# Bank diversification and overall financial strength: International evidence

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## Abstract

There are many studies in the finance and management literature that examine the impact of diversification on performance. Yet, the literature remains inconclusive as for the potential benefits in terms of risk and return. The present study aims to re-examine this issue, while proposing a methodological framework that integrates various bank performance and risk indicators into a single measure of financial strength. Using an international sample of commercial banks, we find that diversification in terms of income, earning assets, and on- and off-balance sheet activities influences positively their financial strength. These results hold when we account for nesting effects, endogeneity, as well as when using an alternative approach for the construction of the financial strength indicator.

**Keywords:** Diversification, Overall financial strength, Multidimensional performance, Banking, Multicriteria

## 1. Introduction

Corporate diversification has been characterized as a central topic of research in the literature with existing studies investigating various issues like its relationship with ownership, top management characteristics, information asymmetry, and organizational divisionalization, to name a few. Perhaps the most well researched strand of this literature is the one linking diversification and performance (Chatterjee and Wernerfelt, 1991; Palich et al., 2000), with early studies going back to the work of Rumelt (1982). However, this topic continues to be central in the research agenda of banking, finance, and management scholars (e.g. Chakrabarti et al, 2007; Goddard et al., 2008; Elsas et al., 2010). One potential reason is that despite the large number of studies, the literature has not yet reached maturity, as it is evident by the little agreement that exists at both the theoretical and empirical level (Palich et al., 2000).

An important issue that has been highlighted in the case of non-financial firms is that while some studies examine the association between diversification and risk-return performance, the vast majority of the literature does not take risk into account (Bettis and Mahajan, 1985). This is surprising considering the importance of risk in managerial decision making (e.g. Miller and Bromiley, 1990) and the theoretical associations between diversification and risk (see e.g. Chang and Thomas, 1989). Additionally, the few studies that investigate the risk-return performance traditionally rely on the standard deviation of return on assets as a measure of risk, an approach that has also been used in studies in banking (e.g. Stiroh, 2004; Goddard et al., 2008). While this risk metric captures the instability of returns, it fails to take into account potential trade-offs, and it does not provide an overall indicator of exposure to the various risks. Yet, the idea that gains on one dimension must be potentially sacrificed on another dimension

(i.e. trade-off) is central in the analysis of financial economics and bank management (Thakor, 2014).

Some banking studies have partially improved upon this by relating diversification to risk using the Z-score index, an indicator of a bank's probability of insolvency (e.g. Stiroh, 2004; Mercieca et al., 2007).[1] This index takes into account not only the standard deviation of return on assets but also the average return on assets and the average equity to assets over a fixed time period. Still, the Z-score is not without its drawbacks. First, there is no guidance as for the number of years that have to be used for the calculation of the standard deviation, with many studies relying on just two or three years. Yet, as shown in Delis et al. (2014) the number of periods considered for the construction of the variance component significantly affects the results. In addition, the requirement of having data for numerous continuous years imposes some restrictions on the number of banks that can be eventually assessed with this kind of analysis. Third, and most importantly, the Z-score focuses on profitability and capitalization ignoring other aspects like liquidity, asset quality, and cost management.

In general, there appears to be limited work in integrating various categories of risk exposures and incorporating risk into performance measures, an approach that could offer the possibility to assess the firm exposures along different dimensions (Miller, 1998; Chang and Thomas, 1989). At the same time, an increasing number of studies highlight the need to take into account the multidimensionality of performance, instead of focusing on individual measures like

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[1] Others examine the association between shareholder value and diversification (e.g. Laeven and Levine, 2007; Elsas et al., 2010). There is no doubt that these studies are very interesting; however, they approach this topic from an entirely different angle, and with specific stakeholders in mind (i.e. shareholders) and they do not consider the financial strength of banks.

profits (see e.g. McKiernan and Morris, 1994; Devinney et al., 2010; Kyrgidou and Syropoulou, 2013).[2]

Motivated by the above discussion, we aim to re-examine the impact of diversification on risk and return, while proposing a methodological framework that integrates various bank characteristics into an overall indicator of financial strength. Thus, we attempt to bring together the literature on diversification and the one on the multidimensional character of firm performance, an issue that has not been properly explored, despite having been suggested as an avenue of future research for over two decades (see Nguyen et al., 1990). For various reasons discussed below, we opt for an application in the banking; however, our methodological approach may be applied in any industry using appropriate financial ratios or other indicators of risk and performance.

Our analysis consists of two parts. First, we estimate a novel overall financial strength indicator (OFSI) that takes simultaneously into account various elements of bank performance (i.e. profitability, expenses management) and risk (i.e. capital risk, credit risk, liquidity risk). Thus, we capture those attributes that are taken into account by bank regulators, credit analysts, and equity analysts, in assessing the financial performance and condition of banks (Golin and Delhaise, 2013).[3] Then, in the second part, we examine whether and how diversification influences banks' overall financial strength.

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[2] For example, McKiernan and Morris (1994) highlight that ""*There as has been a general call for the use of multiple measures (Freeman et al., 1991) to capture 'overall' performance rather than the reliance, as in some studies, on single measures of performance, e.g. profit*" (p. S35). Along the same lines, Devinney et al. (2010) argue that there logical theoretical reasons to believe that performance is fundamentally multidimensional, and they highlight the need for a more robust way of measuring company financial performance. Similarly, Kyrgidou and Spyropoulou (2013) mention that *"...the general literature suggests that business performance is a multi-component construct and calls for the use of multidimensional conceptualizations and measurements..."* (p. 282).

[3] We term our metric indicator of overall financial strength to distinguish it for other measures of performance used in the literature, capturing individual attributes, mainly profitability. Apparently, one could use the term overall financial performance. In some instances, we use the two terms interchangeably in the text. The five elements considered in the present study resemble the ones used in the CAMEL framework to assess the financial condition

Using this overall indicator of financial performance has at least three advantages over the use of single financial ratios or risk indicators employed in earlier studies (e.g. ROA, standard deviation of ROA). First, it provides a general picture about the overall financial strength of banks, instead of focusing on individual aspects like profitability or risk, which provide only partial views. Second, the multicriteria, scenario-based evaluation approach that we use for the construction of the OFSI, allows us to simultaneously take into account the conflicting objectives of managers, and examine multiple scenarios with respect to the way that these objectives contribute to bank financial strength.[4] For instance, managers could increase the bank's interest income in the short-run by approving a high interest loan to a borrower with low creditworthiness. However, this strategy will most likely be associated with problems appearing in the form of non-performing loans (i.e. credit risk). Alternatively, they may try to increase bank returns, by decreasing the liquid assets that they hold. However, this may result in liquidity risk. Nonetheless, prudent managers should aim for profit maximization, while minimizing the non-performing to loans ratio, and maintaining liquidity, capital adequacy, etc. As discussed above, the adopted multicriteria approach allows us to consider these conflicting goals, and the associated trade-offs, during the estimation process. Third, the decision of managers to diversify, affects various bank attributes, and not only profitability. For example, changing the earning assets portfolio mix, to include more loans and less other earning assets, will impact liquidity since loans are generally considered to be illiquid assets. This decision will also change the total

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of banks in terms of Capital (i.e. capital risk), Asset quality (i.e. credit risk), Management (i.e. expenses management), Earnings (i.e. profitability) and Liquidity (i.e. liquidity risk). Thus, CAMEL refers to a checklist of the bank's attributes that are viewed as critical in evaluating its financial performance and condition (Golin and Delhaise, 2013). Building on this general CAMEL framework, supervisory agencies in the United States estimate the CAMEL ratings. However, these ratings are confidential, being disclosed only to senior bank management and to the appropriate supervisory personnel. Thus, in the context of the present study we estimate a new overall financial performance indicator that considers simultaneously the aforementioned bank-specific attributes.

[4] Delis et al. (2014) also highlight that financial intermediaries make risky decisions simultaneously with the perception about expected profits and of the level of other bank characteristics, mainly capital and liquidity.

capital ratio of the bank, as loans and let us say bonds are assigned different weights in risk-weighted capital regulatory ratios. Finally, a bank that holds higher proportions of loans may have to devote more resources on the screening and monitoring of the quality of its portfolio compared to a bank that invests in bonds and other earning assets, a managerial strategy than can be associated with higher expenses.

There are numerous reasons for which the banking sector provides an interesting case study for our research. First, in recent years we have witnessed great changes in the composition of banks' earning assets portfolio, the relative importance of on-and off-balance sheet activities, and a general shift away from traditional interest income generating activities into non-interest income related services (Stiroh, 2004; Elsas et al., 2010). Second, the empirical evidence on the diversification of banking institutions provides conflicting results and to some extent, the results depend on the employed measure (e.g. Stiroh, 2004; Demirgüç-Kunt and Huizinga, 2010). Third, risk is an integral part of the banking business, and bank managers ought to consider this while deciding about their strategy. Fourth, banks face various regulations like restrictions on their activities, capital requirements (e.g. Basel I, II, III) and liquidity requirements (e.g. Basel III) that could influence their diversification strategy. Fifth, there are some concerns in the literature as for whether aggressive diversification strategies in the past resulted in increased risk taking and poor performance that led to the financial crisis (Berger et al., 2010).[5] By examining an

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[5] Within this context, DeYoung and Torna (2013) also make an important contribution to the literature by looking at the impact of diversification on bank failures during the recent crisis. However, their study is limited to the US banking sector, and it may not be possible to generalize their findings at an international context, where banks will be declared bankrupt (or saved) under different laws and for potentially different political or regulatory reasons (see Petitjean, 2013; Cole and Cadogan, 2014). Furthermore, diversification may have a different impact on financial strength (regardless of its definition) in developing and developed countries, as bank managers in the former group of countries may be less efficient in managing non-traditional activities (see e.g. Lozano-Vivas and Pasiouras, 2010). There is no doubt that the approach of DeYoung and Torna (2013) allows them to look at really troubled banks, without relying on an estimated risk indicator; however, at the same time this makes their work subject to the general shortcomings of the business failure literature (see Balcaen and Ooghe, 2006). For example, one needs to classify banks as failed or non-failed and it is difficult to consider the population of "grey zone" banks. Additionally,

international sample around the years of the crisis, the present study examines whether or not the diversification strategy of banks proved helpful during this difficult time period.

The rest of the paper of the paper is structured as follows. Section 2 provides a background discussion. Section 3 describes the methodological framework used in the present study, and Section 4 presents the variables and the data. Section 5 discusses the results and Section 6 concludes.


## 2. Background discussion

The resource-based theory of the firm asserts that increasing levels of product diversification should influence performance positively due to economies of scope and scale, and economic quasi-rents, which generate a competitive advantage (see Geringeret et al., 2000). Furthermore, firm resources (e.g. financial, human) and know-how (e.g. managerial, technological) can create value when shared across businesses (e.g. Farjoun, 1998; Prahalad and Bettis, 1986), without being perfectly mobile across firms. Thus, firms that will strategically diversify to take advantage of such resources should perform better than single-business firms and the ones that diversify for less strategic reasons (Palich et al., 2000; Miller, 2006). Additionally, this pool of resources provides diversified firms with greater flexibility in terms of sources of debt and equity, since in addition to external sources they can also rely on internally generated resources to cover their capital needs (Lang and Stulz, 1994). On top of this flexibility, the management of the diversified firm could allocate the resources better than external markets due to information asymmetries (Lang and Stulz, 1994).

the application of the failure definition to an arbitrarily chosen year or time period involves a certain 'selection bias' and may result in 'contaminated' populations.

Managerial decisions to diversify have often been linked to the aim of decreasing risk (Bettis and Mahajan, 1985). For example, Chang and Thomas (1989) mention that a firm can diversify into less risky product markets, and the more it diversifies the more it can spread industry-specific risk. Additionally, the lower risk and the associated reduced probability of bankruptcy may have positive implications in terms of the firm's debt capacity and cost of capital (Seth, 1990; Palich et al., 2000).

All the above suggest that diversification will exercise a positive impact on performance and a negative impact on risk. Yet, the literature also discusses a number of conditions under which diversification will not bring the expected outcomes. These include the strain on top management due to efforts to manage a diverse portfolio of business, coordination costs, organizational diseconomies, internal conflicts, and other inefficiencies that may arise (see Palich et al., 2000). Assuming that these costs outperform the associated benefits of diversification, then one should expect a negative impact on performance. The diversification strategy may also fail to reduce risk if the new businesses are correlated with existing businesses.

Arguments in the banking literature follow a similar form of reasoning. For example, Barth et al. (2004) outline several theoretical reasons for restricting bank activities (and thus limiting their opportunity to diversity) as well as alternative reasons for allowing banks to participate in a broad range of activities. For example, on the negative side they emphasize among other things the conflicts of interest that arise when banks engage in diverse activities, and the moral hazard problems that are associated with greater opportunities to increase risk through an engagement in a broader range of activities. On the positive side, Barth et al. (2004) discuss the utilization of economies of scale and scope, the potential increase in the franchise value of banks, and the diversification of income sources that could result in more stable banks.

Furthermore, theoretical studies claim that diversification makes it cheaper for institutions to achieve credibility in their role as screeners or monitors (e.g. Diamond, 1984).

As in the case of research on non-financial firms, the empirical results in the banking literature are also mixed. For example, Stiroh (2004) finds that there is no relationship between the expansion into non-interest income-generating activities and the return on equity. Mercieca et al. (2007) do not find evidence of direct diversification benefits within and across business lines; however, they report an inverse association between non-interest income and bank profitability. More recent studies, contradict these findings. Using an international sample, Demirguc-Kunt and Huizinga (2010) find that the diversification towards non-interest activities has a positive impact on the return on assets, and Sanya and Wolfe (2011) reach similar conclusions using a sample from eleven emerging economies. Similarly, some studies find that diversification does not translate into reductions in risk (e.g. Demsetz and Strahan, 1997), others report that banks experience a decrease in risk (e.g. Sanya and Wolfe, 2011; Shim, 2013), an increase in risk (e.g. Stiroh, 2004, 2006; Lepetit et al., 2008), and there are also studies finding that this relationship depends upon the employed measure of risk (e.g. Allen and Jagtiani, 2000; Baele et al., 2007). Finally, Acharya et al. (2006) suggest that banks can experience diseconomies of diversification that arise in the form of a worsening of the credit quality of loan portfolio simultaneously with a fall in bank returns, possibly due to worse monitoring, adverse selection, higher overheads, or a combination of these factors. This could explain why some studies report a positive (Chiorazzo et al., 2008) and others a negative association (Stiroh, 2004; Demirguc-Kunt and Huizinga, 2010) between income diversification and risk-adjusted returns.

## 3. Methodology

### 3.1. Dependent variable - estimating the overall financial strength indicator

To construct the OFSI we use a scenario-based multicriteria approach, taking into account five financial criteria: the total capital adequacy ratio (TCAR), the problem loans to total loans ratio (PLR), the cost to income ratio (COST), return on assets (ROA), and the liquid assets to deposits and short term funding ratio (LIQR).[6] We select these ratios considering their use by international regulators (e.g., total capital adequacy ratio) and their association to the categories of the CAMEL framework.

In the adopted multicriteria framework, the banks are evaluated through an additive value function of the five aforementioned ratios, i.e.:

$$V = w_{TCAR}f_{TCAR} + w_{PLR}f_{PLR} + w_{COST}f_{COST} + w_{ROA}f_{ROA} + w_{LIQR}f_{LIQR} \tag{1}$$

where $w_{TCAR}$, $w_{PLR}$, $w_{COST}$, $w_{ROA}$, and $w_{LIQR}$ are non-negative tradeoffs of the five ratios, representing their relative importance in the evaluation model (the tradeoffs are assumed to sum up to one) and $f_{TCAR}, f_{PLR}, f_{COST}, f_{ROA}, f_{LIQR}$ are monotone marginal value functions of the ratios normalized in [0, 1]. The overall performance score (global value) ranges in [0, 1] with higher values indicating higher overall performance. The marginal value functions decompose the overall performance of the banks into its five dimensions, thus indicating the performance of the banks at the ratio level. The additive model is well founded from a theoretical point of view (Keeney and Raiffa, 1993) and has been used in a wide range of evaluation problems under multiple criteria.

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[6] Apparently, one could use qualitative indicators of managerial quality (e.g. experience, education, etc.) However, such data were not available in our case. Furthermore, one could use an indicator of efficiency derived from frontier function techniques. Nonetheless, this could complicate our analysis, possibly without having a major impact on the final results. Therefore, as in Barth et al. (2002) and Poghosyan and Čihák (2009) we use the cost to income as a proxy for managerial quality.

To evaluate the financial strength of the banks under different scenarios, as for the weightings of the performance indicators (financial ratios), we follow a simulation approach. Simulation methods have become popular in multiple criteria decision analysis for handling the uncertainties involved with respect to the set of preferential parameters of evaluation models and/or the data (Lahdelma and Salminen, 2001; Tervonen and Figueira, 2008). In this study, we follow this approach in order to build a comprehensive evaluation of the banks under different scenarios for both the ratios' tradeoffs and the marginal value functions of the additive evaluation model. The process is based on sampling different evaluation models, uniformly distributed over the set of all additive value functions, which can be obtained with non-negative tradeoffs that sum up to one and monotone marginal value functions defined in [0, 1]. Each of the sampled models provides an evaluation of the banks from a different point of view, with respect to the relative importance of the financial ratios and their aggregation. Taking into consideration the distribution of the results over multiple evaluation scenarios enables the construction of a comprehensive index of the overall financial strength of the banks, taking into account the evaluations' distribution under different evaluation assumptions. Following the suggestions of Tervonen and Lahdelma (2007) on the implementation of such simulation-based approaches to multicriteria evaluation problems, we consider a large set of 10,000 scenarios, which is sufficient to achieve robust results. The details for the scenario generation process (i.e., the sampling of random evaluation model) are given in Appendix I.

Under each scenario $k$, the banks are evaluated with a randomly generated additive model $V_k$ and are classified into five rating (financial strength) classes: very strong, strong, medium, weak, very weak. The classification is performed so that the banks are approximately normally distributed in the classes. In particular, let $V_{ik}$ denote the global value (overall financial strength

score) of bank $i$ according to the additive model under scenario $k$, and $p_k^t$ the t% percentile of the global values (i.e., $V_{1k}$, $V_{2k}$, …) for all banks under the same scenario. Then, a bank $i$ with $V_{ik} \leq p_k^{10}$ is assigned to the class of very weak performers, to the class of weak banks if $p_k^{10} < V_{ik} \leq p_k^{32.5}$, to the medium class if $p_k^{32.5} < V_{ik} \leq p_k^{67.5}$, to the class of strong banks if $p_k^{67.5} < V_{ik} \leq p_k^{90}$, or to the class of very strong performing banks if $V_{ik} > p_k^{90}$.

The final OFSI for each bank $i$ is constructed by aggregating its ratings under all specifications (scenarios) for the evaluation model (1), as follows:

$$OFSI_i = \underbrace{\sum_{r=1}^{r} \pi_{ir} r}_{\bar{r}_i} + \underbrace{\sum_{r=1}^{5} \pi_{ir}[1 - e^{-a_i(r-\bar{r}_i)}]}_{F_i} \tag{2}$$

where $\pi_{ir}$ is the percentage of evaluation scenarios under which bank $i$ is classified in category $r$ (1-very weak, 2-weak, 3-medium, 4-strong, 5-very strong). The OFSI for a bank $i$ consists of two components: the expected rating ($\bar{r}_i$) of the bank and the risk component $F_i$. The risk component introduces a risk adjustment to the expected rating, taking into consideration the variability of the distribution of the ratings of the banks over all evaluation scenarios. The introduction of the risk component is in accordance with the volatile global banking environment, and enables the distinction between adverse scenarios that put a bank at risk and positive scenarios. The risk component is modelled as a weighted average of partial risk factors specified by the negative exponential function $1 - e^{-a_i(r-\bar{r}_i)}$ on the basis of the deviations of the banks ratings (over all evaluation scenarios) from the expect rating, with $a_i$ being a risk aversion constant. The negative exponential function is commonly used for modelling risk aversion (Kirkwood, 2004). It is bounded by above by one and its concave form implies that the penalty assigned to negative deviations from the expected rating ($r < \bar{r}_i$) outweighs the "premium"

associated with positive deviations ($r > \overline{r_i}$). For a bank that is consistently classified in the same rating throughout all evaluation scenarios, the risk component equals zero.

In accordance with common practices on bank rating systems (Sahajwala and Van den Bergh, 2000), the OFSI is scaled between 1 and 5, with higher values indicating better performance. Under this scaling scheme, the risk aversion parameter $a_i$ is specified for each bank so that at the worst possible evaluation case, $OFSI_i$ equals one, i.e.:

$$\overline{r} + [1 - e^{-a_i(r - \overline{r_i})}] = 1 \Rightarrow a_i = -\frac{\ln(\overline{r_i})}{1 - \overline{r_i}}$$

With this specification the risk adjustment component for bank $i$ ranges in $[1 - r_i, 0]$. Furthermore, given that the risk aversion parameter is a decreasing function of $\overline{r_i}$, decreasing absolute risk aversion is assumed. Thus, the risk adjustment is higher for banks that perform poorly on average (i.e., low values of $r_i$), whereas for banks that perform better on average the risk adjustment is reduced. Finally, the OFSI is consistent with the second-order stochastic dominance principle (Levy, 2010). In particular, assuming two banks A and B, such that A second-order stochastically dominates B according to the distributions of the banks' ratings over all evaluation scenarios, then $OFSI_A > OFSI_B$.

*3.2. Econometric analysis*

In the second part of the analysis, the OFSI serves as the dependent variable in the estimation of the following equation:

$$OFSI_{ijt} = \alpha + \beta X_{ijt} + \gamma Z_{jt} + \varepsilon_{ij}$$

where the OFSI of bank *i* that operates in country *j* at time *t* is written as a function of a vector of bank-level variables (including diversification), *X*; variables that capture the macroeconomic, regulatory, banking sector and other country conditions common to all banks in country *j* at time *t*, *Z*; and the error term $\varepsilon_{ijt}$. Given that we have a panel dataset, we estimate a fixed effects model with robust standard errors clustered at the bank level. The use of the fixed-effects over the random-effects estimator is supported by the Schaffer and Stillman (2010) robust version of the Hausman type test which is more appropriate with robust or cluster robust standard errors.

To examine the robustness of our results, we conduct sensitivity analysis using two alternative techniques. First, considering that individual banks are nested in countries over a number of years we employ a Hierarchical Linear Modeling (HLM) or else known as Multi-Level Modeling (MLM).[7] Second, we use the limited information maximum likelihood (LIML) method to control for the potential endogeneity of diversification.

## 4. Variables and data

### 4.1. Diversification indices

As in previous studies, the construction of our diversification indices is restricted by data availability (e.g., Laeven and Levine, 2007; Baele et al., 2007). Laeven and Levine (2007) mention that ideally one would like detailed data on each bank's underwriting of securities, brokerage services, assets securitization, etc. However, such data are not available. Furthermore, for the vast majority of banks, no data exist for the gross revenues per category, other than

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[7] This approach has been recently used in studies that examine firm performance (Goldszmidt et al., 2011), capital structure (Kayo and Kimura, 2011), and IPOs underpricing (Engelen and van Essen, 2010). However, to the best of our knowledge, there are no applications of HLM in the cross-country literature on bank diversification. The advantage of this technique is that it accounts for the fact that the data have different levels of aggregation and it provides error terms that control for the potential dependency due to nesting effects (e.g., Newman et al., 2010).

interest income and we have to rely on net figures consistent with earlier studies (e.g., Laeven and Levine, 2007; Elsas et al., 2010). Therefore, we construct three Herfindhal-Hirshman type diversification indices that provide a general indication about the diversity of banks, in terms of income, earning assets, and balance sheet composition. In general higher values indicate higher diversification.

Following Elsas et al. (2010), our income-based diversification indicators captures diversification across the four main types of bank income, namely interest income, commission income, trading income, other operating income. It is calculated as follows:

$$DIV_{inc} = 1 - \left[ \left( \frac{INT}{TOR} \right)^2 + \left( \frac{COM}{TOR} \right)^2 + \left( \frac{TRAD}{TOR} \right)^2 + \left( \frac{OTH}{TOR} \right)^2 \right]$$

where: INT is the gross interest revenue, COM is the net commission revenue, TRAD is the net trading revenue, OTH stands for other net operating income, and TOR is the total operating income. Consistent with Elsas et al. (2010) we: (i) calculate TOR as the summation of the absolute values of INT, COM, TRAD and OTH[8], and (ii) we use gross interest revenue so that the income diversity measure is not unduly distorted by the profitability of income related activities. Theoretically this index takes values between zero (fully specialized bank) and 0.75 (i.e., fully balanced revenue mix from the four business segments).

The earning assets-based diversification index is constructed by considering the two major categories of bank earning assets, namely net loans and other earning assets (e.g., Elsas et al., 2010). Again, we opt for a Herfindhal-Hirshman index of the following form:

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[8] Elsas et al. (2010) suggest this approach as otherwise the use of negative net revenue values would result in negative shares for some revenue streams and shares greater than one for other revenue streams. Therefore, $DIV_{inc}$ would be strongly influenced by business segment performance and could take values much higher than 0.75.

$$DIV_{asset} = 1 - \left[ \left( \frac{LOAN}{LOAN + OEA} \right)^2 + \left( \frac{OEA}{LOAN + OEA} \right)^2 \right]$$

where LOAN denotes the net loans and OEA stands for other earning assets (e.g., securities, bonds, etc.). A higher value indicates a more diversified mix. A value of zero reveals a complete concentration, while a value of 0.5 illustrates an even split between loans and other earning assets.

Finally, the balance sheet based diversification index takes into account the values of total assets, and off-balance sheet activities, and it is constructed as follows:

$$DIV_{bs} = 1 - \left[ \left( \frac{TAOB}{TAOB + OBS} \right)^2 + \left( \frac{OBS}{TAOB + OBS} \right)^2 \right]$$

where TAOB denotes the total assets on balance sheet, and OBS stands for off-balance-sheet items such as managed securitized assets reported off-balance sheet, guarantees, acceptances and documentary credits reported off-balance sheet, committed credit lines, and other contingent liabilities. The interpretation of $DIV_{bs}$ is same as the one of $DIV_{asset}$.


*4.2. Control variables*

In all the regressions, we use the natural logarithm of total assets (LNAS) to control for bank size. [9] Furthermore, we use numerous country-level control variables that capture the macroeconomic environment, regulatory policies, banking and financial sector conditions, and institutional development. Most of them are standard control variables in the banking literature so in what follows we provide only a very brief discussion, whereas further information about

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[9] We do not include financial ratios as these where considered during the first part of the analysis for the construction of the OFSI. The bank-specific fixed effects allow us to control for other time-invariant bank characteristics not captured in our specifications.

the definition, construction, and sources for the collection of all the data is available in Appendix II. First, we control for the impact of macroeconomic conditions using the real GDP growth (GDPGR) and the inflation rate (INFL). Second, we use indices for regulations that relate to the three pillars of Basel II, namely capital requirements (CAPRQ), private monitoring (PRMON) and supervisory power (OFFPR), as well as to restrictions on bank activities (ACTRS). Third, we control for the general level of economic freedom and institutional development using the composite indicator of the Heritage Foundation (ECONFR). Fourth, we control for various conditions in the banking sector using: (i) the private credit by deposit money banks to GDP ratio (CREDIT), as an indicator of the banking sector's development, (ii) the assets concentration of the three largest banks (CONC), and (iii) the country-level Z-score of the banking sector (TBANKZ), as an indicator of stability.

*4.3. Data*

We collect data from various sources. Bank-specific data are obtained from OSIRIS database of Bureau van Dijk. This database contains information on listed and large unlisted (or delisted) banks from around the world. Given the international coverage of our study, we focus on commercial banks so as to obtain a more homogenous sample. We start with a sample of approximately 1,600 banks. After excluding banks with missing data and erroneous information we end up with a sample of 1,204 commercial banks operating in 111 countries between 2001 and 2010. This results in an unbalanced panel dataset of 8,051 observations. We complement this dataset with various country-level variables that we collect from various sources (see Appendix II). Table 1 presents descriptive statistics about the variables that we use in both parts of the analysis. Table 2 presents the correlation coefficients.

## 5. Empirical results

### 5.1. Overall financial strength indicator

Table 3 presents summary statistics for the OFSI over all years of the analysis. For comparison purposes, except for the overall results, separate statistics are also given for different country types (major advanced - MADV, advanced - ADV, transition - TRANS, developing - DEVG). The annual averages are presented, together with the corresponding coefficients of variation. The coefficient of variation provides a measure of the OFSI dispersion among the banks in each year. However, the coefficient of variation does not indicate the diversity of the banks' ratings over the different scenarios considered for the calculation of the OFSI, as explained earlier. In that regard, for each bank we have also calculated the Herfindahl-Hirschman index (HHI) to measure the diversity of its ratings over the 10,000 specifications of the additive evaluation model (i.e., evaluation scenarios). Following the notation introduced earlier, the HHI for a bank-year observation $i$, is expressed as follows:

$$HHI_i = \sum_{r=1}^{5} p_{ir}^2$$

The HHI equals one when the bank-year observation $i$ is consistently assigned into a specific rating class across all evaluation scenarios, whereas when there is complete uncertainty on the ratings (i.e., $p_{i1} = \ldots = p_{i5} = 0.2$), then HHI equals 0.2. Table 3 presents the average HHI for all bank observations in each year.

Table 4 and Figure 1 provide some insight into the relationship between the OFSI and the financial ratios that constitute its building blocks. Table 4 shows the averages of the ratios for different ranges of the OFSI, together with the Pearson's correlation coefficient between the ratios and the OFSI. Figure 1 provides a more detailed graphical illustration of the relationship between the OFSI and the financial ratios (the figures show the average OFSI at 20 bins of the ratios defined by their 5, 10, …, 95, 100% percentiles). The results indicate that ROA is the ratio most strongly related to the OFSI, followed by PLR. The averages of the ratios for different OFSI ranges follow a monotonic trend, which is confirmed from the illustrations in Figure 1.

[Insert Table 4 and Figure 1 Around Here]

*5.2. Regressions – base results*

Tables 5 to 7 present the regression results of the fixed effects model with robust standard errors clustered at the bank level. We start with a simple model (column 1) that includes the natural logarithm of a bank's total assets, real GDP growth and inflation, so that we can make maximum use of our sample. Then, we estimate additional models, where we control for alternative country-specific factors. Note that the number of observations varies along the regressions, depending on the missing values for the country-level variables.

All three measures of diversification, namely $DIV_{inc}$ (Table 5), $DIV_{asset}$ (Table 6), and $DIV_{bs}$ (Table 7), enter the regressions with a positive and statistically significant coefficient. Thus, diversification in terms of income, earning assets portfolio mix, and on-and off-balance sheet activities tends to improve the overall financial strength of the banks.

[Insert Tables 5-7 Around Here]

In column (2), we add the four regulatory variables. The inclusion of these variables in the regressions has no impact on the relationship between diversification and OFSI. With regards to the regulatory variables, we observe that private monitoring and capital requirements have a positive and statistically significant impact on financial strength. However, supervisory power and restrictions on activities do not appear to influence the OFSI. Furthermore, it should be mentioned that the inclusion of additional variables in the regression in column 5 results in an insignificant CAPRQ. The insignificance of most of the regulatory variables poses some questions as for the effectiveness of regulations. However, it should be stressed out that while there are studies revealing a significant association of these variables with bank outcomes (e.g., Pasiouras et al., 2009) others mention that many of them, and especially capital requirements and supervisory power are not significant determinants of bank stability, development, net interest margin or performance (see Barth et al., 2004; Demirgüç-Kunt et al., 2004). One potential reason is that these indices capture regulations at the books and not what actually happens in practice. Thus, these indices cannot reveal potential shortcomings in the actual implementation of the regulations.[10] Nonetheless, one could also easily argue that our results, which cover the period 2001-2010, illustrate exactly what we observed during the financial crisis. That is the existing regulations did not serve their purpose in safeguarding against excessive risk taking in banking institutions around the world.

In column (3) we add the index of economic freedom. This variable enters the regression with a positive coefficient; however, this is statistically insignificant in most of the specifications and it has no impact on our main findings. The specification in column (4) includes three

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[10] Further regressions show that some of them appear to have a significant influence when we consider the dynamic model or the multi-level model; however, with the exception of PRMON their impact on OFSI is not robust across the estimations.

additional variables that account for various conditions in the banking sector. We observe that lower credit to GDP ratio, lower concentration, and higher stability of the banking sector as measured with the Z-score increase the OFSI. The impact of diversification on OFIS remains positive and statistically significant. Finally, the specification in column (5) includes all the variables in the regression, to account for potential omitted variables bias. Our findings remain the same. Thus, it appears that the impact of diversification on bank financial strength is not influenced by the control variables that we use. Despite this observation, we continue our analysis by considering some additional country-variables that we discuss in our sensitivity tests in the following section.

## 5.3. Sensitivity analysis

### 5.3.1. Exploring the impact of the crisis and additional country-specific attributes

To mitigate further any concerns about omitted variable bias, we consider some additional country-level variables that may be correlated with OFSI, by adding them one at a time to the equation of column (5) in Tables 5 to 7.  In particular, we consider: (i) the ratio of central bank assets to GDP, (ii) the ratio of stock market capitalization to GDP, (iii) an alternative indicator of institutional development (INSTEDV) that replaces ECONFR, while measuring voice and accountability,  political stability and absence of violence, government effectiveness, regulatory quality, rule of law, control of corruption and (iv) a sub-index of INSTDEV, that serves as an enforcement index (ENFIND) and focuses on regulatory quality, rule of law, control of corruption. Our results remain robust to the inclusion of these variables in the regressions (see Tables 8 and 9).


[Insert Tables 8 and 9 Around Here]

Furthermore, we consider a dummy variable for developing and transition countries (DEVGTRANS =1) in an attempt to account for potential characteristics that differentiate them from major advanced and advanced countries (DEVGTRANS=0), and we interact this variable with the diversification indices (DEVGTRANS*DIV). As shown in Table 10, we find a positive and statistically significant interaction in the case of income, a positive but insignificant interaction in the case of assets, and a negative and statistically significant interaction in the case of OBS. [11] Thus, banks in less developed countries benefit more than the ones in developed countries from income diversification but they benefit less when they diversify their activities in terms of on-balance-sheet and off-balance sheet activities.[12] To some extent this finding could be explained by the potential inexperience of bank managers in developing and transition countries in handling OBS activities, and it is partially consistent with the results of Lozano-Vivas and Pasiouras (2010) who find that OBS activities improve the profit efficiency of banks in major advanced countries; however, they worsen the profit efficiency of banks in developing countries.

[Insert Table 10 Around Here]

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[11] Being time-invariant, the dummy variable (DEVGTRANS) was automatically dropped from this equation during the estimation of the model due to the fixed effects. To ensure that the presented results are not driven by omitted variable bias, we re-estimated this specification using the multi-level mixed- model that we discuss in the next section. This model does not drop the dummy variable from the analysis and we continue to find a positive and statistically significant coefficient for the interaction term in the case of income, a negative and statistically significant coefficient in the case of OBS, and an insignificant effect in the case of earning assets diversification.

[12] The positive relationship between income diversification and financial strength is partially consistent with evidence for non-financial firms by Chakrabarti et al. (2007). Using a sample of manufacturing firms operating in six Asian countries, they conclude that diversification improves performance only in the least developed environments.

Finally, we include a dummy variable that takes the value of one for the years 2007 to 2010 and the value of zero for the rest of the years (see Table 11).[13] Thus, we aim to capture the impact of the crisis. Furthermore, to examine the role of diversification over this period, we also use the interaction of CRISIS with the diversification indices. As expected, we find that CRISIS has a negative impact on OFSRI. What is interesting though is the positive and statistically significant impact of the interaction of the crisis dummy with $DIV_{inc}$ and $DIV_{asset}$. Thus, income and earning asset diversification appears to mitigate the adverse effect of the crisis on bank financial strength.

[Insert Table 11 Around Here]

*5.3.2. Simultaneous control for alternative measures of diversification*

In the so far discussed results, consistent with earlier studies, we included the diversification indices in the analysis one at a time. The main reason for this is that the simultaneous inclusion of all the indices in the regressions could result in some form of double counting. For example, the share of interest income and non-interest income will depend upon the decision of banks to diversify between loans (i.e. interest income generating activities) and other earning-assets (i.e. non-interest income generating activities) or more generally on the diversification between on- and off-balance sheet (i.e. fee income generating) activities. However, considering that the correlation coefficients between the three indices turned out to be rather low, we also estimated our base model while including them simultaneously in the regressions. The results in Table 12 remain the same.

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[13] The use of 2007 as a cut-off point is consistent with Hasan et al. (2013) and Anginer et al. (2014), among several others.

### 5.3.3. Accounting for nesting effects

In this section we employ the HLM approach, which simultaneously models regressions at both the bank- and country-level. Thus, by modelling each level of the hierarchy, multilevel models consider that banks within a country are more similar to one another than banks from different countries. The model is fitted using an interactive maximum likelihood algorithm in which the fixed and random effects are estimated simultaneously until the model converges.[14] In its combined form the model can be written as follows:

$$OFSI_{ijt} = \underbrace{a + \beta X_{ijt} + \gamma Z_{jt} +}_{\text{fixed components}} \underbrace{u_{ij} + e_j + \varepsilon_{ijt}}_{\text{random components}}$$

Where *OFSI, X* and *Z* are defined as before. The random variables $u_{i,j}$ and $e_j$ allow the intercept ($\alpha + u_{ij} + e_j$) to be random and unique to every bank and country. The term $\varepsilon_{i,jt}$ is the residual. So, the above model assumes that the intercept is random and all slope coefficients are fixed, implying that all slope parameters are identical across banks and countries. However, this model can be extended so that some coefficients can be specified to differ across banks and/or countries in a stochastic manner. As the main question of the present study is to explore the relationship between diversification and financial strength at the bank-level, it could be argued that this relationship is not identical across banks. Therefore, we estimate one more specification which incorporates, in addition to the random intercepts, a random coefficient for the effect of $DIV_{ijt}$ on $OFSI_{ijt}$, while all other coefficients remain fixed. Thus, this approach yields both fixed and random effects estimates for the bank-level diversification index. In this case, the above equation becomes:

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[14] We also estimated the model using maximum restricted likelihood (REML). Our main results hold.

$$OFSI_{ijt} = a + \beta\,X_{ijt} + \gamma\,W_{jt} + u_{0\ ij} + u_{1\ ij}DIV_{ijt} + e_{j} + \varepsilon_{ij}$$

The results of a likelihood-ratio test favour the model that allows for a random bank-specific regression line over the model that allows only for a bank-specific shift. In all the cases, the diversification indices enters with a positive and statistically significant coefficient, indicating that controlling for potential dependency due to nesting effects does not influence our main findings (see Table 13).

[Insert Table 13 Around Here]


*5.3.4. Accounting for endogeneity*

The potential endogeneity of diversification has been recently discussed in the banking literature (e.g. Goddard et al., 2008; Elsas et al., 2010). The underlying idea is that diversification itself might be an endogenous choice, and some of the observed association between income, earning assets and on-off balance sheet diversification and OFSI could be due to the reason that safer banks choose to diversify more across the various categories. In other words, so far we have assumed that diversification influences bank safety, but not vice versa.

Therefore, we re-estimate our model using instrumental variable regressions to control for the endogeneity between OFSI and diversification. Ideally we would like to use exogenous variables as instruments; however, it is very challenging to find strictly exogenous regressors to econometrically account for a potential endogeneity.[15] Therefore, we follow numerous earlier studies and we use lagged variables of diversification as instruments (e.g. Elsas et al., 2010)

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[15] We tried various industry and country-level variables that could serve as exogenous regressors like the index of regulatory restrictions on bank activities (e.g. Laeven and Levine, 2007), the real GDP growth (e.g. Dastidar, 2009), the share of diversified banks in the country (e.g. Laeven and Levine, 2007), and the average net interest margin of the banking sector. However, the identification tests indicate that these variables are not valid instruments.

With this instrument alone our equations will be exactly identified and this allows receiving under-identification and weak identification tests for the validity of the instrument. To receive the results of an over-identification test for our estimated models, we complement the lagged diversification with a bank-specific indicator of merger and acquisition activity (MERG). [16] As discussed in Laeven and Levine (2007) and Elsas et al. (2010), mergers can be related to diversification since they constitute an important strategic instrument for banks to manage their level of diversification.

We use the LIML method (Anderson and Rubin, 1949, 1950) that is well suited for dynamic panel estimations and may perform better than 2SLS and GMM in various occasions (see Baltagi, 2005; Bascle, 2008; Alonso-Borrego and Arellano, 1999). [17] Eventually, the OFSI is now regressed on its lag, the instrumented diversification and the remaining control variables. As can be seen in Table AIII.7 the above mentioned instruments pass the under-identification, weak identification and over-identification tests; thus, being valid instruments on the basis of these criteria. The results in Table 14 indicate that the instrumented diversification indicators enter the regressions with a positive and statistically significant coefficient.

Another potential source of endogeneity in the above setting may be the inclusion of the lagged dependent variable (i.e. OFSI) as control variable in the regression specification. To

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[16] As in Laeven and Levine (2007) we use information from the Bureau van Dijk database to trace the history of each bank in our sample, and we create a dummy that indicates whether a bank merged with or acquired at least one other bank or not. To account for the fact that M&As will have a long-term impact on bank attributes and their diversification decisions we assign the value of one on the year of the acquisition and all the years that follow, and the value of zero otherwise (i.e. years prior to the M&A and banks with no M&A activity).

[17] As discussed in Bascle (2008), the advantages of LIML estimation are that: (i) it is median unbiased, (ii) it is virtually unbiased even with weak instruments, and it may perform better than 2SLS estimation, (iii) in the case of small sample sizes, LIML estimation has been characterized as "the most reliable" estimator (Blomquist and Dahlberg, 1999). Anderson et al. (2010) and Akashi and Kunitomo (2012) discuss further cases under which the LIML estimator is quite attractive over alternative approaches like the generalized method of moments, the empirical likelihood, the within-groups, and the random-effects quasi maximum likelihood. Alonso-Borrego and Arellano (1999) also compare the GMM and LIML methods by means of simulations. Monte Carlo and empirical results show that the GMM can exhibit large biases when the instruments are poor, while LIML remains essentially unbiased.

check for the robustness of our results, we also estimate our regression specification without the lagged dependent variable (see e.g. Aebi et al., 2012) and we find that our main results remain the same.

[Insert Table 14 Around Here]

*5.3.5 Alternative approach for the estimation of the OFSI*

In constructing the OFSI discussed in the previous section, we did not impose any assumptions on the ordering of the financial ratios with respect to their relative significance. In this section, we test a slightly different alternative approach that is similar to the one used by Moody's in the estimation of their bank financial strength rating (BFSR). In particular, the simulations for the weightings of the ratios are now performed assuming that the cost to income ratio (an indicator of the banks' efficiency) is assigned a lower weight compared to the profitability (ROA), liquidity (LIQR), capital adequacy (TCAR), and asset quality (PLR) ratios, i.e., $w_{TCAR}$, $w_{PLR}$, $w_{ROA}$, $w_{LIQR} \geq w_{COST}$. Furthermore, the five dimensions of the banks' performance are assigned a total weight of 70%, whereas the remaining 30% is assigned to the lowest performing factor (which differs between the banks), after combining profitability and cost efficiency. This adjustment puts additional emphasis on the dimension where a bank performs worst. Thus, the evaluation model (1) is now expressed as follows:

$$V = 0.7(w_{TCAR}f_{TCAR} + w_{PLR}f_{PLR} + w_{COST}f_{COST} + w_{ROA}f_{ROA} + w_{LIQR}f_{LIQR}) +$$
$$0.3 \min \left\{ \frac{w_{ROA}f_{ROA} + w_{COST}f_{COST}}{w_{ROA} + w_{COST}}, f_{TCAR}, f_{PLR}, f_{LIQR} \right\}$$

The performance scores obtained from this evaluation approach are very similar to the ones of the OFSI model used in the previous sections (Pearson and Spearman correlations: 0.95; mean root-square deviation: 0.28), and the results of the regressions remain the same.

## 6. Conclusions and implications

The question of whether banks should focus on traditional banking or whether they should offer a wide array of services has generated a lively debate among academics, policy makers, and practitioners. Theory and existing empirical evidence provide conflicting views. In practice, we observed that over the last decade numerous banks around the world tented to diversify and enhance the portfolio of services that they offer. This diversification may influence various bank attributes; nonetheless, one of the most important questions is how it influences the overall financial strength of banks.

This study attempted to answer this question by using a sample of over 1,000 banks operating in 111 countries. First, we constructed a novel overall financial strength indicator taking into account various elements of bank risk and performance. Then, we examined the impact of bank diversification in terms of income, earning assets, and on-and-off balance sheet activities diversity on financial strength.

Our main finding is that diversification improves the overall financial strength of banks. This holds for different forms of diversification, including income, earning assets portfolio mix, and on- and off-balance sheet activities. Furthermore, we revealed that income diversification can be more beneficial for banks operating in less developed countries. Nonetheless, we observed the opposite in the case of diversification between off-balance sheet and on-balance sheet activities. Additionally, the results showed that the impact of the crisis on financial strength

can be less severe with the use of earning assets diversification. We performed a number of robustness tests, by controlling for various country-specific variables, and we also used alternative techniques for the estimation of both the overall financial strength indicator and the regressions. Our main finding remained the same across the various estimations.

These findings have important implications for bank managers who have a substantial financial and professional interest in their firm, regulators whose job is to monitor that bank managers behave in such a way that ensure safe and sound banking practices, and customers whose relationship with the bank could be jeopardized by deterioration in banks' financial strength. For example, at the policy level, the regulatory restrictions on bank activities vary widely across countries. Our results suggest that policy makers should direct their efforts toward ensuring adequate bank diversification. At the firm level, we find that diversification improves overall financial strength, implying that managers should perceive diversification as an important strategic decision. However, our findings in relation to the development status of the economy show that some banks in some countries may be favoured more by following specific forms of diversification, which are possibly aligned better with their expertise, along with technological advances, and managerial know-how in the industry. Similarly, the results in relation to the financial crisis, also point to the conclusion that managers choosing specific forms of diversification over others may end up managing a safer and sounder bank.

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**Table 1 – Descriptive statistics**

|  | Mean | St. Dev. | N |
|---|---|---|---|
| Panel A:  Variables used in first part of the analysis | | | |
| TCAR | 14.95 | 5.94 | 8051 |
| PLR | 4.47 | 4.87 | 8051 |
| COST | 66.77 | 30.94 | 8051 |
| ROA | 0.94 | 1.87 | 8051 |
| LIQR | 23.43 | 20.25 | 8051 |
| Panel B:  Variables used in second part of the analysis | | | |
| DIV$inc$ | 0.285 | 0.143 | 8051 |
| DIV$asset$ | 0.389 | 0.105 | 8051 |
| DIV$bs$ | 0.206 | 0.146 | 8051 |
| LNAS | 14.917 | 2.466 | 8051 |
| GDPGR | 3.158 | 3.809 | 8051 |
| INFL | 4.186 | 4.908 | 8051 |
| CAPRQ | 5.250 | 1.313 | 7882 |
| OFFPR | 11.829 | 1.904 | 7852 |
| PRMON | 6.411 | 0.926 | 7852 |
| ACTRS | 2.670 | 0.513 | 7882 |
| ECONFR | 67.142 | 10.610 | 8022 |
| CREDIT | 67.371 | 40.166 | 7691 |
| CONC | 41.570 | 19.597 | 7833 |
| TBANKZ | 21.158 | 9.898 | 7843 |
| CBASSET | 6.165 | 5.594 | 7297 |
| MCAPGDP | 77.273 | 54.950 | 7501 |
| BONDGDP | 110.002 | 66.720 | 6113 |
| INSTDEV | 0.548 | 0.850 | 8051 |
| ENFIND | 0.658 | 0.921 | 8051 |

Note: Variables are defined in Appendix II