0.107	0.095	7.510	0.000
	M	0.107	0.107	0.020	0.988
$INTANGIBLE\_TA_{t-1}$	U	0.002	0.002	2.170	0.030
	M	0.002	0.002	-0.270	0.789
$SIZE_{t-1}$	U	6.828	6.887	-1.230	0.218
	M	6.830	6.858	-0.430	0.664
ROA_{t-1}	U	0.003	0.005	-5.600	0.000
	M	0.003	0.004	-1.270	0.205
$COST\_INCOME_{t-1}$	U	0.925	0.707	3.050	0.002
	M	0.757	0.794	-0.550	0.583
RWA_{t-1}	U	0.751	0.596	4.530	0.000
	M	0.666	0.633	0.570	0.569
$COMMERCIAL_{t-1}$	U	0.317	0.216	10.180	0.000
	M	0.316	0.316	0.040	0.969
$COOPERATIVE_{t-1}$	U	0.462	0.534	-6.100	0.000
	M	0.462	0.457	0.360	0.717
$SAVINGS_{t-1}$	U	0.175	0.210	-3.630	0.000
	M	0.176	0.182	-0.530	0.599
$DUMMY\_M\&A_{t-1}$	U	0.085	0.068	2.900	0.004
	M	0.085	0.086	-0.120	0.908
$NATIONALIZED_{t-1}$	U	0.025	0.013	4.430	0.000
	M	0.025	0.025	0.020	0.980
AD_HOC_{t-1}	U	0.014	0.007	3.550	0.000
	M	0.014	0.014	-0.030	0.974
SCHEMEt-1	U	0.296	0.282	1.280	0.201
	M	0.296	0.289	0.500	0.617

Note: The Table reports the means of variables used in the logit regression and the differences in means in the two subsamples, before the matching and after the matching. U refers to unmatching sample and M to the matching sample.

Table 6. The effect of migration on bank performance

ATET	Coef.	Std. Err.	[95% Conf.	Interval]
ROA_t - ROA_{t-1}	-0.0022*	0.0013	-0.0049	0.0004
ROA_{t+1} - ROA_t	0.0047**	0.0023	0.0001	0.0092
ROA_{t+2}- ROA_{t-1}	0.0016	0.0011	-0.0006	0.0039
Z_t - Z_{t-1}	-0.7365*	0.4122	-1.5444	0.0714
Z_{t+1} - Z_t	1.2381***	0.5064	0.2455	2.2307
Z_{t+2} - Z_{t-1}	0.3364	0.6123	-0.8638	1.5365
C_I_t – C_I_{t-1}	-0.0545	0.1553	-0.3589	0.2498
C_I_{t+1} – C_I_t	-0.1408*	0.0750	-0.2879	0.0063
C_I_{t+2} – C_I_{t-1}	-0.1607	0.2026	-0.5578	0.2365
RWA_t – RWA_{t-1}	-0.0520	0.0428	-0.1359	0.0320
RWA_{t+1} – RWA_t	0.0385	0.0390	-0.0380	0.1149
RWA_{t+2} – RWA_{t-1}	-0.1175*	0.0679	-0.2506	0.0157

Note: Table reports results of the average treatment effect on treated. The outputs are: ROA as proxy of bank's profitability, Z-score as proxy of risk of default, the cost income ratio as proxy of bank's cost efficiency, RWA is the risk weighted assets density and is a proxy of risk appetite. We test the effect on different time windows. The matching variables are those used in the main analysis to measure the propensity score. Number of matches is equal to 4. "***", "**" and "*" indicate 1%, 5% and 10% significance levels, respectively.

Table 7 Robustness check: the effect of migration on bank performance in different windows

ATET	Coef.	Std. Err.	[95% Conf.	Interval]
ROA_{t+2} - ROA_t	0.0050*	0.0028	-0.0004	0.0105
ROA_{t+1} - ROA_{t-1}	-0.0001	0.0008	-0.0017	0.0015
ROA_{t+2} - ROA_{t+1}	0.0009	0.0008	-0.0008	0.0025
Z_{t+2} - Z_t	0.0469	0.5381	-1.0078	1.1016
Z_{t+1} - Z_{t-1}	0.6726*	0.3860	-0.0840	1.4293
Z_{t+2} - Z_{t+1}	-0.6862	0.4891	-1.6447	0.2724
C_I_{t+2} – C_I_t	-0.0368**	0.0632	-0.1607	0.0870
C_I_{t+1} – C_I_{t-1}	-0.2205	0.2480	-0.7066	0.2655
C_I_{t+2} – C_I_{t+1}	0.1050	0.0812	-0.0541	0.2641
RWA_{t+2} – RWA_t	-0.0582	0.0438	-0.1441	0.0277
RWA_{t+1} – RWA_{t-1}	-0.0162	0.0411	-0.0967	0.0643
RWA_{t+2} – RWA_{t+1}	-0.0623	0.0579	-0.1757	0.0512

Note: Table reports results of the average treatment effect on treated. The outputs are: ROA as proxy of bank's profitability, Z-score as proxy of risk of default, the cost income ratio as proxy of bank's cost efficiency, RWA is the risk weighted assets density and is a proxy of risk appetite. We test the effect on different time windows. The matching variables are those used in the main analysis to measure the propensity score. Number of matches is equal to 4. "***", "**" and "*" indicate 1%, 5% and 10% significance levels, respectively.

Table 8. Robustness check: the effect of migration on bank performance with 2 matches

ATET	Coef.	Std. Err.	[95% Conf.	Interval]
$ROA_t - ROA_{t-1}$	-0.0021	0.0015	-0.0050	0.0008
$ROA_{t+1} - ROA_t$	0.0049**	0.0023	0.0003	0.0094
$ROA_{t+2} - ROA_t$	0.0054**	0.0029	-0.0002	0.0110
$ROA_{t+1} - ROA_{t-1}$	0.0001	0.0009	-0.0017	0.0019
$ROA_{t+2} - ROA_{t+1}$	0.0007	0.0009	-0.0011	0.0024
$ROA_{t+2} - ROA_{t-1}$	0.0029	0.0019	-0.0008	0.0067
$Z_t - Z_{t-1}$	-0.8611	0.4130	-1.6707	-0.0516
$Z_{t+1} - Z_t$	1.0114**	0.5220	-0.0117	2.0344
$Z_{t+2} - Z_t$	0.1830	0.5392	-0.8738	1.2399
$Z_{t+1} - Z_{t-1}$	0.5953	0.3967	-0.1822	1.3729
$Z_{t+2} - Z_{t+1}$	-0.8462	0.5204	-1.8661	0.1738
$Z_{t+2} - Z_{t-1}$	0.6053	0.6275	-0.6247	1.8352
$C\_I_t – C\_I_{t-1}$	-0.1277	0.1629	-0.4469	0.1915
$C\_I_{t+1} – C\_I_t$	-0.1516**	0.0781	-0.3048	0.0015
$C\_I_{t+2} – C\_I_t$	-0.0423	0.0646	-0.1688	0.0842
$C\_I_{t+1} – C\_I_{t-1}$	-0.2268	0.2573	-0.7311	0.2775
$C\_I_{t+2} – C\_I_{t+1}$	-0.1277	0.1629	-0.4469	0.1915
$C\_I_{t+2} – C\_I_{t-1}$	-0.2361	0.2104	-0.6485	0.1764
$RWA_t – RWA_{t-1}$	-0.0503	0.0460	-0.1405	0.0398
$RWA_{t+1} – RWA_t$	0.0494	0.0451	-0.0390	0.1377
$RWA_{t+2} – RWA_t$	-0.0942	0.0701	-0.2316	0.0433
$RWA_{t+1} – RWA_{t-1}$	-0.0024	0.0435	-0.0875	0.0828
$RWA_{t+2} – RWA_{t+1}$	-0.1092	0.0968	-0.2989	0.0805
$RWA_{t+2} – RWA_{t-1}$	-0.1493**	0.0880	-0.3218	0.0232

Note: Table reports results of the average treatment effect on treated. The outputs are: ROA as proxy of bank's profitability, Z-score as proxy of risk of default, the cost income ratio as proxy of bank's cost efficiency and RWA is the risk weighted assets density and is a proxy of risk appetite. We test the effect on different time windows. The matching variables are those used in the main analysis to measure the propensity score. Number of matches is equal to 2. "***", "**" and "*" indicate 1%, 5% and 10% significance levels, respectively.

Table 9. The effects of migration of banks involved in a M&A operation or received state aids

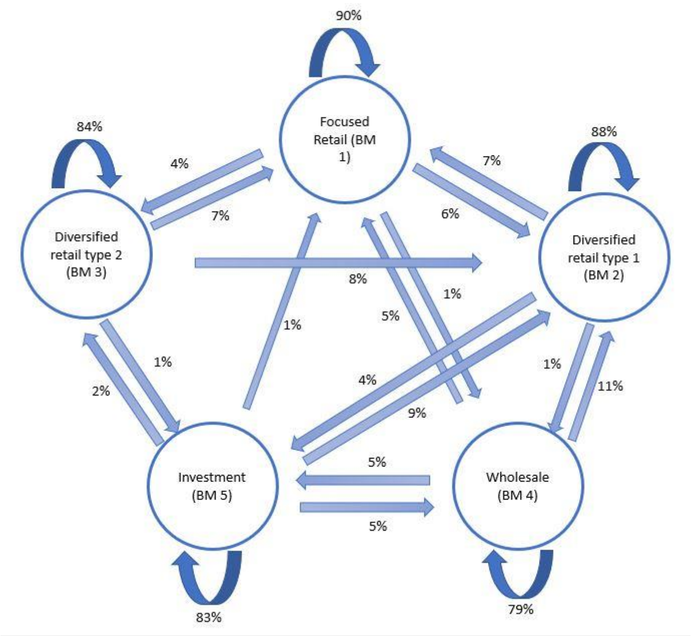
ATET	Coef.	Std. Err.	[95% Conf.	Interval]
Panel A Effects of migrations of banks involved in M&A operations				
ROA_t - ROA_{t-1}	-.0150022	.0128583	-.0402039	.0101996
ROA_{t+1} - ROA_t	.004422**	.002239	.0000336	.0088103
ROA_{t+2}- ROA_{t-1}	.0029134	.0031269	-.0032153	.0090421
Z_t - Z_{t-1}	.1759296	.2507554	-.3155421	.6674012
Z_{t+1} - Z_t	.4637314	.4082963	-.3365147	1.263977
Z_{t+2} - Z_{t-1}	.1349561	.6158672	-1.072121	1.342034
$C\_I_t – C\_I_{t-1}$	.0115337	.1684964	-.3187132	.3417806
$C\_I_{t+1} – C\_I_t$	-.2990694**	.1590799	-.6108603	.0127214
$C\_I_{t+2} – C\_I_{t-1}$	-.0447326	.0626491	-.1675226	.0780574
$RWA_t – RWA_{t-1}$	-.4308085	.4118636	-1.238046	.3764292
$RWA_{t+1} – RWA_t$	-.0065828	.007671	-.0216176	.008452
$RWA_{t+2} – RWA_{t-1}$	-.5024491	.4895315	-1.461913	.457015
Panel B Effects of migrations of banks involved in M&A operations as acquiror				
ROA_t - ROA_{t-1}	-.0208519	.0219128	-.0638002	.0220965
ROA_{t+1} - ROA_t	.0036573	.0030642	-.0023483	.009663
ROA_{t+2}- ROA_{t-1}	.0035947	.0031018	-.0024847	.009674
Z_t - Z_{t-1}	.0289132	.3910668	-.7375636	.79539
Z_{t+1} - Z_t	.0474671	.2646981	-.4713316	.5662658
Z_{t+2} - Z_{t-1}	-.0911122	.836017	-1.729675	1.547451
$C\_I_t – C\_I_{t-1}$	-.052933	.0714162	-.1929063	.0870403
$C\_I_{t+1} – C\_I_t$	.0787106	.1026171	-.1224151	.2798363
$C\_I_{t+2} – C\_I_{t-1}$	-.0801996	.0794439	-.23559069	.0755076
$RWA_t – RWA_{t-1}$	-.7155809	.7085288	-2.104272	.6731101
$RWA_{t+1} – RWA_t$	-.0092069	.0082913	-.0254577	.0070438
$RWA_{t+2} – RWA_{t-1}$	.0124723	.012608	-.012239	.0371836
Panel C Effects of migrations of banks that received ad hoc state aids				
ROA_t - ROA_{t-1}	.007365	.0105776	-.013366	.0280967
ROA_{t+1} - ROA_t	.0141339	.0132469	-.0400973	.0118294
ROA_{t+2}- ROA_{t-1}	.0024181	.0060683	-.0094755	.0143117
Z_t - Z_{t-1}	1.901254***	.6753461	.5776004	3.224908
Z_{t+1} - Z_t	-1.267367*	.7629866	-2.762793	.2280591
Z_{t+2} - Z_{t-1}	.5410098	.5934779	-.6221855	1.704205
$C\_I_t – C\_I_{t-1}$	.2152646	.664245	-1.086632	1.517161
$C\_I_{t+1} – C\_I_t$	-.5380557	.7359963	-1.980582	.9044706
$C\_I_{t+2} – C\_I_{t-1}$	-.3783504	.3917152	-1.146098	.3893973

$RWA_t - RWA_{t-1}$	-.0058175	.0191495	-.0433497	.0317148
$RWA_{t+1} - RWA_t$	.0151243	.0106448	-.0057392	.0359877
$RWA_{t+2} - RWA_{t-1}$	.0193503	.0281934	-.0359077	.0746083

Note: Table reports results of the average treatment effect on treated. The outputs are: ROA as proxy of bank's profitability, Z-score as proxy of risk of default, the cost income ratio as proxy of bank's cost efficiency and RWA is the risk weighted assets density and is a proxy of risk appetite. We test the effect on different time windows. The matching variables are those used in the main analysis to measure the propensity score. Number of matches is equal to 4. "***", "**" and "*" indicate 1%, 5% and 10% significance levels, respectively.

List of Figure

Figure 1 Transition chart for the period 2005-2016 and final composition of banks among different business models[13]



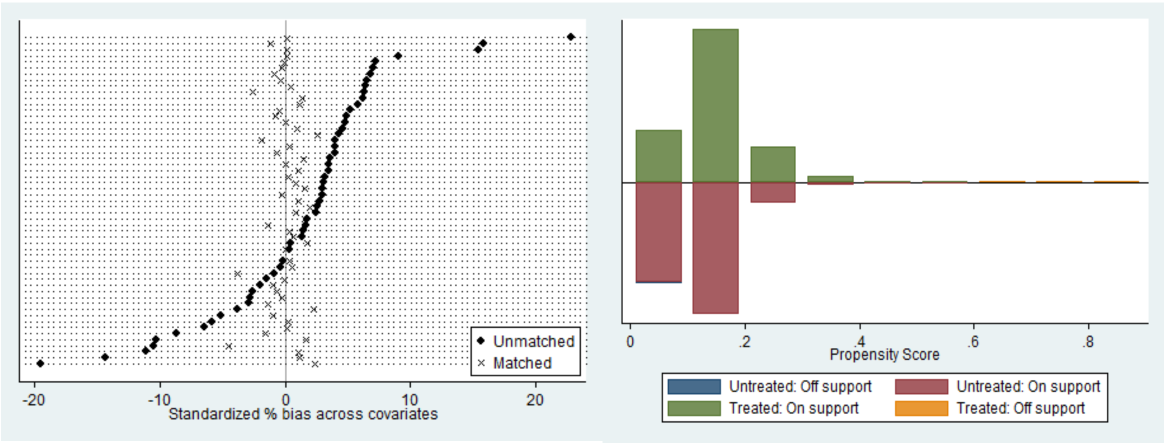
Composition	Focused retail	Diversified type 1	Diversified type 2	Wholesale	Investment	Tot
Pre_crisis	33.73%	14.11%	39.47%	4.55%	8.13%	100.00%
Crisis	35.91%	34.80%	14.76%	8.01%	6.51%	100.00%
Recovery	36.25%	38.11%	12.07%	6.84%	6.73%	100.00%
Total period	36.01%	35.79%	14.25%	7.27%	6.69%	100.00%

Note: The figure gives the share of banks that belong to a specific model in one period switching to another model
(or remaining assigned to the same model) in the next period.
The Table shows the distribution of banks among the different business models during the pre-crisis, crisis and recovery period, and finally the distribution over the total period.

[13] When the transition between two business models is not shown, it means that the migration is lower than 1%.

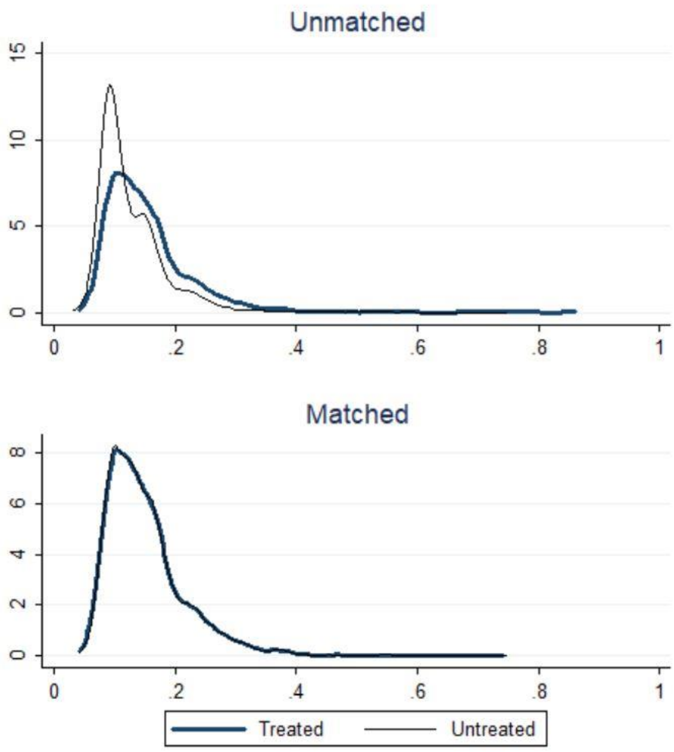
Figure 2. Graphic-test after matching

Panel A *Panel B*



Note: Panel A displays the Dot chart showing standardized % bias for each covariate before and after matching. Panel B shows the distribution of the propensity score both of treated and untreated banks.

Figure 3. Distribution of Propensity score before and after the matching procedure



Note: Figure shows the distribution of the propensity score before and after the matching procedure. Treated refers to the migrating banks and Untreated to non-migrating banks.