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EUROPEAN BANKS STRADDLING BORDERS: RISKY OR REWARDING?

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JEL Classification: E44, G21, G28

Keywords: International Banking, Bank Regulation, Financial Stability, Risk, Geographical Diversification

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European Banks Straddling Borders: Risky or Rewarding?

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1. Introduction

Are European banks that straddle borders better off in terms of their risk-return profile? And does it matter where they expand to? Theoretically, diversifying across borders is expected to be risk-reducing as long as there is a non-perfect correlation across country specific risks. From that perspective banks should expand to countries that differ from their home country in economic and financial conditions. Using a unique dataset with cross-border exposures of the 61 largest European banks, our study provides an answer to these questions. First, we investigate the impact of cross-border banking on the risk-return profile of banks. Second, we examine empirically whether banks are investing more in countries with dissimilar economic and financial conditions.

With the continuing move towards financial integration, cross-border banking has gained increasing attention in the academic literature over the last years. Cross-border banking may not only impact individual banks but may have wider consequences for the real economy and the financial system.[1] Wider benefits from cross-border banking may, among others, arise from non-financial firms being more resilient against domestic crises via access to credit from non-local banks (Keeton, 2009; Hoffmann and Sørensen, 2015), or from more efficient banking sectors through increased competition from foreign banks (Schoenmaker and Wagner, 2013). In contrast, there are also studies that find that the entry of foreign banks in a country may have negative consequences. For example, during a crisis foreign banks may reduce their lending more than domestic banks, thereby contributing to the cyclicality in lending (Popov and Udell, 2012; De Haas and van Lelyveld, 2010; De Haas and van Horen, 2012; Hoggarth et al., 2013).

In our paper, we however focus on the impact of cross-border banking, i.e. geographical diversification, on individual banks. While diversification in general has the potential to reduce risk (Markowitz, 1952), there are opposite views on whether geographical diversification is beneficial for banks. Levy and Sarnat (1970) state that geographical diversification can generate positive effects as there is a non-perfect correlation across country specific risks, thereby reducing the risk in an internationally diversified portfolio. Winton (1999) however argues that geographical diversification is not always beneficial, for example when banks have loans with high downside risks or when banks expand into sectors where they have little expertise. In addition, the further a bank away from its home country, the more difficult it may be to manage. On the empirical side, one strand of the literature on geographical diversification indicates risk-reducing effects (e.g. Liang and Rhoades, 1988; Deng and Elyasiani, 2008),

[1] See, for example, Goldberg (2009), for an overview of the consequences of globalisation in banking.

while other studies argue that cross-border banking has no significant impact on the risk-return profile of a bank, or that it may even lead to higher insolvency risk or negative spill-over effects (e.g. Hughes et al., 1996).

A common weakness in most studies that focus on the impact of cross-border banking is that they do not take into account the economic conditions of the regions or countries where banks expand to. Based on theory, this is an important factor as it is assumed that the beneficial effects of geographic expansion depend on the correlations among country or region specific risks (Levy and Sarnat, 1970). Recently, Faia et al. (2017), Goetz et al. (2016) and Meslier et al. (2015) also raised this point of criticism. The latter two studies both consider potential diversification gains for US banks, and take into account a measure for dissimilarity between the economic conditions of banks' home and host states. Hence, Goetz et al. (2016) find that geographic expansion only reduces risk when banks expand into regions that are economically dissimilar in terms of income growth. Meslier et al. (2015) find that the dispersion in unemployment rates influences the beneficial impact of diversification. Faia et al. (2017) analyse 15 European Global Systemically Important Banks (G-SIBs) and find, in line with the aforementioned studies, that geographical expansion pays off, especially in countries with different business cycle co-movement, whereas the business cycle is measured by GDP growth.

Our paper, which focuses on European banks, makes two novel contributions to the literature. First, we investigate the impact of geographical diversification on banks by linking banks' cross-border positions, and country-specific conditions of those positions, to the risk-return profile of banks. We distinguish between structural and cyclical differences in economic and financial conditions across countries. With this approach we are better able to understand the risk diversification mechanism of cross-border banking. Second, and in order to understand the determinants of cross-border banking, we investigate which factors drive the cross-border positions of banks. In other words, are banks inclined to invest more in countries with dissimilar economic and financial conditions?

Our focus on the European banking sector is especially relevant in light of the ongoing financial integration within the European Union. This increases the scope for risk sharing through cross-border banking, but also poses the question what the impact is for banks. Focussing on the 61 largest European banks we cover approximately 66% of total European banking assets. Moreover, we use a unique hand-collected dataset and thereby cover all foreign exposures of banks. Previous studies often consider the foreign exposures of banks by considering banks' foreign subsidiaries. However, as banks also invest cross-border via branches and direct lending, using data solely on subsidiaries may lead to a significant

underestimation of banks' cross-border positions. This is also apparent from the study by Hüttl and Schoenmaker (2016), who show that somewhat less than half of the cross-border investments stems from branches.

Our results first of all show that geographical diversification has a positive impact on the risk-return profile of a bank. More interestingly, we find evidence that banks that diversify more into economically dissimilar countries reduce both their insolvency risk – as measured by the z-score – and their variability in net income. We do not find any relation between cross-border banking and a bank's net income. Second, and by investigating the determinants of banks' cross-border positions, we find that banks invest significantly more in countries that are, from an economic and financial perspective, more similar to their home country. In contrast to what could be expected from a theoretical point of view, we do not find any evidence that banks are inclined to invest more in dissimilar countries. Thereby, banks do not fully utilize the diversification opportunities that we find to arise from investing in more dissimilar countries.

Our findings contribute to the policy discussions on the progress of the single European banking market and thereby, on the treatment of cross-border lending in the regulatory framework and in supervision. While it was expected that the creation of the European Banking Union would foster cross-border banking, the foreign activities of banks remain at low levels. Schoenmaker and Véron (2016), who assess the state of the European banking union eighteen months after its implementation, state that barriers to the completion of the single market still exist. These barriers stem from a discouraging approach towards cross-border activities, for example by national supervisors that keep local capital and liquidity requirements, thereby negatively affecting cross-border subsidiaries.

The remainder of our paper is organised as follows. Section 2 presents our data and an overview of the cross-border positions of the 61 largest European banks. Section 3 studies the impact of geographical diversification on a bank's risk-return profile, and specifically zooms in on the impact of investing in more dissimilar countries. Section 4, as a second step, investigates whether banks are actually inclined to invest in dissimilar countries. Section 5 summarizes the main findings and concludes.

2. Cross-border positions

One of the challenges in this area of research is to get a complete overview of the cross-border positions of banks, as there are no regular reporting standards for banks' foreign exposures split by country. Moreover, only considering banks' subsidiaries, as previous studies that focus on European countries often do (see, for example, García-Herrero and Vázquez, 2013; Fang and van Lelyveld, 2014), may lead to a significant underestimation of a bank's foreign activities. Hüttl and Schoenmaker (2016) consider the share of EU assets held by branches and subsidiaries headquarted in other EU countries and third countries over total banking assets, and the data indicate that somewhat less than half of the foreign investments stems from branches. Therefore, and in order to get a complete overview of banks' cross-border positions, including those via branches, we use a unique hand-collected dataset.[2] Our sample consists of 61 European banks over the years 2010-2015.[3] We intentionally left out the global crisis period, as this may significantly influence the results. Focusing on this sample, we cover approximately 66% of total European banking assets based on end-2015 data. Data on cross-border positions are primarily obtained from annual reports, and, when needed, supplemented with data stemming from the public EBA stress tests conducted in 2011 and 2013, and CRD IV country-by-country reporting.

Due to the absence of a standard reporting format some assumptions and simplifications had to be made. First of all, the majority of banks report their foreign exposures in loans or assets, but some banks use the net income as the reporting unit. As we are especially interested in banks' credit exposures to other countries, we had an order of preference for exposures reported in i) loans; ii) assets; and iii) net income.[4] Second, we aimed for cross-border exposures at the country level as for our analysis we link home and host country characteristics. However, sometimes only information on banks' exposures to a group of countries (e.g. Western Europe) or continents (e.g. Asia) was available. In those cases, we simply reported the exposures to groups of countries or continents, and defined country characteristics – such as credit-to-GDP or unemployment - at a group or continent level by taking the (GDP weighted) average of all countries belonging to that group or continent. Third,

[2] Our data does not distinguish between the type of foreign lending, i.e. via branches, subsidiaries or direct lending, as we focus on the question whether geographical diversification is beneficial for the bank as a whole. Relevant studies that focus on the type of bank internationalisation include Cerutti et al. (2007) and De Haas and van Lelyveld (2006).

[3] These are banks with total assets of EUR 100 billion in either 2015 or 2010. Only the Belgian bank Dexia and the German bank WestLB are left out, as with the restructuring of Dexia in 2010, a large part of the portfolio is now with Belfius bank, while Dexia operates as a "bad bank". WestLB was split into three parts (of which one was a bad bank) in 2012 and significantly decreased its assets since then.

[4] If the reported net income from a country is negative, we treat this as zero exposure.

the data collection resulted in an almost complete overview of the foreign exposures of the 61 European banks. For only a small portion of foreign exposures – 3.6% of the total foreign exposures or 1.1% of the total assets – we do not know to which region or country these belong. This is the case when banks report their remaining foreign exposures as "other" without mentioning the countries belonging to this group.

The 61 banks in our sample invest together in 138 countries. Table 1 provides an overview of the geographical exposures for all banks in our dataset, grouped by country, while Table A.1 in the Appendix provides this information for all individual banks. On average, banks invest the majority, 56.8%, of their assets in their home country. Their foreign exposures are mainly held in other European countries (21.9%) and North America (10.9%). Exceptions are UK and Spanish banks, respectively investing 19.3% in Asia and 9.2% in South America.

Table 1: Geographical distribution of assets per country

This table shows the domestic exposures and foreign exposures by region for the 61 European banks in our dataset, grouped per country. The data is based on end-2015 numbers, and weighted by total banking assets.

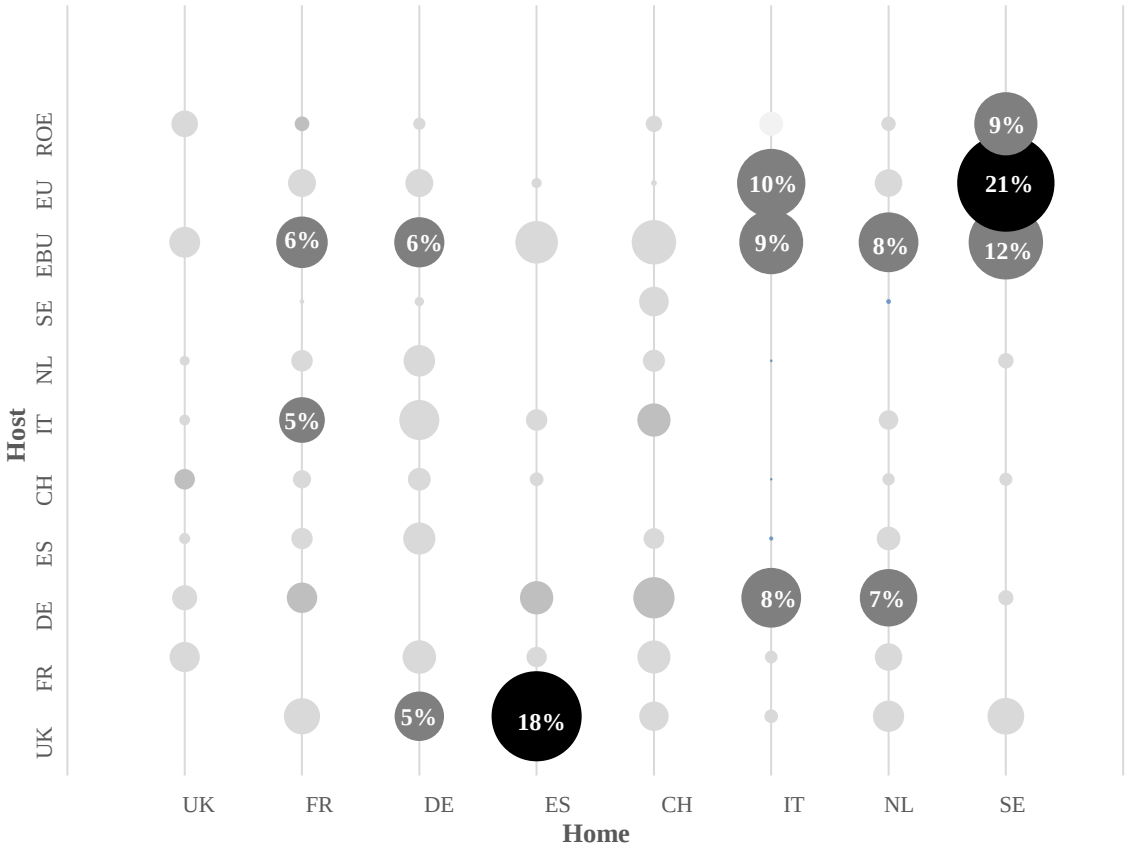
Home country	Banks (#)	Assets (in € bln)	Home	Rest of Europe	North America	South America	Asia	Africa	Oceania
FR	6	7,120	66.4%	20.4%	7.4%	0.9%	3.4%	1.3%	0.2%
UK	6	6,795	55.0%	8.8%	14.5%	0.2%	19.3%	1.5%	0.7%
DE	13	4,391	50.2%	24.7%	14.4%	1.8%	7.9%	0.9%	0.1%
ES	6	3,009	47.4%	26.9%	13.0%	9.2%	3.6%	0.0%	
NL	5	2,174	61.2%	23.5%	5.9%	1.3%	4.2%	0.1%	3.2%
CH	4	1,953	40.4%	19.5%	31.5%	0.9%	7.7%		
IT	5	1,944	67.7%	29.3%	1.1%	0.6%	0.9%	0.5%	
SE	4	1,429	48.8%	46.3%	3.8%	0.0%	1.1%		
DK	2	627	67.0%	33.0%					
BE	2	429	59.2%	37.1%	1.6%	0.0%	1.6%	0.2%	0.2%
AT	2	338	35.8%	58.6%	0.7%	0.0%	4.6%	0.1%	
NO	1	270	62.0%	26.1%	5.7%	2.7%	1.8%	0.6%	1.1%
IE	2	234	71.9%	28.1%					
FI	1	125	82.9%	14.6%	0.8%		0.3%		
GR	1	111	87.5%	12.2%				0.3%	
PT	1	101	75.1%	13.3%	1.9%	0.4%	4.9%	4.4%	
Weighted average			**56.8%**	**21.9%**	**10.9%**	**1.6%**	**7.5%**	**0.8%**	**0.4%**

As the majority of the foreign assets is invested in European countries, Figure 1 shows the distribution of these cross-border positions across European (groups of) countries for the eight countries with the largest banking sectors. Together these data represent 49 banks and approximately 61% of total European banking assets. Especially Spanish and Swedish

banks show a large cross-border exposure towards one country, with Spanish banks investing the majority of their total European cross-border exposures in the UK and Swedish banks in Denmark. Moreover, the majority of the cross-border activities by the eight largest European banking sectors takes place within the European Banking Union and the UK. Only Italian and Swedish banks invest a relatively large amount in other European countries. For Swedish banks, the exposures are however mainly concentrated in countries relatively close to Sweden, namely Finland, Norway and Denmark.

Figure 1: Geographical distribution of European assets by main countries

This figure shows the cross-border loans of 49 banks in 8 countries to European (groups of) countries as a % of the total cross-border loans of those 49 banks. Hence, the circles together sum up to 100%. The 8 countries – and thereby the 49 banks - are selected based on the size of the financial sector and are United Kingdom (UK), France (FR), Germany (DE), Spain (ES), Switzerland (CH), Italy (IT), The Netherlands (NL) and Sweden (SE). The size and color of the circles reflect the size of the exposures, whereas black depicts an exposure of > 15%, dark grey between 5% and 15% and light grey < 5%. On the vertical axes, "EBU" refers to other countries in the European Banking Union, "EU" to the remaining EU countries and "ROE" finally includes all remaining European countries.



3. The impact of cross-border banking on banks' risk-return profile

3.1 Previous findings

A variety of studies investigates the impact of cross-border banking on bank risk, return, risk-adjusted return or insolvency risk, with contradictory findings so far. For example, Morgan and Samolyk (2003) investigate the impact of geographical diversification for US banks, and find that while it increases the lending capacity of banks and the banking system, it does not increase the profits of individual banks or reduce the risk in their portfolios. In contrast, and again focusing on US banks, Deng and Elyasiani (2008) find that geographical diversification is associated with risk reduction, but that a larger distance between a bank and its branches increases bank risk. Buch et al. (2013) consider diversification effects for German banks and conclude that the impact of internationalization differs across banks, while Acharya et al. (2006) point to a non-linear relation between banks' return and diversification whereas they expect that the relation between these two depends on a bank's risk level.[5]

The aforementioned studies do not explicitly take into account *where* banks expand to. Yet, as stated before, the location of banks' cross-border positions is an important factor as risk diversification is assumed to take place when banks expand to countries with non-perfectly correlating risks. Recently, a couple of studies provided some indication for this. For example, considering banks from G-7 countries and Spain, García-Herrero and Vázquez (2013) investigate whether diversifying internationally yields higher risk-adjusted returns. Their results show that a larger asset allocation to foreign subsidiaries yields higher returns, but also increases risk; overall, they observe an improvement in the risk-adjusted return. By distinguishing between expanding business to industrial and emerging countries, the authors find that the beneficial impact is more pronounced for banks with subsidiaries in emerging countries, possibly as a consequence of the very low correlations with the domestic economic conditions. Thus, their findings indicate that taking into account the economic conditions of the regions or countries where banks expand to matter. Fang and van Lelyveld (2014) focus on the potential benefits of internationalization while keeping in mind the dispersion in economic conditions across countries. By applying a correlation matrix approach, they calculate the international diversification effects for the world's 49 largest banks, and use the output gap as a measure for country-specific risks. They find that the benefits of international diversification can be substantial, up to a reduction of 8% of credit risk. They also differentiate between banking groups that are active in OECD countries only and those that have activities in at least

[5] Other relevant studies include, Liang and Rhoades (1988), Chong (1991), Hughes et al. (1996), Demsetz and Strahan (1997), Hayden et al. (2007), and Goetz et al. (2013).

one non-OECD country. Bank with activities in both OECD and non-OECD countries do better in terms of credit risk. Hence, the potential for risk reduction is higher as the business cycles are less synchronized between OECD and non-OECD countries.

For US banks, the studies conducted by Goetz et al. (2016) and Meslier et al. (2015) consider potential diversification gains by taking into account a measure for dissimilarities in economic conditions between banks' home and host states. Goetz et al. (2016) consider the geographical distribution of deposits, taking into account both subsidiaries and branches, and find that geographic expansion only reduces risk when banks expand into regions that are economically dissimilar in terms of income growth. Likewise, Meslier et al. (2015) find that the dispersion in unemployment rates influences the beneficial impact of diversification. The authors also assess whether the benefits of geographical expansion differ across bank size, but find that diversification benefits banks of all sizes. Faia et al. (2017) conduct a similar study for the 15 European G-SIBs. They find that expanding to countries that exhibit lower business cycle co-movement decreases a bank's riskiness as measured by either CDS prices or loan loss provisions.

In our paper we follow the approach taken Faia et al. (2017), Goetz et al. (2016), and Meslier et al. (2015) and explicitly control for dissimilarities between a bank's home and host country. Yet, first of all, we estimate a baseline model in which we control for the impact of a geographically diversified portfolio on banks' risk-return profile. As a second step, we control for the dissimilarities in economic and financial conditions between a bank's home and host country.

3.2 Data and methodology

To assess the impact of geographical diversification on banks, we estimate the following baseline model:

$$r_{b,t} = \alpha_b + \gamma_t + \beta_1 * (1 - HHI_{b,t}) + \sum_{k=5}^{K} \beta_k X_{b,t-1} + \varepsilon_{b,t} \quad (1)$$

where $r_{b,t}$ is either the natural logarithm of i) bank's return on assets (ROA); ii) the standard deviation of its ROA, or iii) the z-score, at year *t* for bank *b*.[6] The z-score is defined as follows;

$$z - score_{b,t} = \frac{Leverage\ ratio_{b,t} + ROA_{b,t}}{\sigma(ROA_{b,t})} \quad (2)$$

[6] As the ROA can take on negative values, we compute the natural logarithm as ln ROA = ln(1 + ROA)

where a bank's leverage ratio ($\text{Leverage ratio}_{b,t}$) is measured by the bank's Tier 1 capital divided by its total assets. $\text{ROA}_{b,t}$ denotes the return on assets and is defined as the ratio of a bank's net income over its total assets, whereas $\sigma(ROA_{b,t})$is the standard deviation of this measure. The standard deviation is based on a six period moving window using semi-annual data, and represents the variability in a bank's net income. The z-score represents the number of standard deviations that a bank's ROA has to drop before the bank is insolvent. Hence, the higher the z-score, the more standard deviations away from failure, and the healthier a bank. α_b and γ_t represent the bank-specific and time fixed effects respectively, and $\varepsilon_{b,t}$ is the error term.

$HHI_{b,t}$ represents the Herfindahl-Hirschmann Index of geographic dispersion, and is calculated as the sum of bank *b*'s squared exposures in different host countries. The index ranges from zero (perfect diversification) to one (all exposures in one country). In the regression specification we subtract this number from one, so that the more geographically diversified a bank is, the higher the value of this variable. This variable hence measures the extent of geographical diversification by banks. In line with theory, we expect a positive coefficient of this variable on a bank's z-score and ROA, while a negative coefficient is expected for the bank's standard deviation of its ROA.

While the HHI is a good variable to measure geographical diversification of banks, it does not take into account any characteristics of the countries banks invest in. Hence, to investigate whether geographic diversification improves the risk-return profile of banks, specifically when banks expand into countries with different economic and financial conditions, we construct a variable that allows us to control for expanding into dissimilar countries. Following Goetz et al. (2016), and based on the idea of Zenga (2001), we decompose the HHI into two components. One component picks up the geographical diversification of banks *within* countries (be it in similar or dissimilar countries in terms of economic and financial conditions), while the other considers the extent to which banks diversify *between* economically similar and dissimilar countries.

Hence, for each bank we decompose the HHI into these two components, which we call the within and between component:

$$HHI_{b,t} = HHI_{b,t}^{between} * \overline{HHI}_{b,t}^{within} \tag{3}$$

where $HHI_{b,t}^{between}$ is the Herfindahl-Hirschmann Index of the foreign loans *between* similar and dissimilar countries for bank *b* at time *t*. This can be written as follows:

$$HHI_{b,t}^{between} = (X_{b,t}^{dissim})^2 + (X_{b,t}^{sim})^2 \tag{4}$$

where $X_{b,t}^{dissim}$ represents the total share invested in dissimilar countries and $X_{b,t}^{sim}$ the total share invested in similar countries.

The second component in (3), $\overline{HHI}_{b,t}^{within}$, represents the weighted arithmetic mean of the HHI for diversification *within* similar and dissimilar countries. This is:

$$\overline{HHI}_{b,t}^{within} = \frac{1}{HHI_{b,t}^{between}} * [\sum_{m=1}^{M}(x_{b,m,t}^{dissim})^2 + \sum_{n=1}^{N}(x_{b,n,t}^{sim})^2] \quad (5)$$

where $X_{b,t}^{dissim}$ and $X_{b,t}^{sim}$ again respectively represent the total share invested in dissimilar and similar countries. $x_{b,m,t}^{dissim}$ and $x_{b,n,t}^{sim}$ respectively are exposures (shares) towards a single dissimilar country *m* and similar country *n*. Hence, $X_{b,t}^{dissim} = \sum_{m=1}^{M}(x_{b,m,t}^{dissim})$ and $X_{b,t}^{sim} = \sum_{n=1}^{N}(x_{b,n,t}^{sim})$.

We classify a country-pair as either similar or dissimilar as follows. For robustness, we use the five different specifications to measure how dissimilar a bank's home and host country are. That is, for each cross-border loan of bank *b* we consider the absolute difference between a bank's home country *i* and host country *j* in terms of i) GDP per capita ($GDPcapita_{|i-j|,t}$) ;ii) credit-to-GDP ratio ($creditGDP_{|i-j|,t}$) ;iii) unemployment rate ($unemployment_{|i-j|,t}$) ;iv) annual GDP growth ($GDPgrowth_{|i-j|}$); and v) output gap ($outputgap_{|i-j|,t}$).[7] These five indicators measure different economic phenomena, and can be grouped into two categories. GDP per capita and credit-to-GDP are expected to pick up structural differences in economic and financial conditions, and are expected to have a more permanent effect on the foreign loan allocation. The latter three indicators (unemployment, GDP growth and the output gap) aim to measure cyclical dissimilarities in economic conditions. Based on each of these measures of dissimilarity and for all country-pairs, we compute a simple dummy variable, where one implies dissimilar countries and zero similar countries. This is done as follows. For each year *t* and for each home country *i* we assign a host country *j* as dissimilar from *i* if the measure of dissimilarity between *i* and *j* is higher than the median difference between *i* and all other countries. Vice versa, similar countries have measures below the median. Hence, for each home country *i* we distinguish two equally sized groups of countries: countries that are similar to country *i* and countries that are dissimilar.

In our regression analysis, and for ease of interpretation, we again subtract the diversification measures from one. Hence, inserting the decomposition of the HHI measure into our regression model results in:

[7] The latter measure is calculated using the Hodrick-Prescott (HP) filter, which removes the cyclical component of the time series. The HP filter is applied to quarterly GDP series.

$$r_{b,t} = \alpha_b + \gamma_t + \beta_1 * (1 - HHI_{b,t}^{between}) + \beta_2 * (1 - \overline{HHI}_{b,t}^{within}) + \sum_{l=5}^{L} \beta_l X_{b,t-1} + \varepsilon_{b,t} \quad (6)$$

In both regression specifications (1) and (6), $X_{b,t-1}$ includes bank specific control variables. All variables are lagged one year to overcome potential endogeneity issues. We have five control variables. First of all, the natural logarithm of banks' total assets ($ln\ Total\ assets_{b,t-1}$) is included. We expect a positive coefficient of this variable on a bank's z-score and its ROA, as larger banks can benefit from economies of scale (Hughes and Mester, 2013). Second, the cost-to-income ratio ($cost - to - income_{b,t-1}$) is taken into account to control for the impact of lower cost efficiency. A high cost-to-income ratio is expected to increase banks' income variability, and to reduce banks' z-score and ROA. Third, the Tier 1 leverage ratio ($Tier\ 1\ leverage_{b,t-1}$) is included to control for the higher risk absorbing capacity of well capitalized banks and is hence expected to have a positive impact on a bank's z-score. Fourth, we control for the share of problem loans on a bank's balance sheet (ln $Problemratio_{b,t-1}$). Problem loans are defined as the sum of the non-performing loans, impaired loans and other problem loans.[8] Fifth, we include a measure for the share in non-interest income of total operating income ($Share\ non - interest\ income$ (%)) as a larger reliance on non-interest income is found to be associated with more volatile bank returns (see for example Stiroh, 2004). Moreover, in the regressions where banks' z-score or the variability in income is used a dependent variable, we also control for the ROA ($ROA_{b,t-1}$).

All balance sheet data are obtained from the SNL Financial Database, and when needed complemented with data from Bankscope or (semi) annual reports. Various data sources from the IMF and World Databank were used to collect data on the economic and financial indicators. Table 2 provides the descriptive statistics for all banks in our dataset. There is a strong variation in bank characteristics. The relatively high problem loan ratios and the wide dispersion among countries is due in part to the aftermath of the crisis. Especially the GIIPSC[9] countries still suffer from a high level of non-performing or problem loans on their balance sheets. This is also shown in the fifth column of Table 2. The share of problem loans on the balance sheet in these countries is more than twice as high as the European average. Moreover, the average ROA of these countries is negative, and the variability in income, as measured by the standard deviation of the ROA, is higher than the European average.

[8] According to the definition from the SNL Financial Database.
[9] GIIPSC stands for Greece, Italy, Ireland, Portugal, Spain and Cyprus: the countries that suffered most during the aftermath of the global crisis.

The final two columns of Table 2 provide the averages for a diversified and focused (i.e. less diversified) subsample of banks. Hence, in each year *t* from 2010 to 2015, banks are divided into two groups based on whether their diversification measure (1 - HHI) in year *t* is below (focused) or above (diversified) the median. The data shows that, on average, the diversified banks have a i) bigger size; ii) higher Tier 1 leverage ratio; iii) higher ROA; iv) less volatile ROA; and v) lower problem ratio.

Table 2: Bank descriptive statistics (2010-2015)

This table shows descriptive statistics for the variables used in regressions (1) and (6) for all 61 European banks over the years 2010-2015. The sixth and seventh column provide the averages of these variables for two different subsamples based on whether a bank's diversification measure (1-HHI) in year *t* is below (focused) or above (diversified) the median. The right column provides the variable means for GIIPSC countries only.

						GIIPSC	**Focused**	**Diversified**
	Mean	**Median**	**10%**	**90%**	**St. Dev.**	**Mean**	**Mean**	**Mean**
Total Assets (in € mrd)	517	265	117	1,308	526	348	387	692
Tier 1 leverage (%)	4.74	4.62	2.93	6.50	1.64	5.53	4.64	4.87
ROA (%)	0.001	0.003	-0.004	0.006	0.009	-0.004	0.000	0.002
St. Dev. ROA	0.003	0.001	0.000	0.006	0.005	0.006	0.003	0.002
Z-score	65.4	41.4	7.4	142.5	83.0	28.1	64.3	66.9
Problem ratio (%)	7.20	4.15	0.78	17.7	8.40	15.9	7.41	6.92
Cost-to-income (%)	61.8	61.7	44.3	81.7	23.1	62.9	60.3	63.9
1 – HHI	0.45	0.42	0.10	0.81	0.27	0.37	0.21	0.68
Non-interest income(%)	23.3	22.6	9.0	36.3	11.8	24.1	22.9	23.8

For our analysis it is important that the risk and return measures do not only vary through banks, but also exhibit variability for individual banks over time. Table A.2 in the Appendix shows the means for all variables per year, and the within and between standard deviations. First of all, one can see that banks improved their capital position over the last years, as indicated by the increasing Tier 1 leverage ratio. This, together with the improved ROA, resulted in a higher average z-score. Moreover, the table also indicates that the variables vary over banks as well as over years.

Table 3: Decomposition of the diversification measure (1-HHI)

This table shows the decomposition of the HHI measure into two components. The *within* component represents the weighted average diversification of banks within similar and dissimilar countries, while the *between* component measures the diversification of banks between similar and dissimilar countries. Whether a country is similar or dissimilar from a bank's home country is determined by five different measures.

	1-HHI within	**1-HHI between**
GDP per capita	0.419	0.065
Credit-to-GDP	0.367	0.161
Unemployment	0.342	0.196
GDP growth	0.379	0.137
Output gap	0.361	0.167

Table 3 shows the average values of the two components of the diversification measure. Note that, at a bank level, equation (3) implies that the undecomposed HHI equals the product of the HHI within and HHI between components. Hence, this table shows to what extent the HHI measure is determined by banks' activities in dissimilar countries, i.e. the HHI between component. The higher the value for 1-HHI between, the more banks diversify in countries with dissimilar economic and financial conditions. Table 3 however shows that the diversification between similar and dissimilar countries is limited, and that the diversification within countries is greater.

Table A.3 in the Appendix shows the correlation matrix for the variables used in the regression. The diversification variable (1-HHI) positively correlates with a bank's z-score and its ROA, indicating benefits from geographical diversification. The correlation with the standard deviation of a bank's ROA is, contrary to our expectations, however also (slightly) positive. The correlation matrix also shows that a bank's z-score and its standard deviation of its ROA have a high correlation. Hence, the denominator of the z-score, i.e. the standard deviation of the ROA, largely determines a bank's z-score.

3.3 Results

As a first step, regression specification (1) was estimated, i.e. without controlling for whether banks expand into similar or dissimilar countries. Table 4 shows the regression results. The odd numbered columns show the impact of geographic diversification on a bank's z-score, ROA and variability in ROA for all banks in our sample, while the even numbered columns shows this for a limited sample of banks, i.e. excluding banks from GIIPSC countries.

First, the positive and significant coefficient for the diversification variable (*1-HHI*) in the first column indicates that the more internationally diversified a bank is, the higher its z-score and thus the healthier the bank. Both a bank's share of problem loans on its balance sheet

and its ROA significantly influence its z-score, where a higher amount of problem loans results in a lower z-score and a higher ROA in a higher z-score, as expected. While the coefficients for the cost-to-income ratio and the Tier 1 leverage ratio show the expected signs, these variables do not significantly contribute to our model.

Second, the third column of Table 4 shows that diversifying across borders benefits banks through a lower variability in their net income, as indicated by the significant and negative coefficient for the diversification measure *1-HHI*. Regarding the control variables, a significant impact of a bank's problem loan ratio and its ROA on a bank's variability in net income can be observed. Moreover, a high share of problem loans increases the variability in net income.

Third, the fifth column of Table 4 presents the regression results where the ROA is used as the dependent variable. Contrary to the significant impact of geographic diversification on a bank's z-score and variability in ROA, the results in this column show that the extent of geographic diversification has no significant impact on a bank's ROA. Moreover, also the coefficients for all control variables, except the size variable, are insignificant. The negative coefficient for the size variable contradicts our hypothesis of economies of scale. The explanatory power of this model is relatively low when compared with the results from columns (1) and (3).

Columns 2, 4 and 6 of Table 4 show the regression results where the banks from GIIPSC countries are excluded. The exclusion of these banks slightly influences the coefficients and significance of the coefficients. Banks' capitalization now has a significant (positive) impact on a bank's z-score. The impact of the cost-to-income ratio on a bank's z-score is now significant and has, in line with our expectations, a negative impact. The other findings are similar, i.e. geographic diversification improves banks' z-score and decreases the variability in banks' net income, while there is no significant impact on banks' ROA. If we compare the explanatory power of the regression models including and excluding banks from GIIPSC countries, larger differences can be observed. For the regressions where the z-score and standard deviation of ROA are used as the dependent variables, the explanatory power of the model almost doubles when not taking into account banks from GIIPSC countries. Therefore, for the next step in our analysis, we both show the regression results excluding the banks from GIIPSC countries and including the banks from GIIPSC countries.

Table 4: The impact of geographic diversification

This table shows the regression results from equation (1) over the period 2010-2015. The dependent variables are in the top row. Standard errors are clustered at the bank level, and reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	ln Z-score	**ln Z-score**	**ln σ(ROA)**	**ln σ(ROA)**	**ln ROA**	**ln ROA**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Diversification measures						
1-HHI	1.793**	1.902*	-1.802***	-2.383***	-0.002	-0.0003
	(0.804)	(1.008)	(0.657)	(0.880)	(0.010)	(0.004)
Control variables						
ln Total Assets (t-1)	-0.406	-0.709	0.415	0.633	-0.016**	-0.002
	(0.491)	(0.489)	(0.455)	(0.446)	(0.008)	(0.002)
Tier 1 leverage (t-1)	2.112	9.184***	5.980*	1.438	-0.106	-0.006
	(5.120)	(2.239)	(3.267)	(1.355)	(0.088)	(0.014)
ln Problem ratio (t-1)	-0.317***	-0.256***	0.249***	0.249***	0.002	-0.0003
	(0.085)	(0.065)	(0.068)	(0.060)	(0.002)	(0.000)
ln ROA (t-1)	19.447***	61.311***	-21.156***	-61.462 ***		
	(3.079)	(0.165)	(3.668)	(14.064)		
Cost-to-income (t-1)	-0.266	-0.664**	-0.072	0.286	0.002	-0.001*
	(0.222)	(0.256)	(0.238)	(0.335)	(0.002)	(0.000)
Share non-interest income (t-1)	-1.125	1.173	1.146	1.181	-0.008	0.008
	(1.315)	(1.770)	(1.047)	(1.047)	(0.013)	(0.005)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Including GIIPSC	Yes	No	Yes	No	Yes	No
R^2 adj.	19.9%	30.3%	15.3%	25.8%	6.8%	5.3%
# Obs.	352	269	354	269	359	273

Table 5: The impact of geographic diversification on banks' z-score (excl. GIIPSC)

This table shows the regression results from equation (6) over the period 2010-2015 for a subsample of banks, i.e. excluding banks from GIIPSC countries. The dependent variable is the natural logarithm of a bank's z-score. Standard errors are clustered at the bank level, and reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	GDP per capita	Credit-to-GDP	Unemploy-ment	GDP growth	Output gap
	(1)	(2)	(3)	(4)	(5)
Diversification measures					
1-HHI within	1.218	1.432	1.474*	1.848**	1.173
	(0.903)	(0.939)	(0.830)	(0.737)	(0.768)
1-HHI between	4.033***	1.078	1.072	0.741	1.042*
	(1.378)	(0.941)	(0.706)	(0.522)	(0.585)
Control variables					
ln Total Assets (t-1)	-0.487	-0.697	-0.722	-0.747	-0.644
	(0.469)	(0.488)	(0.509)	(0.487)	(0.494)
Tier 1 leverage (t-1)	9.778***	9.158***	9.711***	7.741***	9.226***
	(2.318)	(2.251)	(2.396)	(2.305)	(2.337)
ln Problem ratio (t-1)	-0.217***	-0.253***	-0.258***	-0.244***	-0.252***
	(0.061)	(0.069)	(0.066)	(0.058)	(0.067)
ln ROA (t-1)	64.347***	62.263***	61.057***	59.720***	62.821***
	(16.047)	(16.428)	(16.656)	(16.262)	(16.459)
Cost-to-income (t-1)	-0.771**	-0.683**	-0.678**	-0.665**	-0.715***
	(0.254)	(0.259)	(0.264)	(0.254)	(0.260)
Share non-interest	1.698	1.208	1.235	1.163	1.372
income (t-1)	(1.788)	(1.781)	(1.788)	(1.728)	(1.784)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
R^2 within	32.0%	29.8%	29.9%	30.7%	29.8%
# Obs.	269	269	269	269	269

Tables 5 and 6 show the regression results for a limited sample, i.e. excluding banks from GIIPSC countries, where the diversification measure is decomposed into the two components. Tables A.4 and A.5 in the Appendix show similar results for the full sample of banks. The sign and significance of the control variables are not significantly impacted by the decomposition of the diversification measure. Therefore, by discussing the results we only focus on the impact of the diversification measures. Moreover, as it turned out that diversification did not have any significant impact on the ROA of banks, we do not show regression results where the ROA is used as a dependent variable.[10]

[10] Moreover, the regressions – of which the results are not shown in the paper – showed that the decomposed diversification measure does not have a significant impact on a bank's ROA.

Table 6: The impact of geographic diversification on banks' variability in income (excl. GIIPSC)

This table shows the regression results from equation (6) over the period 2010-2015 for a subsample of banks, i.e. excluding banks from GIIPSC countries. The dependent variable is the natural logarithm of a bank's standard deviation of its ROA. Standard errors are clustered at the bank level, and reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	GDP per capita	Credit-to-GDP	Unemploy-ment	GDP growth	Output gap
	(1)	(2)	(3)	(4)	(5)
Diversification measures					
1-HHI within	-1.755**	-1.782**	-1.849**	-2.009***	-1.737**
	(0.760)	(0.812)	(0.807)	(0.676)	(0.669)
1-HHI between	-3.844***	-1.209	-1.306**	-1.070**	-1.331**
	(1.294)	(0.955)	(0.621)	(0.454)	(0.534)
Control variables					
ln Total Assets (t-1)	0.436	0.605	0.643	0.629	0.596
	(0.429)	(0.449)	(0.468)	(0.452)	(0.453)
Tier 1 leverage (t-1)	0.909	1.473	0.740	2.548*	1.655
	(1.447)	(1.347)	(1.464)	(1.325)	(1.562)
ln Problem ratio (t-1)	0.213***	0.246***	0.251***	0.238***	0.242***
	(0.061)	(0.064)	(0.059)	(0.055)	(0.060)
ln ROA (t-1)	-64.078***	-62.680***	-61.116***	-60.886***	-62.828***
	(13.347)	(0.141)	(14.293)	(14.134)	(13.937)
Cost-to-income (t-1)	0.376	0.312	0.302	0.295	0.339
	(0.350)	(0.339)	(0.345)	(0.336)	(0.346)
Share non-interest income (t-1)	-0.696	-0.282	-0.301	-1.174	-0.464
	(1.853)	(1.837)	(1.845)	(1.791)	(1.842)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
R^2 within	27.5%	24.9%	25.2%	25.7%	25.4%
# Obs.	269	269	269	269	269

Table 5 shows the impact of the two diversification components on a bank's z-score. The positive coefficients of *1-HHI within* in all columns indicate that international diversification within countries in general improves a bank's z-score. However, not all variables are significant. The significant and positive coefficients of *1-HHI between* in columns (1) and (5) indicate that diversifying more into countries with a GDP per capita or output gap that is more different from that of a bank's home country results in a higher z-score. Table 6 considers the impact of diversification on a bank's variability in net income. The highly significant and negative coefficients of *1-HHI within* in all columns show that diversifying internationally reduces the variability in a bank's ROA. Moreover, banks that diversify more into countries that are dissimilar in terms of GDP per capita, unemployment rates, GDP growth

or the output gap, experience an even higher beneficial impact from cross-border banking as indicated by the significant and negative coefficients of *1-HHI between.*

For robustness, Tables A.4 – A.5 in the Appendix show the regression results for the full sample of banks, i.e. including the banks from GIIPSC countries. The results are quite similar, i.e. geographical diversification has a positive impact on a bank's z-score and decreases the variability in income. Moreover, the benefits from diversification can be even higher when banks invest more in economically and financially dissimilar countries.

To conclude, our findings show evidence for benefits arising from cross-border banking. Banks that are more geographically diversified have lower insolvency risk, and experience less variability in their income. Moreover, these benefits from diversification can be even higher when banks invest more in countries that differ more from their home country in economic and financial conditions. Therefore, as a next step, the following section investigates whether banks utilize these potential benefits by investing in dissimilar countries. It does so by applying a gravity model to investigate the determinants of banks' cross-border positions.

4 Determinants of banks' cross-border positions

4.1 Previous findings

Banks that go abroad can do so for a variety of reasons. Why and where banks go abroad has been studied extensively in the academic literature (e.g. Vander Vennet, 1996; Niepmann, 2015; Buch, 2000; Berger et al., 2016; Huizinga et al., 2014). These studies all point to factors that could be determinants of banks' cross-border positions, such as different taxation policies between the home and host country. However, yet another reason why banks may invest across borders is because of the risk diversification that may arise when there is a non-perfect correlation among country-specific risks. This implies that dissimilarities in economic and financial conditions could, at least from a theoretical point of view, be seen as a reason by banks to go abroad. While this theory is often cited in the academic literature on cross-border banking, there are almost no studies that investigate whether banks are indeed attracted to more dissimilar countries. The study by Heuchemer et al. (2009) can be seen as an exception. The authors consider cross-border lending in the Eurozone and find that cross-border loan granting is mainly promoted by the similarity of financial systems, in terms of credit-to-GDP ratio's, rather than financial development differences.

Therefore, in this section, we follow the approach taken by Heuchemer et al. (2009) and relate banks' cross-border lending to dissimilarities in economic and financial conditions

between the home and host country. In our model we control for other variables that are used in the standard gravity models and that are found to have an impact on cross-border banking. These are, among others, the distance and bilateral trade flows between the home and host country and whether these countries share a border and currency. In addition, we add variables that capture the dissimilarities in economic and financial conditions between the home and host country.

4.2 Methodology and data

A gravity model is estimated to investigate the determinants of banks' foreign loans:

$$\frac{Loans_{b,i,j,t}}{Assets_{b,t}} = \alpha_b + \gamma_t + \delta_j + \sum_{k=2}^{K} \beta_k X_{i,j,t} + \sum_{l=K+1}^{L} \beta_l Y_{i,j} + \sum_{m=L+1}^{M} \beta_m GIIPSC_j + \varepsilon_{b,i,j,t} \quad (7)$$

where $\frac{Loans_{b,i,j,t}}{Assets_{b,t}}$ is the amount of loans of bank *b*, headquartered in country *i*, held in country *j* at time *t* as a percentage of the total assets of bank *b* at time *t*. α_b, γ_t and δ_j respectively denote home country *i*, host country *j*, and year *t* fixed effects and $\varepsilon_{b,i,j,t}$ represents the residual term.

$X_{i,j,t}$ includes time-varying country-pair variables. First of all, this includes our main variables of interest, i.e. the variables that aim to capture dissimilarities in economic and financial conditions. For consistency with the previous section we use the five measures previously introduced. These are the absolute value of the difference between a bank's home country *i* and host country *j* in terms of i) GDP per capita ($GDPcapita_{|i-j|,t}$) ; ii) credit-to-GDP ratio ($creditGDP_{|i-j|,t}$); iii) unemployment rate ($unemployment_{|i-j|,t}$); iv) annual GDP growth ($GDPgrowth_{|i-j|}$); and v) output gap ($outputgap_{|i-j|,t}$). The variable $ln\,trade_{i,j,t}$, is defined as the natural logarithm of the bilateral trade between a bank's home and host country, and is a time-varying country-pair control variable. Bilateral trade is often used as an explanatory variable in gravity models that explain international (financial) assets holdings, and is found to have a strong relationship with financial linkages between countries (see for example Portes and Rey, 2005; Aviat and Coeurdacier, 2007). Hence, we use this variable in our gravity model to explain banks' cross-border loans, and we expect the bilateral trade variable to have a positive coefficient.

$Y_{i,j}$ represents the time-invariant country-pair variable distance ($ln\,distance_{i,j}$), and the dummy variables common border ($common\,border_{i,j}$) and common currency

($common\ currency_{i,j}$).[11] The distance is defined as the physical distance between the home country i and host country j and in the regression model the natural logarithm of this variable is taken. We expect a negative coefficient as the further away from a bank's home country the higher are the expected information costs or psychical transportation costs, and the less attractive foreign loan granting and monitoring will be.[12] The common border variable is a dummy that equals one when a bank's home and host country share a border, and zero otherwise. This variable is negatively related to the distance variable, and therefore, a positive coefficient on the foreign loan investments is expected. Likewise, the common currency variable is a dummy variable that equals one when the home and host country share a similar currency. Previous research shows that countries that share a currency, trade more with each other (see Rose, 2000). Moreover, Sander et al. (2013) explicitly studied the contribution of the euro as a common currency for international banking within the Economic Monetary Union (EMU) and found that the euro boosted cross-border banking within the EMU. Hence, a positive coefficient of the common currency variable on the amount of foreign loans is expected.

Lastly, we control for the impact of the euro area debt crisis by including a dummy variable for the countries that were most severely hit, i.e. Greece, Ireland, Italy, Portugal, Spain and Cyprus ($GIIPSC_j$). The timespan of our dataset includes the euro area debt crisis that started in 2011, and a negative coefficient for this variable is expected as foreign banks may have disinvested in these countries.

We collected data for all aforementioned variables, for all 138 countries in our sample. The data on the distance between the home and host country and whether or not the home and host country share a common border stem from GeoDist, the CEPII[13] distance dataset.[14] Information on bilateral trade is obtained from the International Monetary Fund (IMF) Direction of Trade Statistics (DOTS) dataset. For only 10 countries not all data were available over the full time horizon. In that case the continent average was used, and when needed, adjusted by the country's GDP relative to the continent average GDP (e.g. for bilateral trade).

[11] The dummy variable common currency is not purely time invariant as within the time span of our sample Estonia (2011), Latvia (2014) and Lithuania (2015) introduced the euro.
[12] Buch (2005) shows that despite the technological revolution – that is expected to lower information costs – distance remains an important factor in determining international bank lending. She therefore suggests to be careful in interpreting distance as a proxy for information costs only. Due to the link between foreign bank lending and trade, the distance variable may capture transportation costs as well.
[13] Centre d'Etudes Prospectives et d'Informations Internationales.
[14] In cases of missing data, the distance between capitals was taken from http://www.distancefromto.net/

Table 7 shows the descriptives for the main independent variables that are used in our model, i.e. country-specific economic and financial development measures, per continent. The large dispersion in the indicators across countries becomes immediately visible from this table. While Europe, North America and Oceania show the highest GDP per capita and credit-to-GDP ratios, the impact of the global financial crisis is also best visible for these countries, as indicated by the lower GDP growth numbers

Table 7: Economic and financial development indicators per continent

This table shows the averages of the economic and financial development indicators per continent, over the years 2009-2015.

	Europe	South America	North America	Asia	Africa	Oceania
GDP per capita (in EUR)	27,187	2,676	36,127	4,834	1,548	42,234
Credit-to-GDP	92%	47%	49%	105%	36%	126%
Unemployment	10.7%	7.4%	7.7%	4.5%	12.6%	5.6%
GDP growth	0.58%	3.57%	2.35%	4.29%	4.42%	1.96%
Output gap	-0.63%	-0.43%	-0.46%	-0.52%	-0.31%	-0.13%

Table A.6 in the Appendix shows the correlation matrix for the country-pair and host country-specific control variables used in the regression model. As expected, the common currency, common border and distance variable are highly correlated with each other. However, we do not observe very high correlations (above 0.8) between any of the variables and therefore multicollinearity is not expected to be an issue in our model specification. The correlation matrix also shows that the economic and financial dissimilarities between countries increase with distance, and decrease when countries share a border or currency. Hence, countries that are geographically more close to each other are more similar in terms of their economic and financial situation.

4.3 Results

As a first step, a baseline gravity model was estimated, i.e. controlling only for the so-called standard gravity explanatory variables. The first column of Table 8 shows the outcomes for the gravity model that controls for the distance and bilateral trade flows between a bank's home and host country, and whether or not the home and host country share a border and currency. Moreover, a dummy is included when the host country belongs to the group of GIIPSC countries. All coefficients have the expected sign, although the coefficients for common border

and common currency are not significant.[15] Hence, banks invest significantly more in countries with whom they trade more, and in countries that are closer to their home country and do not belong to the GIIPSC countries.

As the majority of the gravity variables are time-invariant country-pair variables, the second column of Table 8 shows the regression results when country-pair fixed effects are included. The explanatory power of the model increases, and the (time-varying) bilateral trade variables remains significant. As including country-pair fixed effects corrects for all time-invariant country-pair variation in the model, including distance, culture etc., there is a lower risk of omitted variables. Hence, for the remainder of the analysis, we consider the model including country-pair fixed effects.

Columns (3)-(7) in Table 8 show the regression results when variables that control for dissimilarities in economic and financial conditions are added to the model. The coefficients for the five different dissimilarity measures all have negative signs, implying that banks invest less in countries that are more different from their home country. Only the coefficients for the variables that capture dissimilarities in unemployment levels and the output gap are not significant. Hence, banks tend to invest significantly less in countries with a more dissimilar GDP per capita, credit-to-GDP ratio or GDP growth.

To conclude, the results show that banks are more inclined to invest in similar, rather than in dissimilar countries. This especially holds when *structural* economic and financial development measures are considered, e.g. the GDP per capita and credit-to-GDP ratio. Hence, we do not find evidence that banks are inclined to invest more in countries that have more different economic and financial conditions. While, purely based on portfolio diversification theory, we expected them to invest in more dissimilar countries, as doing so can improve the risk-return profile as shown by our results in the previous section.

We can think of a couple of reasons why banks do not invest that much in dissimilar countries. First of all, banks may not only invest cross-border for pure diversification reasons, but their specialism towards a certain industry (e.g. agriculture) or business line (e.g. mortgages) may induce them to invest in specific countries. Moreover, countries with exposures to the same industry sectors may also be exposed to the same (sector-specific) shocks, or may have more synchronized business cycles through similar production patterns (Imbs, 2014). Second, we find that trade is an important determinant for explaining cross-border investments. The more countries trade with each other the stronger the linkages and the

[15] These variables turn however significant when the bilateral trade variable is removed.

more economically similar the countries may be (see also Goldberg, 2009). Third, other factors, such as distance and culture may influence a bank's decision to invest in certain countries; banks may have a preference for investing in countries that are closer by and more familiar to their home country.

Table 8: Gravity model

This table shows the results from the gravity model, as specified in equation (7). The dependent variable is the ratio of loans granted by banks in home country *i* to host country *j* at time *t* over the total assets of bank *b* at time *t*. Banks' domestic exposures are excluded. All regressions are estimated by Ordinary Least Squares (OLS) and standard errors are clustered at the bank level and displayed in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	(1) **Baseline**	**(2)** **Baseline country-pair FE**	**(3)** **GDP per capita**	**(4)** **Credit-to-GDP**	**(5)** **Unemployment**	**(6)** **GDP growth**	**(7)** **Output gap**
Country-pair variables							
Dissimilarity measure			-0.136*	-0.252***	-0.076	-0.272*	-0.397
			(0.082)	(0.094)	(0.074)	(0.157)	(0.270)
ln Trade	0.624***	0.077*	0.069*	0.072*	0.073*	0.076*	0.076*
	(0.124)	(0.039)	(0.040)	(0.039)	(0.038)	(0.039)	(0.039)
Common border (0/1)	0.133						
	(0.262)						
ln Distance	-0.440**						
	(0.214)						
Common currency (0/1)	0.278						
	(0.265)						
GIIPSC (0/1)	-2.672***						
	(0.795)						
Home country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Host country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Home*host FE	No	Yes	Yes	Yes	Yes	Yes	Yes
R^2 adj.	60.1%	74.4%	74.9%	74.9%	74.9%	74.9%	74.9%
# Obs.	5,427	5,427	5,427	5,427	5,427	5,427	5,427

5 Conclusion

Financial integration is ongoing, and so is the interest in the implications of cross-border banking. While cross-border banking may have wider consequences for the real economy and the financial system, this paper focuses on the impact of geographical diversification on individual banks. From a theoretical point of view, diversifying across borders is expected to be risk-reducing as long as there is non-perfect correlation across country specific risks. This implies that banks should expand to countries that differ from their home country in economic and financial conditions.

Our results show that geographical diversification decreases bank risk. Next, we find that the beneficial impact from diversification can be higher when banks invest in countries that are more dissimilar from their home country in economic and financial conditions. This result is hence consistent with the view that diversification is risk-reducing, and that banks can diversify idiosyncratic risks away by investing in countries with more dissimilar economic and financial conditions. We do however not find a significant impact from cross-border banking on a bank's net income.

Our findings also show that banks do not fully utilize these diversification opportunities, as they mainly invest in countries that are more similar to their home country, especially when considering structural economic and financial development measures, i.e. the GDP per capita and credit-to-GDP ratios. Our result that banks are at least not consistently lending to more dissimilar countries also contradicts our hypothesis that – purely based on portfolio diversification theory – banks are expected to invest in more dissimilar countries, as doing so can improve the risk-return profile. Banks may however invest cross-border for other reasons than diversification. For example, banks that are specialized towards a certain industry or business line may be induced to invest in more similar countries. Moreover, we find that bilateral trade is an important determinant for cross-border banking, and the more countries trade with each other the more similar their economies may be.

Our results contribute to the policy discussions on the progress of the single European banking market, and on the treatment of cross-border lending in the regulatory framework and in supervision. Currently, most banks still have a domestic focus, implying that their foreign activities are rather low, even as it was expected that the creation of the European Banking Union would foster cross-border banking. Moreover, Schoenmaker and Véron (2016) argue that barriers to the completion of the single market still exist. These barriers are stemming from a discouraging approach towards cross-border activities, thereby negatively affecting cross-border subsidiaries.

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7 Appendix

Table A.1 Geographical distribution of assets per bank, 2015

Name	Total assets 2015 (in € bln)	Home	ROE	North America	South America	Asia	Africa	Oceania
HSBC Holdings	2,218.6	36.4%	6.0%	15.5%	0.4%	39.4%	0.3%	1.9%
BNP Paribas	1,994.2	25.0%	46.9%	14.7%	2.8%	7.8%	2.6%	0.2%
Crédit Agricole Group	1,698.9	80.8%	10.5%	4.5%	0.1%	2.9%	0.7%	0.2%
Deutsche Bank	1,629.1	26.0%	27.6%	31.4%	1.2%	12.9%	0.4%	0.3%
Barclays	1,519.9	39.5%	20.0%	31.0%	0.2%	4.1%	5.0%	0.1%
Banco Santander	1,340.3	28.4%	42.4%	15.3%	14.1%			
Société Générale	1,334.4	71.6%	17.8%	6.8%	0.6%	1.7%	1.5%	
Groupe BPCE	1,166.5	91.0%	2.8%	4.2%	0.1%	0.8%	0.8%	0.4%
Royal Bank of Scotland Group	1,106.5	82.6%	5.2%	9.5%		2.7%		
Lloyds Banking Group	1,094.6	96.4%	2.5%	1.0%		0.2%		
UBS Group	866.9	32.8%	24.1%	33.5%	1.1%	8.5%		
UniCredit	860.4	40.2%	56.7%	1.2%	1.2%	0.6%		
ING Bank NV	838.5	36.4%	46.7%	5.7%	0.2%	7.0%	0.1%	4.0%
Credit Suisse Group	754.7	27.0%	19.8%	42.3%	1.0%	9.9%		
Banco Bilbao Vizcaya Argentaria(BBVA)	750.1	39.1%	13.5%	23.5%	10.3%	13.6%		
Crédit Mutuel Group	739.8	87.9%	8.9%	2.1%		1.1%		
Intesa Sanpaolo	676.5	85.0%	10.3%	1.5%	0.1%	1.8%	1.4%	
Coöperatieve Rabobank	670.4	73.7%	6.3%	9.9%	2.9%	2.4%	0.1%	4.7%
Nordea Bank	646.9	27.8%	69.5%	1.3%	0.0%	1.3%		
Standard Chartered	589.7	18.0%	9.9%	9.5%	0.3%	58.7%	3.4%	0.2%
Commerzbank	532.6	52.2%	34.4%	7.7%		5.7%		
KfW Gruppe	503.0	35.0%	37.0%	3.0%	8.0%	11.0%	6.0%	
Danske Bank	441.2	55.4%	44.6%					
Deutsche Zentral-Genossenschaftsbank	408.3	81.7%	12.5%	1.5%	0.9%	3.4%		
ABN AMRO Group	390.3	73.3%	15.4%	3.4%	2.1%	4.3%		1.4%
CaixaBank	344.3	85.9%	11.5%	0.3%	0.7%	2.3%	0.4%	
Svenska Handelsbanken	275.3	59.3%	34.1%	6.6%				
Skandinaviska Enskilda Banken	272.5	62.6%	30.3%	4.3%		2.7%		
DNB ASA	270.1	62.0%	26.1%	5.7%	2.7%	1.8%	0.6%	1.1%
Nationwide Building Society	265.4	95.0%	5.0%					
KBC Group	252.4	51.6%	43.5%	1.3%	0.1%	2.7%	0.4%	0.4%
Swedbank	234.6	78.6%	15.1%	6.4%				

Landesbank Baden-Württemberg	234.0	71.3%	19.0%	7.2%	0.7%	1.8%	
La Banque Postale	218.7	99.1%	0.9%				
Bayerische Landesbank	215.7	76.9%	16.1%	5.9%	0.4%	0.7%	0.1%
Banco de Sabadell	208.6	63.4%	29.5%	3.5%	3.5%		
Bankia	207.0	85.7%	13.7%	0.3%	0.3%		
Erste Group Bank	199.7	44.3%	54.8%		0.0%	0.6%	0.2%
Raiffeisen Gruppe Switzerland	189.2	95.0%	5.0%				
Nykredit Holding	185.4	94.6%	5.4%				
Norddeutsche Landesbank Girozentrale	181.0	85.2%	10.6%	1.2%	1.2%	1.8%	
Belfius Banque	177.0	70.0%	28.0%	2.0%			
Landesbank Hessen-Thüringen Girozentrale	172.3	85.7%	8.1%	6.2%			
Banca Monte dei Paschi di Siena	169.0	95.2%	4.4%	0.4%		0.3%	
Banco Popular Español	158.7	92.0%	6.4%	1.6%			
NV Bank Nederlandse Gemeenten	149.5	88.5%	11.5%				
Zürcher Kantonalbank	142.0	85.9%	9.3%	3.1%	0.4%	1.3%	
NRW Bank	141.2	71.1%	28.9%				
Raiffeisen Zentralbank Österreich	138.4	23.6%	64.0%	1.8%		10.5%	
Bank of Ireland	131.0	62.7%	37.3%				
OP Financial Group	125.1	82.9%	14.6%	0.8%		0.3%	
Volkswagen Financial Services	121.3	46.8%	33.9%		6.6%	12.7%	
Banco Popolare Società Cooperativa	120.5	98.2%	1.5%	0.2%	0.2%	0.0%	
Unione di Banche Italiane	117.2	98.0%	1.8%	0.1%	0.1%	0.1%	
SNS REAAL	114.8	98.9%	1.0%				
National Bank of Greece	111.2	87.5%	12.2%				0.3%
DekaBank Deutsche Girozentrale	108.0	98.7%	1.3%				
Allied Irish Banks	103.1	83.5%	16.5%				
Caixa Geral de Depósitos	100.9	75.1%	13.3%	1.9%	0.4%	4.9%	4.4%
HSH Nordbank	97.0	57.1%	10.7%	11.8%	2.8%	14.5%	3.1%
Landesbank Berlin	47.5	81.7%	12.7%	5.5%			

Table A.2: Descriptives per year: Risk-return model

This table shows the descriptive statistics of our dataset of 61 banks for the years 2010 until 2015, as well as the overall, between and within standard deviations. The between standard deviation represents the variation between years, whereas the within standard deviation represent the standard deviation within individual banks.

	Standard deviation			Mean					
	Overall	**Between**	**Within**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Total Assets (in € mrd)	526	523	69	516	543	535	487	519	517
Tier 1 leverage (%)	1.65	1.35	0.96	4.41	4.38	4.63	4.97	4.98	5.49
ROA (%)	0.009	0.005	0.008	0.002	-0.002	-0.001	0.001	0.002	0.003
St. Dev. ROA	0.005	0.004	0.003	0.002	0.003	0.003	0.003	0.002	0.002
Z score	83.0	62.8	54.4	44.9	51.9	69.9	72.9	85.7	94.6
Problem ratio (%)	8.40	7.76	3.28	5.99	6.77	7.81	8.65	8.14	7.63
Cost-to-income (%)	23.1	15.9	16.8	59.0	62.4	70.2	60.2	61.5	61.2
1 – HHI	0.27	0.27	0.04	0.46	0.45	0.44	0.44	0.45	0.44
Non-interest income (%)	11.8	11.3	3.3	22.6	22.9	23.9	23.9	23.7	24.2

Table A.3: Correlation matrix: Risk-return model

This table shows the correlation among the explanatory variables used in the regression model specified in equation (1) and (6).

	Total Assets	**Tier 1 leverage**	**ROA**	**σ(ROA)**	**Z-score**	**Problem ratio**	**Cost-to-income**	**1 - HHI**	**Non-interest income**
Total Assets	1								
Tier 1 leverage	-0.286	1							
ROA	0.116	0.006	1						
σ(ROA)	-0.116	0.154	-0.489	1					
Z-score	0.071	0.128	0.588	-0.945	1				
Problem ratio	-0.022	0.260	-0.370	0.639	-0.553	1			
Cost-to-income	0.139	0.068	-0.266	0.196	-0.142	0.213	1		
1 – HHI	0.484	0.099	0.212	0.004	0.066	0.019	0.050	1	
Non-interest income	0.232	-0.152	-0.066	0.107	-0.128	-0.034	0.371	0.071	1

Table A.4: The impact of geographic diversification on banks' z-score (full sample)

This table shows the regression results from equation (6) over the period 2010-2015 for the full sample. The dependent variable is the natural logarithm of a bank's z-score. Standard errors are clustered at the bank level, and reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	GDP per capita	**Credit-to-GDP**	**Unemploy-ment**	**GDP growth**	**Output gap**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Diversification measures					
1-HHI within	1.035	1.043	1.257*	1.525**	0.933
	(0.761)	(0.661)	(0.701)	(0.592)	(0.598)
1-HHI between	3.702***	2.009**	0.706	0.506	1.321**
	(1.153)	(0.785)	(0.633)	(0.468)	(0.511)
Control variables					
ln Total Assets (t-1)	-0.213	-0.382	-0.372	-0.458	-0.279
	(0.478)	(0.500)	(0.507)	(0.497)	(0.497)
Tier 1 leverage (t-1)	2.961	2.493	2.376	0.649	2.684
	(5.083)	(4.833)	(5.319)	(5.141)	(5.123)
ln Problem ratio (t-1)	-0.277***	-0.301***	-0.314***	-0.299***	-0.316***
	(0.082)	(0.084)	(0.085)	(0.079)	(0.089)
ln ROA (t-1)	19.857***	18.066***	19.430***	21.037***	19.236***
	(2.925)	(3.470)	(3.254)	(2.992)	(3.094)
Cost-to-income (t-1)	-0.315	-0.266	-0.291	-0.291	-0.321
	(0.213)	(0.232)	(0.228)	(0.216)	(0.221)
Share non-interest	-0.977	-1.036	-1.109	-1.116	-0.886
income (t-1)	(1.280)	(1.352)	(1.360)	(1.308)	(1.333)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2 adj.	21.5%	20.1%	19.2%	20.1%	20.0%
# Obs.	352	352	352	352	352

Table A.5: The impact of geographic diversification on banks' variability in income (full sample)

This table shows the regression results from equation (6) over the period 2010-2015 for the full sample. The dependent variable is the natural logarithm of a bank's standard deviation of its ROA. Standard errors are clustered at the bank level, and reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	GDP per capita	**Credit-to-GDP**	**Unemploy-ment**	**GDP growth**	**Output gap**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Diversification measures					
1-HHI within	-1.424**	-1.230**	-1.306**	-1.491***	-1.245**
	(0.645)	(0.578)	(0.631)	(0.499)	(0.533)
1-HHI between	-2.723***	-1.488**	-0.865	-0.566	-1.261***
	(1.269)	(0.584)	(0.538)	(0.396)	(0.438)
Control variables					
ln Total Assets (t-1)	0.312	0.402	0.399	0.457	0.353
	(0.448)	(0.462)	(0.475)	(0.465)	(0.455)
Tier 1 leverage (t-1)	5.580*	6.058*	5.774	7.089**	5.892*
	(3.298)	(3.335)	(3.462)	(3.159)	(3.143)
ln Problem ratio (t-1)	0.222***	0.242***	0.249***	0.232***	0.249***
	(0.071)	(0.069)	(0.069)	(0.064)	(0.069)
ln ROA (t-1)	-21.319***	-20.734***	-21.137***	-22.541***	-21.147***
	(3.669)	(3.905)	(3.829)	(3.566)	(3.708)
Cost-to-income (t-1)	-0.044	-0.058	-0.049	-0.052	-0.026
	(0.238)	(0.243)	(0.246)	(0.238)	(0.245)
Share non-interest	1.087	1.139	1.145	1.154	0.982
income (t-1)	(1.059)	(1.071)	(1.081)	(1.017)	(1.061)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2 adj.	16.2%	14.9%	14.6%	15.3%	15.2%
# Obs.	354	354	354	354	354

Table A.6: Correlation matrix: Gravity model

This table shows the correlation among the explanatory variables used in the regression model specified in equation (7)

	Common border$_{i,j,t}$	**Ln distance$_{i,j}$**	**Trade$_{i,j,t}$**	**Common currency$_{i,j}$**	**GIIPSC$_j$**	**GDP growth$_{\|i-j\|,t}$**	**GDP gap$_{\|i-j\|,t}$**	**Unemploy-ment$_{\|i-j\|,t}$**	**Credit-to-GDP$_{\|i-j\|,t}$**	**GDP capita$_{\|i-j\|,t}$**
Common border$_{i,j,t}$	1									
Ln distance$_{i,j}$	-0.532	1								
Trade$_{i,j,t}$	0.350	-0.338	1							
Common currency$_{i,j}$	0.435	-0.447	0.277	1						
GIIPSC$_j$	0.079	-0.140	0.140	0.451	1					
GDP growth$_{\|i-j\|,t}$	-0.099	0.182	-0.104	-0.101	-0.027	1				
GDP gap$_{\|i-j\|,t}$	-0.076	0.077	-0.128	-0.064	0.031	0.720	1			
Unemployment$_{\|i-j\|,t}$	-0.080	0.156	-0.110	0.006	0.148	0.101	0.105	1		
Credit-to-GDP$_{\|i-j\|,t}$	-0.203	0.293	-0.331	-0.314	-0.170	0.073	0.040	0.018	1	
GDP capita$_{\|i-j\|,t}$	-0.229	0.330	-0.366	-0.320	-0.209	0.112	0.080	0.096	0.546	1