Board Suitability and performance in European banks: A machine learning application

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30 July 2019
Preliminary version
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Abstract

This paper studies one of the most important mechanisms of the European bank corporate governance regulation that is the individual and collective suitability of banks board of directors. Differently from the mainstream literature, we analyse the characteristics of the board through a comprehensive approach that is able to summarise the different profiles considered in the European regulation on board's suitability and to consider possible non-linearity between variables (i.e. skills, knowledge, experience, commitment of time as well as diversity). We in fact use Self-Organising Maps (SOMs) – a methodology that is new in studies on corporate governance - to cluster the large listed European banks in different groups in terms of suitability of their boards with regards to regulatory provisions. Then we perform a panel analysis to investigate the effects of the various degree of suitability on the performance of banks in terms of financial and market performance, riskiness and risk-adjusted performance. Results show that banks with the most suitable boards are also those obtaining better performance and limiting risk exposure.

Key words: Banks, corporate governance, SOMs, fit & proper, board suitability, machine learning

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1. Introduction

Weak governance in banking institutions has been blamed to have a pivotal role in the burst and development of the international financial crisis. Thus, in the aftermath of the crisis, regulators have increasingly improved bank corporate governance rules – and particularly those concerning the board of directors – to enhance the implementation of sound practices and ensure the effective and prudent management of banking institutions.

In Europe, the new governance paradigm has been fully designed by the Directive 36/2013 (CRD4)[1] that, among other goals, acknowledges the crucial importance of the individual and collective "suitability" of the management body (i.e. the board of directors) and its members. More specifically, the Directive stipulates that banks board must be suitable in terms of i) competence, i.e. individual skills, knowledge and professional expertise, etc.; ii) diversity, i.e. demographic diversity (e.g. gender, age, geographical provenance, etc.), but also educational and professional background diversity; iii) independence of directors and balance of power and iv) time commitment of directors.

In the regulatory design, "board suitability" is considered a very important prerequisite of (good) governance that is able to bring value to the bank not only in terms of shareholders' profitability, but also and more importantly in terms of value for all the stakeholders and effective risk management. Despite this intuitive relationship, the wide literature on bank corporate governance has provided mixed and contrasting results on the contribution of board quality and structure to bank performance (for a review see de Haan and Vlahu, 2016; Fernandes et al., 2017; John et al., 2016). Relevant empirical studies focus on performance – usually proxied by some measures of return – and only recently they also address the effect of board governance on bank's riskiness and risk-adjusted performance (Aebi et al., 2012; Ellul and Yerramilli, 2013). Besides, they are mainly focused on the US experience, whereas cross country studies in the European context are still rather scarce. Finally, and most importantly, they evaluate the impact of single board characteristics independently from the others and usually assume a linear relationship between board characteristics, although - as underlined also by regulators – board features should be comprehensively evaluated, as a unity made of different profiles.

Board diversity, and especially gender diversity, emerges as the most investigated feature in the recent literature, however a stronger presence of women in banks boards is not always associated with improved performance and risk (Adams and Ferreira, 2009; Carter et al., 2003; Farrel and Hersch, 2005; Nguyen et al., 2015). Also the effect of directors' education and financial expertise has

[1] The Directive was issued in mid 2013 and it gradually entered into force starting from 2014.

been increasingly investigated, but evidence is mixed and most studies focus on a single European country (Germany: Hau and Thum, 2009; Italy: Locatelli et al., 2018; Spain: Cuñat and Garicano, 2010).

We contribute to the scarce stream of empirical studies in the European context by providing a first analysis of the “degree of suitability” of the board of large listed European banks and the relationship between boards suitability and bank performance and risk. More specifically, we exploit a proprietary dataset, based on hand-collected information about more than 700 directors of 40 large listed banks form 11 European countries, and we apply Self-Organising Maps (SOMs), a machine learning methodology (Somers and Casal, 2017), to assess: i) to what extent, right after the new CRD4 regulatory framework entered into force, European banks comply with the new board suitability rules and ii) whether a greater proximity to the new board governance paradigm has a positive impact on bank financial performances and risk. Thus, we provide a first attempt to evaluate the effectiveness of the new European regulation on ‘board suitability’ by verifying whether a greater proximity to the new board governance rules has a positive impact on performances and risk control and management.

The novelty of this study lies in the following aspects: i) by levering on a hand-collected dataset containing very detailed information on 28 different attributes of banks boards and boards members, including features such as banking and financial competences, education and professional background, our analysis covers a number of board features that are crucial in terms of “suitability”, but that have not been thoroughly investigated so far; b) we employ a machine learning technique, i.e. SOMs, that is able to manage complexity in the dataset as well as non-linear relationships between variables and allows for jointly exploring at the board level the 28 attributes under analysis. Despite a huge literature corpus testifying applications in other Economic and Management field of research, so far SOMs have been applied only rarely in the corporate governance literature (Somers et al,2016); c) we evaluate the effectiveness of board suitability in delivering value with a wide set of performance and risk indicators, also including risk-adjusted performance measures, that are less commonly employed in the bank governance literature.

Results overall show that: i) European banks can be grouped into four clusters characterized by different board profiles and by different degrees of proximity to the board ‘suitability rules’; ii) banks with the most suitable board governance show better performance and lower exposure to risks.

The paper is structured as follows: the second section illustrates the context of our study and our hypotheses; the third section describes the methodology; the fourth section presents and discusses the clusters of banks that have been arranged applying SOMs to banks board features and the results of the panel analysis assessing the impact of board suitability on performances. The last section concludes.

2. Context and hypotheses development

Over the last two decades regulators have paid growing attention to bank governance and specifically to the structure and quality of the board of directors. The burst of the international financial crisis has increased the interest of regulators for this and has triggered a process of reinforcement of banks' corporate governance rules. In Europe the first step for the introduction of the new governance paradigm is the issuance of the Directive 36/2013 (also known as CRD4). The Directive highlights that the previous regulatory framework was not effective in promoting sound corporate governance practices for two reasons: i) the very general and often non-binding provisions on governance, ii) the unclear role of the competent authorities in overseeing governance. Moreover, the Directive traces the responsibility of good governance back to the phase of board designation. In fact, it clearly indicates the main principles and standards that shareholders should consider (and authorities should supervise) when appointing members of the management body[2].

The Directive plainly states that each member of the board, especially those members sitting on the board committees, should: i) have high competence, knowledge, qualifications and skills and experience in banking necessary to ensure proper and prudent management of the institution; ii) be selected as to ensure that the composition of the board complies with the principle of diversity in terms of age, gender, geographical provenance and educational and professional background, etc. to allows for a variety of views and experiences and independent opinions and critical challenge inside the board in the process of decision making, thus avoiding the phenomenon of 'group thinking' typical of homogenous groups and facilitate independent opinions and constructive challenging in the process of decision making (Bantel and Jackson, 1989; Faleye et al., 2017); .iii) be such as to ensure that the interests of all internal and external stakeholders are duly considered and that an adequate number of independent directors sit in the board ; iv) spend adequate time to perform her/his role to cover all the subjects in depth and especially to assess the main risks of the banking business, thus implying that a high number of directorships would preclude the director's oversight performance.

[2] In the Directive the term Management body is intended to embrace all existing structures (one-tier, two-tier or other board structure) without advocating any particular one.

In the years following the issuance of the Directive, member states, national and European authorities (EBA, ESMA, ECB) have further detailed the above principles, naming them alternatively “Fit and proper” requirements or “Suitability” of the board. In 2017, the European Banking Authority (EBA) jointly with European Securities and Market Authority (ESMA) published the Guidelines (ESMA-EBA, 2017). Furthermore, in 2018 the European Central Bank (ECB) published the updated Guide to fit and proper assessments (ECB, 2018) that, in line with the joint ESMA and EBA Guidelines on suitability, explains in detail the policies applied by the ECB when evaluating boards of significant credit institutions. Nonetheless, the CRD4 can still be viewed as the cornerstone in the current regulatory framework on board governance and the year 2013 represents a turning point for the introduction the new board paradigm.

Overall, board suitability requirements are designed to enable the board to keep all the risks under control and ensure the effective and prudent management of the bank and governance regulation in banking is mainly risk governance regulation (Srivastav and Hagendorff, 2016). Regulators expect that suitable boards allow for better performance and a more effective risk management at the same time.

This study aims at examining the quality and structure of the boards in charge at the end of 2014 to assess to what extent the boards comply with the new requirements that were set forth in the 2013 Directive and entered into force starting from 2014. We expect that at that time European banks were variously closer to the board ‘suitability rules’. As a second goal, we assess whether a greater proximity to board governance rules has a positive impact on bank financial performances, thus providing an evaluation of the effectiveness of the new regulatory framework. In this study and in line with previous literature, the quality of board governance (i.e. suitability) is assumed to positively affect performance thus delivering value to the firm (Payne et al., 2009).

3. Methodology

3.1. Sample and dataset

The empirical analysis examines a sample of 40 large listed banks from 11 European countries (see Table 1). We focus on listed banks because usually they have to comply with more stringent and levelled disclosure and accounting rules in terms of board quality and composition; this should allow for a higher cross-country comparability. Besides, we are interested also in understanding how financial markets evaluate bank governance. Finally, being closely monitored by the market they should react more promptly to, or even anticipate, the introduction of the new board governance paradigm.

<< Table 1 goes approximately here>>

Information on the individual members of the boards are retrieved from various sources, including annual reports, governance reports, personal curriculum vitae available on the bank website or through other public sources. Overall, we hand-collected broad information for 710 directors[3]. In detail, for each member we select 28 features that according to the European regulation are crucial in assessing the individual and collective suitability of the management body (Table 2). These features shed light on the following profiles:

- Competence, i.e. educational background of board members (proxied by the attainment of a university degree/ post graduate degree), professional background, financial competences, etc;
- Diversity, in terms of demographic aspects, education and work experience;
- Independence and balance of power, i.e. percentage of independent/executive directors, etc.;
- Time commitment in terms of degree of attendance to board meetings and number of other mandates/offices;
- Structure and composition of the board.

Other variables concerning bank financials data are obtained through the Orbis Bankfocus and SNL Financial databases, while macroeconomic data are retrieved from the World bank database.

<< Table 2 goes approximately here>>

3.2. Empirical design

To gauge the quality and structure of the boards in charge at the end of 2014 and to assess their proximity to the new board paradigm introduced by the CRD4, we exploit the features of Self-Organising Maps (SOMs). The SOM (Kohonen, 1982, 1997) is a machine-learning algorithm which processes data to extract the main features without any explicit analytic formula to explain dependencies among the variables, applying an inductive rather than a deductive method (Chung-Fern Wu, 1994; Zhang et al., 1999; McNelis, 2005). In this light, the SOM offer an alternative approach to data analysis considering the bank's situation as a multi-faceted non-linear combination of all boards' variables, rather than evaluating the variables *per se.*

[3] Our sample includes all the directors sitting in any of the management bodies of the bank, e.g. management and supervisory boards for two-tier model; board of directors for one-tier model; board of directors and board of auditors for the other models.

By applying SOMs to the banks of our sample we can analyse jointly the different characteristics/profiles of the boards in charge at the end 2014 and evaluate similarities between banks' board. As a result, we can group banks into clusters and visualize the resulting patterns (Hastie et al., 2005), and by coupling SOM outcomes to the analysis with traditional methods we are able to rank the clusters in terms of proximity to the suitability rules (i.e. 'suitability clusters').

In the second step of our empirical analysis we test the relationship between the 'proximity to the suitability rules' and bank financial performances through a panel regression that puts into relation the bank performance as dependent variable (variously measured) and the suitability of governance, identified through a dummy variable for each of the 'suitability clusters'. Since board decisions need time to produce their effects on bank performance (Grove et al 2011, Beltratti & Stulz, 2012; Sun & Cahan, 2009), we analyse the performance of a three-year period ending in 2016.

We detail the methodological steps taken in the following paragraphs.

3.3. Self-Organizing Maps (SOMs)

The Self-Organizing Map or SOM (Kohonen, 1982) is a computational model extending the intuition of Willshaw and Von Der Malsburg (1976, 1979) who discovered that some areas of the brain develop specialized structures in different areas, with a high sensitivity for a specific input pattern.

The SOM can be represented as a 2-D projection plane with units (the neurons) arranged in either a rectangular or hexagonal shape, as shown in Figure 1.

<<Figure 1 goes approximately here>>

The SOM algorithm is an ensemble of computational tasks aimed at mimicking the neurobiological process, which maps different sensory inputs onto corresponding areas of the cerebral cortex in an orderly fashion. The key elements in the biological process are the competitive learning and the principle of 'the winner taking all': all the units are excited with the same signal, but only one will produce the highest response thus automatically becoming a candidate to the receptive basin for that specific pattern. The Self-Organizing algorithm goes one-step further, generalizing the 'winner takes all' idea into that of the winner taking the most. According to this principle, when a pattern is presented to the SOM, the related information is retrieved not only by the best neuron, but also by its closest neighbours, according to a proper (mathematical) similarity criterion. In this way, neurons in the map organize themselves, and connectivity structures are formed, which are topology preserving with respect to input data, that is: similar input items are located close to each other in the 2-D projection plane.

The SOM training can be summarized in the following steps performed in a sequential way. Let us denote by **x** an input pattern, then:

1. Evaluate the distance between ***x*** and each neuron of the SOM;
2. Select the neuron (node) with the smallest distance from ***x***. This is the winner neuron or Best Matching Unit (BMU);
3. Correct the position of each node according to the results of Step 2, in order to preserve the network topology.

Steps 1.–3. can be repeated either once or more than once for each input pattern: a good stopping criterion generally consists in taking a view to the Quantization Error (QE), i.e. a weighted average over the Euclidean norms of the difference between the input vector and the corresponding BMU. When QE goes below a proper threshold level, say for instance 10^{-2} or lower, it might be suitable to stop the procedure. In this way, once the learning procedure is concluded, the organization of the SOM is the projection of the input space it into a lower dimensional space with closer nodes representing neighbour input patterns.

From the operative viewpoint, when running the SOM algorithm on our dataset, we examined various grid dimensions choosing the best one, with respect to QE index values. We therefore describe and discuss the results obtained by training a 4×5 map with a rectangular topology, reaching a QE of 0.00316 (very close to zero).

One of the positive sides of the SOM is that it offers a platform for further visual investigations towards three directions. First, the direct output of the SOM procedure is the s.c. U-Matrix, as shown in Figure 2.

<<Figure 2 goes approximately here>>

In summary, the U-Matrix nodes (hexagons) are coloured according to their distance one to each other: yellow colouring between the neurons means a large distance and hence a more pronounced difference among associated values in the input space.

Second, in order to visualize clusters, knowledge discovery can be driven by an incremental *k*-means clustering procedure, which was stopped when the lowest average distance between clusters (less within-group distance between data points in the cluster) was reached. The ending point of the procedure was chosen according to the s.c. elbow point criterion, as shown in Figure 3: if one plots the percentage of variance explained by the clusters against the number of clusters, the first clusters will add much information (explain a lot of variance), but at some point, the marginal gain will drop, giving an angle in the graph. The number of clusters is chosen at this point, hence the “elbow criterion”.

<<Figure 3 goes approximately here>>

In Figure 3 the number of clusters is on the horizontal axis and the value of the average distance within clusters is given on the vertical axis: the elbow point corresponds to an overall number of four clusters and we divided the SOM accordingly, as illustrated in Figure 4. The figure uses a coding similar to that illustrated in the case of the U-Matrix: hexagons represent the neurons, colors associated to clusters represent the distances between neurons; in this case, however, the color difference indicates that data points in the identified regions are farther apart, i.e. different tones of yellow are associated to largest intra-group distances, blue and lighter colors to smaller distances.

<<Figure 4 goes approximately here>>

Third, it is possible to visualize the contribution of each variable in the input space by using the s.c. components maps. Each component map can be interpreted as a sliced version of the SOM visualizing the relative component distributions of the input data. By comparison of different slices, it is possible to derive whether two components correlate or not. Consider for instance Figure 5 where we show three components, representing as many variables. Comparing them two by two, we can say that components represented in maps (a) and (c) are correlated as the distribution of both low values (blue and green shaded nodes) and higher values (yellow shaded nodes) is similar. On the contrary, the component appearing in the map (b) is anti-correlated to the variables in maps (a) and (c), as the nodes outlook is at the opposite.

<<Figure 5 goes approximately here>>

To conclude, we considered an additional visualization tool we refer to as DNA matrix, consisting in a colored matrix whose rows (in our case: the banks) are variously colored depending on the color associated to each variable in the component maps. Color conventions as early discussed and described apply. In this way, it is possible to obtain an overall representation of the “DNA features” of each bank without loosing the simplicity of the 2-D visualization as offered by the SOM. Results are visible in Figure 6.

<<Figure 6 goes approximately here>>

Multiple reading keys are suggested by Figure 6. By rows, we can search for banks sharing similar DNAs, i.e. similar sequence of colors. On the other hand, by columns we can explore how many banks share similar level of the examined variable.

3.4. Panel regressions

We perform a panel analysis to test whether the degree of suitability of bank board impacts on: i) financial and market performance; ii) banks riskiness and iii) risk-adjusted performance. The degree of suitability of bank boards is proxied by dummy variables referring to the clusters identified using SOMs (Table 3). To proxy financial and market performance we use three different measures (return on average assets – ROA, return on average equity – ROE – and stock returns – r_i), consistently with the traditional empirical approach in the banking and governance studies (among others, Bøhren and Strøm, 2010; Minton et al., 2014, Arnaboldi et al., 2018). Then, we employ three measures of risk: risk-weighted assets to total assets (RWA/TA) as measure of the overall exposure to risks; non-performing loans to gross loans (NPL/GL) as a proxy of credit risk; the standard deviation of stock returns (sd_i) to capture market perception of bank' riskiness. Finally, we also employ risk-adjusted performance measures to capture the bank ability to adequately remunerate risks. The first measure we use is return on risk-weighted assets, computed as the ratio between net income and risk-weighted assets (RoRWA); second, we employ the ratio between net income and total regulatory capital (RoTRC); finally, in a stock market perspective, we also use the annualised stock returns over the annualised standard deviation of returns (r_i/sd_i), as a sort of modified Sharpe ratio.

We model performance, risk and risk-adjusted performance as the outcome of board features and a set of control variables, according to the following relation:

$$perf_{i,t} = f\left(cluster_i; X_{i,t}; Y_{i,t}\right) = \alpha + \beta c_i + \gamma' X_{i,t} + \delta' Y_{i,t} + \varepsilon_{i,t}$$

Where:

- $Perf_{i,t}$ is the performance indicator chosen for bank *i* at time *t*;
- $Cluster_i$ is a dummy variable representing the cluster of governance obtained using the SOM operationalised on the features of boards in charge at the end of 2014;
- $X_{i,t}$ is a set of firm characteristics at time *t* for bank *i* including: size, proxied by the natural logarithm of total assets and its squared value to catch any non-linearity in the relationship, business model, proxied by the ratio of deposits to total assets (Dep/TA) and the weight of gross loans to total assets (GL/TA). When measuring performance with ROE we also control for capitalization, measured by equity to total assets (E/TA);

- $Y_{i,t}$ includes a list of control variables describing the economic and market conditions of the country where the bank *i* is headquartered at time *t*, including GDP growth (GDP_g) and the level of interest rate, proxied by the interest rate on long-term sovereign debt (y10bond). Additionally, in a further specification of the model, we control for those countries experiencing a severe banking crisis in the years following the burst of the financial crisis (i.e. Italy, Spain, Portugal and Ireland - ISPI). When the dependent variable is a stock market measure, we control also for the domestic stock market returns (r_mkt);
- α, β, γ and δ are the coefficients;
- ε is the robust error.

For more details on the variables employed, see Table 3.

To test the relationship between board characteristics and performance we employ a panel regression with random effects and robust standard errors on our sample for the period 2014-2016. While the dummy 'Cluster' refers to 2014 and does not change, all the other variables refer to the three-years period ending in 2016. This choice is consistent with the fact that the effect of corporate governance on performance may not materialize in one year and it is a well-established approach in the relevant empirical literature (Grove et al., 2011; Beltratti & Stulz, 2012). Besides, introducing a time lag between the 'Cluster' variables, on the one hand, and performance and controls variables, on the other, is useful in addressing possible endogeneity issues - and more precisely reverse causality - that may arise when exploring the relationship between board structure and performance.

Indeed, the governance-performance relationship is fraught with endogeneity issues. As reported in a number of studies (among others, Hermalin and Weisbach, 2003; Schultz et al., 2010) these can be classified into three main types: simultaneity (or reverse causality), concerning the direction of the relationship and the possibility that governance might be simultaneously determined with performance; unobserved heterogeneity, i.e. the possibility that both governance and performance are driven by a third unobservable factor, and dynamic endogeneity, that arises as a consequence of past performance shaping the current governance setting and also the current performance.

As a partial solution for the unobserved heterogeneity and in line with previous studies (Arnaboldi et al. 2018; Fan et al, 2019; Sheikh et al., 2018) we include in the regressions bank-specific controls (e.g. size and business model proxies) and country features (i.e. macroeconomic and market conditions). This set of controls allows to account for unobserved firm- and country-specific characteristics that could influence the relationship between performance and governance. Additionally, we control for a high number of governance features to reduce the omitted variable bias at least in relation to board governance characteristics.

In fact, in contrast to other empirical analyses (Anginer et al., 2018; Fan et al., 2019), we cannot address potential endogeneity using a general panel regression with fixed effect. This is because the independent variables of interest –i.e. those related to the 'governance clusters' - are represented by time invariant dummies[4]. This characteristic also prevents us from applying dynamic GMM, i.e. a methodology that is increasingly exploited in the governance empirical literature (Campbell and Minguez-Vera, 2010; Capezio et al., 2011; Garcia Martin and Herrero, 2018; Schultz et al., 2010; Sheikh et al., 2018; Wintoki et al., 2012)[5]. Both difference and system GMM, in fact, remove the fixed effects within a panel when the equations to be estimated are differenced.

<< Table 3 goes approximately here>>

4. Results

4.1. Bank clusters and proximity to the 'suitability rules'

By employing the SOMs we classify the banks of our sample into four different groups (Figure 4). We have explored the features of the board 'model' adopted by each cluster using two types of analyses: a visual analysis, based on the so called component maps that make possible the visualization of the contribution of each variable for the different clusters and the DNA Analysis, and a more traditional analysis based on the descriptive statistics of each cluster (Table 4).

<< Table 4 goes approximately here>>

The features of the four clusters are briefly described as follows.

Cluster #1: "*highly diversified, skilled, independent and committed*". This cluster includes 8 banks mainly based in Spain and UK and mainly adopting a one-tier governance model. The boards of these institutions have a smaller size than sample average and are characterized by the highest gender diversity and the highest percentage of independent directors – in line with a low presence of executive directors – as well as by a high presence of foreign directors. Despite the small size of the board, concentration of power among directors – proxied by the number of directors who chair a

[4] Cluster dummies are generated by SOMs based on governance characteristics as recorded at the end of 2014. The SOM, in its standard configuration, is not suitable to track changes in governance features over time. We could, in fact, apply SOMs algorithm to data related to other years, but each application would generate new clusters that are not strictly comparable with those of previous/following years in terms of number of clusters and governance features. In a future perspective applying the T-SOM algorithm of Sarlin et al. (2012) might add some insight for a dynamic understanding of the governance features.

[5]Another approach that is seldom used in the governance-performance literature is IV-regression. However, similarly to other studies, we could not find one (or more) suitable instrumental variable(s), considering all the board features already included in our analysis (see discussion by Aebi et al., 2012).

board committee over the total number of directors – is lower than for the other clusters. Besides, the time commitment of board members is very high.

In terms of educational background – proxied by the type of bachelor degree -, directors in this cluster are the most qualified – i.e. we find the smallest percentage of members without a university degree and the highest percentage holding a post degree– and also the most diversified, with a significant percentage of members holding degrees in law and quantitative studies (e.g. STEM degrees, i.e. Statistics, Engineering and Physics, Mathematics), besides those with a background in economics and/or management. 1 out of 4 directors has (gained) a professional experience as a legal/fiscal/strategic advisor/consultant; 94% of them have worked in other financial institutions, thus accruing significant skills in banking and finance (B&F score above sample average).

Cluster #2: "*small, international, skilled but not enough independent*". The board of these 10 banks is characterized on average by the lowest number of directors, among which non-executives represent the highest percentage in comparison to the other clusters. But at the same time the board has the lowest participation of independent directors. Nearly 1 out of 4 directors is a woman (more than the sample average) and 1 out of 3 is foreign, and their members are the youngest on average (57 years old) but with the highest age diversity. Despite directors tend to have a relatively higher number of other mandates/offices in other management bodies, the time committed to the bank is slightly higher than the overall average. The percentage of directors who are more directly involved in the board committees' activity is lower than in the other clusters, suggesting that power is more concentrated: this may be due to low presence of independent directors and/or to the smaller size of the board.

The vast majority of board members (85%) are or have been a manager or an executive and has accrued an extensive experience in the banking and financial sector, as shown by the highest level of the B&F score. Moreover, almost 90% of directors have previously had a professional relationship with the same bank or group where they now sit. Their educational background is concentrated on economics, management and/or accounting studies and to a lesser extent on law and/or political sciences, while a very small minority have a quantitative background. Finally, despite this group of banks has the highest incidence of directors without a university degree, more than one third has attained also a post-degree diploma and a percentage higher than the sample average has studied abroad.

Cluster #3: "*large, less skilled, older and busy*" This cluster includes 13 banks mainly located in Italy and Spain. This cluster is the most diversified in terms of governance model (46% one-tier, 23% two-tier and 31% other models). The average number of board members is the largest in our sample, diversification is very low and the presence of executive/non-independent member rather high. Besides, power tends to be concentrated in the hands of few members who chair the committees. On average directors are older than their peers in the other clusters and half of them have an educational background in economics and/or management with a minority that have a curriculum in STEM or law. Directors have a diversified professional background that goes from manager to academic position to entrepreneur; 30% of them are professional independent directors and this may also explain why the average number of other mandates is the highest in our sample. However, skills and competences in Banking and Finance are the lowest.

Cluster #4: "*scarcely diversified, less committed and independent*". The last cluster includes 9 banks mainly located in Germany and Italy. These banks are characterized by management bodies that alike the previous cluster are quite numerous – probably due to the prevalence of a two-tier governance model - but scarcely diversified in terms of gender and nationality and with a higher percentage of executives and/or non-independent directors. Participation of directors to board meetings is the lowest one, despite directors do not have many other offices compared to sample mean. Educational background is focussed on economics and/or management despite a relevant component of the board has attained a degree in law and only a very small part of the board has completed post-degree studies or studied abroad. The professional background of board directors is rather diverse although most members are or have been manager, board director and consultant/advisor. Competence in banking and finance is lower than for the previous clusters, although a third of the board has accrued a previous experience in the same bank.

Overall, we find that large European banks are rather heterogeneous in terms of board quality and composition and that they are variously closer to the new board paradigm. To gauge the relative degree of suitability of the four clusters we have computed a Suitability Score (Table 5) as follows:

- To each feature of each board profile[6] we have assigned a score from 1 (i.e. worse) to 4 (i.e best) according to the "suitability rules".
- For *competence*, the higher the percentage or the level of directors holding a feature, the higher the score.
- For *diversity*, demographic diversity is desirable and hence the higher the diversity, the higher the score, e.g. when evaluating the feature "gender diversity" the higher the percentage of

[6] The Suitability Score does not include the features related to the profile 'Structure', i.e. the governance model adopted by the bank, the size of the board and the rate of turn-over of director in the last 4 years, because there is not an a priori relationship between these attributes and performance and risk.

women sitting in the board, the higher the assigned score. With reference to diversity in educational background and professional experience, the features are interpreted as "more diverse" (and desirable) when there is greater heterogeneity. Hence, the higher the heterogeneity in the board, the higher the score assigned. Heterogeneity in these two cases is proxied by the Blau Index, that is computed $B = 1 - \sum_{i=1}^{k} {p_i}^2$, where p is the percentage of directors in a given category, and k the total number of categories. The Blau Index varies between 0 and $(k–1)/k$, where 0 stands for maximum concentration (or minimum heterogeneity) and the maximum value, indicates maximum diversity. In the case of educational diversity, the maximum value for the Blau is 0.75 (four categories) and in the case of professional background it is 0.8 (five categories).

- With regards to the feature *independence and balance of power*, following the indication given by the regulatory framework, the higher the percentage of executives and the higher the power concentration, the lower the score. While the higher the presence of independent directors, the higher is the score.
- Finally, *time commitment* features are represented by the presence at meetings and the number of other offices held. The higher the first element, the higher the score. On the contrary, the higher is the number of other offices held, the lower the score because it implies (ideally) that directors have less time to dedicate to the bank.
- To get a final *suitability score*, all the single scores are summed (Table 5). The maximum score achievable by a cluster (and a bank) is 72 (4 points for each of the 18 features). The lowest is 18 (1 point for each of the 18 features).

<< Table 5 goes approximately here>>

The Suitability Score confirms the intuitions emerged from the previous analysis and shows that banks in Cluster #1 and Cluster #2 are the most suitable ones. Indeed, Clusters #1 shows on average the strongest competence, the highest independence and the highest time-commitment, whereas Cluster #2 shows the highest diversity and the largest presence of foreign directors, despite being the less independent and with a higher concentration of power.

The board of directors of the banks in Cluster #3 and #4 appear less 'suitable' and further away from the new board regulatory paradigm. Nonetheless, also for the most suitable clusters we find room for improvement in terms of collective suitability; as an example, the highest average percentage of women on the board is 26%, which is a rather low percentage, even lower than the gender quota imposed by the French and Italian law.

4.2. Board suitability and bank performance

The new regulatory paradigm builds on the assumption that a better governance (more skilled directors and a more diversified and committed board) is able to better control and monitor management, thus yielding the bank to better performance and risk management. Despite the inconclusive results of the literature on the impact of single board characteristics on performance, the literature generally agrees that overall good governance – variously measured and proxied – indeed should be able to produce value creation.

Results of the panel regressions shed some light on the relationship between board suitability and performance, risk and risk-adjusted performances. In detail, the estimations of the model where the dependent variable is ROA, ROE or stock return (Table 6-Panel A) show that board suitability influence bank performance: coefficients of the dummies Cluster #1 and Cluster #2 - the most suitable boards according to regulatory provisions - have a positive sign and are statistically significant. This confirms that board quality and, more precisely, collective suitability has a positive influence on the management of banks, that ultimately achieve better performance. As a rough idea of the effect of good governance, banks in cluster #1, i.e. with the highest suitability score, yield on average a ROA that is 0.7-0.8% higher than banks with the less suitable boards, i.e. cluster #4 (sample mean equal to 0.18%) and a ROE that is 8.6-9.4% higher (sample mean equal to 2.34%). This evidence suggests that the new 'suitability rules' enhance the shareholders' value creation.

With reference to bank specific control variables, we find a negative sign for one of the proxies of the business model (GL/TA) suggesting that banks focussing on traditional credit intermediation achieve poorer performance. Among country-specific variables, the most evident result concerns the location of banks in countries that experienced a severe banking crisis and the high level of sovereign interest rate that is a proxy of high country risk and of the negative macroeconomic context. Finally, not surprisingly, bank stock returns are mainly influenced by market returns[7].

The significance of the models appears quite high, with linear regressions explaining around 25 to 31% of the data. Additionally, in unreported statistics, the chi-squared statistics confirm the validity of the overall models.

<< Table 6 goes approximately here>>

[7] As noted by Hermalin and Weisbach (1998), differently from earning measure, stock returns are more influenced by investors expectations rather than by the actual/recent bank situation. This may explain why the stock-market performance is less influenced than ROA and ROE by the governance cluster.

When looking at the board ability to control and limit risk, results are less straightforward and vary depending on which proxy of risk is used (Table 6-Panel B). When, we focus on credit risk – proxied by non-performing loans to gross loans (NPL/G)– both the dummies for Cluster#1 and #2 are negative and significant, suggesting that more suitable boards of directors can better manage and control risk. But if we look at a more general measure of bank risk, i.e. Risk-weighted assets to total assets (RWA/TA), results are less meaningful.

Control variables show signs that are consistent with the expected relation. Size shows a negative sign while size^2 shows a positive sign, hinting that larger banks can diversify risk, but the marginal beneficial effect of diversification decreases after a certain size threshold. As expected, a higher weight of gross loans increases risk, and especially credit risk. The positive sign of interest rate on sovereign bonds may be explained by a higher riskiness of the country where the bank is located that in turn influence bank riskiness. Finally, in line with our expectations, banks located in countries more severely hit by the economic crisis (ISPI) present a larger amount of risks.

With reference to market risk, measured by the standard deviation of returns, again Cluster #2 appears to have lower risk, although, in general, investors seem to attach more importance to macroeconomic variables.

Overall, these findings are consistent with the existence of the deposit guarantee scheme, that might represent an incentive to take on more risk in the interests of shareholders (Beltratti and Stulz (2009). On the other hand, poor-quality boards may allow executives to take less risks to protect their benefits from control.

Finally, when considering risk-adjusted performance measures based on financial statements items (RoRWA and RoTRC) we observe that – again – the two clusters with the most suitable board features (Cluster #1 and Cluster #2), are the ones achieving better performance per unit of risk (Table 6-Panel C). The same holds for the adjusted market-return, but only for Cluster #1. With reference to control variables, size contributes positively to return on risky assets up to a certain point when the positive effect is milder (size squared is negative) and disappears when controlling for ISPI countries. On the other hand, as expected risk-adjusted performances are lower the higher the interest rate on sovereign bonds that increase the riskiness of the context where banks operate, and is also lower the higher the involvement of banks in the credit intermediation business. Additionally, domestic market returns play a key role and positively affects banks risk-adjusted performance.

5. Alternative specifications

To tackle the potential endogeneity concerns, we perform two additional empirical analyses. First, to address potential reverse causality issues we restrict the period of the panel analysis to 2015-2016 and hold the cluster dummies fixed at 2014 (Table 7). Results overall confirm that banks in clusters that are more in line with the regulatory paradigm, i.e. more suitable boards, enjoy better performance both in terms of operating performance, risk management and risk-adjusted performance

<< Table 7 goes approximately here>>

Second, in line with previous work (Grove et al 2011), we perform cross-sectional regressions using as dependent variable the average performance for the years 2014- 2016 or, alternatively, for the years 2015- 2016, and independent and control variables constant as at the end 2014 (Table 8). In this way we reduce the time trend of the dependent variable and we try to curb dynamic endogeneity (Beltratti and Stulz, 2012). Results confirm that in most of the specifications tested, governance suitability provides the expected results on performance (i.e. more suitable boards of Cluster#1 and #2 have higher performance and risk-adjusted performance and lower risk). Control variables, however show lower statistical significance than in the panel regression.

<< Tables 8 and 9 go approximately here>>

6. Conclusions

Our study contributes to the scarce stream of empirical studies on the relation between board characteristics and performance in the European banking context. The analysis covers the period 2014-2016 thus considering the reinforcement of the regulatory design of governance mechanisms, started right after the burst of the international financial crisis and culminating in the issuance of the CRD4 Directive in 2013. In this new regulatory context, a new board governance paradigm has emerged and board suitability has become a very important prerequisite of (good) governance.

As a first contribution our study provides an evaluation of the degree of suitability of the boards in charge at the end 2014 with reference to a sample of 40 large listed European banks. By using Self-Organising Maps (SOMs) – a machine learning methodology which allows for a comprehensive and inductive analysis of the relationships between board features and is innovative in studies on governance – we have analysed jointly (i.e. at the board level) the different characteristics/profiles of the boards and obtained four clusters of banks that have been ranked in terms of proximity to the 'suitability rules'. Our results overall indicate that at the end of 2014 two groups of banks have more suitable boards, i.e. they are closer to board regulatory prescriptions. The first group is characterised as having boards that are "*highly diversified, skilled, independent and committed*", while the second group has "*small, international, skilled but not enough independent"* boards. The vast majority of the banks that belongs to these two groups adopt a one-tier governance model. The other two clusters present less suitable management bodies and therefore room for improvements, especially in terms of competence and diversity. Nonetheless, according to our results, even the "most suitable" clusters of banks may reach higher level of suitability by improving specific attributes, such as gender diversity and balance of power.

As a second contribution, we provide new evidence on the relationship between board features and performance. We extend the traditional approach by looking also at various configurations of risk and risk-adjusted performances. Our results support the hypotheses that a higher degree of suitability of the board of directors positively affects bank economic and financial performance and risk-adjusted performance, and, to a lesser extent, also the ability to control risks.

Overall our results suggest that right after the issuance of the new governance paradigm, a number of European banks were closer than others to the suitability standards set by regulators. Our evidence on the positive relationship between individual and collective board suitability and performance represents, on the one hand, an incentive for banks to further improve their board attributes and, on the other hand, confirms that regulation is going in the right direction, thereby enhancing effective and prudent management.

References

Adams, R. B., Akyol, A. C., & Verwijmeren, P. (2018). Director skill sets. Journal of Financial Economics, 130(3), 641-662.

Adams, R. B. (2010). Governance of banking institutions. Corporate Governance: A Synthesis of Theory, Research, and Practice, 451-467.

Adams, R. B., & Ferreira, D. (2009). Women in the boardroom and their impact on governance and performance. Journal of financial economics, 94(2), 291-309.

Adams, R. B., Akyol, A. C., & Verwijmeren, P. (2018). Director skill sets. Journal of Financial Economics, 130(3), 641-662.

Aebi, V., Sabato, G., & Schmid, M. (2012). Risk management, corporate governance, and bank performance in the financial crisis. Journal of Banking & Finance, 36(12), 3213-3226.

Anginer, D., Demirguc-Kunt, A., Huizinga, H., Ma, K. (2018) Corporate governance of banks and financial stability. Journal of Financial Economics, 130, 327–346.

Arnaboldi, F., Casu, B., Kalotychou, E., & Sarkisyan, A. (2018). The performance effects of board heterogeneity: what works for EU banks?. The European Journal of Finance, 1-28.

Avigdor, A., Braun, D., Konkin, J., Kuzmycz, D., & Ferdman, B. M. (2007). Workgroup inclusion, diversity, and performance. In Annual Meeting of the Academy of Management. Philadelphia.

Bantel, K. A., & Jackson, S. E. (1989). Top management and innovations in banking: does the composition of the top team make a difference? Strategic management journal, 10(S1), 107-124.

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

Bøhren Ø. & Strøm R.Ø. (2010). Governance and Politics: Regulating Independence and Diversity in the Board Room. Journal of Business Finance and Accounting, 37(9-10), 1281-1308.

Campbell, K., Vera, A.M. (2010). Female board appointments and firm valuation: Short and long-term effects. Journal of Management and Governance, 14(1), 37-59.

Capezio, A., Shields, J., O'Donnell, M. (2011). Too Good to be True: Board Structural Independence as a Moderator of CEO Pay-for-Firm-Performance. Journal of Management Studies, 48(3), 487-513

Carter, D. A., Simkins, B. J., & Simpson, W. G. (2003). Corporate governance, board diversity, and firm value. Financial review, 38(1), 33-53.

De Haan, J., & Vlahu, R. (2016). Corporate governance of banks: A survey. Journal of Economic Surveys, 30(2), 228-277.

EBA-ESMA (2017) Guidelines on the Assessment of Suitability of Members of the Management Body and Key Function Holders, EBA-GI-2017-12.

ECB (2018) Guide to fit and proper assessments - Updated in May 2018 in line with the joint ESMA and EBA Guidelines on suitability.

Ellul, A. and Yerramilli, V. (2013). Stronger Risk Controls, Lower Risk Evidence from U.S. Bank Holding Companies. The Journal of Finance, 68, 1757-1803.

Fan, Y., Boateng, A., King, T., MacRae, C. (2019). Board-CEO friendship ties and firm value: Evidence from US firms. International Review of Financial Analysis, https://doi.org/10.1016/j.irfa.2019.101373

Erkens, D. H., Hung, M., & Matos, P. (2012). Corporate governance in the 2007–2008 financial crisis: Evidence from financial institutions worldwide. Journal of corporate finance, 18(2), 389-411.

Faleye, O., Hoitash, R., & Hoitash, U. (2018). Industry expertise on corporate boards. Review of Quantitative Finance and Accounting, 50(2), 441-479.

Farrell, K. A., & Hersch, P. L. (2005). Additions to corporate boards: the effect of gender. Journal of Corporate finance, 11(1-2), 85-106.

Fernandes, C., Farinha, J., Martins, F. V., & Mateus, C. (2017). Supervisory boards, financial crisis and bank performance: do board characteristics matter?. Journal of Banking Regulation, 18(4), 310-337.

García Martín, C.J., & Herrero, B. (2018). Boards of directors: composition and effects on the performance of the firm, Economic Research-Ekonomska Istraživanja, 31(1), 1015-1041, DOI: 10.1080/1331677X.2018.1436454

Hardwick, P., Adams, M., & Zou, H. (2011). Board characteristics and profit efficiency in the United Kingdom life insurance industry. Journal of Business Finance & Accounting, 38(7-8), 987-1015.

Hermalin, B., Weisbach, M. (2003). Board of directors as an endogenously-determined institution: A survey of the economic literature. Economic Policy Review, 9, 7–26.

John, K., De Masi, S., & Paci, A. (2016). Corporate governance in banks. Corporate Governance: An International Review, 24(3), 303-321.

Kohonen T. (1982) Self-organized formation of topologically correct feature maps. Biological Cybernetics 43, 59–69.

Locatelli, R., Schena, C., Tanda, A., & Uselli, A. (2018). Diversity measures and quality of banks' boards: the Italian case. Journal of Financial Management, Markets and Institutions, 6(2), 1850009.

Lopez-Rubio E., Palomo E.J. & Dominguez E. (2014) Bregman divergences for growing hierarchical self-organizing networks. International Journal on Neural Systems **24**, 1450016.

Mehran, H., Morrison, A. D., & Shapiro, J. D. (2011). Corporate governance and banks: What have we learned from the financial crisis?. FRB of New York Staff Report, (502).

Minton, B., Taillard, J., & Williamson, R. (2010). Board composition, risk taking and value: Evidence from financial firms. SSRN Electronic Journal.

Mishra, C. S., & Nielsen, J. F. (2000). Board independence and compensation policies in large bank holding companies. Financial Management, 51-69.

Nguyen D.D.L., Hagendorff J., & Eshraghi A. (2015), Which Executive Characteristics create Value in Banking? Evidence from Appointment Announcements, in Corporate Governance: An International Review, n. 23(2), pp. 112-128.

Payne, G. T., Benson, G. S., & Finegold, D. L. (2009). Corporate board attributes, team effectiveness and financial performance. Journal of Management Studies, 46(4), 704-731.

Richard, O. C. (2000). Racial diversity, business strategy, and firm performance: A resource-based view. Academy of management journal, 43(2), 164-177.

Schultz, E. L., Tan, D. T., & Walsh, K. D. (2010). Endogeneity and the corporate governance-performance relation. Australian journal of Management, 35(2), 145-163.

Sheikh, M.F., Shah, S.Z.A., Akbar, S. (2018). Firm performance, corporate governance and executive compensation in Pakistan. Applied Economics, 50(18), 2012-2027.

Somers, M. J., & Casal, J. (2017). Introducing Neural Computing in Governance Research: Applying Self-Organizing Maps to Configurational Studies. Corporate Governance: An International Review, 25(6), 440-453.

Srivastav, A., & Hagendorff, J. (2016). Corporate governance and bank risk-taking. Corporate Governance: An International Review, 24(3), 334-345.

Ultsch A., Siemon H.P., (1990). Kohonen's self-organizing feature maps for exploratory data analysis, in *Proceedings of the International Neural Networks,* Kluwer Academic Press, 305–308.

Willshaw D J & von der Malsburg C. (1976) How patterned neural connections can be set up by self-organization. Proceedings of the Royal Society, London, Series B **194**, 431–445.

Willshaw D J & von der Malsburg C. (1979) A marker induction mechanism for the establishment of ordered neural mappings: its application to the retinotectal problem. Philosophical Transactions of the Royal Society, London, Series B 287, 203–243.

Figures

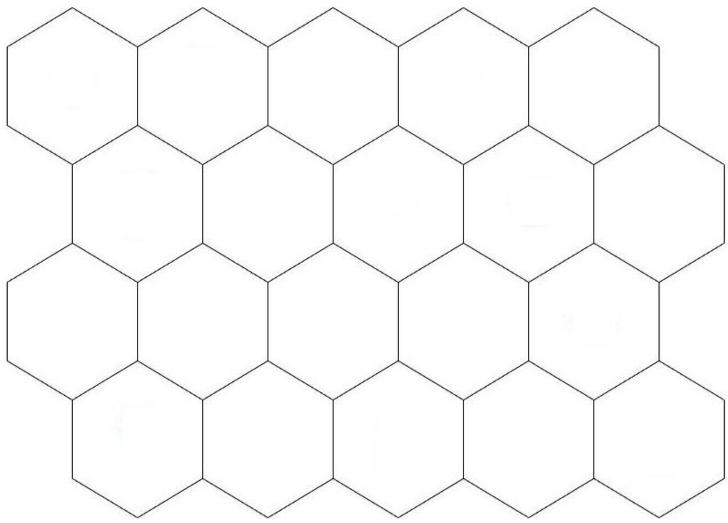

Figure 1. A SOM with rectangular shape

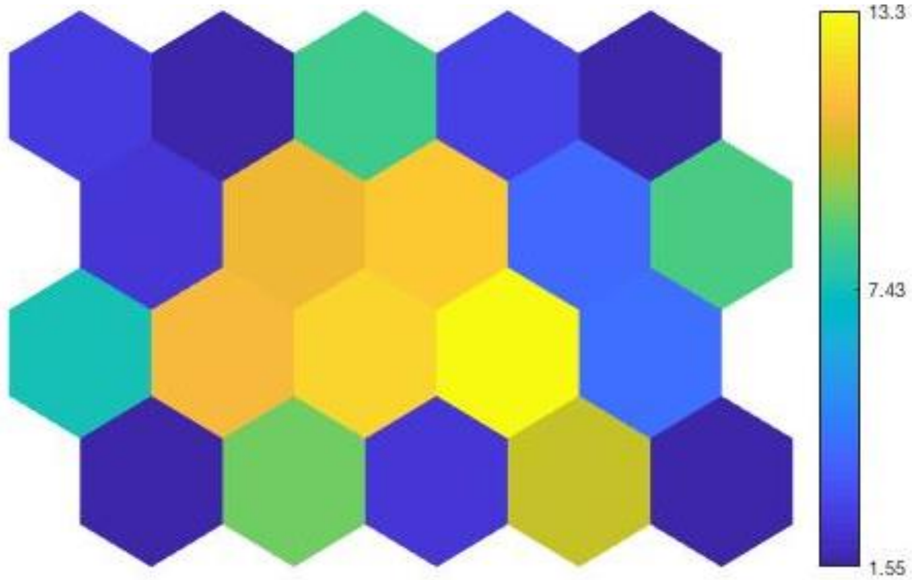

Figure 2. An example of U-Matrix

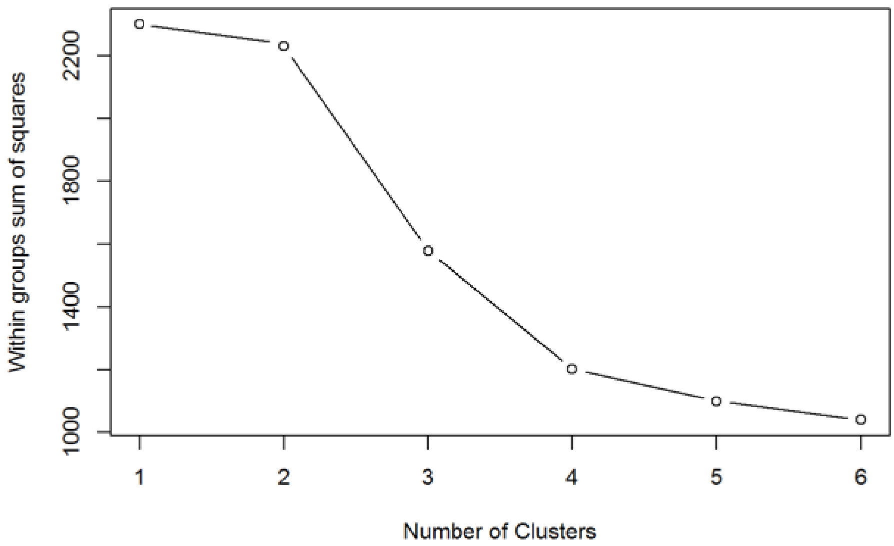

Figure 3. Elbow criterion to define the number of clusters

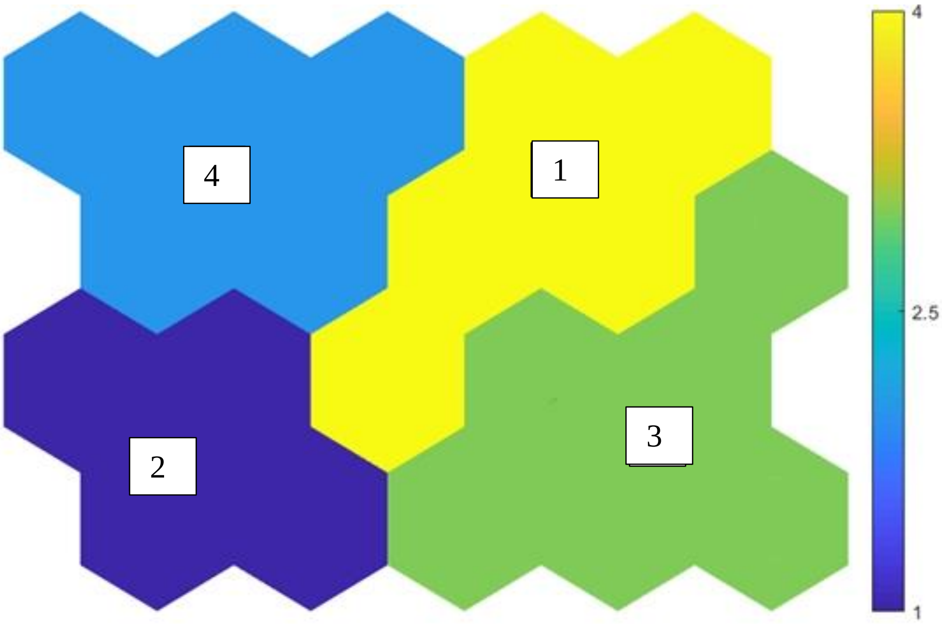

Figure 4. Clusters in the SOM map

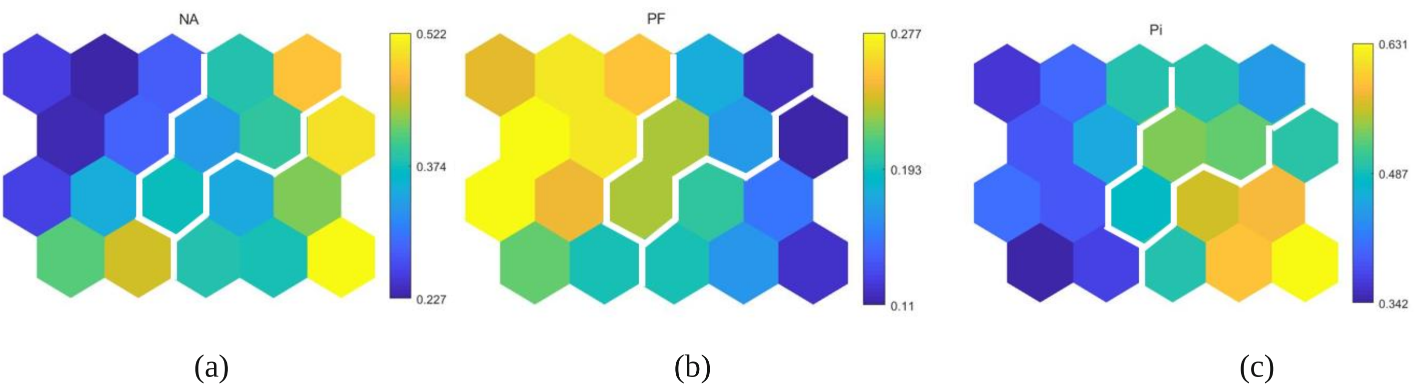

Figure 5. Examples of components maps.

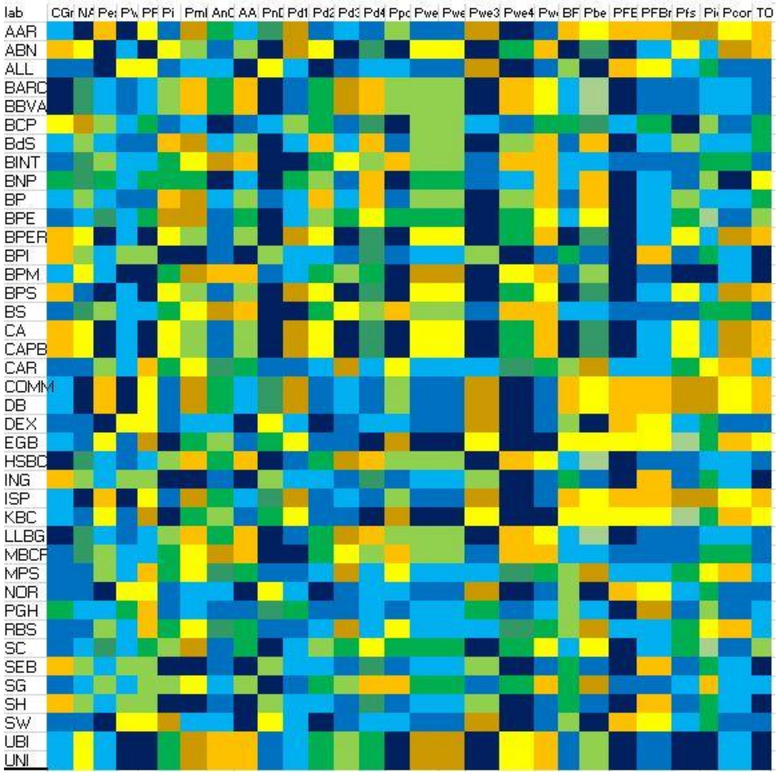

Figure 6. DNA matrix for the examined sample.

Tables

Table 1: List of banks in the sample

Country	Number of banks	Total assets per country (million euros)
Austria	1	196,287
Belgium	2	492,294
France	3	4,974,940
Germany	3	2,316,577
Ireland	2	143,748
Italy	10	2,168,747
Netherlands	2	1,379,723
Portugal	2	118,990
Spain	6	2,618,997
Sweden	4	1,476,242
UK	5	6,961,593
Total	**40**	**22,848,138**

Table 2: List of variables for the analysis of board governance

Variable name	*Variable definition*
	DIVERSITY
Demographic Diversity	
% WOMEN	Percentage of women
% FOREIGN	Percentage of foreign directors
CV Age	Coefficient of Variation of board members' age, computed as the standard deviation of directors age of each board divided by the average age of the board
Diversity in education	
% BUSINESS & ECO	Percentage of directors with a degree in Economics, Management, Business, Administration, etc
% LAW	Percentage of directors with a degree in Law or Political science
% STEM	Percentage of directors with a degree in quantitative disciplines (Mathematics, Engineering, Statistics, Physics)
% OTHER DEGREE	Percentage of directors with a degree in other disciplines
Diversity in work experience	
% ACADEMICS	Percentage of directors with experience as a university professor/academic
% CONSULT	Percentage of directors with experience as a legal/fiscal/strategic consultant
% MANAGER	Percentage of directors with experience as a manager, director, executive
% ENTREPR	Percentage of directors with experience as an entrepreneur
% OTHER EXP	Percentage of directors with other work experience
	COMPETENCE
Education	
% DEGREE	Percentage of directors holding a bachelor degree
% POST DEGREE	Percentage of directors with a post graduate degree
% FOR STUDIES	Percentage of directors that have studied abroad
Work competences	
% INT EXP	Percentage of directors with international experience
BF SCORE	Banking and Finance Score expressing the number of different roles in which the director obtained knowledge on banking and finance issues. It is computed as follows: for each director we record if he/she has at least one experience in a bank or other financial institution as manager, director, consultant, professor/academic, or in the same bank. If the director has at least one experience in a given category, we assign 1 point. If he/she has experiences in all the categories, the score is 5, the maximum achievable. Score at board level is obtained by averaging all the BF Scores obtained for the single directors.
% BOARD	Percentage of directors that have one or more experiences in other boards
% BANK	Percentage of directors that have one or more experiences in banking and finance board of directors
% SAME	Percentage of directors that have one or more professional experiences in the same bank in any role (manager, director, etc.) that can increase knowledge of the specific bank environment
	TIME COMMITMENT
PRESENCE	Percentage of meetings attended by directors

OTHER OFFICES	Average number of other offices held by the directors in other boards or supervisory bodies
INDEPENDENCE & BALANCE OF POWERS	
% EX	Percentage of executive directors
% INDEP	Percentage of independent directors
POWER CONC	It is a measure of concentration of power in the board. It is computed as =1-(number of directors in committees /number of directors in the board)
STRUCTURE	
CG MODEL	One-tier, Two-tier, Other board governance model
N DIR	Number of directors
TURNOVER	Past turnover of members from 2010 to 2014

Table 3: List of variables for the analysis of the performance-governance relationship

Variable name	*Variable definition*
DEPENDENT VARIABLES (*PERF*)	
Return	
ROA	Return on average assets
ROE	Return on average equity
r_i	Annualized stock return of firm i
Risk	
RWA/TA	Risk weighted assets/total assets
NPL/GL	Non-performing loans/gross loans
sd_i	Annualized standard deviation of stock returns for firm i
Risk-adjusted performance	
RoRWA	Return on risk weighted assets (net income/RWAs)
RoTRC	Return on total regulatory capital (net income/TRC)
r_i/sd_i	Annualized returns over annualised standard deviation for firm i
EXPLANATORY VARIABLES	
Cluster1	A dummy variable equal to 1 if the bank pertains to cluster 1 and 0 otherwise
Cluster2	A dummy variable equal to 1 if the bank pertains to cluster 2 and 0 otherwise
Cluster3	A dummy variable equal to 1 if the bank pertains to cluster 3 and 0 otherwise
Cluster4	A dummy variable equal to 1 if the bank pertains to cluster 4 and 0 otherwise (omitted from regressions)
Control variables and Other variables	
Size	Natural log of total assets
Size2	(Natural log of total assets) squared
gl_ta	Gross Loans/total assets
dep_ta	Deposits and short term funding/total assets
e_ta	Equity/total assets
gdp_g	GDP growth rate
Y10bond	Yield on 10-year maturity government bond
r_mkt	Annualized index returns of the domestic stock market of firm i
ISPI	Dummy for banks headquartered in Italy, Spain, Portugal, Ireland

Table 4: Sample means for the full sample and for the Suitability Clusters

CLUSTER PROFILE	1	2	3	4	FULL SAMPLE
COMPETENCE					
% DEGREE	98.9	79.2	95.2	94.2	91.7
% POST DEGREE	40.7	36.4	37.7	32.6	36.8
% FOR STUDIES	23.7	24.6	20.9	16.9	21.5
% INT EXP	47.6	45.4	35.3	40.9	41.6
BF SCORE	1.992	2.137	1.486	1.698	1.798
% BANK	94.4	99.5	87.8	92	93
% BOARD	95	93.1	93.3	94.5	93.8
% SAME	6.3	91.2	12.5	30.6	35
DIVERSITY					
% WOMEN	25.9	24.2	20.2	20.3	22.4
% FOREIGN	21.5	31.2	11.7	15.9	19.5
CV AGE	0.046	0.057	0.045	0.051	0.057
DEGREE					
% BUSINESS & ECO	43.9	53.6	52.9	55.5	51.9
% LAW	24.6	12.4	19.4	23.2	19.5
% STEM	16.5	8.7	15.9	7.1	12.3
% OTHER DEGREE	13.9	4.5	7	8.3	8
PROFESSIONAL EXPERIENCE					
% ACADEMICS	7.5	1.8	14.8	10.9	9.2
% CONSULT	25.2	7.7	23.3	22.4	19.6
% MANAGER	11.6	85.3	18.7	42.3	39.2
% ENTREPR	8	0	13	0.5	5.9
% OTHER EXPERIENCE	47	5.2	30.3	23.2	25.8
INDEPENDENCE & BALANCE OF POWERS					
% EX	21.1	18.3	21.4	24	21.1
% INDEP	61.6	44.8	47.6	47.3	49.8
POWER CONC	24.1	28.4	28.3	25.1	26.8
TIME COMMITMENT					
PRESENCE (%)	96.5	95.99	95.56	91.45	95.06
OTHER OFFICES	2.88	3.88	4.6	1.92	3.47
STRUCTURE					
CG MODEL PREVAILING	One-tier	One-tier	One-tier or other	Two-tier	One-tier
N DIR	15	13	21.15	20.56	17.75
TURNOVER	44.1	53.4	53.6	56.7	52.4
SIZE (TOTAL ASSETS IN TH EUROS)	8,348,486	2,978,956	6,546,855	4,973,841	22,848,138
N OF BANKS	8	10	13	9	40

Table 5: Suitability Score

CLUSTER / PROFILE	1	2	3	4	*MAX SCORE*
COMPETENCE (8 FEATURES)	23	19	14	14	*32*
DIVERSITY (5 FEATURES)	15	15	9	10	*20*
INDEPENDENCE & BALANCE OF POWERS (3 FEATURES)	11	6	6	7	*12*
TIME COMMITMENT (2 FEATURES)	7	5	3	5	*8*
TOTAL SCORE	**56**	**45**	**32**	**36**	***72***

We assign a score from 1 (worse) to 4 (best) to each feature of each profile and we sum them. The scores are assigned according to the new regulatory governance paradigm, e.g. for gender diversity: the higher the percentage of women in the board, the higher the score. With reference to educational and professional background we have computed the Blau index as a proxy of diversity and the higher the Blau index, the higher the score assigned.

Table 6: Results of the panel regressions. Sample period 2014-2016

*The regressions estimate the relation between financial and market performance/risk/risk-adjusted performance and governance clusters over the period 2014-2016. Cluster dummies are held constant at 2014. The sample includes 40 large listed European banks. Detailed definitions of the variables are provided in Table 3. *, **, *** indicate respectively 10, 5 and 1% significance levels.*

Panel A: Financial and market performance

Variable	***ROA***				***ROE***				***Stock returns***			
	A		B		C		D		E		F	
Cluster1	0.744	***	0.756	***	8.626	*	9.436	*	29.765	*	34.670	*
Cluster2	0.658	***	0.653	***	13.672	***	12.143	***	27.834		23.128	
Cluster3	0.204		0.217		5.764		7.437		20.516		25.866	
Size	3.798		3.742		36.037		26.294		55.122		34.012	
Size^2	-0.103	*	-0.101		-0.950		-0.702		-1.420		-0.915	
GL/TA	-0.020	**	-1.930	**	-0.301	*	-0.149		-0.473		-0.072	
DEP/TA	0.005		0.489		-0.028		-0.023		0.157		0.225	
E/TA					2.553		3.244	*				
GDP_g	-0.012		-0.012		-0.390	*	-0.310		-4.143	**	-3.742	**
y10bond	-0.157	**	-0.150	*	-3.911	**	-2.391		3.106		7.963	*
ISPI			-0.060				-10.397	***			-27.788	*
r_mkt									2.132	***	2.070	***
Constant	-33.829		-33.301		-334.698		-250.954		-544.373		-349.273	
Number of banks	40		40		40		40		40		40	
R2 overall	0.253		0.253		0.283		0.312		0.260		0.284	

Panel B: Risk

Variable	***RWA/TA***				***NPL/GL***				***sd_i***			
	G		H		I		L		M		N	
Cluster1	7.575		4.781		-5.673	*	-7.846	**	-10.409	*	-10.280	*
Cluster2	-8.767	*	-8.238	*	-6.819	*	-6.219	**	4.421		1.985	
Cluster3	2.961		0.337		1.474		-0.639		-6.995		-6.390	
Size	-102.024	***	-98.352	**	-46.896	**	-44.082	***	6.201		-1.111	
Size^2	2.511	**	2.452	**	1.215	**	1.169	***	-0.158		0.031	
GL/TA	0.343	**	0.271		0.236	***	0.202	***	0.025		0.094	
DEP/TA	-0.035		-0.036		-0.013		-0.032		0.001		-0.038	
GDP_g	0.069		0.045		-0.044		-0.056	**	0.463		1.102	**
y10bond	1.602	***	1.343	**	0.926	***	0.781	***	5.337	**	8.396	*
sd_mkt									2.196	**	2.617	***
ISPI			9.183	*			7.076	**			-7.589	
Constant	1050.082	***	1002.700	***	446.763	**	410.340	**	-73.585		-15.926	
Number of banks	39		39		39		39		40		40	
R2 overall	0.506		0.580		0.540		0.610		0.356		0.381	

Panel C: Risk-adjusted performance

Variable	RoRWA				RoTRC				r_i/sd_i			
	O		P		Q		R		S		T	
Cluster1	1.678	***	1.858	***	12.444	***	13.113	***	0.549	*	0.573	
Cluster2	2.094	***	1.975	***	13.040	***	12.537	***	0.313		0.308	
Cluster3	0.545		0.715		5.030		5.673		0.525		0.536	
Size	10.285	*	9.564		45.937		42.981		0.669		0.665	
Size^2	-0.273	*	-0.256	*	-1.248		-1.178		-0.017		-0.017	
GL/TA	-0.040	*	-0.028		-0.332	*	-0.286		0.011		0.012	
DEP/TA	0.001		0.003		0.058		0.067		-0.001		-0.000	
GDP_g	-0.052		-0.044		-0.259		-0.221		-0.095	***	-0.091	***
y10bond	-0.529	**	-0.418	*	-2.646	*	-2.157		-0.157		-0.091	
ISPI			-0.850				-3.329				-0.195	
r_mkt									0.038	***	0.039	***
sd_mkt									-0.055	**	-0.044	
Constant	-93.400		-86.530		-403.209		-357.227		-5.867		-6.232	
Number of banks	40		40		40		40		40		40	
R2 overall	0.317		0.333		0.255		0.261		0.255		0.253	

Table 7: Results of the panel regressions. Sample period 2015-2016

*The regressions estimate the relation between financial and market performance/risk/risk-adjusted performance and governance clusters over the period 2015-2016. Cluster dummies are held constant at 2014. The sample includes 40 large listed European banks. Detailed definitions of the variables are provided in Table 3. *, **, *** indicate respectively 10, 5 and 1% significance levels.*

Panel A: Financial and market performance

Variable	***ROA***		***ROE***		***Stock returns***	
	A1	B1	C1	D1	E1	F1
Cluster1	0.557 ***	0.576 ***	6.025	6.322	45.541 ***	47.202
Cluster2	0.528 **	0.506 **	8.925 ***	7.461	32.353 *	28.018
Cluster3	-0.028	-0.005	1.096	2.522	28	30.821
Size	4.825 *	4.75 *	57.09	50.761	74.646	63.054
Size^2	-0.13 *	-0.128 *	-1.509	-1.346	-1.994	-1.722
GL/TA	-0.021 **	-0.019 *	-0.246 *	-0.12	-0.421	-0.177
DEP/TA	0.002	0.003	-0.076	-0.072	0.003	0.048
E/TA			1.225	1.823		
GDP_g	-0.015	-0.014	-0.278	-0.227	-4.417 **	-4.036 **
y10bond	0.012	0.055	-0.835	1.553	-9.73	-3.037
ISPI		-0.145		-9.132		-20.635
r_mkt					2.61 ***	2.532 ***
Constant	- 43.529 *	- 42.836 *	- 524.214	- 473.533	- 693.043	- 587.135
Number of banks	40	40	40	40	40	40
R2 overall	0.223	0.223	0.215	0.244	0.344	0.354

Panel B: Risk

Variable	***RWA/TA***		***NPL/GL***		***sd_i***	
	G1	H1	I1	L1	M1	N1
Cluster1	7.695	4.581	-5.14 *	-6.639 **	-9.207	-9.831 *
Cluster2	-7.001	-6.124	-6.815 **	-6.348 **	3.095	1.305
Cluster3	1.807	-0.842	1.264	-0.088	-6.074	-6.124
Size	-41.622	-39.212	-41.31 **	-40.474 **	1.366	2.696
Size^2	0.914	0.882	1.074 **	1.071 **	-0.023	-0.056
GL/TA	0.117	-0.003	0.293 ***	0.266 ***	-0.059	-0.029
DEP/TA	-0.027	-0.033	0.027	0.014	0.044	0.033
GDP_g	-0.114 *	-0.122 *	-0.022	-0.028	0.866 ***	1.228 ***
y10bond	5.506 ***	4.747 ***	0.989 **	0.81 *	3.741	7.064
sd_mkt				4.666 *		-5.111
ISPI					2.65 ***	2.868 ***
Constant	385.41 **	371.297 **	385.41 **	371.297 **	-38.371	-59.826
Number of banks	38	38	39	39	40	40
R2 overall	0.596	0.663	0.543	0.598	0.342	0.348

Panel C: Risk-adjusted performance

Variable	***RoRWA***				***RoTRC***				***r_i/sd_i***			
	O1		P1		Q1		R1		S1		T1	
Cluster1	1.459	**	1.583	**	9.698	**	10.232	**	0.817	**	0.814	**
Cluster2	1.809	***	1.654	***	10.844	***	10.032	***	0.338		0.338	
Cluster3	0.158		0.317		1.672		2.391		0.678	*	0.677	*
Size	12.194	*	11.683	*	56.597		54.237		0.735		0.726	
Size^2	-0.323	*	-0.311	*	-1.528		-1.474		-0.021		-0.02	
GL/TA	-0.035		-0.023		-0.321	*	-0.265		0.01		0.01	
DEP/TA	-0.007		-0.004		0.016		0.028		0		0	
GDP_g	-0.051		-0.044		-0.29		-0.242		-0.102	***	-0.102	***
y10bond	-0.42		-0.128		-0.764		0.71		-0.396	**	-0.404	*
ISPI			-0.995				-4.689				0.022	
r_mkt									0.045	***	0.045	***
sd_mkt									-0.059		-0.061	
Constant	-111.459	*	-106.77	*	- 502.38		-480.833		-5.683		-5.545	
Number of banks	39		39		40		40		40		40	
R2 overall	0.301		0.315		0.212		0.22		0.315		0.315	

Table 8: Results of the cross-section regressions. Average performance for the period 2014-2016

*The regressions estimate the relation between the average financial and market performance/risk/risk-adjusted performance over the sample period 2014-2016 and governance clusters and controls variables that are held constant at 2014. The sample includes 40 large listed European banks. Detailed definitions of the variables are provided in Table 3. *, **, *** indicate respectively 10, 5 and 1% significance levels.*

Panel A: Financial and market performance

Variable	***ROA***				***ROE***				***R_i***			
	A2		**B2**		**C2**		**D2**		**E2**		**F2**	
Cluster 1	0,832	**	0,836	**	11,71	**	10,956	*	42,856	*	43,131	*
Cluster 2	0,764	**	0,8	***	18,067	***	16,544	***	27,571		27,966	
Cluster 3	0,249		0,247		6,347		6,166		33,15		33,448	
Size	2,958		2,968		5,29		0,981		-19,369		-17,655	
Size^2	-0,081		-0,081		-0,179		-0,066		0,446		0,403	
GL/TA	-0,016		-0,017		-0,214		-0,153		0,159		0,155	
DEP/TA	0,008		0,007		0,049		0,053		0,035		0,013	
GDP_g	-0,058		-0,063		-1,93	**	-1,8	*	-3,342		-3,276	
y10bond	-0,313	*	-0,379	**	-9,57	***	-6,564	*	-34,655	**	-36,269	*
ISPI			0,128				-6,307				2,479	
E/TA					2,36	*	2,669	*				
r_mkt									-0,347		-0,399	
constant	-25,67		-25,634		-21,066		10,808		244,139		230,721	
Number of banks	40		40		40		40		40		40	
Adj-R2	0,17		0,145		0,37		0,367		0,229		0,202	

Panel B: Risk

Variable	***RWA/TA***				***NPL/GL***				***sd_i***			
	G2		**H2**		**I2**		**L2**		**M2**		**N2**	
Cluster 1	4,053		4,584		-8,604	**	-8,413	**	-13,645	*	-6,384	
Cluster 2	-7,628		-4,326		-9,983	***	-7,805	**	-8,398		-14,291	*
Cluster 3	-1,428		-1,82		-0,923		-0,998		-4,588		-1,765	
Size	-15,364		-17,462		-25,749		-21,451		18,038		68,632	
Size^2	0,233		0,297		0,698		0,591		-0,441		-1,701	
GL/TA	-0,212		-0,319		0,295	**	0,22		0,153		0,357	*
DEP/TA	0,193		0,23		-0,013		-0,032		-0,384		-0,174	
GDP_g	-0,221		-0,788		1,166		1,126		5,111	***	9,431	***
y10bond	10,536	***	3,605		4,497	**	0,336		9,575	**	23,372	***
ISPI			12,476	*			8,519	**			-47,98	***
E/TA												
r_mkt												
sd_mkt									2,202	***	6,324	***
constant	229,886		260,149		219,9		187,697		-191,773		-808,427	*
N	39		39		39		39		40		40	
Adj-R2	0,591		0,61		0,488		0,528		0,492		0,664	

Panel C: Risk-adjusted performance

Variable	**RoRWA**				**RoTRC**				**ri/sd**			
	O2		**P2**		**Q2**		**R2**		**S2**		**T2**	
Cluster 1	2,115	**	2,114	**	14,625	**	14,635	**	0,732		0,642	
Cluster 2	2,612	***	2,602	***	15,399	***	15,479	***	0,459		0,524	
Cluster 3	0,804		0,804		6,155		6,152		0,651		0,702	
Size	7,822		7,819		33,13		33,154		-0,725		-1,302	
Size^2	-0,211		-0,211		-0,921		-0,922		0,019		0,033	
GL/TA	-0,025		-0,025		-0,256		-0,259		0,022		0,022	
DEP/TA	0,011		0,011		0,108		0,108		-0,002		-0,012	
GDP_g	-0,234		-0,233		-1,202		-1,212		-0,124	*	-0,171	**
y10bond	-1,347	***	-1,329	**	-6,254	**	-6,403	**	-0,773	*	-1,271	**
ISPI			-0,035				0,289				1,208	
E/TA												
r_mkt									-0,007		-0,026	
sd_mkt									-0,033		-0,125	*
constant	-68,387		-68,397		-275,76		-275,678		7,819		16,578	
N	40		40		40		40		40		40	
Adj-R2	0,318		0,294		0,228		0,201		0,174		0,183	

Table 9: Results of the cross-section regressions. Average performance for the period 2015-2016

*The regressions estimate the relation between the average financial and market performance/risk/risk-adjusted performance over the sample period 2015-2016 and governance clusters and controls variables that are held constant at 2014. The sample includes 40 large listed European banks. Detailed definitions of the variables are provided in Table 3. *, **, *** indicate respectively 10, 5 and 1% significance levels.*

Panel A: Financial and market performance

Variable	*ROA*				*ROE*				*r_i*			
	A3		**B3**		**C3**		**D3**		**E3**		**F3**	
Cluster 1	0,718	**	0,719	**	9,304	**	8,46	*	48,846	**	48,242	**
Cluster 2	0,738	***	0,745	***	14,7	***	12,996	***	31,888	*	31,02	*
Cluster 3	0,033		0,033		1,504		1,301		32,892		32,238	
Size	3,137		3,139		20,055		15,233		-56,46		-60,23	
Size^2	-0,085		-0,085		-0,558		-0,431		1,355		1,449	
GL/TA	-0,014		-0,014		-0,129		-0,061		0,042		0,052	
DEP/TA	0,008		0,008		0,051		0,055		-0,002		0,047	
GDP_g	-0,101		-0,102		-2,319	**	-2,174	**	-5,014	*	-5,157	*
y10bond	-0,286	*	-0,298	*	-7,185	***	-3,821		-42,71	***	-39,16	*
ISPI			0,023				-7,057				-5,451	
E/TA					1,214		1,56	*				
r_mkt									-0,669		-0,555	
sd_mkt												
constant	-27,551		-27,544		-163,126		-127,462		644,899		674,404	
N	40		40		40		40		40		40	
Adj-R2	0,13		0,1		0,28		0,289		0,337		0,314	

Panel B: Risk

Variable	*RWA/TA*				*NPL/GL*				*sd_i*			
	G3		**H3**		**I3**		**L3**		**M3**		**N3**	
Cluster 1	4,773		5,707		-8,264	*	-8,081	*	-12,94	*	-7,365	
Cluster 2	-5,853		-1,958		-9,548	**	-7,458	**	-9,136		-13,661	*
Cluster 3	-1,995		-2,379		-0,657		-0,729		-4,215		-2,047	
Size	-25,378		-27,311		-29,46		-25,335		29,882		68,734	
Size^2	0,48		0,539		0,79		0,686		-0,723		-1,69	
GL/TA	-0,257		-0,386	*	0,295	**	0,223		0,08		0,237	
DEP/TA	0,197		0,241		-0,017		-0,035		-0,289		-0,128	
GDP_g	-0,498		-1,173		1,105		1,067		4,768	***	8,085	***
y10bond	10,309	***	2,299		4,194	**	0,201		9,554	**	20,148	***
ISPI			14,277	*			8,176	**			-36,844	***
E/TA												
r_mkt												
sd_mkt									2,276	***	5,442	***
constant	334,214		365,454		257,957		227,052		-315,853		-789,38	
N	38		38		39		39		40		40	
Adj-R2	0,59		0,62		0,473		0,507		0,512		0,636	

Panel C: Risk-adjusted performance

Variable	*RoRWA*				*RoTRC*				*ri/sd*			
	O3		**P3**		**Q3**		**R3**		**S3**		**T3**	
Cluster 1	2,157	***	2,142	***	12,567	**	12,484	**	0,832	*	0,782	*
Cluster 2	2,676	***	2,601	***	14,749	***	14,098	***	0,495		0,531	
Cluster 3	0,428		0,43		2,787		2,812		0,654		0,682	
Size	8,91		8,879		30,375		30,184		-2,042		-2,36	
Size^2	-0,239		-0,238		-0,846		-0,842		0,052		0,059	
GL/TA	-0,021		-0,019		-0,207		-0,188		0,018		0,018	
DEP/TA	0,011		0,012		0,102		0,107		0,001		-0,005	
GDP_g	-0,362		-0,352		-1,899		-1,819		-0,153	**	-0,179	**
y10bond	-1,393	***	-1,254	**	-5,68	**	-4,462		-0,963	**	-1,238	**
ISPI			-0,266				-2,357				0,666	
E/TA												
r_mkt									-0,016		-0,026	
sd_mkt									-0,029		-0,08	
constant	-78,593		-78,605		-251,103		-251,772		21,31		26,142	
N	39		39		40		40		40		40	
Adj-R2	0,33		0,308		0,175		0,151		0,266		0,25	