The Imitation Game: To Conform or To Perform

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Abstract

The concept of imitation introduces new rules in shaping the behavior of organizations. Little has been written about the imitation behavior of banking organizations and its role in business performance. In the banking sector, imitation can manifest in various ways, such as the adoption of similar investment strategies, loan markets, risk management techniques, or business models. This paper offers new insights into understanding how the production process, business performance, and risk perception of banking institutions are amplified or dampened through imitative behavior. We propose a novel two-step framework that classifies banks into reference clusters upon business activities and targets. To test these arguments, we surveyed the European banking network for the period spanning from 2011 to 2021. The results provide evidence that imitative behavior in banks is influenced by factors that cause them to either align with or diverge from the consensus of their peers. We argue that banks undertake imitation, against their own ex ante business strategy, that factor-based imitation guide bank business models, which can boost risk-taking and deteriorate business performance. This, in turn, contributes to the propagation of risky and non-sustainable practices, systemic failures, and financial instability.

Keywords: imitation; banks; cluster analysis; risk perception; bank performance.

I. Introduction

No bank is an island. However, do banks exhibit imitative behavior regarding the perception of risk and performance, and what motivates them? The concept of banking productive efficiency involves the evaluation of feasible improvements in the input-output space by increasing outputs and efficiency without absorbing further resources (Farrell, 1957). Nevertheless, banks today face unique and numerous risks over the medium to long term, such as information asymmetries, moral hazards and adverse selection, high uncertainty, regulatory arbitrage opportunities, internationalization, and so on. Thus, it is vital for all stakeholders to properly assess the bank's business model, which plays an important role in determining asset allocations and risk-taking profiles, as well as what is conducive (or disruptive) to technical efficiency and bank's objectives within the network they operate. In this context, the good performance of one bank's structure, practices and behavior may serve as a role model for other banks with similar objectives, amplifying or dampening behavior resembling "mimetic".

Banks may manifest different types of imitation behavior from various perspectives, conceptually. From the perspective of neo-institutional theory, imitation primarily relies on the concept of *mimetic isomorphism* (DiMaggio and Powell, 1983; Haunschild and Miner, 1997; Dacin et al., 2002), where organisations adopt similar structures, practices, and behaviors of others within or outside the industry, in response to similar environmental pressures and uncertainty. From a perspective rooted in both economics and management, information asymmetry and information cascades can prompt imitative behavior. Organisations tend to copy others, disregarding their private information as this reduces the risk associated with decision-making in an uncertain environment. This behavior can be conceptualized as imitating competitive moves (Tirole, 1990), or as copying decision-making processes based on the information available in the environment (Sharfstein and Stein, 1990; Banerjee, 1992; Abrahamson and Rosenkopf, 1993; Avery and Zemsky, 1998). However, the specific outcomes sought through imitation may differ, such as gaining legitimacy, achieving a competitive advantage, or adjusting the return/risk profile.

Focusing on banking institutions, the discussion above is supported by the fragmented nature of the relevant literature. Starting from the early studies of Jain and Gupta (1987) and Rajan (1994) that showed banks exhibiting a "pack instinct" by imitating each other's business activities, a handful of studies has been conducted to examine the factors that contribute to imitation among banks on issues such as investment decisions based on information inferred from the decisions of others (Barron and Valev, 2000; Acharya and Yorulmazer, 2008), flight-to-quality under uncertainty (Stever and Wilcox, 2007), banks' lending patterns and herding behavior in loan markets (Uchida and Nakagawa, 2007; Berlin, 2009; Calmès and Théoret, 2014), banks' responses in liquidity risk (van den End and Tabbae, 2012), informational cascades in the syndicated loan markets (Wu et al., 2013), bank competition (Allen et al., 2012) and the role of reference strategic groups in guiding banks in their mimetic behaviors (Barreto and Baden-Fuller, 2006).

Following up on these arguments, we believe there are some fundamental gaps in our understanding of what the process of "imitation behavior" for banks entails, suggesting the need for a deeper and more careful analysis of the factors underlying such decisions. These gaps in the literature and can be encapsulated by the following generic questions: Who imitates what and what does imitation entail? Do banks amplify or dampen imitation behavior in response to changes in certain factors? Do banks engage in selective imitation as a response to these changes, such as to 'look good,' conform to imposed rules, or embrace imitation as a cover for poor business performance? How do the generic characteristics of banks affect the level of imitation? Is banks' imitation behavior associated with out- or under-performance?

This paper develops a series of hypotheses intended to bridge these gaps. We suggest a factor-based framework to detect imitation behavior among banks and document its impact on business performance and risk perception. The first step is based on reference groups derived from a clustering approach of nearest neighbours (Philippas et al., 2023), with each cluster being endogenously restricted to peer banks in the network with similar response to influencing factors. In the second step, we propose two multivariate regression schemes to measure performance and efficiency in accordance with banks' objectives. These schemes examine the simultaneous dynamic responses (*sensitivity*) of production function in relation to either reference clusters or target-based groups of factors. We use fine-grained European panel data to test imitation behavior and its resulting effects on the performance of the European banking network. Our study covers the period of 2007–2022 and approximately 121 banking institutions, comprising 27 European Union countries.

Our empirical study makes several contributions. We offer a novel rationale for the concept of imitation behaviour in the banking industry, differentiating from mimetic isomorphism, which is reflected in changes of bank business model and in measuring performance. We propose a novel framework to understand banks imitating each other with respect to specific factors of interest. We also develop innovative schemes for measuring and replicating the proximity-based reference clusters, as well as the dynamic influence on the production function of financial intermediation. Unique to the literature, we show that the degree of banks' imitation behaviour is contingent upon the proximity-based context in which they operate, adjusting their strategies and business models in a way so that they "look like the mass" or imitate to cover their poor business performance. This also indicates the trade-off any bank faces between the pressure to be compliant and the pressure to perform (legitimacy versus economic need). This focus on proximity-based groups, on imitation of peers, and on the effect of imitation behavior on the production process, is novel to the literature. We also demonstrate that banks tend to imitate each other during periods of higher economic uncertainty when they are more vulnerable, creating a relationship between risk perception and the arbitraging of influencing factors. We finally argue that the amplification (or dampening) of imitation among banks is not a consequence of size alone, but of their credit exposure. This finding is both in line with the information asymmetry hypothesis proposed by Banerjee (1992) and Avery and Zemsky (1998).

The paper is organized as follows. We first provide the conceptual framework and hypothesis development by offering new insights for imitation behavior of banking institutions that is centred on factor's reference group. We then show why banks engage in similar undertake actions and we explain why factor-driven actions enhance imitation and affect performance and risk perception. Next, we provide a detailed description of the data, and we present our research design. Finally, we provide the results, discussion, and conclusions. More detailed results of our analyses are provided in the accompanying Supplement.

II. Conceptual Underpinnings and Hypotheses

Our conceptual design for identifying imitation behavior in the banking sector is articulated through a path that begins with the main theoretical backgrounds, the assumptions of our framework, and the hypotheses to be tested at the empirical level of analysis. The first step is to delineate the scope of our framework. We focus on inter-organizational imitation, where practices implemented by one or more organizations (i.e., banks) increase the likelihood of similar choices being adopted by other organizations (Haunschild and Miner, 1997). We also acknowledge imitation at the organizational level (Rivkin, 2000), emphasizing on the relationship between a banking institution and its environment, as well as its market positioning, rather than the replication of activities among banks. The banking environment consists of the surrounding conditions determined by internal factors in the network, such as the activities of competitor banks, and external factors like regulatory authorities, economic factors, social-cultural factors, international trends, and more. These factors have the potential to impact the activities, operations, and decisions of banking institutions. It is important to note that this relationship is bidirectional, meaning the environment can influence a bank's activities, but the bank's activities can also have a partial impact on the environment. Lastly, we assume a topology of various banking institutions that differ in size (i.e., small, medium, large banks), structure (e.g., customers, processes, practices, etc.), openness and relationships, activities, and different regulatory frameworks. This reflects the heterogeneity of the network, which is further supported by the different generic business models employed by banks.

Next, two additional fundamentals should be considered beforehand when focusing on the banking sector: (i) the interconnectedness of the banking network, and (ii) the objectives of the bank to be achieved through the implementation of its business model. Interconnectedness within the banking network refers to the relationships between different banking institutions, how this connection has an impact on their risk appetite, and the ways in which they depend on each other to carry out their business operations. When banks are closely interconnected, the bad performance of one bank can have a cascading effect on other banks, leading to an increased perception of risk for all banks in the network. This can result in a lack of trust in the banking system, ultimately leading to instability. From the arbitrage theory perspective, when banks encounter adverse conditions, they tend to become more similar as risk increases, seeking diversification and internationalization opportunities (Ongena et al., 2013; Berger et al., 2017; Philippas et al, 2023). In the event of a significant number of bank failures, regulators may decide to bail out the failed banks (Acharya and Yorulmazer, 2008) and impose strict domestic regulations across the banking sector. However, the effects on bank risk-taking may vary depending on each bank's corporate governance structure (Laeven and Levine, 2009). Conversely, when the number of failures is low, the surviving banks are forced to take over the failed banks, raising the risk of the surviving banks failing as well. Hence, understanding the level of interconnectedness within the banking network is related to how banks may exhibit imitative behavior for achieving feasible improvements.

The second fundamental for a bank is related to accomplishing objectives within the competitive landscape of banking. Given that a bank's activities are closely tied to its business model, achieving feasible improvements in technical efficiency becomes important for the bank manager. The manager feels pressure to meet profit-oriented targets based on the volume of business activities, which may lead them to act similarly to their competitors. The good performance and improvements in one bank's business model can serve as a role model for other banks pursuing similar goals, amplifying imitation, and exerting a substantial influence on the stability of the banking system. Amplifying imitation behavior within banking competition may also provide insights into how investment decisions are influenced by network dynamics and inform strategies for managing risks. However, this is not feasible to the same degree for all banks in the network, and it could potentially lead a number of them to negative outcomes such as deterioration of lending standards, misallocation of lending resources, asset price bubbles, increased systemic risks, and exacerbation of the business cycle (Allen and Gale, 2004; Berger et al., 2009; Allen et al., 2012; Akins et al., 2016; Philippas et al., 2023). Lastly, certain regulatory and governance rules, such as the capital adequacy requirement that imposes limits on banks' activities and narrows their decision-making options, may also compel banks to seek and exploit similar regulatory arbitrage opportunities. For example, if a bank believes it will be bailed out in the event of severe financial distress, it may be incentivized to engage in imitation behavior by participating in collective risk-taking and management strategies, aiming to increase their profits without significantly raising the risk of bankruptcy.

Hypotheses Development

How imitation behavior is conceptualized? There is a considerable body of relevant literature that offers diverse streams of theoretical perspectives on imitation behavior in organizations (Ordanini et al., 2008). Two foundational frameworks have prevailed and shed light on the relation between environmental uncertainty and inter-organizational imitation.[1] The first framework explores the

[1] Other contributing theories oriented towards resource-based imitation adopt the concepts of *industrial organization* (Tirole, 1990), organizational learning (Levitt and March, 1988), decision-making (Conlisk, 1980; Pingle, 1995), and resource-based (Dierickx and Cool, 1989; Reed and DeFilippi, 1990; Rivkin, 2000).

explanation offered by the concept of *mimetic isomorphism* in neo-institutional theory (DiMaggio and Powell, 1983). It posits that organizations undergo changes over time as a response to uncertainty and tend to resemble other organizations operating in the same environment, i.e., they are isomorphic.[2] The foundational relevant literature encompasses various issues, including diversification decisions (Fligstein, 1991), corporate acquisition choices (Haunschild, 1993), entering new markets (Haveman, 1993; Westphal et al., 1997), choices of investment bankers (Haunschild and Miner, 1997), decisions on market positioning (Greve, 1998), new organizational forms (Lee and Pennings, 2002), internationalization (Davis et al. 2000; Henisz and Delios 2001; Brouthers et al. 2005). Barreto and Baden-Fuller (2006) provided further analysis on the trait-based imitation, testing the role of reference strategic groups in guiding banks' mimetic behaviors.

The second framework poses that organizations with less information than others tend to align their behavior with the informed ones (Sinclair, 1990; Sharfstein and Stein, 1990; Banerjee, 1992; Bikhchandani et al., 1992; Abrahamson and Rosenkopf, 1993; Avery and Zemsky, 1998). This stream of the literature suggests that certain factors such as risk perception, competition, informational cascades and asymmetries, quality of information, adverse consequences, and the risk of failure can prompt organizations to adopt various imitative behaviors, including investment choices, competitive reactions, and copying processes and practices of others. This occurs either due to a spurious behavior (rational, information-based) when facing similar circumstances, or it can be intentionally (irrational behavior) where organisations disregard their own information and follow each other's lead.

Both theories consider imitation as the way to reduce the risk of individual decisions. The difference lies in their objectives when engaging in imitation. In mimetic isomorphism, firms would copy to gain legitimacy for their actions, while in the context of information cascades firms disregard their private information to overcome perceived competitive disadvantages and improve their position in the market, even if it means accepting a lower return/risk profile for their decisions in order to resemble potential failures. Essentially, in both cases imitators are willing to forego potentially higher profits that could result from individual choices in response to environmental pressures and uncertainty. They prioritize legitimacy, lower returns, and avoiding the responsibility of making their own decisions by adopting decisions that have already proven to be successful or less harmful for other organisations.

Novel to the literature, we suggest adopting a comprehensive factor-based framework of imitation, when focusing on banking sector. Firstly, we define imitation as the tendency for banks to conform or adopt to changes in behavior, and to infer commonalities in asset allocations. This shift in behavior has the potential to revise risk perception (risk aversion or risk-taking) and deviate from fundamental business values, even resulting in episodes of asset busts (Avery and Zemsky, 1998; Schmitt and

[2] Causes of uncertainty and how to cope with uncertainty in the environment are examined through the lens of the neo-institutional theory (DiMaggio and Powell, 1983; Deephouse, 1996; Kraatz, 1998; Lieberman and Asaba, 2006).

Westerhoff, 2017). We address imitation within banks as a selective decision. A bank receives a stimulus from the environment of its peer banks and decides to conform, intentionally imitate, or do nothing. This assumption distinguishes imitation (i.e., exhibiting homogeneity) from similarity (i.e., the degree to which banks behave in a comparable manner) as response to the same stimulus (Lieberman and Asaba 2006). Moreover, we argue that banks exhibit interdependent behavior when responding to conductive factors of banking environment, even though the impact of each factor may vary. This updating process explains managers' investment decisions, relying on rational inattention when acquiring information (Andrei and Hasler, 2015; Kacperczyk et al., 2016; Philippas et al., 2021).

Building on this context, we propose adopting a process centered on factor-based reference groups, which are formed based on the factors of the banking environment. The reference groups, referred to as clusters hereafter, can play a significant role in amplifying or dampening banks' imitative behavior, creating a ripple effect that drives banks towards more generic profiles. Under our approach, although Bank A may seem to share many characteristics with Bank B, it may be classified as similar to Bank C due to its response to changes in the factors of bank environment. The influence of factors is measured by *target-relevant ratios* that banks aim for to achieve good performance. These ratios are typical metrics used to measure the internal performance of each bank and assess the impact of external factors. These metrics may influence the production process, facilitate feasible improvements, and reshape a bank's objectives. Accordingly, we formulate the following hypothesis:

Hypothesis 1: *Banks imitate the generic behavior of their reference group (cluster), which is formed based on their outputs of the production function and the influence of the factor (ratio) of the bank environment.*

The second question of our framework relies on the idea that imitation behavior within reference groups is initiated by environmental factors, but the level of responsiveness exhibited by banks depends on their targets, prompting them to imitate or not. We present a series of arguments regarding whether banks engage in selective imitation. Firstly, selective imitation is subject to the "nature" of factors (ratios) that determine the reference groups, which we distinguish to *conformity ratios* and *proximity ratios*. A conformity ratio suggests that banks conform in their response to the ratio, leading to a certain level of homogeneity. To put it simple, banks copy the dominant common norms due to imposed rules and regulations, as they are required to do so. A proximity ratio suggests that banks are close to one another by choice in terms of productivity based on their response to the ratio, leading to a certain level of clustering. Banks copy behaviours of certain groups to mitigate risks, mask poor performance or emulate the practices already taken by high-performing peers. Additionally, a proximity ratio also serves as a metric of competitiveness, guiding banks to adopt similar or divergent strategies and practices based on their intentions.

Haunschild and Miner (1997) classified imitation based on the criterion of targeting into three categories: the *frequency-based* imitation (copying the dominant behavior), the *trait-based* imitation (copying the behavior of certain groups of firms), and the *outcome-based* imitation (copying a behavior believed to be associated with good performance in another firm). Following Haunschild and Miner (1997), we argue that banks follow a hybrid scheme of imitation. Banks may copy the dominant norms imposed (frequency-based imitation derived from conformity ratio) or choose to copy similar groups or optimal performances (i.e., trait-based, and outcome-based imitation derived from proximity ratio). Hence, our approach lies in the underlying mechanisms that triggers a selective imitative behavior that goes beyond typical herding, market informational frictions, pay-off externalities, and legitimacy-based groups. We therefore formulate the following hypothesis:

Hypothesis 2: *Banks choose to imitate specific profiles, engaging in selective imitation triggered by reference groups (conformity ratios vs. proximity ratios).*

As a result of the second hypothesis, heterogeneity among banks presents a critical challenge and plays a key role to technical efficiency, and, consequently, imitation. Bank operations can significantly differ due to their discrete characteristics, such as size, market share, country of origin, focus on converting deposits into loans or investment securities, and more. To give an example, small banks have limited investment choices, inevitably face a narrow set of strategic options, making them inclined to follow a specific group. Other differentiating factors may include economic conditions in the operating environment, risk appetite, customers' profiles, and so on. The heterogeneity of banks directly relates to their business objectives, leading to unobserved clustering behavior within the banking network. Consequently, a bank's generic characteristics may further influence selective imitation. Based on this, we formulate the third hypothesis:

Hypothesis 3: *Imitation behavior is subject to certain banks' classification criteria: size, economic importance, and credit exposure.*

The last question in our framework is related to the consequences of banks' imitation behavior within the network. If we hypothesize that banks imitate their peers, we pose the question: Do banks outperform or underperform when imitating? On the one hand, imitating might be beneficial for business performance, as it allows banks to mitigate risk and leverage collective resources more effectively. This should hold particularly true for smaller banks that lack the resources and expertise to develop their own innovative strategies. Imitation can also lead to greater stability in the banking sector, as banks adopt similar risk management practices. On the other hand, if not controlled, imitation can lead to overreactions that could have significant consequences for the banking sector. For example, if all banks within a reference group are following the same strategies, it may lead to a situation of oversupply where there are too many similar products or services available, which can drive down profits for all. To assess performance in a dynamic manner with respect to imitation, we explore the influence of the ratios (environmental factors) and how they reflect on over(-under) performance, also targeting to specific business areas. When comparing the performance of production outputs between unconditional forms (i.e., without the application of ratios) and conditional forms (i.e., with the application of ratios), we examine the intensity of imitation behavior in relation to the performance and risk perception of banking network. Based on this, we formulate the following hypothesis:

Hypothesis 4: *Is imitation behavior associated with bank's outperformance or underperformance?*

III. DATA

Our dataset consists of a series of annual balance sheet indicators, derived from the Orbis and Refinitiv databases, as well as from our own research. The sample spans 27 members of the European Union from 2007 to 2022, and includes a diverse array of 121 European banks, varying in size, type, and other characteristics. The European banking industry was chosen as the empirical setting due to its global significance as a banking sector. It comprises a selection of banks originating from different European economies, all operating within a common (or similar) European regulatory framework. By focusing on a multi-country banking sector unified by this regulatory framework, we aim to underline heterogeneity and effectively assess the impact of factors influencing the European banking environment.

We select banks for our sample based on three criteria. The first criterion involves including all banks that fall under the direct supervision of the European Central Bank (ECB) within the Single Supervisory Mechanism (SSM) framework. We utilize a recent version of this list (as of July 2022), provided by the ECB Banking Supervision Authority. The second criterion is based on the ECB's size inclusion criterion, specifically whether a bank's total asset value exceeds EUR 30 billion. The final criterion considers the ECB's assessment of the bank's economic importance, both to the respective domestic economy and to the overall European economy, from a market operations perspective.

These criteria are policy-relevant and aligned with the principles of the European Central Bank, national central banks, and the implementation of the Single Supervisory Mechanism in 2014. This implementation was accompanied by an increase in technical efficiency across all banks' input and output dimensions. Acharya (2009) asserts that banks experience more pronounced consequences when they possess characteristics such as being "large", "essential", or "unique", which resemble the previously stated criteria. Empirical evidence also demonstrates the importance of a bank’s size in relation to systemic risk and its ability to access international financial markets (Acharya et al., 2014; Cai et al., 2018). Lastly, the economic importance criterion entails a discretionary approach in determining which banks are significantly important for the economy. This approach allows us to introduce the countercyclical dimension to better monitor systemic risk and its transmission channels across the European banking network (Lang and Forletta, 2020).

Inputs and Outputs

Humphrey and Pulley (1997) identified two main approaches for input-output selection: (i) the *production approach*, which characterizes banks as service producers aiming to minimize operating costs, and (ii) the *financial intermediation approach* (Sealey and Lindley, 1977), which perceives banks as financial intermediaries that use capital and labor to convert liabilities into assets. Recent surveys conducted by Fethi and Pasiouras (2010) and Paradi and Zhu (2013) pointed out that the financial intermediation approach evaluates better the performance of financial institutions. We follow the financial intermediation approach for our analysis.

As inputs, we choose the following items (thousands in *EUR*, in natural log values): (i) *fixed assets* as proxy for network size and physical presence, (ii) *labor (and related) expenses* as proxy for total labor costs, and (iii) *total customer deposits* to address how banks provide payment and liquidity services in addition to intermediation services, which are treated as non-discretionary inputs (Fethi and Pasiouras, 2010). As outputs, we consider the following items (thousands in *EUR*, in natural log values): (i) *loans* (net, to customers and banks), (ii) the *other earning assets* which includes stocks, derivatives, bonds, and anything that generates income other than loans. The final sample size contains 152 banking institutions, with well-diversified business activities. Our sample is dominated by Credit institutions (141 in total) while Financial Holding and Mixed Financial Holding companies (11 in total) have more diversified business activities, although there are ring-fencing mechanisms implemented for reporting and supervisory purposes.

Factors of the Banking Environment

We suggest a list of ratios (factors) that quantify the influence of the banking environment on bank performance and soundness. These ratios serve as control variables by assessing each bank against its peers with similar behavior and response to the ratio, allowing for classification of banks into *clusters*. Additionally, the ratios categorized by target-relevant area, based on quantitative and qualitative criteria, while preserving the complexity of banks' business models and objectives. The choice of ratios allows for flexibility in experimentation, enabling the derivation of different environmental factors in for the production process. Consequently, we establish the following ratios.

We start by assessing the intensity of banks in terms of *activity* and *performance*, represented by two ratios: the ratio of *other securities to total assets* and the *cost-to-income* ratio (CIR), given by total operating expenses to total operating income. A lower (higher) CIR shows more (less) efficient bank operations. The other securities to total assets ratio show the activity on trading assets over total assets. The CIR shows the relationship between income and the cost of acquiring that income, categorizing banks based on their various operations, as each bank operation is likely to have different average operating expenses and income, resulting in a different average cost-to-income ratio.

Next, we pertain to *credit quality*, which is represented by the ratio of *non-performing loans* (NPLs) *to gross loans*. This ratio shows the extent of deterioration of the quality of loans granted but also the risk attitude to lend customers with a good (bad) credit profile (Matousek et al., 2015). High (low) values show that the bank has a loose (tight) credit policy, providing an indication of rationing credit policies for traditional and less aggressive banks, which are expected to maintain a low ratio. The third area of interest is centered around *profitability* with two ratios as proxies: the *net interest margin* (NIM), and the *return on average assets* (ROAA). NIM is defined as net income to earning assets and captures market power and interest rate policy followed by a bank while ROAA is a typical ratio of profitability.

The fourth grouping of ratios focuses the bank's *riskiness* and is represented by two proxy ratios. The first is the *off-balance sheet liabilities to total assets* ratio, which masks liabilities by removing them from the balance sheet. Off-balance sheet items are contingent assets or liabilities of great importance for investors when assessing a company's financial riskiness. Using off-balance sheet activities, banks can generate high profits and, at the same time, can avoid regulatory costs or taxes through off-balance sheet activities, as reserve requirements and deposit insurance premiums are not imposed on off-balance sheet activities. However, off-balance sheet activities can entail high risk for several reasons. First, off-balance sheet items are difficult to identify within bank's financial statements as they often only appear in the accompanying notes or can be hidden liabilities (e.g., assets that can suddenly become almost completely illiquid, before investors are aware of the company's financial exposure). Moreover, off-balance sheet activities can involve risks such as market, operational, foreign exchange, and credit risks, which might affect bank's solvency and liquidity in domestic and international markets. The second proxy is the *leverage multiplier* (LM), which is defined as total assets to total shareholders' equity and subordinated debt. This definition is used by the Office of the Superintendent of Financial Institutions (OSFI) and is based on total regulatory capital as defined in Basel II. This ratio is relevant for the analysis as it measures the risk associated with non-capital funding of the overall balance sheet and it is not subject to the model and measurement errors associated with asset risk calculations.

When assessing financial stability, which encompasses regulatory attitude and liquidity, we include the *capital adequacy ratio* (CAR), and the *liquidity ratio* (LR). The CAR refers to core capital of the bank, which includes equity capital and disclosed reserves, and describes the capital adequacy. It is a regulatory ratio that shows the ability of a bank to absorb losses stemming from exposure to risk using own funds. Minimum regulatory requirements are in place for each bank depending on its business model, though depending on its business model on risk exposure and attitude to risk of each bank, significant variations can be observed. On the other hand, we proxy liquidity performance with LR, defined as liquid assets (including cash and cash equivalents, public securities, and secured short-term loans) over total assets. It measures the degree to which a bank has access to stable funding sources or whether it can withstand adverse shocks that might trigger the need to liquidate assets. Both CAR and LR can exhibit low values; however, high values may indicate issues in asset management.

The last group of environmental factors is associated with the macroeconomic conditions of the European economies. We introduce three countercyclical metrics to monitor the influence of systemic risk on the banking sector: (i) the *gross loans to GDP*, which shows the credit exposure, (ii) *total assets to GDP*, which shows the share of banks and the impact on economic activity, and (iii) *inflation rate*. These metrics serve as dimensions that complement traditional approaches for measuring risk at banking institutions. Credit to gdp gap: Unlike the conservation countercyclical capital buffer (CCyB), which is fixed, our macro-oriented measures evolve within a long-term trend of growth, credit, and size (as a percentage of GDP) by country.

Preliminary Analysis

Figure 1 illustrates the average values for inputs, outputs, and ratios, as well as their linear trends for the years studied (see Online Supplement, Table A1). The figures indicate the substantial variability of the variables over time. This variability should be considered along with the significant deviation from the mean for a high number of banks, highlighting the significant changes in bank operations over time. On the input side, the average values of *fixed assets* and *total customer deposits* show an increasing trend, while the *labor expenses* remain relatively flat over time. This flat line suggests that banks are becoming more efficient in their labor costs, resulting in greater profits. On the output side, *loans* increased, while *other earning assets* had a significant declining trend until 2017, and then increased halfway until 2020.

When considering ratios, we observe mixed but significant results that motivate to further analysis through our clustering approach. Activity (*other securities to total assets*) significantly declined from 2016 onwards, while *CIR* significantly increased, particularly after 2016, indicating slower performance and lower efficiency of bank operations. However, credit quality and profitability increased. Riskiness was higher for the off-balanced items, while solvency and liquidity had a trend towards higher levels over time. Finally, for the macro dimension, there is a slow negative slope for size and credit, in a very uncertain and volatile environment. Given that the ratios exhibit very low correlations with inputs and outputs, with some exemptions (Table A1, in the accompanying Online Supplement), we argue that the chosen ratios seem to be good choice in the context of our study to explore the heterogeneity of banks and determine meaningful reference groups.

[Figure 1 here]

IV. Research Design and Results

Consider the production function for a set of banks that uses inputs ($\boldsymbol{X}$) to produce outputs ($\boldsymbol{Y}$). Banking environmental factors ($\boldsymbol{Z}$) may influence the production function without being neither inputs nor outputs:

$$F(\boldsymbol{XY}|\boldsymbol{Z}) = \left\{(x, y|z) \in \mathbb{R}_{+}^{p+q} \middle| f_{XY|Z}(x, y|z) > 0\right\} \tag{1}$$

where $f_{XY|Z}(x, y|z)$ denotes the conditional production set on $\boldsymbol{Z}$. We assume that the production function in Eq. (1) is reflected in the following general regression form:

$$Y_{it}^{(1,2)} = F\left(X'_{it}\beta_j^{(1,2)}, Z'_{it}\gamma_k^{(1,2)}\right) + U_{it}^{(1,2)} \tag{2}$$

where the superscript $(1, 2)$ denotes the output-specific, subscripts t and i are the time and bank unit respectively, $Y_{it}^{(1,2)}$ is the vector of outputs (i.e., $y^{(1)}$ for *loans* and $y^{(2)}$ for *other earning assets*), X_{it} is the vector of inputs (i.e., *fixed assets* (x_1), *labor expenses* (x_2) and *total customer deposits* (x_3)), $\beta_j^{(1,2)}$ are the coefficients for inputs with $j = 1,2,3$; Z'_{it} is the vector of ratios that influence the output vector, with coefficients $\gamma_k^{(1,2)}$ and $U_{it}^{(1,2)}$ is the vector of idiosyncratic shocks.

4.1 Imitation behavior centered on factor-based reference groups

We initiate our empirical investigation by examining the presence of factor-based reference groups within the pooled network of European banks in response to ratios reflecting the banking environment. As clustering method, we extend the approach of Philippas et al. (2023).[3] The approach is distinct from other clustering approaches as it is based on a fit criterion between three-dimensional factors, namely the two outputs of production process and the environmental factor (ratio), for the positioning of a bank within the network that exhibits imitative behavior. We do not assume any control variable (e.g., country of origin, SSM listed or not, large vs. small bank, etc.), associated with the respective clusters. We contend that factor-based groups should be formed freely, solely based on behavior.

Clusters for Inputs

First, the clustering approach is applied for the inputs per year. The results return two reference clusters for all years in the sample, a result that should be expected since all banks use the same input orientation. This is a first difference between our paper and the typical business models suggested by Ayadi et al. (2011; 2014). We argue that banks utilize their inputs through two discrete business models, retail-oriented and wholesale banks, and therefore the distinguish between retail-oriented and wholesale banks with regards to input side is clear under the financial intermediation approach followed in principle by banks. The retail-oriented bank model relies on customer deposits as the primary funding source and maintains high levels of loss-absorbing capital. In contrast, the wholesale bank model, similar to investment banks, has a lower proportion of customer deposits in total liabilities and relies extensively on wholesale markets for funding.

[3] The interested reader may find a brief illustration with the technical details of the clustering approach in the Technical Appendix.

We then run the clustering approach to the three-dimensional scheme of two outputs and each ratio, by year. The results assign each bank to a corresponding cluster. We observe a higher number of clusters for all the outputs-ratio schemes (ranging from 3 up to 7 clusters per ratio). Given that the number of peer banks for a cluster may vary across ratios, any interpretation should be associated to the ratio. The presence of multiple clusters with varying aggregate number of banks enhances the diversity of the target-relevant business activities across banks, indicating evidence of factor-based arbitrage, as we call it in our paper, which aligns with the imitation behavior observed within these clusters. This finding is consistent with both Hypotheses 1 and 2 in our study. Clusters that consist of a large (small) number of banks are typically indicative of certain dominant (trait and outcome-based) behavior. Essentially, clusters with a large number of banks tend to follow the consensus path in terms of their target-relevant business activities, which we refer to as mimetic behavior under proximity in our paper. This is because these banks choose to align themselves with the majority of their network with respect to specific proximity. In other words, these banks opt for similar actions as their network with regards to the ratio of interest, and they follow the crowd (the center of the cluster). This, in turn, affects the intermediation process and ultimately uncertainty and systemic risk, as the production function is determined by the content of the target that they prior chose to follow (or not).

Finally, we perform a posterior analysis based on the results of the clustering approach. We generate the effect variables for each ratio and calculate the average values for each cluster and for all variables of interest, i.e., inputs, outputs, and ratios. Figure 2 shows an illustration of the output-ratio averages per cluster, revealing intriguing findings that are consistent with the argument of Hypothesis 2. The average values for the two outputs vary significantly from one cluster to the next for each ratio. Moreover, the average values of the ratios also deviate among themselves in each cluster. These findings support our Hypothesis 2, which states that clusters are classified based on the presence of a large (small) number of banks that converge (are discrete) to (from) specific bank profile, as reflected by the average values per cluster, i.e., engaging in selective imitation. Therefore, the selective mimicry state is evident in the average values within each cluster for each ratio. Imitation behavior is less pronounced for inflation, despite the high number of clusters, suggesting a higher diversity among banks due to varying levels of influence from inflation at both country-level and across countries.

(Figure 2 goes about here)

We examine the top 15% quantile (>85th percentile) of banks that have been identified as having "big size", "high credit quality", and "significant economic importance", based on the criteria noted above. Under the same criteria, we also examine the bottom 15% quantile of banks (<15th percentile) that have been identified as having "small size", "low credit quality", and "low-significant economic importance". This choice results in approximately 20 to 25 banks per case (Appendix C in the accompanying Supplement). Figure 3 illustrates the aggregate findings. The figures show that 15% quantile banks exhibit a higher and more volatile level of mimicry than top 15% banks (for all criteria), which is consistent with the information asymmetry hypothesis (Banerjee, 1992), i.e., they face information disadvantage and tend to imitate more. Therefore, Hypothesis 3 is valid when we examine mimetic behavior under specific controlled features, such as size, economic importance, and credit exposure, which have a greater impact on the level of mimetic behavior exhibited by banks. By validating the Hypothesis 3, we argue that bank competition may induce excessive risk taking due to risk shifting, since banks have a stronger incentive to increase their exposures by lowering their lending standards (Hellman et al., 2000; Allen and Gale, 2004; Boyd and De Nicoló, 2005; Jimenez et al., 2013). (Figure 3 goes about here)

Multivariate Analysis

In the second step, we implement a system of equations for the outputs of production function, using the seemingly unrelated regression (SUR) method (Zellner, 1962). We estimate two modelling extended schemes, derived from Eq. (2). The first scheme considers the impact of ratio Z_{it} within each g-cluster. We refer to this form as *conditional-to-clusters* scheme. Thus, the SUR model takes the form:

$SUR\left(Y_{it}^{(1,2)}, X_{it}^{(1,2)}, Z_{it} \middle| Z_i \sim g - cluster\right)$ or else; $Y_{gi,t}^{(1,2)} = D'_{gi,t}\beta_j^{(1,2)} + U_{gi,t}^{(1,2)}$ (3)

where $D_{gi} = [X_{it}\ u.c.of\ Z_{gi,t})]$ that includes the set of inputs (X) and ratio(s) (Z) that enters as proximity-based factor in the production function, whereas the data are $\{Y_{gi}, D_{gi}), g = 1,2,..,G\ and\ i = 1,2,\dots,n(g)\}$ and g indexes are a set of G clusters. The average values define the cluster consensus for each output.

The second scheme, that we call *conditional-to-bucket* scheme, includes the group of *effect variables*. The effect variables are generated by taking the dynamic feature of clustering be attached on the ratios. Hence, Eq. (2) takes the form:

$$Y_{it}^{(1,2)} = X'_{it}\beta_j^{(1,2)} + Q(Z)'_{it}\gamma_j^{(1,2)} + U_{it}^{(1,2)} \quad (4)$$

where $Q(Z)$: $eff_g(z) = g \circ z_{it}$. The term $g_s \circ z_{it}$ represents the Hadamard-product i.e., the element-by-element multiplication of the cluster-oriented vector with the vector of Z values. We focus on the significance of the coefficients $\gamma_j^{(1,2)}$ in each equation.

The main difference between the two schemes is the way of considering the effect of ratios as influencing factor. The first scheme captures the banks around the centroid of the cluster, while the second scheme captures the cluster intensity in a dynamic way. Since we observe a bank to participate either dynamically or within a cluster in the panel data, we can assume that same banks may be very prone to large values of the ratios while others are less prone within different clusters, over time.

When implementing the SUR modelling schemes, we obtained intriguing comparative results regarding the dynamic character of banks' mimetic behavior in the network. The detailed tables of results are presented in Appendix D in the accompanying Supplement. First, we obtained the results of unconditional forms (simple and extended form) of the production function, using Eq. (2). The coefficients of all inputs are statistically significant. We observe a higher influence of capital and a lower impact of labor and deposits. This suggests that banks are investing in capital and technology to improve output efficiency. This result is not surprising, as it shows that the input productivity for the study period of 2011-2021 is homogeneous. In the extended unconditional form, we add the ratio to the simple form. When considering the ratios, we observe mixed results. Some ratios (e.g., impaired loans, NIM, LM, ROAA) have a significant impact (positive or negative) on the production process for both outputs, while others have no significance (i.e., inflation and off-balance sheet liabilities). The other securities, LR and gross loans are statistically significant with different sign for each output. Finally, the CIR, CAR and total assets to GDP have an impact only on one output. The estimated results are in line with the findings from clustering analysis, supporting the first three Hypotheses.

Using Eq. (3) and (4), we obtain the results on SUR conditional-to-cluster and conditional-to-bucket schemes, and further compared with the findings depicted in unconditional forms. Hypothesis 4 suggests that banks out- or underperform due to mimetic behavior. Table 1 presents a comparative analysis of the aggregate results derived from the estimated unconditional and/or conditional forms. Consistent with Hypothesis 4, in the case of the SUR conditional-to-cluster scheme, we find that the average coefficients for fixed assets, labor expenses, and total customer deposits vary not only between clusters but also among the different ratios of system equations. Notably, the average coefficient values in the conditional form among clusters differ from those in the unconditional form, indicating diverse mimetic behavior due to proximity. This suggests that banks exhibit capital intensity towards some clusters, labor intensity in others and focus on customer deposits in others when producing their outputs, all depending on their proximity (i.e., selective imitation as in Hypothesis 2). When examining ratios, a significant mimetic behavior is evident in credit exposure, liquidation, capital adequacy, cost-to-income ratio, off-balance sheet, impaired loans, leverage, and other securities, to varying extents. In these cases, many banks tend to be grouped together, amplifying the mimetic behavior due to the perceived risks. However, in the other cases, banks are more evenly distributed and there is not a proportionate increase in the number of clusters.

In the case of the SUR conditional-to-bucket scheme, we observe some interesting findings. First, the average coefficients for fixed assets, labor expenses, and total customer deposits remain largely unchanged. Hence, the utilization of different buckets does not result in a substantial change to the inputs' contribution to the production function. The effect of proximity for each bucket differs from the "per cluster" scheme in two respects: the coefficients exhibit reduced sensitivity, and there is a stronger emphasis on performance instead of activity. Although these banks may have distinct business activities and strategies, they still tend to imitate their peers over time, displaying some variations in their operations as a reaction to changes in influencing factors that raise their risk perception and less to risks related to bank-specific risks, systemic risk, and macroeconomic conditions. This behavior is associated with bank performance and appears to be a behavior of conformity, adopting a mainstream approach as a safeguard against poor business performance.

(Table 1 goes about here)

The findings above receive two complementary interpretations. First, the ratios are close enough to their buckets indicating specific strategies and behavioral business activities through mimicry as response, justified by the high number of peers. Secondly, irrespective of contextual similarities, it requires a relatively higher number of clusters to diversify and present a discrete banks' behavior. On the contrary, when fewer banks are involved in a cluster, it suggests that only few neighbours (e.g., leading banks) would suffice to fit SUR regressions due to close similarities in operations (presumably the case for some big banks) or that banking operations are specific enough that form distinct clusters, as shown in Figure 3.

DISCUSSION AND CONCLUSION

The paper advances our understanding of mimetic behavior in organization theory, specifically in the banking sector, and has significant conceptual and empirical implications relevant to risk perception and bank performance. We developed a two-step framework to classify banking institutions into reference groups based on their influencing factors in the production process. This framework presents how banks amplify or dampen their imitative behavior subject to specific conditions and leading them to either converge or deviate towards from the group's consensus. By using the concept that argues an organization's environment influences it, we shed light on the complex and diverse nature of banks' behavior due to influencing factors. We explore the mechanisms through which specific factors may shape bank behavior in relation to peer banks, potentially leading to changes in their business models. To test our arguments, we provide an empirical setting using the European banking network, which includes banking institutions from 27 European countries and Norway.

Previous research on imitation within the network of banking corporations has primarily focused chiefly on legitimacy, competition, and lending patterns and herding behavior in loan markets (Barreto and Baden-Fuller, 2006; Uchida and Nakagawa, 2007; Allen et al., 2012). In contrast, we classify banking institutions into reference groups based on dominant factors that influence their targets (output) in the production function. The aim of this classification is to examine how proximity to peer banks influences bank behavior. Proximity is defined as the degree of commonality between institutions, shaped by the influencing factors (ratios). Unique to the literature, our findings show that the number of banks in a group may vary greatly depending on the proximity-based ratios and, as a result, the interpretation of behavior should be relative to the specific environment.

Our clustering approach is solely based on proximity-based ratios, which allows us to argue that banks with a large number of peers in a group tend to follow a mainstream representative path and are more susceptible to the impact of each dimension that the influencing ratios yield. This new evidence highlights the importance of considering the target-relevant ratios when analysing bank behavior and risk perception. In turbulent economic periods, banking institutions tend to feel uncertain about their own risk perception and look to the actions of others for guidance and validation of their own decisions. This can result in a trend, which can amplify risks and contribute to financial instability. Hence, understanding how these factors affect the banking system can inform strategies for risk management and business activities (Avery and Zemsky, 1998; Schmitt and Westerhoff, 2017). A complementary finding is that specific groups of banks classified by size, economic importance and credit exposure are associated with higher levels of imitation, confirming the role that conditioning the reference cluster plays, especially for banks with no observable commonalities. It can be therefore deduced that our proposed approach achieves the purpose of conditioning the reference set, a finding that is consistent with the information asymmetry hypothesis (Banerjee, 1992).

Consequently, we highlight the existence of mimetic behavior among banks, which is contingent upon the influencing factors they are exposed to. Banks that exhibit this behavior respond to these factors in a manner that causes them to "look alike". At the same time, some banks choose to differentiate themselves from the crowd and exhibit a contrarian behavior with regards to these factors. The former banks observe the distribution of the environment of their peers and follow the crowd (the centre of the distribution) without considering their own business model and the associated risk, while the latter group of banks adopt a discrete path to avoid potential undesired consequences if mimetic behavior turns out to put them in a worse position.

The results of our empirical setting, using dynamic conditional schemes, show evidence of the significant impact of mimetic behavior on business performance and risk-taking, highlighting important findings. Mimetic behavior is proximity-driven and is followed by banks that want to look alike with specific profiles associated with their business activities and risk perception. Our modelling schemes effectively capture the dynamic proximity-based mimetic behavior, while reflecting the arbitrage, information asymmetries, and the diversity of bank operations' performance. On the other hand, mimetic behavior is associated with declining bank performance in response to changes in the main aspects of banks' targets, such as profitability, liquidity (short-term), activity and solvency (long-term). Banks tend to imitate more in a vulnerable banking industry over time, suggesting that they are interconnected through bilateral exposures and crossholdings of assets. Such mechanisms amplify the effects of idiosyncratic shocks, resulting in correlated outcomes that are important in explaining contagion triggered by solvency and liquidity constraints, with major consequences during turmoil periods.

Finally, considering results for each bucket separately, we find very similar behavior across ratios, except for inflation due to high heterogeneity of countries' economies. Our findings are of importance for determining the size of the peer banks along with mimetic behavior, subject to proximities. Therefore, we argue that the proposed framework reveals the diversity of banking institutions, but also highlights how optimizing proximities separately for each bank can produce more meaningful results, specifying a successful strategy and better business activities and performance. Our findings also highlight an important feature: when a bank optimizes its business model separately, it might be more desirable in the presence of banks with heterogeneous operations. Remaining close to the proximity average may result in a biased review of a bank's performance.

These contributions must be considered along with the limitations of the study, which also suggest several directions for future research. First, while reference clusters confirm the mimetic behavior with respect to business activities reflected by dominant ratio, heterogenous unobservable factors may prevail which have to do with private data of bank loan and securities portfolios that other banks are not aware of, or exogenous domestic and international prevailing or imposed conditions for part of banks that impose imbalances in the banking network. We believe that such analyses within specific conditions of the banking environment context can yield new insights for the research on organization theory in banking efficiency. Another potential limitation of our study is that the sample focuses solely on European banking network. Although the sample consists of several different (most of them are multinational) banks from many European countries, there are two drawbacks. First, the SSM banks in the sample operate under the restricted regulatory framework of the ECB, leaving less room for regulatory arbitrage. In contrast, non-SSM banks can exercise more decentralized decision-making, which may affect mimetic behavior since they can diversify in a more flexible way. Second, some international banking institutions, such as US or Swiss banks with branches in the European banking network, are not included in our sample and could act as leaders in the mimetic behavior process.

Future studies based on mimicry in banking networks in domains such as technology, retailing goods and services, information diffusion, investment strategies, and financial services represent an important avenue of research since banks are driving economic growth, sustainability, and financial services. Research in directions such as these may enhance understanding of the effects of imitation as a response to information asymmetries, bank competition, poor performance as well as enhance knowledge on patterns of business activities, governance and processes highlighted in classic and contemporary theories in international business.

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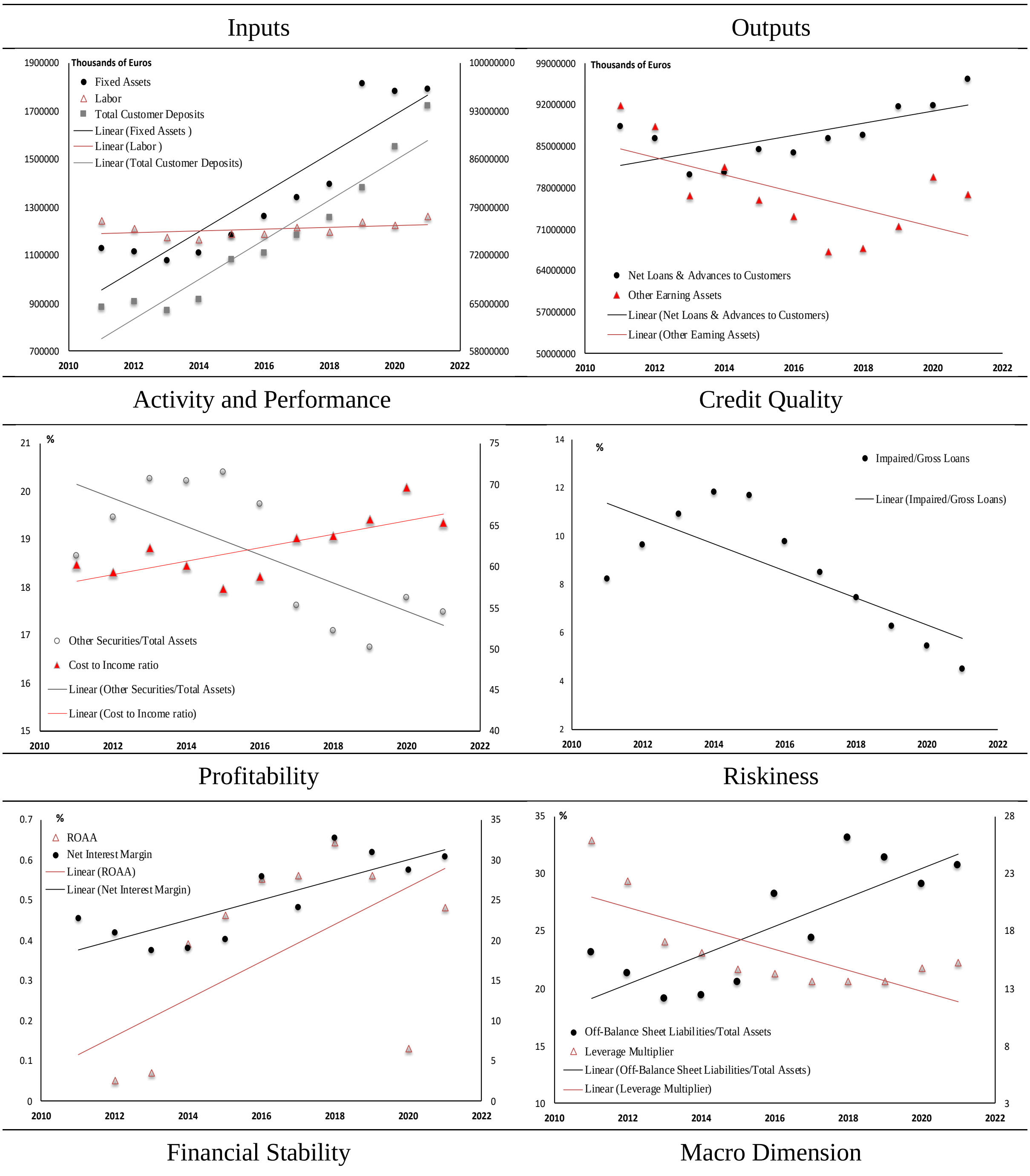
FIGURES

Figure 1. Average values for inputs, outputs, and ratios

Notes: The figure plots the average values (vertical axes) of inputs, outputs, and ratios for each year (horizontal axes). The linear lines illustrate the slope of averaging over the years in the sample. The tables with detailed analysis are provided in Table A1 in the accompanying Online Supplement.



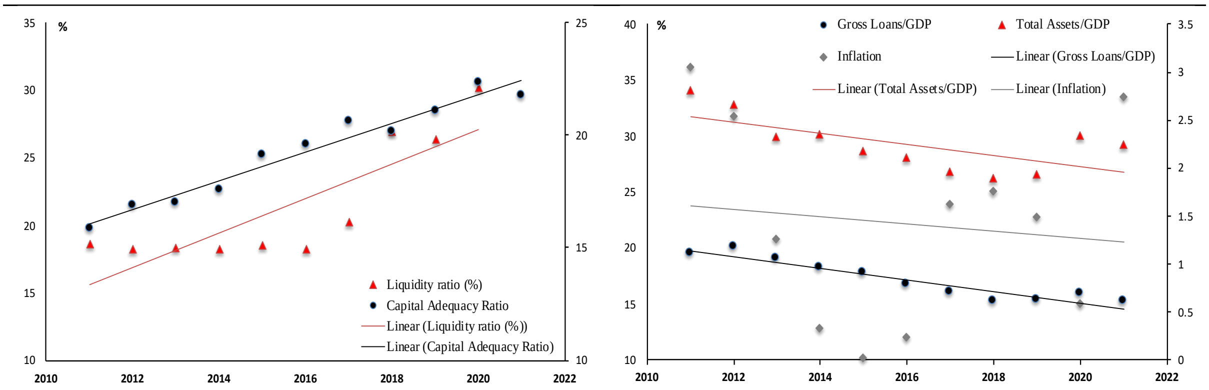
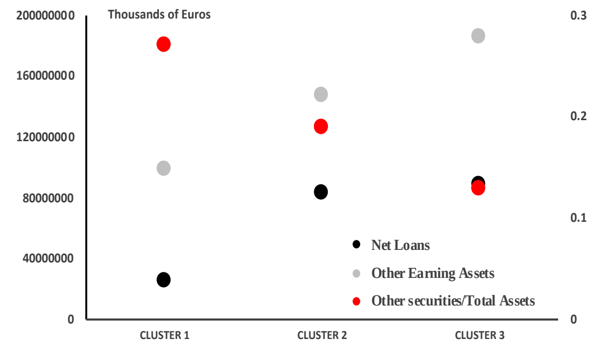


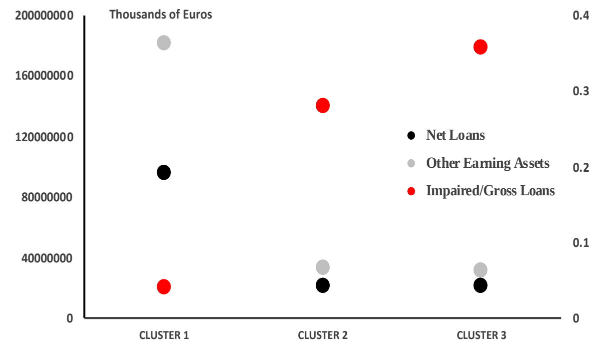
Figure 2. Average values for outputs-ratios schemes, by cluster

Notes: The figure plots the average values (vertical axes) for the outputs-proximity schemes by clusters (horizontal axes), over the years in the sample. The tables with detailed analysis are provided in Appendix B, in the accompanying Supplement.

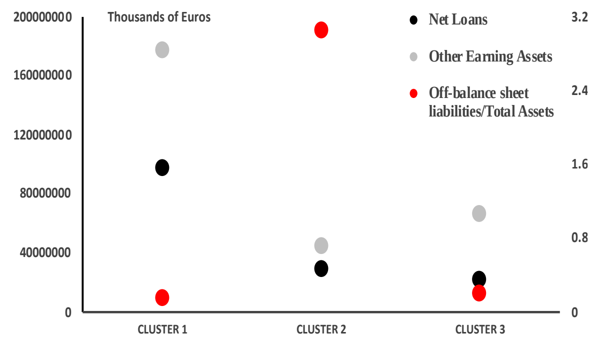
Other securities to Total Assets



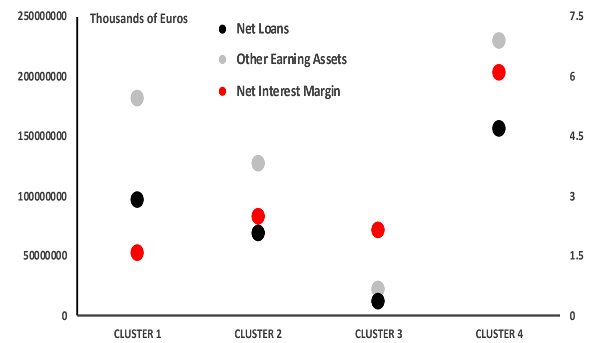
Impaired loans to Gross Loans



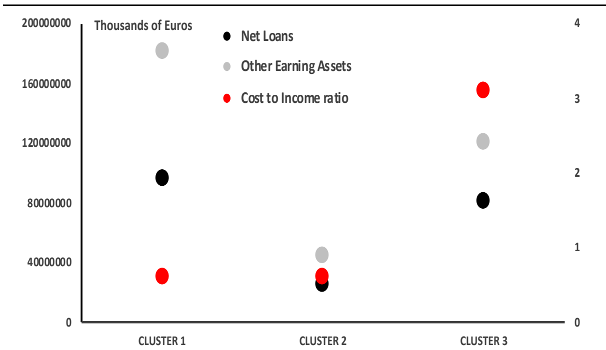
Off-balance Sheet Liabilities to Total Assets



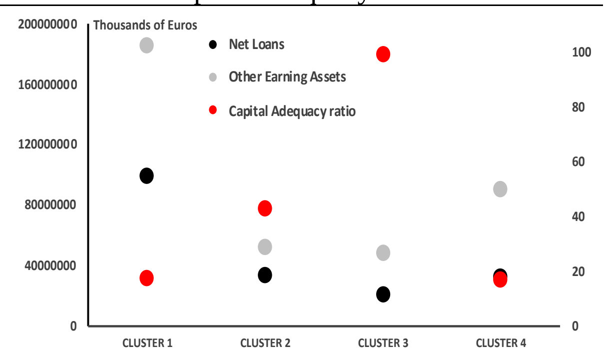
Net Interest Margin



Cost-to-Income Ratio

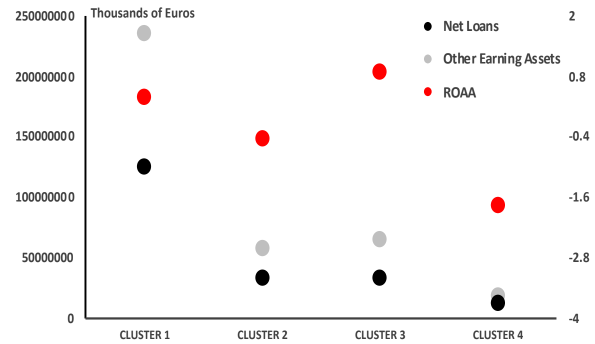


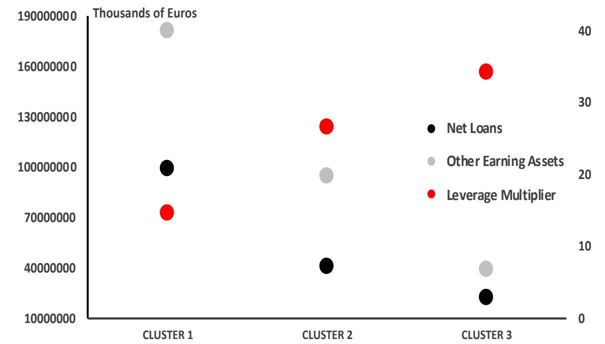
Capital Adequacy Ratio



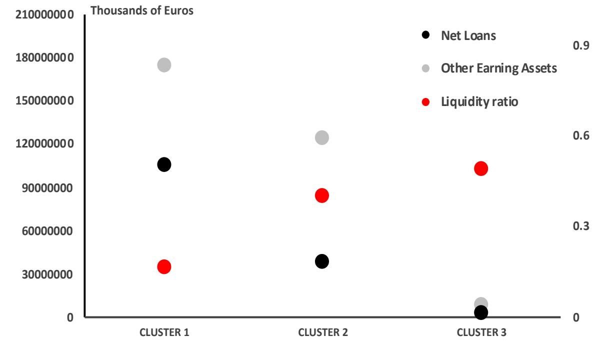
ROAA

Leverage Multiplier

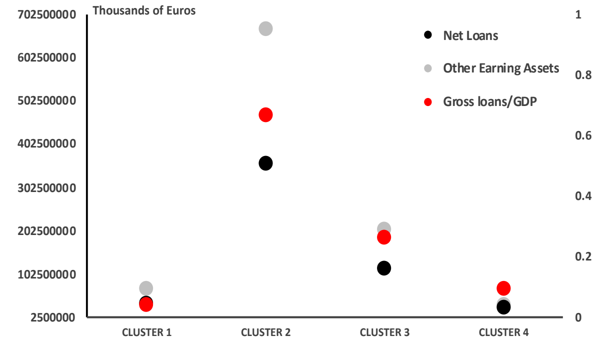




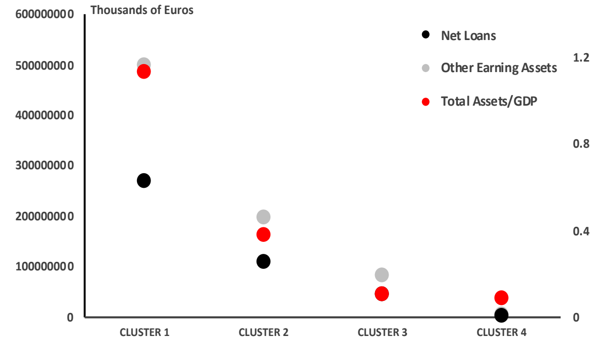
Liquidity Ratio



Gross Loans to GDP



Total Assets to GDP



Inflation

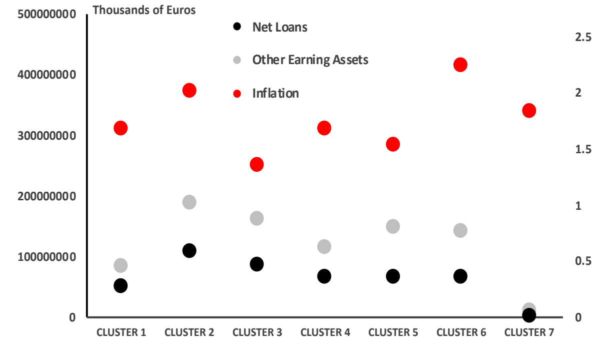
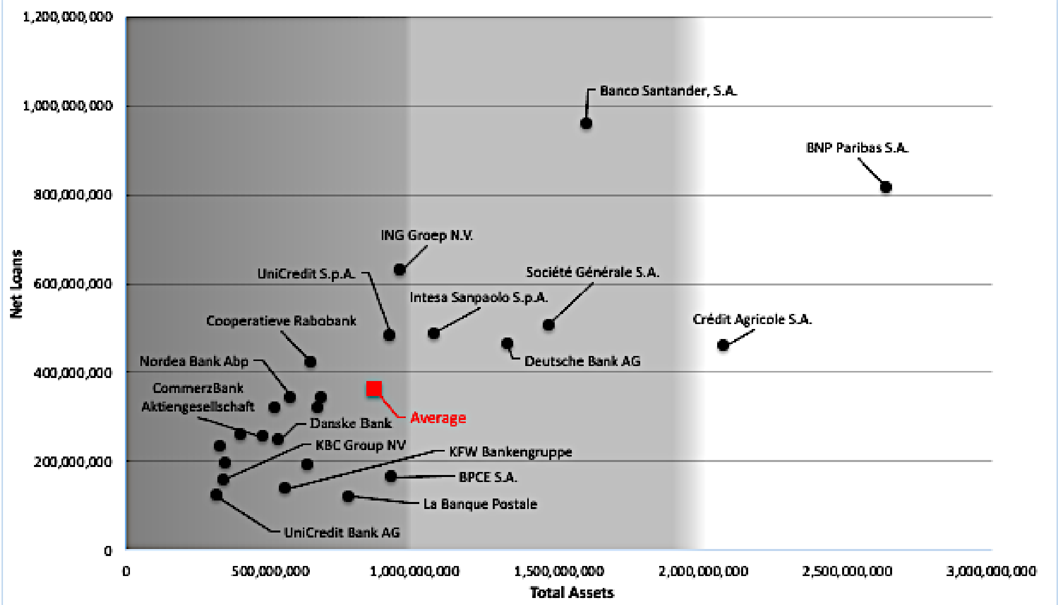


Figure 3. Banks' Classification

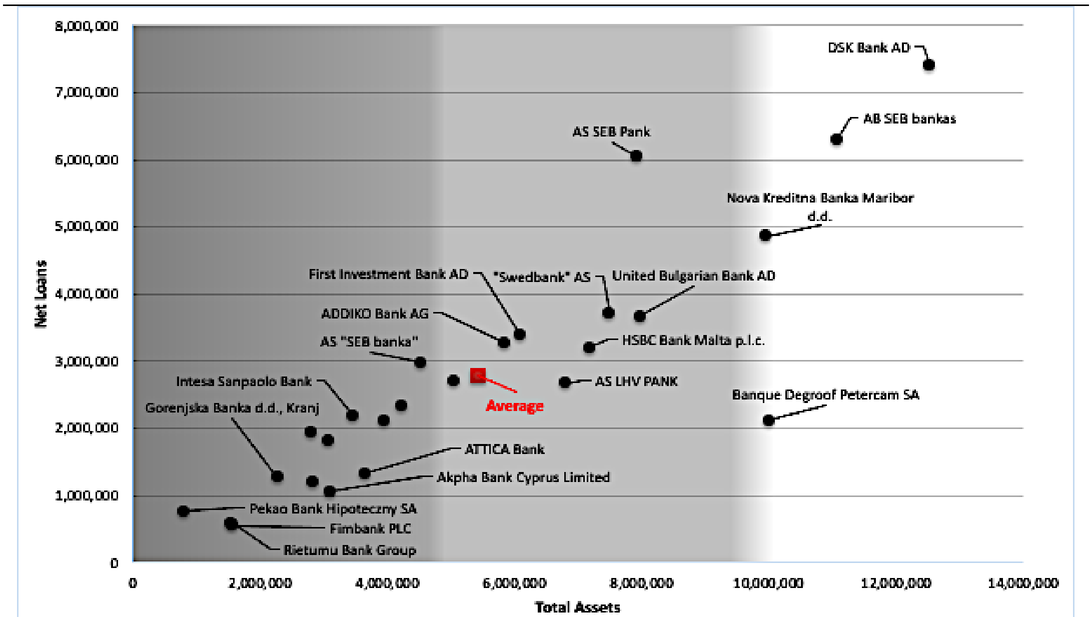
Notes: The figures illustrate the outputs of top and bottom 15% banks based on ECB's criteria of "size," "credit exposure," and "economic importance by share." The heat-map uses a gradual colour scheme, with darker grey indicating low criterion values and pale grey indicating higher values. A red square indicates the average value for the output, calculated from the banks in the top/bottom 15% group.

Size – Total Assets: Loans

Top 15%

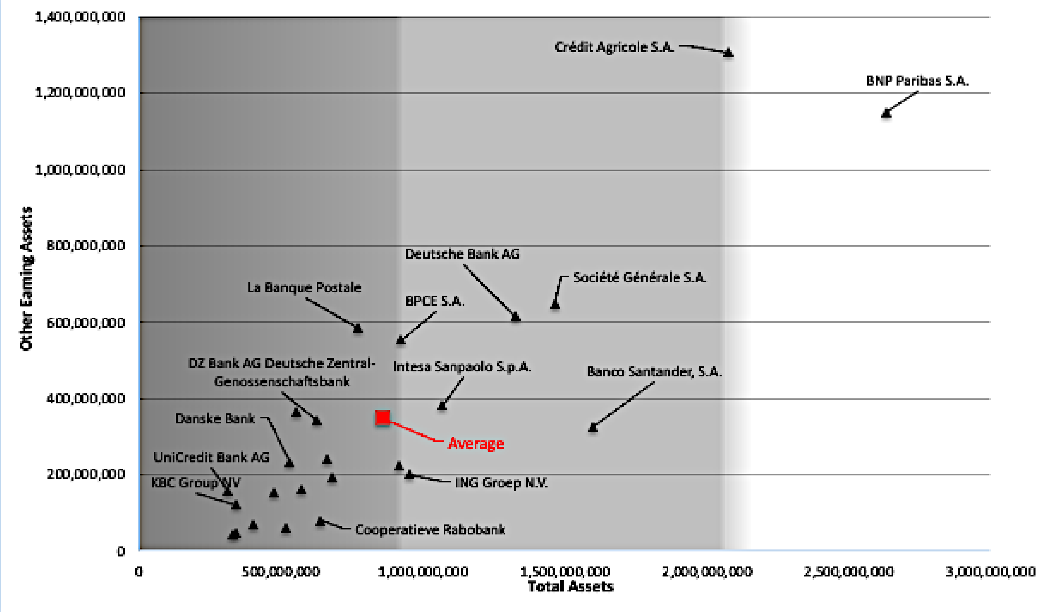


Bottom 15%

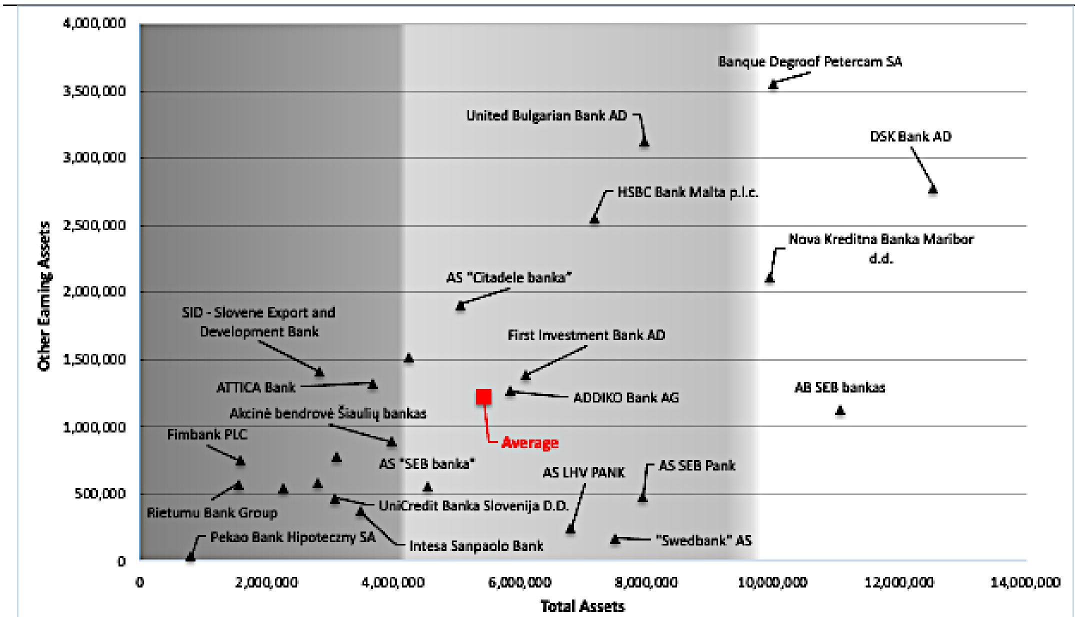


Size – Total Assets: Other Earning Assets

Top 15%

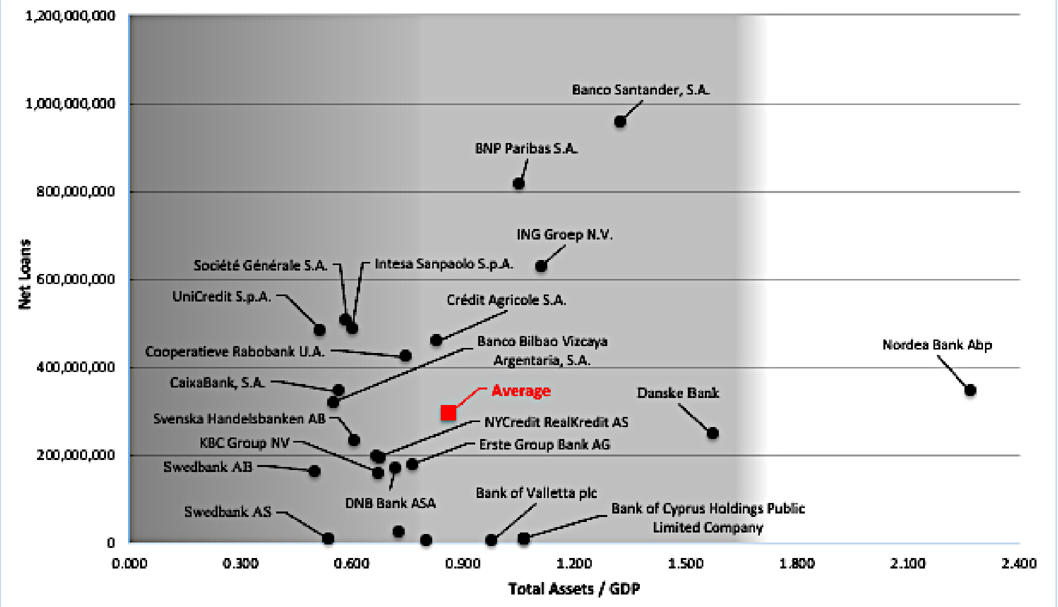


Bottom 15%

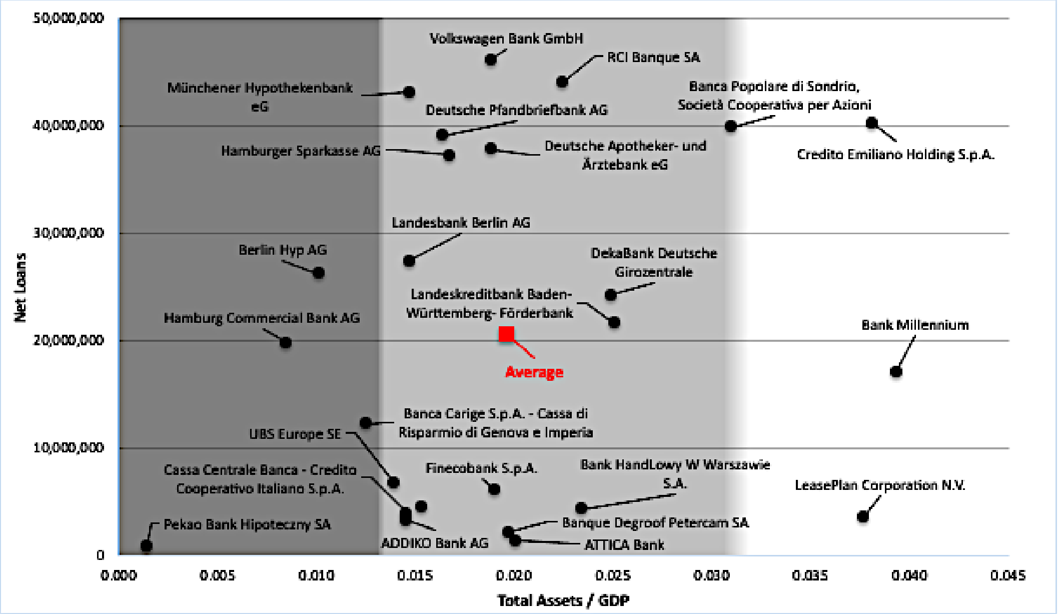


Economic Importance by Size: Total Assets to GDP: Loans

Top 15%

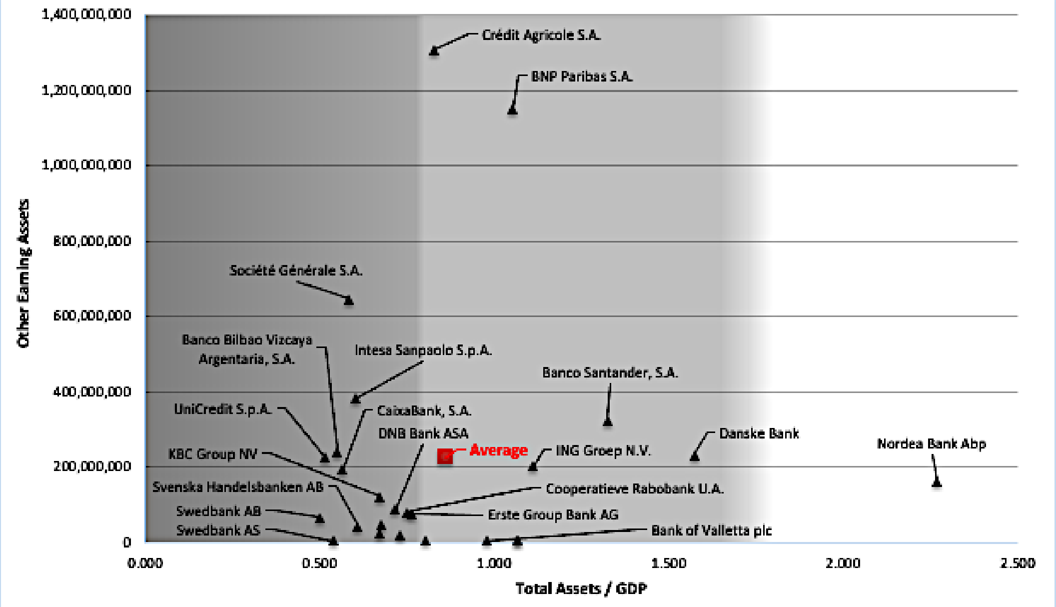


Bottom 15%

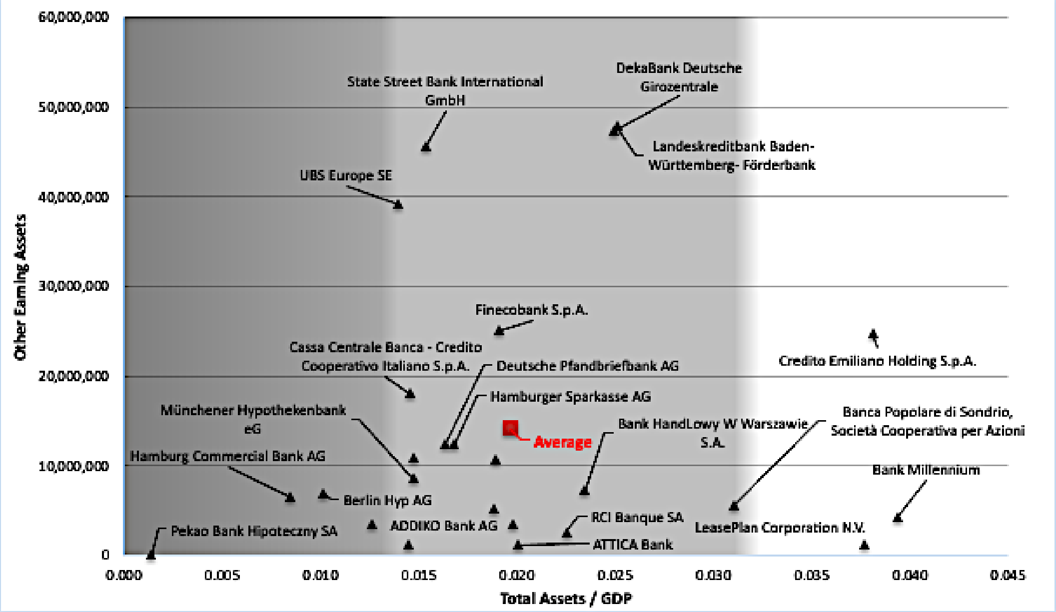


Economic Importance by Size: Total Assets to GDP: Other Earning Assets

Top 15%

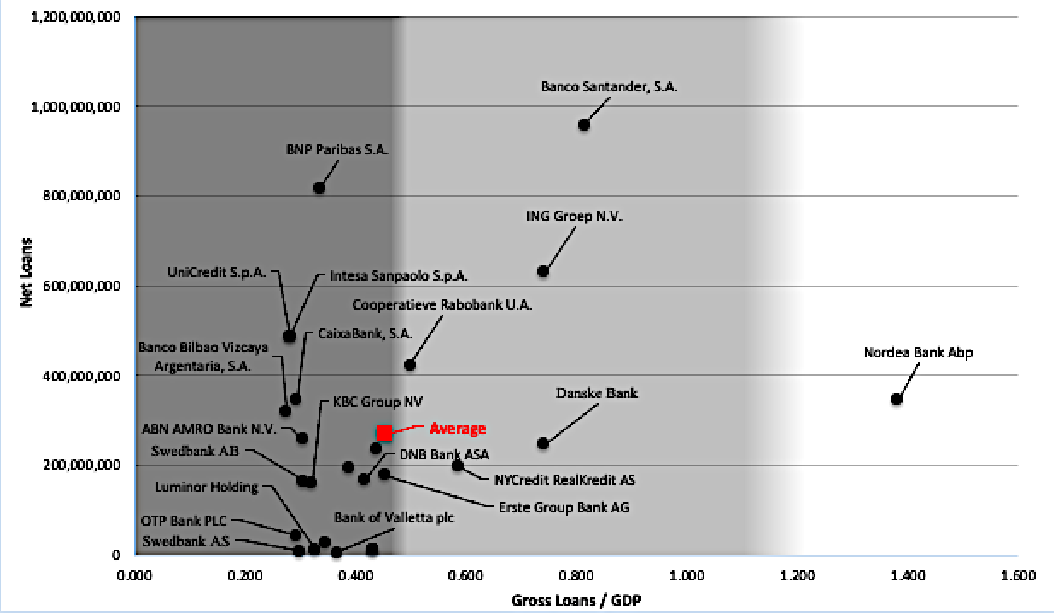


Bottom 15%

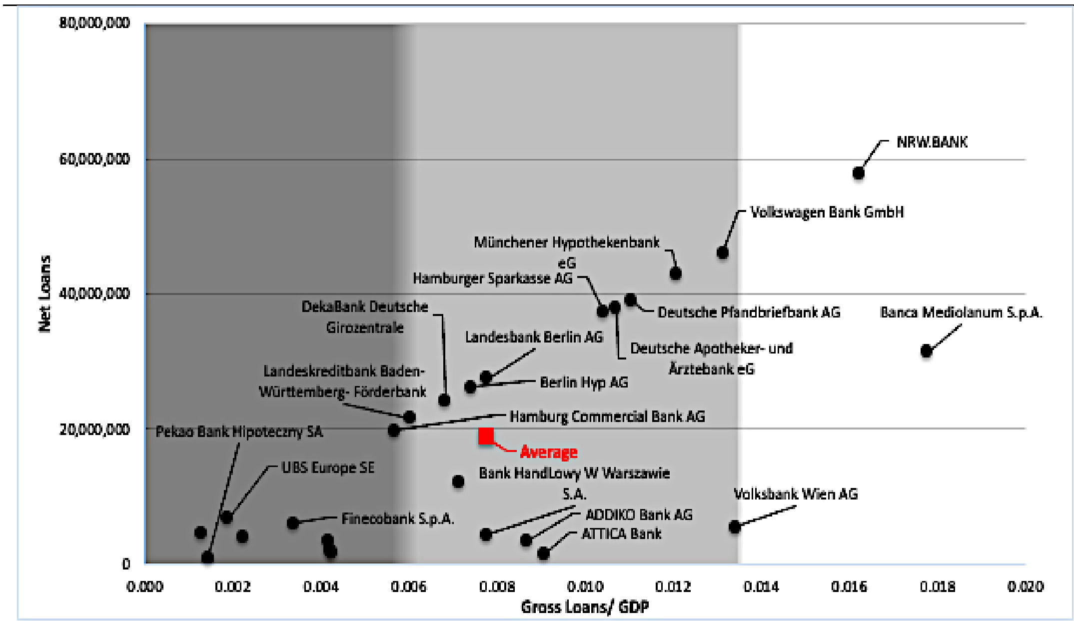


Economic Importance by Credit Exposure: Loans

Top 15%

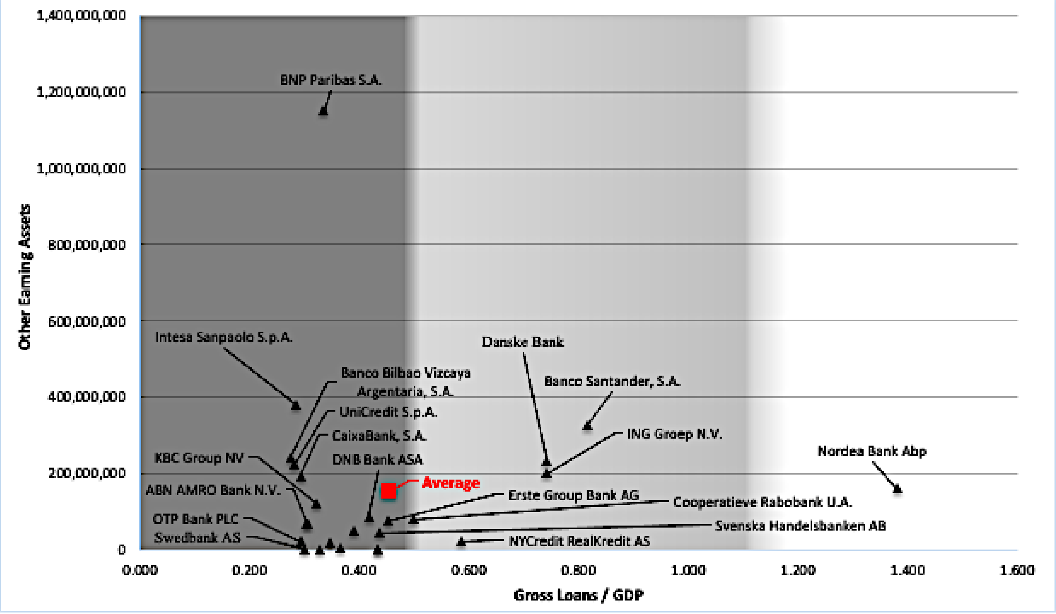


Bottom 15%

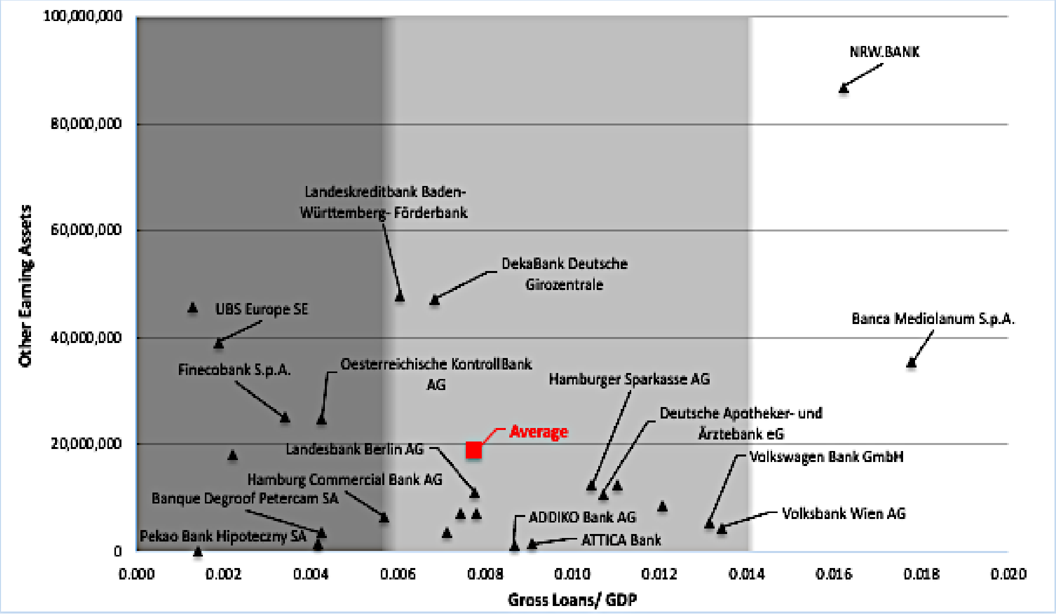


Economic Importance by Credit Exposure: Other Earning Assets

Top 15%



Bottom 15%



TABLES

Table 1. Aggregate results of SUR schemes

Notes: The table presents the coefficient averages per cluster and per proximity in the conditional and the unconditional form, as estimated by SUR schemes. For average values, in the conditional form we took the average of the statistically significant coefficients. Appendix D in the accompanying Supplement reports the exact p-values (3 to 4 digits when needed) in the tables with regression results, while we explicitly discuss economic significance (effect size) with aggregate results in Table 1, at the main body of the paper.

Unconditional form with ratio: Significance and sign

	Fixed Assets	Labor Expenses	Total Customer Deposits
Average coefficient values	0.082	0.275	0.555

Ratios	**Loans**	**Other Earning Assets**
Other Securities to Total Assets	(+)	(-)
Impaired Loans to Gross Loans	(-)	(-)
Off-balance Sheet Liabilities to Total Assets	Not significant	Not significant
Net Interest Margin	(-)	(-)
Cost-to-Income Ratio	Not significant	(+)
Capital Adequacy Ratio	Not significant	(+)
ROAA	(-)	(-)
Leverage Multiplier	(+)	(+)
Liquidity Ratio	(-)	(+)
Gross Loans to GDP	(+)	(-)
Total Assets to GDP	(+)	Not significant
Inflation	Not significant	Not significant

Conditional-to-Cluster Scheme

Average coefficient values	**Fixed assets**	**Labor Expenses**	**Total Customer Deposits**
Cluster 1	0.078	0.319	0.527
Cluster 2	0.208	0.288	0.494
Cluster 3	0.200	0.180	0.582
Cluster 4	0.157	0.069	0.600

Inflation additional clusters

Cluster 5	-	0.467	0.430
Cluster 6	-	0.194	0.667
Cluster 7	0.657	-0.346	0.317

Conditional-to-Bucket Scheme

	Fixed Assets	**Labor Expenses**	**Total Customer Deposits**
Average coefficient values	0.088	0.278	0.545

Comparative Analysis of Aggregate Results of Unconditional and Conditional Forms

	Loans			**Other Earning Assets**		
Ratios	Conditional-to-Cluster	Conditional-to-Bucket	Unconditional form	Conditional-to-Cluster	Conditional-to-Bucket	Unconditional form
Other Securities to Total Assets	Cluster 2	**Yes**	**(=)**	Clusters 1 & 2	**Yes**	**(↓)**
Impaired Loans to Gross Loans	Clusters 1, 2 & 3	**Yes**	**(=)**	Clusters 1 and 2	**Yes**	**(↓)**
Off-balance Sheet Liabilities to Total Assets	Clusters 1 & 3	**Yes**	**Significant**	Cluster 3	**Yes**	**Significant**
Net Interest Margin	Clusters 1 & 2	**Yes**	**(↓)**	Clusters 1, 2 & 3	**Yes**	**(↓)**
Cost-to-Income Ratio	Non	**Yes**	**(=)**	Cluster 1	**No**	**(↓)**
Capital Adequacy Ratio	Clusters 1, 3 & 4	**Yes**	**Significant**	Clusters 1, 2 & 3	**Yes**	**(↓)**
ROAA	Non		**Not significant**	Non		**Not significant**
Leverage Multiplier	Clusters 1, 2 & 3	**Yes**	**(↓), (-)**	Clusters 1 & 2	**Yes**	**(↓), (-)**
Liquidity Ratio	Clusters 2 & 3	**Yes**	**(↓)**	Clusters 1, 2 & 3	**Yes**	**(↓)**
Gross Loans to GDP	Clusters 1, 2 & 3	**Yes**	**(↓)**	Clusters 1 & 2	**Yes**	**(↑)**
Total Assets to GDP	Clusters 1, 2 & 3	**No**	**Not significant**	Clusters 1 & 2	**Yes**	**Significant**
Inflation	Clusters 4, 5, 6 & 7	**No**	**(=)**	Clusters 2, 5 & 7	**No**	**(=)**

TECHNICAL APPENDIX

The clustering approach of Philippas et al. (2021) determines the presence of sub-population clusters within the pooled network of units. The estimation process consists of maximizing the likelihood that all sub-population clusters follow an unknown number of distributions with unknown properties, with respect to an initial condition represented by a control variable across the units.

The mathematical formulation of the Gaussian mixture model is defined as:

$$p(\boldsymbol{\theta}) = \sum_{g=1}^{G} \varphi_g N\left(\boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g\right)$$

where G is the number of the different sub-populations, φ_g the mixture proportions with $0 \leq \varphi_g \leq 1$ and $\sum_g \varphi_g = 1$, while the Gaussian distributions are parameterized by the means $\boldsymbol{\mu}_g$ and the covariance matrices $\boldsymbol{\Sigma}_g$. We also assume that $\boldsymbol{\theta}$ represents the union of all free parameters and no control variable is imposed. The degree to which a bank i, represented as three-dimensional vector $\boldsymbol{x}_i$, belongs to the sub-population g is proportional to $\varphi_g N\left(\boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g\right)$. The process maximizes the likelihood function l of the Gaussian mixture model, using the Expectation Maximization (EM) algorithm.

$$l = \sum_{i=1}^{n} logp(\boldsymbol{x}_i|\boldsymbol{\theta}) = \sum_{i=1}^{n} log\left(\sum_{g} p(g|\boldsymbol{\theta}) \cdot p(\boldsymbol{x}_i|g, \boldsymbol{\theta})\right) = \sum_{i=1}^{n} log\left(\sum_{g} \varphi_g \cdot N\left(\boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g\right)\right)$$

The EM algorithm utilizes an initial condition for $\boldsymbol{\theta}$, and then iterates on two steps: (i) the *E-step* where the $logp(\boldsymbol{x}_i|\boldsymbol{\theta})$ is calculated; (ii) the *M-step* where the $\boldsymbol{\theta}$ is updated to $\boldsymbol{\theta}^*$ using the weights derived from the *E-step*. After the *M-step*, $\boldsymbol{\theta}^*$ is the union of φ_g^*, $\boldsymbol{\mu}_g^*$, and $\boldsymbol{\Sigma}_g^*$, with φ_g^* following the properties of φ_g.

$$\begin{aligned}
\max(L) &= max\left(\sum_{i=1}^{n} logp(\boldsymbol{x}_i|\boldsymbol{\theta})\right) \\
&= max\left\{\sum_{i=1}^{n} log\left(\sum_{g} p(g|\boldsymbol{\theta}) \cdot p(\boldsymbol{x}_i|g, \boldsymbol{\theta})\right)\right\} \\
&= max\left\{\sum_{i=1}^{n} log\left(\sum_{g} \varphi_g \cdot N\left(\boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g\right)\right)\right\}
\end{aligned}$$

In the case of Gaussian mixture models, the formulation becomes:

$$p(g|\boldsymbol{\theta}) \equiv \varphi_g \; and \; p(\boldsymbol{x}_i|g, \boldsymbol{\theta}) \equiv N\left(\boldsymbol{\mu}_g, \boldsymbol{\Sigma}_g\right) \tag{3}$$

Estimating the mixture model requires maximizing a likelihood function. Our modelling setup involves over forty free parameters, a large number compared with a more common setups found in likelihood maximization problems.

The mathematical formulation of a mixture model that consists only Gaussian distributions is:

$$p(\boldsymbol{\theta}) = \sum_{k=1}^{K} \varphi_k N(\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \tag{1}$$

where K is the number of the different sub-populations, φ_k the mixture proportions with $0 \leq \varphi_k \leq 1$ and $\sum_k \varphi_k = 1$, while the Gaussian distributions are parameterized by the means $\boldsymbol{\mu}_k$ and the covariance matrices $\boldsymbol{\Sigma}_k$. Given that K is pre-defined, $\boldsymbol{\theta}$ represents the union of all the other parameters. The degree to which a point $\boldsymbol{x}_i$ belongs to the sub-population k is proportional to $\varphi_k N(\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$. The aim is to maximize the log-likelihood of the model, that is:

$$l = \sum_{i=1}^{n} logp(\boldsymbol{x}_i|\boldsymbol{\theta}) = \sum_{i=1}^{n} log\left(\sum_k p\left(\boldsymbol{x}_{i,k}\middle|\boldsymbol{\theta}\right)\right) = \sum_{i=1}^{n} log\left(\sum_k p(k|\boldsymbol{\theta}) \cdot p(\boldsymbol{x}_i|k, \boldsymbol{\theta})\right) \tag{2}$$

In the case of Gaussian mixture models, the formulation becomes:

$$p(k|\boldsymbol{\theta}) \equiv \varphi_k \ and \ p(\boldsymbol{x}_i|k, \boldsymbol{\theta}) \equiv N(\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \tag{3}$$

The EM algorithm needs an initial condition in terms of $\boldsymbol{\theta}$, that is an initial good guess of the parameters set, and then iterates on the following two steps. During the first step, denoted as the *E-step*, the $logp(\boldsymbol{\theta}|\boldsymbol{x_i})$ is calculated, where $\boldsymbol{x}$ is the available data. During the second step, denoted as the *M-step*, the $\boldsymbol{\theta}$ is updated to $\boldsymbol{\theta}^*$ (i.e. any update is denoted by *) using the weights which came up from the *E-step*. Given the current estimate of the parameter $\boldsymbol{\theta}$, the conditional distribution is determined by Bayes theorem to be the proportional height of the normal density, weighted by a factor $\tau_{k,i}$:

$$\tau_{k,i} = \frac{\varphi_k N(\boldsymbol{x}_i; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_k \varphi_k N(\boldsymbol{x}_i; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)} \tag{4}$$

Next, the M-step becomes:

$$w_k = \frac{1}{n}\sum_{i=1}^{n} \tau_{k,i} \ and \ then \ \ \varphi_k^* = \frac{w_k}{\sum_k w_k} \tag{5}$$

where the means vector and covariance matrix are given by:

$$\boldsymbol{\mu}_k^* = \frac{\sum_{i=1}^{n}\left(\tau_{k,i}, \ \boldsymbol{x}_i\right)}{\sum_{i=1}^{n}\left(\tau_{k,i}\right)} \ \ and \ \boldsymbol{\Sigma}_k^* = \frac{\sum_{i=1}^{n} \tau_{k,i}(\boldsymbol{x}_i - \boldsymbol{\mu}_k)(\boldsymbol{x}_i - \boldsymbol{\mu}_k)'}{\sum_{i=1}^{n} \tau_{k,i}} \tag{6}$$

At the end of this step, $\boldsymbol{\theta}^*$ is the union of φ_k^*, $\boldsymbol{\mu}_k^*$, and $\boldsymbol{\Sigma}_k^*$, with φ_k^* following the properties of φ_k. From a computational perspective, we calculate the model's likelihood right after the *E-step* and, when the difference between two consecutive likelihoods becomes small (e.g. of the order of 10^{-8}) the EM algorithm loop terminates.

The above can give trustworthy results when the sub-population clusters are geometrically well apart. In this case, $p(k|\theta)$ is assigned to each cluster and the EM algorithm finally decouples the sub-population clusters. Problems arise instead when the sub-population clusters are tightly coupled. For populations which are coupled by default, a data point x_i may belong to more than one cluster. To absorb this effect into our mixture framework, we define the likelihood as:

$$l = \sum_{i=1}^{n} log\left[\sum_{k} p(k|\boldsymbol{x}_i, \boldsymbol{\theta}) \cdot p(\boldsymbol{x}_i|k, \boldsymbol{\theta})\right] \; with \; \sum_{k} p(k|\boldsymbol{x}_i, \boldsymbol{\theta}) = \; p(k|\boldsymbol{\theta}) \tag{7}$$

According to the above definition, when the clusters are well apart, it is implied that the cluster $p(k|\boldsymbol{x}_i, \boldsymbol{\theta})$ becomes independent to $\boldsymbol{x}_i$ and so we return to the likelihood formula we initially assumed in equation (2). Therefore, we utilize the innovation on the likelihood given in (7) for our estimation purposes. In our application, a given FI may show commonalities with, and be identified as belonging to, a cluster with other FIs that are not grouped together *a-priori* for supervisory purposes. Each cluster is identified as a three-dimensional object in an environment characterised by an "exogenous type" variable, which allows us to test whether this environment impacts on the identification of clusters.

From a methodological perspective, some details are in order. We do not impose but instead select the number of clusters that minimize the BIC information criterion; therefore, our clusters provide a data efficient and parsimonious way of characterising the entire dataset. Since our clusters are identified as (three-dimensional) objects belonging to a policy environment that pre-assigns each FI to an "exogenous type" (i.e. defined according to the supervisory framework in place), we can test whether this environment has any impact on the identification of clusters, which is entirely data-driven. Using a chi-square test, we test for the following null hypothesis:

H_0: clusters are independent from the given "exogenous type"

We reject the null in all cases where the p-value is less than 0.10; this would mean that our clustering approach is not able to identify commonalities or patterns that are different from those implied by the "exogenous type". In all other cases where p-values are higher than 0.10, we can conclude that identified clusters, and commonalities, are driven by some other, unobserved, factors that are different from (i.e. orthogonal to) the selected "exogenous" one. Table 1 summarizes our findings on every space, by year and exogenous type.