On the cyclical *nature* of finance:
The role and impact of financial institutions

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Over natuurlijke cycli in de financiële wereld:
De rol en impact van financiële instellingen

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Chapter 1: Introduction

The title of this thesis is "On the cyclical nature of finance: The role and impact of financial institutions". Cycles are characterized by a period of strong economic expansion ('boom'), followed by a period of contraction that can even result in a recession ('bust'). In this thesis the cyclical *nature* of finance is of interest, implying that these cycles are the result of a 'natural' process (i.e. a self-generating cyclical mechanism). This means that cycles are not purely caused by exogenous shocks, but that endogeneity plays an important role. Or, in the words of Borio (2014), "financial cycles denote self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constrains, which translate into booms followed by busts". The 'boom' does not just precede the 'bust', but fuels it.

The occurrence of cycles does not only impact the financial system. Endogeneity also implies that the financial system, and the collective behaviour of financial institutions, itself plays an important role in the creation of these cycles. This thesis focuses on the role and impact of financial institutions in the financial cycle. The principle of endogeneity dates back to Minsky (1977) with his 'financial instability hypothesis'. His hypothesis states that financial instability is not the result of exogenous shocks, but the consequence of unsustainable economic expansion and growing indebtedness. This theory was ignored by many economists for a long period. Instead, exogenous factors gained importance in theories on the causes of cycles (Zarnowitz, 1985; 1999). The focus was mainly on business cycles; fluctuations in the economy measured by GDP. Actually, only a few researchers acknowledged the importance of financial cycles due to its relation with the real economy (i.e. the business cycle). Fisher (1933) is the first one who focuses on the interaction between the financial sector and the real economy, and Sinai (1992) provides an overview of the studies on this interaction. The empirical work on financial cycles remains relatively limited. However, the severity of the global financial crisis (2007-2009) caused a renewed interest in the cycle theory in the financial sector.

In contrast to the business cycle a common measure of the financial cycle does not exist. In general, the financial cycle may imply cyclicality in any part of the financial system (e.g. a liquidity or credit cycle), in financial markets or in specific assets (e.g. a housing cycle). This thesis elaborates on the credit cycle (*chapter 2*), the business cycle (*chapter 3*), the liquidity cycle (*chapter 4*) and the financial market cycle (*chapter 5*).

In a recent study, Claessens et al. (2011b) empirically investigate the interaction of business cycles and financial cycles and find evidence for strong linkages between those. Also, Claessens et al. (2011a) and Stremmel (2015) find financial cycles to be highly synchronized with each other. A high synchronization means that disruptions in one market intensify the other. As a consequence of the ongoing financial globalization, cycles are increasingly synchronized across countries resulting in longer-lasting disruptions (as occurred during the global financial crisis (2007-2009). Several studies, e.g. Drehmann et al. (2012) and Aikman et al. (2014), find evidence that financial cycle peaks are closely related to financial crises. Moreover, they find economic recessions being much deeper when they coincide with the contraction phase of the financial cycle. In addition, Borio et al. (2018) find that financial cycles convey information about recessions, since financial cycle measures perform well in predicting recession risk.

The existence of (endogenous) financial cycles that are closely linked to financial crises and that can intensify each other, calls for a better understanding of the underlying dynamics. As mentioned previously, the endogenous character of financial cycles implies they do not only have an impact on financial institutions, but that the collective actions of these parties also play a vital role in the origination of these boom-bust patterns. During periods of economic expansion, the robust macroeconomic environment and the corresponding low risk perception may trigger different types of financial institutions to, for example, increase their risk appetite, loose their lending standards, and expand their balance sheets. This results in a highly leveraged financial sector and an increased vulnerability to economic contractions. Hence, during times when the perceived risk is low, financial imbalances are built up. Vice versa, during times of economic contraction, financial institutions have the tendency to tighten lending conditions, become more risk adverse and decrease their leverage. The collective behaviour of financial institutions amplifies downward market movements. If, for example, all financial institutions sell part of their assets at the same time, the simultaneous sale of assets will obviously result in a further downward pressure on the financial market prices (Shleifer and Vishny, 2010). Even though the principle of endogeneity was largely neglected in previous decennia does not mean it was not present. Endogenous risk is not something that popped up recently. By reviewing the stock market crash of 1987, the LTCM crisis of 1998 and the collapse of the dollar against the yen in 1998, Danielsson and Shin (2003) argue that the greatest damage stemmed from endogenous rather than exogenous factors.

What drives this procyclical and collective behaviour of financial institutions, resulting in endogenous risk? First of all, financial institutions have a tendency to show herding behaviour, or in the words of Keynes (1936), "animal spirits". By realizing that our own judgements may be worthless, it seems reasonable to assume that others are better informed and follow them. Part of the procyclical behaviour of financial institutions may thus be explained by behavioural economics. The financial system, and more specifically the regulatory framework in which financial institutions operate, may also contain elements that induce procyclical behaviour. One element which is often mentioned is mark-to-market valuation, introduced by the joint implementation of Basel II and the new IFRS (Goodhart, 2009). During times of perceived market stress and a potential decline in asset values, banks will be forced to sell assets, since mark-to-market valuation causes changes in assets prices to show up in the balance sheets immediately. Such sales will however (further) drive down market prices of these assets held on other banks' books. Brunnermeier et al. (2009) classify this as an internal amplifying process, whereby falling asset prices lead to deleveraging at banks, which further drives down asset prices and where these losses impact banks' financial positions immediately. The authors identify other elements of the regulatory framework that are less desirable from a systemic perspective since they contain elements, such as market-based measures of risk, that may encourage procyclical behaviour and thereby amplify shocks over the cycle. This scenario does not only apply to banks; similar issues apply to other financial institutions, such as insurance companies and pension funds (*chapter 5*).

In response to the global financial crisis (2007-2009), there is increasing attention for policies that aim to mitigate procyclicality within the financial system, most notably the introduction of macroprudential measures for banks. This can be seen as a major step forward. However, it has to be seen whether these policies will work out as planned, especially since some, such as the countercyclical capital buffer, are to be executed on a discretionary basis. This can lead to the risk of acting too late, or not at all (inaction bias). Besides, the focus should not solely be on banks. A wider macroprudential approach is needed covering other financial institutions, such as insurance companies and pension funds, as well as introducing system-wide measures and targets for credit and housing markets. On top, an effective macroprudential framework actually requires a mind shift by policymakers and regulators as they are able to facilitate a system in which the focus of financial institutions and supervisors is more steered towards endogenous risk rather than exogenous risks. There is enough to gain. For example, banks' internal risk management models still assume that risk is exogenous (Schoenmaker and Wierts, 2016). Institutions still rely on market-based measures for risk. Supervisory practices still focus on capital adequacy and risk soundness at individual institutions instead of contagion risks and other systemic externalities. Stress tests, for example, still only consider exogenous shocks and do not take into account second-round effects, such as contagion risks and amplification mechanisms that we have seen to occur in times of financial stress. Thereby such tests completely miss out on the endogenous nature of risk (Brunnermeier et al., 2009).

In a nutshell; for a long time the focus has been on exogenous risks as the major cause of economic disruptions and financial crises

(Zarnowitz, 1985; 1999). Since the global financial crisis the idea that endogenous factors also play a role in driving the cycle has gained attention. The central theorem in this thesis is that endogeneity within the financial system rather than exogenous shocks are the major cause of financial imbalances. Besides, an underlying driver of this amplification mechanism within the financial system stems from the regulatory framework that still has a very microprudential focus and contains elements that are less desirable from a systemic perspective. In the spirit of economists such as Brunnermeier et al. (2009), this thesis advocates the need for a broader macroprudential framework. The next four chapters of this thesis all focus on the role of financial institutions in a specific part of the financial cycle.

Investigating the role and impact of financial institutions on the financial cycle, this dissertation starts with a chapter (Chapter 2) on the credit cycle. The chapter focuses on the role of foreign funded credit specifically, since foreign funded credit can potentially be more procyclical. The chapter concludes that this type of credit contributes to credit booms. Chapter 3 focuses on the business cycle and explores potential rewarding effects from geographical diversification by banks. It concludes that banks can reduce their risk by diversifying more into countries with an economic cycle that differs from the one of their home country. Chapter 4 focuses on the liquidity cycle and investigates the impact of liquidity regulation on banks' balance sheets. This chapter concludes that liquidity rules are effective from a microprudential point of view. However, these rules do not prevent a liquidity cycle that is characterized by an increased reliance on short-term (liquid) wholesale funding during the upturn of the cycle, in order to finance riskier (liquid) assets. This is followed by de-risking in the downturn. In case multiple banks will sell their liquid assets at the same time, this will have an impact on the financial markets. Chapter 5 pays specific attention to financial market cycles, and the role of insurance companies and pension funds. These parties were always seen as long-term and countercyclical investors, implying that their investment behaviour would stabilize market movements. This chapter however shows that during the global financial crisis, insurers actually acted in a procyclical manner, thereby contributing to market downturns. The remainder of this introduction introduces the individual chapters.

What actually causes a credit cycle? Chapter 2 aims to contribute to a better understanding of what drives the credit cycle, thereby focusing on the role foreign funded bank credit has. The reason for this focus is because the credit that is not locally funded enables the total credit to outgrow the domestic deposit growth. It is thereby assumed that foreign funded credit can potentially be more procyclical as during the upturn of the cycle. Moreover, foreign funded credit is not restricted that much as domestically funded credit by either the domestic deposit base or domestic capital controls aimed at slowing down the credit growth. Besides, during downturns external funding, of which wholesale funding, may dry up. Most studies however focus on the role of credit from foreign banks – and not foreign funded credit – in the credit cycle (e.g. Crystal et al., 2001; de Haas and van Lelyveld, 2006). Foreign funded credit is not exactly similar to credit from foreign banks. For example, credit from foreign banks that is funded by domestic deposits does not belong to foreign funded credit, as it simply is domestically funded. A couple of recent studies by the Bank for International Settlements (Borio et al. (2011); Avdjiev et al. (2012) and Ehlers and McQuire (2017) focus on foreign funded credit, and suggest that especially this type of credit contributes to the high credit growth during the years preceding the global financial crisis.

By analysing credit cycles in 41 countries over the period 1985q1-2015q4, this chapter investigates if foreign funded credit plays a role in booms and bust in credit. The results show that credit booms are associated with an increase in the share of foreign funded credit relative to the total credit in an economy. This points to a procyclical role of foreign funded credit during booms. By investigating the periods preceding booms and busts, the results show that before a credit boom there is actually a significant increase in domestically funded credit relative to foreign funded credit. The availability of credit may provide an explanation, as during the build-up phase of the boom, domestically funded credit is able to fulfil the credit needs. However, during times of rapidly growing credit needs, the domestically funded credit may need to be substituted by foreign funded credit. A high level of foreign funded credit increases the domestic loan-to-deposit ratio and the reliance on external funding. This in turn increases the vulnerability to economic reversals, as external funding – of which wholesale funding – may dry up during downturns.

Over the last decennia there has been a trend towards liberalization, and this has led to increased financial globalization. Globalization provides opportunities, such as growth opportunities for emerging countries and access to new funding sources, for example via foreign funded credit. However, chapter 2 shows that globalization via an increased reliance on foreign funded credit may contribute to boom-bust cycles in credit. Globalization also leads to more synchronized economies; as a consequence booms and busts in different countries occur more and more simultaneously. This finding is not only the case for the credit cycle, as Claessens et al. (2011a) state also business cycles have become more synchronized across countries as a consequence of ongoing globalization However, business cycles are never perfectly synchronized or correlated. This non-perfect correlation in cycles offers opportunities for risk diversification by banks, this is the focus of chapter 3.

Chapter 3 analyses whether geographical diversification by banks pays off. Banks can diversify in a geographical manner by undertaking business outside their home country. In general, diversification can potentially reduce risk (Markowitz, 1952). An important condition for risk reduction via geographical diversification is the existence of non-perfect correlation in economic conditions in countries where the bank expands to (Levy and Sarnat, 1970). This implies that countries should differ from each other with respect to the phase in the economic cycle; in the most extreme case this means being in the upturn or the downturn of the cycle. This condition is however mainly ignored in research on the potential benefits from geographical diversification. Recently, Faia et al. (2017), Goetz et al. (2016) and Meslier et al. (2015) also raised this point of criticism. These studies investigate potential diversification gains for US banks, thereby controlling the economic conditions of the countries the banks expand to. These studies provide some first evidence for diversification gains, especially if banks expand to countries with different business cycle co-movements.

Using a unique dataset with cross-border exposures of the 61 largest European banks over the period 2010-2017, the results of chapter 3 suggest that geographical diversification decreases bank risk. Most importantly, banks can further increase the beneficial impact from cross-border banking by diversifying more into countries with an economic cycle that differs from the one of their home country. By diversifying geographically banks are able to reduce both their insolvency risk as well as their variability in net income. This result is thus consistent with the view that diversification is risk-reducing, and that banks can diversify idiosyncratic risks away by investing in countries that have non-perfectly correlated business cycles. As a second step, chapter 3 examines where banks expand to. Do banks tend to invest more in countries with dissimilar economic conditions? The results show that this is not the case. Banks invest significantly more in countries that are economically more similar to their home country. In contrast to what could be expected from a theoretical point of view, there is no evidence that banks are inclined to invest more in dissimilar countries. Banks do thus not fully utilize the diversification opportunities that we find to arise from investing in more dissimilar countries.

Globalization does not only results in more synchronized economies, but also leads to increased interconnectedness within the financial system and between financial institutions. The financial crisis has shown that the latter can lead to contagion risks in stressed markets. The interbank market turned out to be a rather unstable source of funding during times of decreased market confidence. As a result of increasing losses in the subprime mortgage market in 2007, the trust of banks in one another dropped and banks were less willing to lend money to each other. The interbank market dried up and as a consequence, banks were facing liquidity issues. In response to what happened, the new regulatory framework Basel III – that was implemented in 2015 – also introduced liquidity regulation. .

More specifically, in chapter 4 the impact of liquidity regulation is investigated. Liquidity regulation was introduced in 2015, with the implementation of the Basel III regulation for banks. In the Netherlands, liquidity regulation is already in place since 2003. Chapter 4 analyses Dutch banks' behaviour in case their liquidity position is below their long-term equilibrium. Contrary to most studies that focus on what happens on the asset side of the balance sheet in case of a funding shock (see, for example, Berrospide, 2012; De Haan and van den End, 2013a and 2013b), this analysis lets the data determine the causality. It is found that in case of a shock in their liquidity position, banks adjust the liability side of their balance sheet first. They do so by substituting wholesale funding by more stable deposits. The findings also show that, from a microprudential perspective – i.e. the level of an individual bank - the liquidity rules appear to have been effective, given that a minimum buffer of liquid assets has always been maintained to cover possible outflows.

At the aggregate level – considering the total amount of liquid assets and liabilities of all banks –a procyclical pattern in liquid assets and liabilities is however observed. The results point to an important role of secured wholesale financing for explaining this liquidity cycle. This cycle is characterised by increased risk-taking in the upturn through an increase in short-term wholesale funding that is used to finance riskier but more profitable assets. It is followed by de-risking in the downturn of the cycle, when wholesale funding dries up and needs to be substituted by deposits. This also means that the liquidity buffers are at their lowest when they are needed most. This chapter thus shows that the liquidity regulation – albeit effective from a microprudential point of view - did not prevent a pro-cyclical liquidity cycle driven by secured funding. The systemic element of liquidity risk is simply ignored, while it can have far-reaching consequences. The build-up of liquidity risk during a boom creates vulnerabilities to massive losses when risk perceptions change (Acharya et al., 2011). In case banks are in a need for liquidity at the same time, multiple banks may be forced to sell their assets at distressed prices, thereby accelerating downward price movements in financial markets. That brings us to financial market cyclicality that is the central topic in chapter 5.

Shifting the focus from banks to institutional investors, chapter 5 investigates the investment behaviour of Dutch insurance companies, both life and non-life, and pension funds. With a large and growing amount of assets under management, these parties have the potential to either stabilize or amplify swings in financial markets. Theoretically and given their long-term investment horizon that enables them to endure short-term price movements, life insurers and pension funds are expected to act as shock absorbers in times of financial stress. Whereas banks' liabilities can be simply withdrawn or adjusted, as shown in the previous chapter, the liabilities of insurers and pension funds cannot. Thereby, insurers and pension funds do not face direct selling pressure of their assets. Moreover, these parties often use rebalancing strategies. This 'buy low, sell high' strategy implies buying asset classes that are priced low and selling off asset classes that are priced high. This results in a relatively stable asset allocation; e.g. when equities underperform fixed income they buy more equities, keeping the total equity exposure at the level determined by the long-term strategic asset allocation strategy. At a macro level, this countercyclical investment strategy benefits financial stability as it tempers both upward and downwards price movements. In practice, however, they may decide not to apply rebalancing, for example during market-wide shocks.

Chapter 5 therefore analyses the investment behaviour of insurers and pension funds, including the period covering the global financial crisis. The results show evidence for procyclical investment behaviour by both non-life and life insurers. For pension funds, there is evidence for countercyclical behaviour, but only in non-crisis periods. The difference in findings for pension funds versus insurance companies can be explained by the nature of their business models and differences in regulatory frameworks. Most importantly, pension funds have more recovery options (e.g. increase premiums or apply benefit reductions). Insurance companies do not have these options and therefore face more regulatory pressure to reduce their risk and sell their assets, of which equities, during downturns. At macro level, their procyclical behavior is undesirable, since it intensifies the cyclicality in financial markets.

Chapter 2: Foreign funded credit: funding the credit cycle?

This study investigates what drives the credit cycle, focusing on the role of foreign funded bank credit (FFC). Considering credit cycles in 41 countries over the period 1985-2015, this study finds that credit booms are associated with an increase in the share of FFC in an economy, both in emerging and developed economies and for business as well as for household credit cycles. The impact of FFC on credit booms is however significantly higher in emerging countries. While FFC increases rapidly during the boom, the period preceding the boom is characterized by an in increase in domestically funded credit relative to FFC. FFC thus accelerates credit during the boom. The increased credit needs during a boom may cause the subsitution of domestically funded credit by FFC, as the growth in FFC is less restricted than domestically funded credit, for example by the domestic deposit base.[1]

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[1] I thank, without implicating them, Dirk Schoenmaker and Wolf Wagner for useful comments.

2.1 Introduction

Credit plays an important and dominant role in shaping the business cycle, and has an impact on both the probability and intensity of crises (Schularick and Taylor, 2012). Recent studies have further stressed the relation between credit and financial crises (Jordà et al, 2011; Drehmann et al., 2011). Financial boom-and-bust cycles are not only costly for banks, but also for the broader economy as characterized by sharp output (GDP) declines during the downturn of the cycle (Laeven and Valencia, 2013). Given the positive relation between credit cycles and financial instability, this study investigates what drives the credit cycle, and more specifically, what the role of foreign funded bank credit (FFC) is in the credit cycle.

Most studies consider the impact of foreign bank credit on the credit cycle, where foreign bank credit is based on bank ownership, i.e. the credit granted by banks that are foreign-owned. This study considers that the credit that is most relevant is the credit that is not locally funded, since this enables the total credit to outgrow the domestic deposit growth. Hence, this study focusses not on where the bank resides, but on where the funding comes from. In that respect, this study builds upon previous work by the Bank for International Settlements (BIS) (Borio et al. (2011), Avdjiev et al. (2012) and Ehlers and McGuire (2017)).

FFC can potentially be more procyclical. During the upturn of the cycle, foreign funded credit is not restricted as much as domestically funded credit by either the domestic deposit base or domestic capital controls aimed at slowing down the credit growth. Besides, during downturns, external funding, including FFC, may dry up. The aforementioned BIS studies focus on the period surrounding the global financial crisis (2002-2008) and show that FFC contributed to the rapid credit growth in the run-up to the crisis.

This study extends the analysis in several ways. First of all, instead of only considering the role of FFC before and during the global financial crisis I use a logit model to empirically investigate the role of FFC in explaining credit booms and busts over the period 1985-2015. I do so by identifying country-specific boom and bust periods, since not all countries experience booms and busts at the same time. Second, and in contrast to most studies that consider the determinants of credit booms and busts, by identifying the boom and bust periods I consider the total credit in an economy, including non-bank credit. In the end, what matters for the real economy and financial stability is preventing large swings in total credit in an economy. Kemp et al. (2018) show that the relationship between bank credit and non-bank credit cycles became less synchronized in the period leading up to the financial crisis, pointing to a substitution effect. In general, the importance of non-bank credit is also highlighted in Cizel et al. (2019), especially in advanced economies where non-bank credit on average represents 56% of GDP (with bank credit representing 85% of GDP). The authors also point to differences in cyclicality between bank and non-bank credit, with bank credit being more cyclical. Third, I consider both developed and emerging market economies since previous studies have shown that credit booms in emerging economies are larger and last longer than those in developed countries (Mendoza and Terrones, 2008). Fourth, I investigate whether the impact of FFC on the credit cycle differs for credit provided to different sectors. The two main borrowers of credit are households and non-financial corporations. The rationale for making this distinction is that the cyclical pattern in credit in these sectors may be driven by different factors among differences in the access to non-bank funding. This may in turn influence the role FFC plays in these cycles. One may for example assume that the banking sector, and thereby FFC, matters more for households, as banks are the main provider of credit to households while corporates have better access to market funding (Igan and Tan, 2017). Lastly, besides investigating the role of FFC during credit booms and busts, I also consider its behavior preceding booms and busts.

Through investigating the credit cycles in 41 countries over the period 1985q1-2015q4, this study finds that an increasing share of FFC in total bank credit is positively associated with credit booms. The quarterly change in the share of FFC, however, is not found to be significantly associated with credit busts. These results suggest a procyclical role for FFC during booms. While this holds for both emerging and developed countries, the results are more pronounced for emerging countries. I found no evidence to uphold the expectation that the impact of FFC differs for household versus business credit. By distinguishing the periods before and after 2000, results show that while FFC is associated with business credit booms in both periods, it is only associated with household credit booms in the post-2000 period. This suggests that FFC was used to fulfil the increased demand for credit from households around the mid-2000s. When investigating what happens before a boom or bust, results show that the period preceding the boom is characterized by an increase in the relative share of domestically funded credit. In other words, while before the credit boom domestically funded credit increased relative to FFC, during the boom it is FFC that accelerates credit growth.

The finding that FFC contributes to the cyclicality in credit stresses the importance of macro-prudential measures, such as the countercyclical buffer, to stabilize the credit cycle. Irrespective of the total level of credit, however, the funding base of the credit in an economy should deserves attention. By enabling total credit to outgrow the domestic deposit base, a high inflow of FFC increases the domestic loan-to-deposit ratio and therefore the reliance on external funding. This reliance in turn increases the vulnerability to economic reversals, particularly. Especially since external funding or wholesale funding may dry up during economic downturns. Instruments that are specifically targeted at FFC, e.g. capital control-like instruments, could probably be more effective in this sense.

2.2 Literature and hypotheses

2.2.1 The relation between financial crisis and credit

The relation between credit booms and financial crises underlies the work of Minsky (1977). He introduced a theory of endogenous business cycles where financial imbalances are not driven by external shocks to the economy, but are built up by unsustainable economic expansion and rapid credit growth. It is only much more recently that economists have begun to empirically study the link between credit and financial crises. For example, Schularick and Taylor (2012) explore the relation between domestic credit and financial crises for 14 countries over a period of 140 years. They find that – in line with Minsky's theory – credit plays an important and dominant role in shaping the business cycle, and has an impact on both the probability of crises as well as on the intensity of recessions. Real credit growth and the credit-to-GDP ratio both contribute significantly to the probability of crises. Jordà et al. (2011) use the same dataset, but also consider external imbalances (specifically, long-run current account data). Their finding is however similar; credit trends (and not external imbalances) are the best predictors of financial instability.[2] Drehmann et al. (2011) are specifically interested in variables that signal the pace and size of the build-up phase in business cycles, and find the credit-to-GDP gap (i.e. the deviation of the credit-to-GDP ratio from its trend) to perform best as a leading indicator for financial booms.

These studies (Schularick and Taylor, 2012; Jordà et al, 2011; Drehmann et al., 2011) focus on the relation between credit and financial stability, but do not consider the drivers of credit. To ensure financial stability, it is important to manage imbalances in the credit market. In other words, the strong cyclicality in credit, with excessive credit growth in the upturn and credit crunches in the downturn of the cycle, is a threat to financial stability. This stresses the importance of a better understanding of the drivers of the credit cycle.

2.2.2 Foreign funded credit as a driver of the credit cycle

Several studies have considered the role of foreign banks in explaining credit growth or credit booms. The idea that foreign bank credit may contribute to the cyclicality of credit in a country stems from the fact that foreign banks may rely on funding from their international parent. They are therefore less dependent on local market conditions, enabling them to increase their credit more than domestic banks are able to.

[2] The authors find that external imbalances have played an additional role, but this was more so in the period before World War II, i.e. a period that was characterized by low financialization.

Schoenmaker (2015) shows that the strong credit growth in Ireland during the run-up to the global financial crisis, with total banking assets almost tripling, was fueled mainly by credit flows from foreign banks. The empirical studies on this topic yield mixed results. While some studies find that foreign banks are contributing to financial stability as – in contrast to domestic banks – they do not have to contract their lending (Crystal et al., 2001; de Haas and van Lelyveld, 2006), other studies point to the procyclical role of foreign banks (Popov and Udell, 2010; Bertay et al., 2015).[3]

One important element that may be overlooked is the exact definition of foreign bank credit. Most studies consider foreign bank credit based on bank ownership, i.e. the credit granted by banks that are foreign-owned. This study argues that the credit that is most relevant is the credit that is foreign funded (FFC), since this enables the total credit to outgrow the domestic deposit growth and may contribute to the overheating of the economy.

Table 2.1 provides more information on the definition of FFC, and makes clear the differences between foreign bank credit and FFC. The first three rows in the table represent FFC. In this study a distinction is made between the credit that borrowers obtain directly from abroad (Table 2.1, row 1) and indirectly via local banks that fund themselves abroad, i.e. via the interbank market (Table 2.1, rows 2 and 3).

[3] In the remainder of this section I focus on those studies that are closest to ours. There are more studies that focus on the role of foreign bank credit (e.g. Micco and Panizza, 2006; Claessens and van Horen, 2014, 2017; de Haas and van Lelyveld, 2006; de Haas and van Horen, 2011) or foreign capital inflows (e.g. Elekday and Wu, 2011; Calderon and Kubota, 2012; Lane and McQuade, 2013) as a driver of the credit cycle.

Table 2.1: Non-locally funded credit (FFC)

	Residence of the borrower	Location of the bank (e.g. subsidiary)	Home country of the bank	Funding of the credit	Included in foreign funded credit? (FFC)	Part of foreign bank assets?
(1)	Country X	Outside	Outside	Outside	Yes	Yes
(2)	Country X	Country X	Outside	Outside	Yes	Yes
(3)	Country X	Country X	Country X	Outside	Yes	No
(4)	Country X	Country X	Outside	Country X	No	Yes
(5)	Country X	Country X	Country X	Country X	No	No
(6)	Outside	Country X	Outside	Country X	No	Yes

While FFC is in some aspects quite similar to foreign bank credit (since foreign banks may get their funding from outside the country in which they grant the credit), there are some notable differences. The definition of foreign bank credit is based on the residence of the bank, while FFC is based on the location where the funding comes from. Table 2.1 also makes clear these differences in definitions, as well as the consequences. Assume a borrower is resident in Country X. This borrower borrows money from a bank subsidiary that is located in Country X, but headquartered outside Country X. This bank subsidiary however funds itself by deposits of Country X. This type of credit will be included in foreign bank credit, but excluded in the FFC, since the credit is funded locally (Table 2.1, row 4). Moreover, if such a party – a bank subsidiary in Country X funded with deposits from Country X – grants credit directly to a borrower outside Country X this credit will also be seen as foreign bank credit in Country X, while it has nothing to do with the credit base in Country X (Table 2.1, row 6). In these two examples, therefore, foreign bank credit overstates relative to FFC. On the other hand, in case a bank from Country X – located and resident in Country X – grants credit to this borrower resident in Country X, but obtains the funding for this credit from outside the country, this will be excluded in foreign bank credit but included in FFC (Table 2.1, row 3). In this example, by considering foreign bank credit, one will miss this FFC-included type of credit. It actually deserves attention, however, since this type of credit facilitates the total credit to exceed the domestic deposit base.

While the analyses by Ongena et al. (2013) and Cull and Peria (2013) are not based on FFC, but on bank ownership, the results of their studies imply that the funding base may matter. Cull and Peria (2013) consider the impact of bank ownership on credit growth and they find that in Latin America foreign banks did not contract their loans more than domestic banks before and during the global financial crisis. The authors argue that this is because these foreign banks were mostly funded locally, i.e. through a domestic deposit base. Focusing on Eastern Europe and Central Asia, Ongena et al. (2013) find that both foreign-owned banks and domestic banks that borrow on the wholesale market contract their credit more during a crisis than domestic banks that are funded locally.

This study is closest to some recent studies from the Bank for International Settlements (BIS) that show that it is the FFC that matters most in explaining rapid credit growth (Borio et al. (2011), Avdjiev et al. (2012) and Ehlers and McGuire (2017)).[4] Borio et al. (2011) show that in Ireland, Hungary and the Baltic States, the FFC components grew faster than the overall credit to residents during the boom period in 2007-2008. While in larger economies the share of FFC as a percentage of total credit is lower, these economies (e.g. Spain, UK, US) also showed a relatively rapid growth in FFC during the pre-crisis credit boom. Focusing on Asian

[4] In their studies these authors refer to cross-border credit instead of FFC.

countries, Avdjiev et al. (2012) conduct a regression analysis and find that FFC significantly contributed to the total credit-to-GDP growth over the period 2002-2008. Ehlers and McGuire (2017) focus on emerging countries and investigate the impact of both FFC and foreign bank participation on the 2002-2008 credit growth. The latter is measured as all credit that is booked by banks headquartered outside the borrowing country (i.e. also including the credit that is granted by foreign banks, but funded locally). Applying a similar regression analysis as Avdjiev et al. (2012) their results suggest that FFC did contribute to credit growth over the period 2002-2008, but foreign banks do not necessarily have a destabilizing effect since their local operations (locally funded lending) were a source of stability. Hence, the aforementioned studies stress that it is the credit backed by cross-border liabilities (FFC) – and not the total credit extended by foreign banks (foreign bank credit) – that contributed to the rapid credit growth in the period before the global financial crisis. I expand the analysis to investigate more generally the eventual procyclical role of FFC over a longer timeframe and this results in the first hypothesis:

H_1: The share of FFC increases during booms and decreases during busts

Anticipating differences between emerging and developed countries when it comes to the role of FFC, analysis is performed for these two groups of countries. Mendoza and Terrones (2008) find that credit booms in emerging and industrial countries differ, and that credit booms in emerging markets are larger and last longer than those in developed countries. Moreover, they find that while credit booms in emerging countries are often preceded by foreign capital inflows, booms in developed economies are preceded by productivity gains or financial reforms. Besides, Avdjiev et al. (2012) and Ehlers and McGuire (2017) solely focus on emerging countries, and their studies suggest that at least in emerging countries, FFC contributed to the rapid credit growth in the run-up to the global financial crisis. In order to investigate whether the impact of FFC differs for emerging versus developed economies, in this study I consider both types of countries separately. This results in the second hypothesis:

H_2: The (procyclical) impact of FFC is higher for emerging market economies than for developed economies

In this study a distinction is also made between household and business credit cycles.[5] Differences in credit cycles for household credit and business credit may be caused by differences between housing dynamics and the business cycle as these are not perfectly linked (Żelazowski, 2017). Even before the global financial crisis the ECB (2007) observed that while *bank* credit to households and corporates has followed a similar cyclical pattern, the peaks and troughs have been higher and deeper for the latter. An explanation for this finding is that banks may increase their lending to non-financial corporations only after

[5] By investigating the impact of *capital inflows* on the credit cycle, Igan and Tan (2017) make a distinction between credit to households and credit to non-financial corporates. They find that capital inflows increase both credit growth and the probability of credit booms, in both household and non-financial corporate sectors. By splitting capital inflows into FDI, portfolio and other inflows, they find that the impact of other inflows depends on how developed the country's financial sector is. That is, as the main provider of credit to households is banks, the development of the banking sector matters more for household credit growth and only when the banking sector is more advanced, net capital inflows begin to matter for household credit.

the economic recovery has already materialized and corporate balance sheets have improved. On the other hand, banks may be more willing to increase their lending to households earlier in the economic cycle, given that these parties are generally better collateralized. Hence, *bank* credit, and thereby FFC, to corporates may be more cyclical than bank credit to households. This results in the third and final hypothesis:

H_3: The (procyclical) impact of FFC is higher for the business sector than for the household sector

2.3 Data and variable construction

2.3.1 Credit booms and busts

To capture total credit in an economy, i.e. both bank and non-bank credit and both domestic and cross-border credit, I obtained credit series from the Bank for International Settlements (BIS) database on total credit to the non-financial sector (Dembiermont at al., 2013). The dataset contains quarterly data for 43 countries starting in 1961 at the earliest. I consider data from 1985 onwards, since most data (also control variables) are available from that date for most countries. Private credit can be split into credit to households and credit to (non-financial) corporations. I exclude financial centers, thereby focusing on 41 countries.[6]

There is no common definition of credit booms, but most studies define certain periods based on large deviations in the credit-to-GDP ratio

6 Argentina, Australia, Austria, Belgium, Brazil, Canada, Chili, China, Colombia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Malaysia, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Russia, Singapore, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom, and United States. I excluded Luxembourg and Saudi Arabia.

or credit per capita from their (non-linear) trend (e.g. Gourinchas et al., 2001; Mendoza and Terrones, 2008; Barajas et al., 2009; Dell'Ariccia et al., 2015; Cerutti et al., 2017). The exact specifications, i.e. the thresholds used or the construction of the trend, differ however. Real credit growth significantly contributes to the probability of crises (Schularick and Taylor, 2012). Therefore, the real credit per capita is used in place of the credit-to-GDP ratio. The use of the credit-to-GDP ratio also has some drawbacks, as highlighted by Mendoza and Terrones (2008). Most importantly, in case of a decrease in both credit and GDP, the credit-to-GDP ratio may increase if the fall in GDP is higher than the fall in credit.

Hence, for this study I apply the following condition: a credit boom takes place when the growth in real credit per capita provided to the private sector is higher than during a typical business cycle expansion. I use the logarithm of real credit per capita and its deviation from its long-term trend in country i at time t is denoted as l_{it} (i.e. the cyclical component) with its corresponding standard deviation $\sigma(l_i)$. The long-term trend is estimated using the Hodrick-Prescott filter. A credit boom takes place when two conditions are satisfied; i) the year-on-year growth rate of real credit per capita is higher than 20 percent or the positive deviation from the trend (l_{it}) is higher than 1.65 times its standard deviation $\sigma(l_i)$ in a given quarter (i.e. $l_{it} \geq \theta\sigma(l_i)$, with θ_1 = 1.65); and ii) the year-on-year growth rate of real credit per capita is higher than 10 percent or the deviation from the trend (l_{it}) is equal to or higher than its standard deviation $\sigma(l_i)$ (i.e. $l_{it} \geq \theta\sigma(l_i)$, with θ_2 = 1) and the growth in real credit per capita is positive for a period of at least 6 quarters.[7] This

[7] Observations with hyperinflation (> 50%) are excluded, since including them would results in an overestimation of credit busts.

approach is closest to that of Cerutti et al. (2017) as the first condition ensures that a credit boom contains at least one quarter with very high credit growth or a large deviation from the trend, while the second condition ensures that short-lived spikes are left out of the analysis.

Credit busts are identified in a similar fashion. That is, a credit bust takes place when two conditions are satisfied; i) the real credit per capita decreases by at least 10 percent on a year-on-year basis or the negative deviation from the trend (l_{it}) is higher than 1.65 times its standard deviation $\sigma(l_i)$ in a given quarter (i.e. $l_{it} \leq -\theta\sigma(l_i)$, with θ = 1.65); and ii) the real credit per capita decreases by at least 5 percent on a year-on-year basis or the negative deviation from the trend (l_{it}) is equal to or higher than its standard deviation $\sigma(l_i)$ (i.e. $l_{it} \geq \ \theta\sigma(l_i)$, with θ_2 = 1) and the growth in real credit per capita is negative for a period of at least 6 quarters. For robustness, I also consider different specifications by setting the thresholds at different levels.

Figure 2.1: Number of credit booms and busts

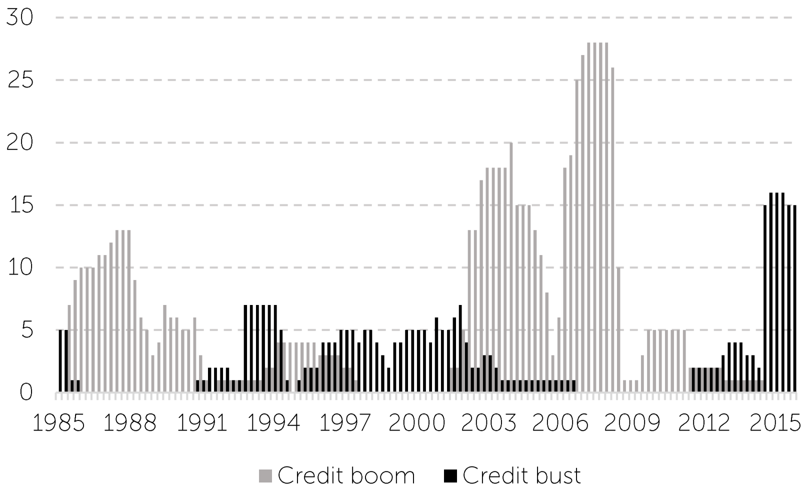

Figure 2.1 shows the total number of credit booms and busts in each quarter. It can be observed that, most credit booms take place during the start of the global financial crisis (2007-2008). The number of busts is generally lower than the number of booms. This relates to the finding that not all credit booms are bad, i.e. not all credit booms are followed by a crisis or credit bust (Barajas et al., 2009, Goetzmann, 2015). Most busts take place around the dotcom crisis (around 2000) or a few years after the global financial crisis (from 2012 onwards).

2.3.2 Data on FFC

As mentioned previously, instead of relying on data on foreign bank ownership, I follow Borio et al. (2011), Avdjiev et al. (2012) and Ehlers and McGuire (2017) and focus on the credit that is backed by cross-border liabilities, also referred to as FFC in this study. The data is obtained from the BIS statistics, both the BIS consolidated banking statistics and the BIS locational banking statistics. From these statistics I first of all collect the credit that banks outside the borrower country directly grant to the non-bank private sector. This is labelled as direct FFC ($\mathrm{FFC}_{\mathrm{i,t}}^{\mathrm{Direct}}$). Secondly, I consider the amount of credit extended by banks in the country that is financed by cross-border liabilities, or, in other words, indirect FFC ($\mathrm{FFC}_{\mathrm{i,t}}^{\mathrm{Indirect}}$). This is the net cross-border borrowing (i.e. the cross-border liabilities minus claims) by banks located in the country.[8] In the analysis, therefore, only positive numbers are taken into account. In case a banking sector has more cross-border loans outstanding than it borrows from other banking sectors, there is no net cross-border borrowing (i.e. a zero observation).[9] For the analysis the focus is on the share of the total FFC to total credit, while total credit is defined as the sum of direct FFC and domestic credit[10]:

$$S\_FFC_{i,t} = \frac{FFC_{i,t}^{Direct} + FFC_{i,t}^{Indirect}}{DC_{i,t} + FFC_{i,t}^{Direct}} \tag{1}$$

whereas $\mathrm{DC}_{\mathrm{i,t}}$ represents the domestic credit (excluding credit to governments), taken from the BIS credit statistics.

[8] For non-BIS reporting countries, BIS reporting banks' net cross-border claims on banks in the country have been used.
[9] A negative number implies that banks in the country, on average, lend money to banks in other countries. Not applying a cap would mean that the net-lending amount would be subtracted from the total non-financial credit in the country, while the outstanding loans are not relevant for the total credit in a country. Actually, one would just underestimate the total credit, and thereby, credit fluctuations, booms and busts.
[10] The net cross-border borrowing by banks (indirect FFC) is by definition included in the domestic credit.

Figure 2.2 below shows the pattern of the share of FFC ($S\_FFC_{i,t}$) before and during credit booms and busts. The share of FFC is indexed at t=0, where t=0 marks the start of the credit boom or bust. The figure on the left shows that shortly after the start of a credit boom the share of FFC credit increases. During the year preceding and at the beginning of the credit boom there is however a decrease in the share of FFC. This implies that not the foreign funded share of credit, but rather the share of domestically funded credit increases in anticipation of a credit boom. During the boom, however, it is the FFC that causes an acceleration in credit. An explanation for this could be that FFC comes later, since it is a more expensive form of credit.

The figure on the right shows that during the three years preceding a credit bust, the share of FFC in total credit decreases, offsetting an increase in the share of domestically funded credit. This suggests a procyclical pattern in FFC. However, the pattern of FFC during a credit bust is less clear; on average there seems to be an increase in the share of FFC during the first three years of the bust. This contradicts the expectations, that is a procyclical impact from FFC, and hence a decreasing share of FFC during busts. It is worth noting however that an increase in the share of FFC does not imply that the FFC itself is increasing; it indicates that the FFC is increasing more than domestic credit.

Figure 2.2: Share of FFC during booms and busts

This figure shows the share of FFC 12 quarters before the boom or busts, and during the first 12 quarters of the boom or bust, taking into consideration that the share of FFC is indexed at t=0 (the start of the boom or bust).

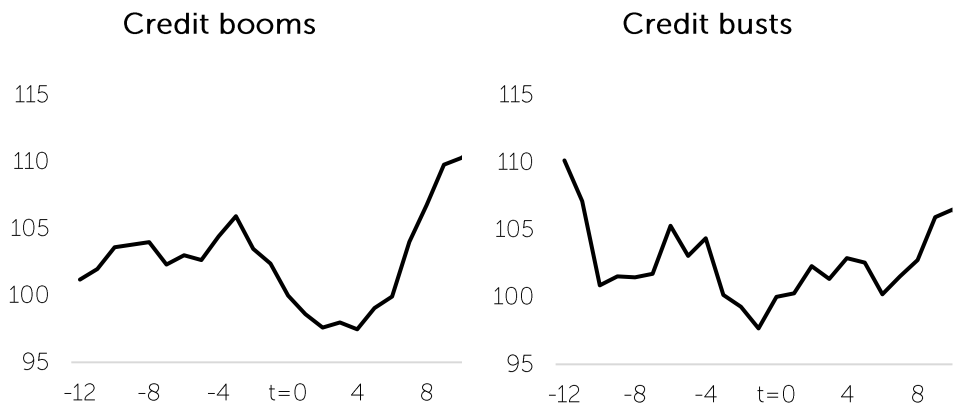

Table 2.2 shows the occurrence and duration of credit booms and busts for the full sample of countries as well as for different subsamples. Considering the first column of this table, the probability of a credit boom in a given quarter is equal to 21.4%. In line with Figure 2.1 credit busts occur less than credit booms and the probability of having a credit bust is generally lower by 8.8%. And with the average duration of a boom being 13.4 quarters versus 9.9 quarters for a bust, booms last on average almost one year longer.

Next, I split the sample of countries into subsamples with respect to the share of FFC in total credit[11] and their economic status (developed or emerging)[12]. In addition, I consider credit booms and busts for

[11] This classification is based on the average share of FFC being higher of lower than the median of all banks.

[12] This classification is derived from the IMF 2010 classification (IMF, 2010). Based on this definition, there are 26 developed countries and 15 emerging countries in this dataset.

household and business credit separately. In looking to the second and third row of Table 2.2, a distinction is made between countries with a high and low share of FFC. On average countries with a high share of FFC experience slightly fewer booms, but more busts than countries with a low share of FFC. Looking at the duration of credit booms and busts, a high share of FFC is associated with longer-lasting busts, but shorter booms.

In the fourth and fifth rows some remarkable differences can be observed between emerging and developed countries. While emerging countries experience slightly fewer booms, the probability of credit busts is much higher for emerging than for developed countries. For emerging countries, in contrast to developed countries, the probability of a boom is not significantly different to the probability of a bust. This corresponds with the finding that in emerging countries credit booms are more likely to end in a financial crisis (or in a credit bust) (Mendoza and Terrones, 2008). Moreover, both credit booms and credit busts last much longer in emerging countries relative to developed countries. For example, while a credit boom only lasts for 10.8 quarters in developed markets, in emerging markets it lasts for 20.9 quarters. On average, booms in emerging markets last around 2.5 years longer than in developed markets.

Rows six and seven show that while there is a larger probability of a credit boom in the household market, the probability of a bust is larger in the business market. And on average, the duration of household credit booms and busts is longer than that of business credit booms.

Table 2.2: Occurrence and duration of credit booms and busts

This table shows the occurrence and duration of credit booms and busts for the full sample of countries as well as for different subsamples.

	Credit booms		Credit busts	
	Occurrence (probabilities)	Duration (in quarters)	Occurrence (probabilities)	Duration (in quarters)
(1) Mean	0.214	13.4	0.088	9.9
(2) High FFC countries	0.208	11.2	0.107	10.9
(3) Low FFC countries	0.219	15.6	0.068	8.1
(4) Emerging countries	0.204	20.9	0.166	12.4
(5) Developed countries	0.217	10.8	0.059	7.1
(6) Household credit	0.279	14.0	0.086	11.5
(7) Business credit	0.195	11.5	0.103	10.2

2.4 Methodology

To test whether credit booms and busts are driven by FFC the following binominal logit model is applied:

$$\mathbb{P}[\gamma_{i,t} = 1] = \delta_t + \mu_i + \beta_1 \Delta S\_FFC_{i,t} + \sum_{j=3}^{J} \beta_j X_{i,t} + \varepsilon_{i,t} \quad (2)$$

where $\delta_{i,t}$ stands for a credit boom, normal period or credit bust, and thereby $\mathbb{P}[\delta_{i,t} = 1]$ is the probability of being in a credit boom, normal period or credit bust in quarter t. Periods that are not classified as either a boom or a bust are classified as a normal period. The main independent $\Delta S\_FFC_{i,t}$ represents the quarterly growth rate of the share of FFC in total credit. In line with hypotheses of a procyclical role of FFC a positive coefficient is expected in booms, such that an increasing share of FFC is positively associated with credit booms. In busts, a negative coefficient is expected such that, in line with the hypotheses, credit busts are characterized by a decreasing share of FFC.

$X_{i,t}$ includes the control variables. First, the market-to-bank ratio is included. This is defined as the ratio of market to bank funding, where market funding consists of debt securities to non-financial institutions obtained from the BIS debt securities statistics. A negative coefficient is expected for the market-to-bank ratio since, first of all, booms and busts seem to occur less in more market-based systems (Cizel et al., 2019; Gambacorta et al., 2014). Besides, when (house) prices drop, banks are constrained in their ability to grant new loans and, consequently, the contraction in bank credit has a negative impact on investment opportunities. This amplification mechanism is found to be higher in more bank-based economies (Langfield and Pagano 2016). Second, as a proxy for the short-term interest rate, the US federal fund rate is included as a control variable.[13] Since periods with low interest rates often coincide with a build-up in credit, a negative coefficient for this variable is expected during a boom while a positive coefficient is expected for bust periods. Third, I consider a country's real GDP growth. An increase in real GDP is expected to go hand in hand with increase in credit, and vice versa. Finally, the inflation rate and trade openness are included, whereas trade openness is measured by the sum of a country's import and export (as obtained from the IMF Direction of Trade Statistics), divided by its GDP. Other control variables that are sometimes used in analyses on credit

[13] Country-specific data on interest rates is not available for all countries and all years. The US federal fund rate is obtained from the Federal Reserve Economic Data.

cyclicality are not available for all countries and/or the period considered.[14] I use both quarter fixed effects δ_t and country fixed effects μ_i, and cluster the standard errors at the country level. Lastly, I exclude observations with hyperinflation (>50% on a quarterly basis).

Table 2.3 shows the correlation matrix. A high correlation – higher than 0.5 – is only observed between the boom and bust variables, implying that booms and busts are concentrated in specific periods. High correlations between any of the independent variables are however not observed, and therefore multicollinearity is not expected to be an issue.

Table 2.3: Correlation matrix

This table shows the correlation among the variables used in the logit model as specified in equation (2).

	Credit boom	Credit bust	ΔS_FFC	MtB ratio	Interest rate	Trade open.	Inflation	ΔGDP
Credit boom	1.000							
Credit bust	0.578	1.000						
ΔS_FFC	-0.031	0.019	1.000					
MtB ratio	-0.128	-0.130	0.007	1.000				
Interest rate	0.109	0.114	0.037	-0.125	1.000			
Trade open.	-0.079	0.001	0.034	-0.030	-0.130	1.000		
Inflation	0.090	0.071	-0.039	-0.101	0.209	-0.067	1.000	
ΔGDP	0.272	0.205	-0.278	-0.024	0.106	-0.017	0.064	1.000

2.5 Results

2.5.1 Baseline results

Table 2.4 shows the baseline results from the logit model. The positive coefficient in column 1 first of all shows that the quarterly growth in the share of FFC is positively associated with credit booms. This implies

[14] These include for example, real effective exchange rate, VIX index, m2-to-reserve ratio or housing prices (e.g. Bezemer and Zhang, 2014).

that during credit booms FFC increases significantly more than domestic credit, supporting hypothesis 1. Column 2 shows that the growth in FFC is negatively related to normal periods (i.e. no boom or bust). However, for credit busts, the results in column 3 do not show any significant relation between FFC and the occurrence of credit busts.

The market-to-bank ratio is negatively associated with credit booms and normal periods, and positively associated with credit busts. This implies that during credit booms and normal periods, bank credit increases significantly more than market funding. And vice versa, during a bust, market funding decreases less than bank credit. This is in line with the expectations and points to the stabilizing role of market funding, thereby supporting the findings of Langfield and Pagano (2016). While the other control variables are not always significant, the coefficients show the expected signs.

Table 2.4: Baseline results

This table shows the regression results from equation (2), estimated by a logit model over the period 1985q1-2015q4. The table shows the marginal effects. Both quarterly and country fixed effects are included, and standard errors are clustered at country level and reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

	Credit boom (1)	Normal (2)	Credit bust (3)
$\Delta S\_FFC_{i,t}$	0.003**	-0.002**	-0.002
	(0.001)	(0.001)	(0.002)
$MtB_{i,t}$	-0.012**	-0.001	0.012***
	(0.006)	(0.005)	(0.004)
$Interest_t$	0.022***	-0.023***	-0.004
	(0.007)	(0.008)	(0.014)
$Openness_{i,t}$	0.009*	-0.002	-0.017***
	(0.005)	(0.005)	(0.006)
$Inflation_{i,t}$	0.007	-0.023	-0.002
	(0.024)	(0.029)	(0.046)
$\Delta GDP_{i,t}$	0.024***	-0.010***	-0.015***
	(0.004)	(0.003)	(0.003)
# Obs.	3,116	3,356	2,230
# Countries	35	39	25
Pseudo R^2	12.58	3.48	7.72
Wald chi2	313.23	43.75	46.48
Prob>chi2	0.000	0.000	0.000

2.5.2 Emerging versus developed countries

Table 2.5 shows the same results, but for subsamples based on whether the country is classified as an emerging or developed according to the IMF (2010) classification. Columns 1-3 show the results for emerging countries. The positive coefficient of the quarterly change in the share of FFC implies that during booms FFC increases relative to domestically funded bank credit. For developed countries the coefficient in column 4 is also significantly positive, but remarkably lower. The results also show that there is a significant difference between the coefficients for emerging versus developed countries. The role of FFC in the credit boom is thus significantly higher for emerging than for developed countries.

While a significant negative coefficient is found for emerging countries for periods that are classified as normal, this is not the case for developed countries. Hence, for emerging countries the share of FFC significantly decreases during periods that are not considered as either a boom or a bust. In line with the baseline results, the table does not point to a relation between credit busts and quarterly growth in the share of FFC.

For developed countries, the coefficient for inflation is significantly positive during booms and significantly negative during busts, as expected. For emerging countries, however, the opposite is shown. This can be explained by the decreasing trend in inflation in these countries, whereas the originally high inflation rates have converged towards the levels in developed countries (Daly and O'Doherty, 2018), and may in turn impact the results.

Table 2.5: Emerging versus developed countries

This table shows the regression results from equation (2), estimated by a logit model over the period 1985q1-2015q4. The table shows the marginal effects. Both quarterly and country fixed effects are included, and standard errors are clustered at the country level reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

	Emerging countries			Developed countries		
	Credit boom (1)	**Normal (2)**	**Credit bust (3)**	**Credit boom (4)**	**Normal (5)**	**Credit bust (6)**
$\Delta S\_FFC_{i,t}$	0.009***	-0.008***	0.000	0.002*	-0.001	-0.002
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
$MtB_{i,t}$	-0.036**	-0.008***	0.008**	-0.008	0.008	0.007
	(0.018)	(0.003)	(0.004)	(0.005)	(0.006)	(0.011)
$Interest_t$	0.034	-0.046*	0.016	0.019***	-0.014	-0.016
	(0.025)	(0.024)	(0.016)	(0.007)	(0.010)	(0.012)
$Openness_{i,t}$	0.007	0.009	-0.009*	0.008	-0.007	-0.007
	(0.011)	(0.015)	(0.005)	(0.005)	(0.005)	(0.009)
$Inflation_{i,t}$	-0.129**	-0.060	0.136***	0.037	0.002	-0.078*
	(0.054)	(0.056)	(0.021)	(0.025)	(0.031)	(0.044)
$\Delta GDP_{i,t}$	0.023***	-0.006**	-0.006	0.024***	-0.016***	-0.018***
	(0.008)	(0.003)	(0.004)	(0.004)	(0.003)	(0.006)
# Obs.	666	1,351	698	2,450	2,756	1,532
# Countries	10	14	10	25	25	15
Pseudo R^2	20.10	10.63	25.93	12.88	4.39	11.27
Wald chi2	385.94	275.80	71.99	367.83	52.22	92.93
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000
		Boom	Normal	Bust		
Chi2(Equality of coefficients)		9.33***	12.41***	0.58		

2.5.3 Household versus business credit

Table 2.6 shows the regression results for household and business credit cycles separately, whereas columns 1-3 show the results for household credit and columns 4-6 the results for business credit. The results are roughly in line with the baseline results. That is, credit booms are associated with a significantly increasing share of FFC, normal periods with a decreasing share of FFC, and no significant relation between the share of FFC in total creditt and the occurrence of credit busts. Against the expectation of differences between household and business credit cycles with respect to the impact FFC may have, the results do not point to any differences between household and business credit cycles.

Regarding the control variables, differences in the coefficients for openness and inflation are shown with respect to the impact they have on household versus the business credit cycles. The impact of openness – the amounts of imports and export relative to a country's GDP – is more significantly related to the business credit cycle. This may be explained by the business sector's credit needs that are – in case of international operations - directly affected by the amounts of imports and exports.

Table 2.6: Household versus business credit

This table shows the regression results from equation (2), estimated by a logit model over the period 1985q1-2015q4. The table shows the marginal effects. Both quarterly and country fixed effects are included, and standard errors are clustered at the country level and reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

	Household credit			Business credit		
	Credit boom (1)	**Normal (2)**	**Credit bust (3)**	**Credit boom (4)**	**Normal (5)**	**Credit bust (6)**
$\Delta S\_FFC_{i,t}$	0.002*	-0.002	-0.003	0.003***	-0.003***	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
$MtB_{i,t}$	-0.009	0.003	0.009***	-0.008	-0.000	0.005*
	(0.006)	(0.006)	(0.003)	(0.005)	(0.004)	(0.003)
$Interest_t$	0.022**	-0.020**	-0.009	0.019***	-0.025***	0.005
	(0.009)	(0.009)	(0.014)	(0.007)	(0.008)	(0.011)
$Openness_{i,t}$	0.005	0.001	-0.013**	0.011***	-0.004	-0.021***
	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.003)
$Inflation_{i,t}$	-0.025	0.020	-0.014	0.008	-0.017	-0.012
	(0.022)	(0.023)	(0.050)	(0.022)	(0.031)	(0.035)
$\Delta GDP_{i,t}$	0.027***	-0.015***	-0.017***	0.020***	-0.007***	-0.010***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)
# Obs.	3,218	3,250	2,330	3,217	3,403	2,585
# Countries	37	38	26	37	40	28
Pseudo R^2	10.54	3.59	6.91	9.50	2.87	7.69
Wald chi2	322.54	101.04	55.28	162.18	36.47	59.59
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000

	Boom	Normal	Bust
Chi2(Equality of coefficients)	2.20	1.92	2.83*

2.5.4 FFC pre-boom and pre-bust

So far, the results in the previous sections point to credit booms being associated with an increasing share of FFC, while FFC is not found to be significantly related to busts. But what happens before the boom or bust? The analysis has focused on the behavior of FFC over the credit cycle so far, without exploring a causal relation. As a next step, I investigate the behaviour of FFC pre-boom and pre-bust. Simply using lagged FFC variables has the disadvantage that actual booms and bust periods are still included in the analysis. Therefore instead of using lagged variables of FFC, I define pre-boom and pre-bust indicator variables. That is, instead of the dependent variable $\mathbb{P}[\delta_{i,t} = 1]$ being the probability of a boom or bust in quarter t, I construct $\mathbb{P}[\delta_{i,t-1;t-c} = 1]$, capturing the period from the first quarter before the boom or bust, t-1, until t-c, where I set c at different levels with c = 2, 4, 8 and 12. In this way I am able to test the behavior of FFC half a year, a year, 2 years and 3 years before the boom or bust. Figure 2.2 already indicated that the share of FFC may act differently before credit booms or busts, as it points to a decreasing share of FFC preceding a credit boom.

Table 2.7 shows the main results of this analysis. Considering column 1-4, the results show that the coefficient for the quarterly growth in the share of FFC turns from significantly positive in the baseline specification to a (in some specifications significantly) negative one. Put differently, during the period – be it half a year, a year, 2 years or 3 years - before a credit boom it is not the share of FFC, but rather the share of domestically funded credit that seems to increase. For example, the negative coefficients for emerging countries and household credit imply that during the year preceding the credit boom, there is a significant decrease in the share of FFC, offsetting an increase in domestically funded credit. This is in line with the pattern in Figure 2.2. Hence, while before the boom there is a significant increase in domestically funded credit relative to FFC during the boom it is the FFC that significantly gains share. This may be explained by the ability to provide credit. In other words, during the build-up phase of the boom, domestically funded credit is able to fulfil credit needs. This type of funding may be preferred as well, since it is generally cheaper. With the continuously growing credit, during a boom this domestically funded credit may need to be substituted by FFC as it is less restricted than domestically funded credit by, as an example, the domestic deposit base.

Columns 5-8 shows the results when the pre-bust period is considered. The coefficients of the quarterly changes in FFC are negative and rather insignificant, just as in the baseline specification. There is some small evidence of a (slightly) significant decrease in the share of FFC, implying that three years before the credit bust, the share of FFC is already decreasing.

Table 2.7: Pre-boom and bust

This table shows the regression results from equation (2) with $\mathbb{P}[\delta_{i,t-1;t-c} = 1]$ as the dependent variable and estimated by a logit model over the period 1985q1-2015q4. The table shows the marginal effects. Both quarterly and country fixed effects are included, and standard errors are clustered at the country level and reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

		Credit boom				Credit bust			
		2-quarter (1)	**4-quarter (2)**	**8-quarter (3)**	**12-quarter (4)**	**2-quarter (5)**	**4-quarter (6)**	**8-quarter (7)**	**12-quarter (8)**
Baseline	$\Delta S\_FFC_{i,t}$	-0.002 (0.002)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.002 (0.002)	-0.000 (0.002)	-0.001 (0.002)	-0.003 (0.002)
	Pseudo R^2	5.26	2.91	3.89	3.09	3.44	2.59	2.52	2.98
Emerging countries	$\Delta S\_FFC_{i,t}$	-0.013 (0.010)	-0.009* (0.005)	-0.002 (0.003)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.003)	-0.002 (0.002)
	Pseudo R^2	16.52	6.88	7.35	3.66	8.29	6.00	4.46	6.96
Developed countries	$\Delta S\_FFC_{i,t}$	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.001 (0.002)	0.001 (0.002)	0.000 (0.002)	-0.001 (0.001)
	Pseudo R^2	4.95	2.91	4.32	4.09	5.75	5.53	5.84	8.14
Household credit	$\Delta S\_FFC_{i,t}$	-0.002 (0.002)	-0.004** (0.002)	-0.002** (0.001)	-0.001 (0.001)	-0.001 (0.002)	-0.000 (0.001)	-0.000 (0.001)	-0.001 (0.001)
	Pseudo R^2	0.74	0.33	1.17	2.11	3.36	3.63	4.23	4.60
Business credit	$\Delta S\_FFC_{i,t}$	-0.002** (0.001)	-0.001 (0.001)	-0.002** (0.001)	-0.002* (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.002* (0.001)
	Pseudo R^2	4.64	3.81	3.40	2.27	5.50	3.91	4.14	3.16

2.5.5 Robustness checks

Two kinds of robustness checks are performed. First of all, I check whether the findings are robust to different specifications for determining credit booms and busts. Table 2.8 below shows the impact of these different settings on the occurrence of booms and busts. By relaxing the thresholds (Table 2.8, column 1) the probability of experiencing a credit boom in a specific quarter increases by more than 50%, i.e. from 0.214 to 0.352. The probability of experiencing a bust also increases, by somewhat less than 50%. Moreover, by relaxing the thresholds also the average duration of booms and busts also increases. And vice versa, by strengthening the thresholds both the occurrence and duration of credit booms and busts decrease.

Table 2.8: Occurrence and duration of credit booms and busts using different thresholds

This table shows the occurrence and duration of credit booms and busts for different thresholds. See section III.A for more information on the thresholds.

	(1) Relaxing threshold	(2) Baseline	(3) Strengthening threshold
Condition 1 - boom	$\theta_1 = 1.3$ Y-o-Y growth > 15%	$\theta_1 = 1.65$ Y-o-Y growth > 20%	$\theta_1 = 2$ Y-o-Y growth > 25%
Condition 2 - boom	$\theta_2 = 0.75$ Y-o-Y growth > 5%	$\theta_2 = 1$ Y-o-Y growth > 10%	$\theta_2 = 1.25$ Y-o-Y growth > 15%
Boom occurrence (in prob.)	0.352	0.214	0.123
Boom duration (in quarters)	15.1	13.4	11.8
Condition 1 - bust	$\theta_1 = 1.3$ Y-o-Y growth < -5%	$\theta_1 = 1.65$ Y-o-Y growth < -10%	$\theta_1 = 2$ Y-o-Y growth < -15%
Condition 2 - bust	$\theta_2 = 0.75$ Y-o-Y growth < -2.5%	$\theta_2 = 1$ Y-o-Y growth < -5%	$\theta_2 = 1.25$ Y-o-Y growth < -10%
Bust occurrence (in prob.)	0.153	0.088	0.040
Bust duration (in quarters)	12.1	9.9	9.5

Table 2.9 shows that the results are robust to either relaxing or strengthening the threshold levels for determining credit booms and busts. That is, the results are in line with the baseline results.

Table 2.9: Robustness check – different thresholds

This table shows the regression results from equation (2), estimated by a logit model over the period 1985q1-2015q4. The table shows the marginal effects. Both quarterly and country fixed effects are included, and standard errors are clustered at the country level and reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

	Relaxing thresholds			Baseline			Strengthening thresholds		
	Credit boom (1)	Normal (2)	Credit bust (3)	Credit boom (4)	Normal (5)	Credit bust (6)	Credit boom (7)	Normal (8)	Credit bust (9)
$\Delta S\_FFC_{i,t}$	0.003**	-0.003**	-0.001	0.003***	-0.002***	-0.002	0.004***	-0.003***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$MtB_{i,t}$	-0.013***	0.004	0.005	-0.012***	-0.001	0.012***	-0.023**	0.006	0.004**
	(0.004)	(0.006)	(0.003)	(0.002)	(0.001)	(0.002)	(0.009)	(0.009)	(0.002)
$Interest_t$	0.028***	-0.031***	-0.005	0.022***	-0.023***	-0.004	0.023*	-0.025*	0.008
	(0.006)	(0.006)	(0.008)	(0.003)	(0.004)	(0.006)	(0.014)	(0.013)	(0.020)
$Openness_{i,t}$	0.006***	-0.001	-0.016***	0.009***	-0.002	-0.017***	0.008	0.010	-0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.009)	(0.007)	(0.008)
$Inflation_{i,t}$	-0.019	0.026	-0.024	0.007	-0.023**	-0.002	-0.032	-0.026	0.049
	(0.028)	(0.024)	(0.026)	(0.012)	(0.012)	(0.016)	(0.027)	(0.039)	(0.075)
$\Delta GDP_{i,t}$	2.462***	-1.079***	-1.264***	0.024***	-0.010***	-0.015***	2.595***	-1.254***	-0.746**
	(0.153)	(0.197)	(0.244)	(0.002)	(0.002)	(0.002)	(0.248)	(0.344)	(0.309)
# Obs.	3,372	3,404	3,026	3,116	3,356	2,230	2,540	2,809	1,178
# Countries	39	40	34	35	39	25	29	33	14
Pseudo R^2	12.37	3.79	7.63	12.58	3.48	7.72	12.85	6.02	16.13
Wald chi2	494.52	162.02	179.11	378.98	124.35	115.45	270.01	47.04	113.44
Prob>chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

As a second type of robustness check, I run the baseline specification for two different subperiods; the period before 2000 (1985-2000) and the period thereafter (2001-2015). Due to data limitations, the results can not be retrieved for emerging countries over the period 1985-2000. The results in columns 4-6 of Table 2.10, covering the period 2001 till 2015, are roughly similar to the baseline results, i.e. credit booms and normal periods are associated with, respectively, an increase and decrease in the share of FFC. Remarkably, the coefficient for emerging countries turns insignificant. For the period 1985-2000 there is also (albeit less) significant evidence for a the procyclical role of FFC in credit booms in the baseline specification. This is not the case for all subsamples, including household credit and developed countries, where insignificant coefficients are shown. The procyclical role of FFC is however present for business credit (note that for emerging countries the observations are too limited to provide any results). The finding that FFC is unrelated to household booms in the pre-2000 period, but related after may be linked to the massive rise of global household debt during mid-2000s. Hence, the – less restricted than domestically funded credit - FFC was used to fulfil the demand for credit from households.

Table 2.10: Robustness check: subperiods

This table shows the regression results from equation (2), estimated by a logit model over the periods 1985q1-2000q4 and 2001q1-2015q4. The table shows the marginal effects. Both quarterly and country fixed effects are included, and standard errors are clustered at the country level and reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

		1985-2000			2001-2015		
		Credit boom (1)	**Normal (2)**	**Credit bust (3)**	**Credit boom (4)**	**Normal (5)**	**Credit bust (6)**
Baseline	$\Delta S\_FFC_{i,t}$	0.002	-0.001	-0.000	0.004**	-0.004*	-0.001
		(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.003)
	Pseudo R^2	25.77	5.28	21.39	17.64	7.47	14.08
Emerging countries	$\Delta S\_FFC_{i,t}$	n.a.	-0.008*	0.000	0.009	-0.009**	-0.001
			(0.005)	(0.002)	(0.005)	(0.003)	(0.003)
	Pseudo R^2	n.a.	25.13	18.71	19.19	12.39	19.21
Developed countries	$\Delta S\_FFC_{i,t}$	0.001	0.000	-0.000	0.003*	-0.002	-0.000
		(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
	Pseudo R^2	26.91	6.54	27.69	19.96	8.59	23.41
Household credit	$\Delta S\_FFC_{i,t}$	0.002	-0.000	-0.001	0.002*	-0.002**	-0.002
		(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
	Pseudo R^2	21.07	7.62	24.76	16.56	7.12	15.45
Business credit	$\Delta S\_FFC_{i,t}$	0.004*	-0.002*	-0.000	0.004**	-0.004**	0.000
		(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
	Pseudo R^2	19.95	3.45	7.72	13.88	6.08	7.88

2.6 Conclusion

Financial boom-and-bust cycles are not only costly for banks, but also for the broader economy as characterized by sharp output (GDP) declines during the downturn of the cycle. The positive relation between credit growth and financial crises – that goes back to the concept of endogenous business cycles of Minsky (1977) – stresses the importance of a better understanding of the drivers of credit growth and credit cycles. Contrary to previous studies that focus on the role of foreign banks in explaining credit cycles, in this study I consider the impact of credit that is not locally funded. The focus is on this type of credit because it enables the total credit to outgrow the domestic deposit growth.

The results of investigating credit cycles in 41 countries over the period 1985-2015 indicate that foreign funded credit (FFC) has a procyclical role in the credit cycle, characterized by an increasing share of FFC during credit booms. While normal periods are associated with a decrease in the share of FFC, no significant relation can be found between credit busts and FFC. The results contradict the expectations of differences between household and business credit with respect to the impact FFC has on the credit cycle. However, when considering the periods before and after 2000 separately, I find that while FFC is associated with business credit booms in both periods, it is only associated with household credit over the post-2000 period. This may relate to the rise in global household (mortgage) debt since the mid-2000s. FFC was thus used to fulfil the increased demand for credit from households.

By investigating the periods preceding booms and busts, the results show that before a credit boom there is actually a significant increase in domestically funded credit relative to FFC. The availability of credit may provide an explanation, as during the build-up phase of the boom, domestically funded credit is able to fulfil the credit needs. However, during times of rapidly growing credit needs, during a boom the domestically funded credit may need to be substituted by FFC, with the latter being less restricted by, for example, the domestic deposit base.

These findings contribute to the policy discussion on credit cycles and globalization. The global financial crisis that started in 2007 – and that was preceded by excessive credit growth during the build-up of the cycle- resulted in some huge losses. This led to the introduction of macroprudential measures, including the countercyclical capital buffer, to dampen the cyclicality in bank credit. However, irrespective of the total level of credit, the funding of the credit in an economy should also get attention at the macro level. By enabling the total credit to outgrow the domestic deposit base a high level or inflow of FFC increases the domestic loan-to-deposit ratio and thereby the reliance on external funding. This in turn increases the vulnerability to economic reversals. Especially since external funding, including wholesale funding, may dry up during downturns. One may argue that a domestically funded credit boom is less of an issue, since the credit is backed by (more stable) domestic deposits. Therefore, instead of steering the total level of credit in an economy, attention should be given to the composition and, more specifically, the funding sources of credit. Instruments that are specifically targeted at FFC, e.g. capital control-like instruments (e.g. Bakker and Chapple, 2002), could be regarded as more effective in this sense. Over the last years the trend has however been on liberalisation and, consequently, globalisation. Given that an increased reliance on external funding can also pose risk, the question here is whether policymakers should consider not just the benefits - such as growth opportunities - but also the challenges stemming from external funding.

Chapter 3: European Banks Straddling Borders: Risky or Rewarding?

Theory suggests that cross-border banking is beneficial as long as there is a non-perfect correlation across country-specific risks. Using a unique hand-collected dataset with cross-border loans for the 61 largest European banks, we find that cross-border banking in general decreases bank risk. Moreover, we find that banks can increase the beneficial impact from cross-border banking by diversifying more into countries with an economic cycle that differs from the one of their home country. However, we find that banks do not fully utilize these diversification opportunities as banks do not tend to invest in countries that are economically dissimilar.[15]

JEL classification: E44, G21, G28

Keywords: International Banking; Bank Regulation; Financial Stability; Risk; Geographical diversification.

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3.1 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 conditions. Using a unique dataset with cross-border exposures of the 61 largest European banks, our study provides an answer to these questions. As a first step, by estimating a gravity model we examine just where banks expand to when they cross borders. Do banks tend to invest more in countries with dissimilar economic conditions in order to reduce risk? As a second step, we investigate the impact of cross-border banking on the risk-return profile of banks. As the extent to which a bank is diversified is expected to be related to its risk profile, i.e. the relation between diversification and risk is assumed to be endogenous, we employ an instrumental variable approach to analyse the impact of diversification on banks' risk-return profile. The outcomes from the gravity model in the first step are used as an input for the construction of the instrument used in the second step.

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.[16] Wider benefits from cross-border banking may arise in

[16] For example, cross-border lending may impact the access to finance for SMEs (Bremus and Neugebauer, 2018). See also Goldberg (2009) for an overview of the consequences of globalisation in banking.

a variety of ways, including from non-financial firms being more resilient against domestic crises via access to credit from non-local banks (Keeton, 2009; Kleimeier et al. 2013; 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 may have negative consequences for a country. 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 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 away a bank is 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), while other studies argue that cross-border banking has no significant impact on the risk-return profile of a bank, or even that it may 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 to which banks expand. 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, where the business cycle is measured by GDP growth.

Our paper makes four novel contributions to the literature. First, in order to understand the determinants of cross-border banking, we investigate which factors drive the cross-border positions of banks. This also provides an answer to the question whether banks are inclined to invest more in countries with dissimilar economic conditions. Second, and closely following Goetz et al. (2015), 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. Third, we thereby distinguish between structural and dynamic differences in economic conditions across countries. Countries may structurally differ with respect to the economic development level, i.e. in terms of GDP per capita. This measure points to the longer-term differences in economic development. On the other hand, countries may differ from each other with respect to the phase in the economic cycle; in the most extreme case this means being in the upturn or the downturn of the cycle. This is measured by the GDP growth and unemployment levels. By distinguishing between structural and dynamic differences in economic conditions we are better able to understand the risk diversification mechanism of cross-border banking. Lastly, to our knowledge, this is the first paper that studies the impact of geographical diversification, thereby taking into account the economic conditions of the regions or countries where banks expand to, for a sample of European banks.

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 of what the impact is for banks. Focussing on the 61 largest European banks we cover approximately two-third 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 from 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 cross-border investments stems from branches.

Our results show first of all that we do not find any evidence that banks are inclined to invest more in dissimilar countries. Instead, we find some evidence that banks tend to invest significantly more in countries with an income per capita that is close to that in their home country. Second, we find that geographical diversification has a positive impact on the risk-return profile of a bank. More interestingly, we find that the more banks diversify into countries with more dissimilar cyclical developments they reduce both their insolvency risk – as measured by the z-score – and their variability in return on assets. However, considering the more structural economic indicator – i.e. GDP per capita– we do not find that investing into more dissimilar countries pays off. Given that banks are reluctant to invest in countries with different economic cycles - despite the positive effect on the risk profile - our findings hence show that banks do not fully utilise the diversification opportunities that we find to arise from investing in more dissimilar economies.

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 investigates the determinants of banks' cross-border positions, and also considers whether banks are more inclined to invest in dissimilar countries or not. Section 4, as a second step, studies the impact of geographical diversification on a bank's risk-return profile, and specifically focuses in on the impact of investing in more dissimilar countries. Section 5 summarizes the main findings and concludes.

3.2 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. Their 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. Our sample consists of the 61 largest European banks, thereby covering approximately two-third of total European banking assets. 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 country-by-country reporting, which is mandatory under the Capital Requirements Directive of 2013 (CRD IV). We have collected data for the period 2010-2017, as these latter two data sources are only available more recently. 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 of whether geographical diversification is beneficial for the bank as a whole (i.e. the ultimate economic risk at a consolidated level is relevant for the group).[17] Table A.3.9 in the Appendix provides a more detailed description of our dataset as well as a link to the public database.

[17] Relevant studies that focus on the type of bank internationalization include Cerutti et al. (2007) and De Haas and van Lelyveld (2006).

Table 3.1: 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-2017 numbers, and weighted by total banking assets.

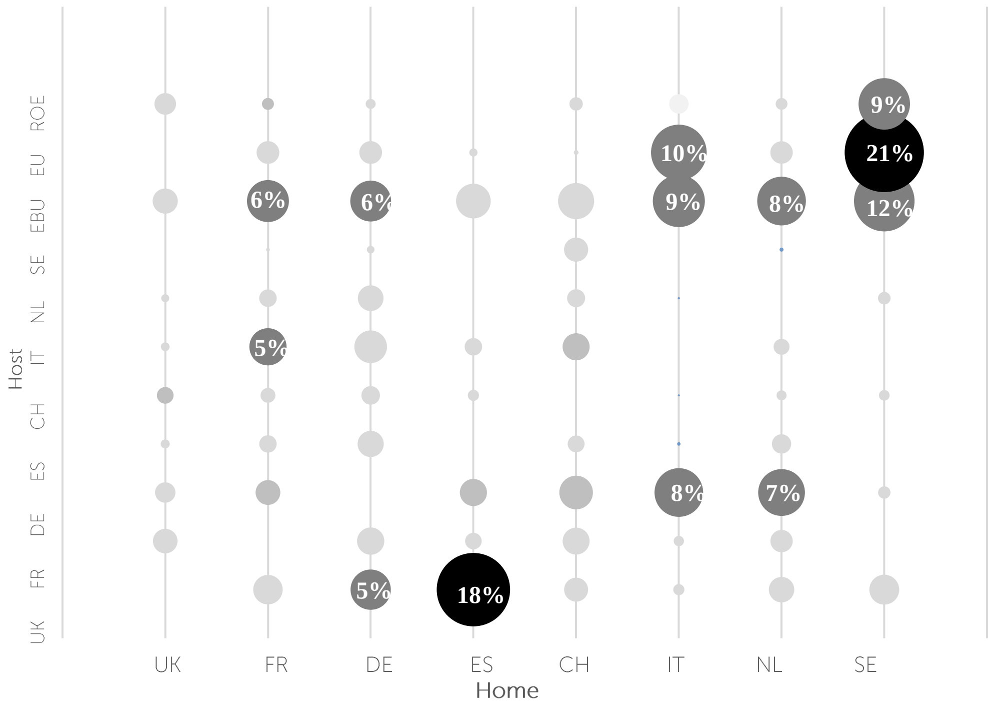
Home country	Banks (#)	Assets (in € bln)	Home	Rest of Europe	North America	South America	Asia	Africa	Oceania
FR	6	7,283	69.6%	19.5%	5.9%	0.8%	3.5%	0.5%	0.3%
UK	6	5,932	55.4%	7.3%	13.2%	0.4%	22.3%	0.3%	1.0%
DE	13	4,119	60.5%	18.8%	13.5%	1.1%	5.2%	0.5%	0.5%
ES	6	3,101	48.9%	24.9%	11.4%	11.9%	3.0%	0.1%	0.0%
NL	5	2,094	56.9%	28.2%	5.7%	1.3%	4.4%	0.1%	3.5%
IT	5	2,061	68.4%	28.5%	1.2%	0.7%	0.7%	0.4%	0.0%
CH	4	1,798	42.9%	19.5%	29.9%	1.0%	6.7%	0.0%	0.0%
SE	4	1,349	50.8%	46.7%	1.9%	0.0%	0.5%	0.0%	0.0%
DK	2	667	65.6%	34.4%	0.0%	0.0%	0.0%	0.0%	0.0%
BE	2	460	61.0%	35.4%	1.9%	0.0%	1.2%	0.2%	0.2%
AT	2	356	34.6%	59.9%	0.6%	0.0%	4.4%	0.2%	0.0%
NO	1	275	69.4%	22.1%	3.9%	2.1%	1.2%	0.5%	0.8%
IE	2	213	73.8%	26.2%	0.0%	0.0%	0.0%	0.0%	0.0%
FI	1	137	85.7%	12.8%	1.0%	0.0%	0.5%	0.0%	0.0%
GR	1	65	87.5%	11.2%	0.0%	0.0%	0.0%	0.8%	0.0%
PT	1	93	73.0%	12.9%	1.7%	0.5%	7.2%	4.6%	0.0%
Weighted average			**59.5%**	**21.1%**	**9.5%**	**1.9%**	**7.2%**	**0.3%**	**0.6%**

The 61 banks in our sample invest together in 138 countries. Table 3.1 provides an overview of the geographical exposures for all banks in our dataset, grouped by country, while Table A.3.10 in the appendix provides this information for all individual banks. On average, banks invest the majority, 59.5%, of their assets in their home country. Their foreign exposures are mainly held in other European countries (21.1%) and North

America (9.5%). Exceptions are UK and Spanish banks, respectively investing 22.3% in Asia and 11.9% in South America.

Figure 3.1: Geographical distribution of European assets by main countries

This figure shows the cross-border loans of 49 banks in eight countries to European (groups of) countries as a percentage of the total cross-border loans of those 49 banks. The eight 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, of which 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.



As the majority of the foreign assets is invested in European countries, Figure 3.1 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. Spanish and Swedish in particular 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, however, 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 Denmark, Finland, Norway and the Baltics.

3.3 Determinants of banks' cross-border positions

3.3.1 Previous findings

As a first step, we examine the determinants of banks' cross-border positions. Banks that go abroad 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; Houston and Ma, 2012). These studies all point to factors that could be determinants of banks' cross-border positions, such as differences in taxation or regulation between the home and host country. 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 conditions could, at least from a theoretical point of view, be seen by banks 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 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 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 include, 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 conditions between the home and host country. Besides investigating whether banks tend to invest in more dissimilar countries, the standard gravity model is also used for the construction of the instrumental variable in the second part of the paper where we examine the impact of diversification on banks' risk-return profile.

3.3.2 Methodology and data

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

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

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 structural and dynamic dissimilarities in economic indicators. The absolute values of the difference between a bank's home country *i* and host country *j* in terms of GDP per capita ($GDPcapita_{|i-j|,t}$) points to the structural dissimilarities. For dynamic dissimilarities the unemployment rate ($unemployment_{|i-j|,t}$) and annual GDP growth ($GDPgrowth_{|i-j|,t}$) are considered. Second, the variable $ln\, trade_{i,j,t}$, is included as a time-varying country-pair control variable and defined as the natural logarithm of the bilateral trade between a bank's home and host country. 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 ($common\, border_{i,j}$), common currency ($common\, currency_{i,j}$) and common legal origin ($legal\, origin_{\,i,j}$).[18] 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 transportation costs, and the less attractive foreign loan granting and monitoring will be.[19] 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. Rose (2000) was the first who investigated the impact of currency unions on trade, and found evidence for a large and positive impact of a single currency on trade. This finding has however not been confirmed by subsequent studies; by using alternative estimation techniques and

[18] 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.
[19] 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 advises care 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.

additional explanatory variables, several academics were able to greatly reduce the estimated impact of a currency union on trade (for an overview see Campbell, 2013). For the Euro area specifically, Sander et al. (2013) studied the contribution of the euro as a common currency for international banking within the Economic and 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 include a variable that is equal to 1 if the home and host country have the same legal origin and a positive coefficient is expected for this variable.

We also include a time-variant host country variable $Gov_{\mathrm{j,t}}$ to control for the quality of a host country j's governance. This indicator is constructed based on six separate variables, which have been produced by Kaufmann et al. (2011), being country scores for i) voice and accountability ii) control for corruption; iii) government effectiveness; iv) political stability and absence of violence/terrorism; v) regulatory quality; and vi) rule of law. As these variables all relate to a country's governance and are highly correlated with each other, we take the simple mean of the variables to construct our governance variable. As a higher score means better governance, we expect a positive coefficient for this variable.

Lastly, we control for the countries that suffered from high levels of sovereign debt by including a dummy variable for the countries Greece, Ireland, Italy, Portugal, Spain and Cyprus ($GIIPSC_j$). A negative coefficient for this variable is expected as foreign banks may have disinvested in these countries during the sample period 2010-2017.

We have 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[20] distance dataset.[21] Information on bilateral trade is obtained from the International Monetary Fund (IMF) Direction of Trade Statistics (DOTS) dataset. There were just 10 countries for which 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). Data on the legal origin is obtained from the paper of La Porta et al. (1999). Finally, data on the governance indicators are obtained from the Worldbank (Kaufmann et al., 2011).

Table 3.2 shows the descriptives for the main independent variables that are used in our model, i.e. country-specific economic development measures, per continent. The large dispersion in the indicators across countries is immediately visible in this table. While Europe, North America and Oceania show the highest GDP per capita, the aftermath of the global financial crisis is also best visible for these countries, as indicated by the lower GDP growth numbers.

Table A.3.3.11 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

[20] Centre d'Etudes Prospectives et d'Informations Internationales.
[21] In cases of missing data, the distance between capitals was taken from http://www.distancefromto.net/

distance, and decrease when countries share a border or currency. Hence, countries that are geographically closer to each other are also more similar in terms of their economic situation.

Table 3.2: Structural and dynamic dissimilarity measures per continent

This table shows the averages of the economic and financial development indicators per continent, over the years 2010-2017.

	Europe	South America	North America	Asia	Africa	Oceania
GDP per capita (in EUR)	23,555	4,195	36,046	14,134	2,385	45,006
Unemployment	10.3%	7.4%	7.7%	4.5%	12.6%	5.6%
GDP growth	1.70%	3.72%	2.21%	5.19%	4.18%	3.31%

3.3.3 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 3.3 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, currency and the same legal origin. Moreover, the score on a host country *j*'s governance is included, and a dummy that is equal to one when the host country belongs to the group of GIIPSC countries. All coefficients have the expected sign, although the coefficients for common border and governance are not significant.[22] Hence, banks invest significantly more in countries i) with whom they trade more; ii) with whom they share the same legal origin; iii) with whom they share the same currency; iv) that are

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

closer to their home country; and v) that do not belong to the GIIPSC countries.

Columns 3 and 4 in Table 3.3 show the regression results when variables that control for dissimilarities in economic conditions are added to the model. The negative and significant coefficient for the GDP per capita variable implies that banks tend to invest less in countries with an income per capita that differs from that in their home country. Put differently, banks are more inclined to invest in countries that are more similar in terms of GDP per capita. However, we do not find any significant impact from dissimilarities in GDP growth and unemployment.

Table 3.3: Gravity model

This table shows the results from the gravity model, as specified in equation (1). The dependent variable is the natural logarithm of 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 country-pair level and displayed in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	Baseline		Dissimilarity	
	(1)	(2)	(3)	(4)
Dissimilarity measures				
GDP per capita$_{\lvert i-j\rvert,t}$			-0.695***	-0.210*
			(0.191)	(0.113)
Unemployment$_{\lvert i-j\rvert,t}$			0.021	0.030
			(0.124)	(0.079)
GDP growth$_{\lvert i-j\rvert,t}$			0.154	0.054
			(0.651)	(0.382)
Control variables				
ln Trade	0.665***	0.178***	0.628***	0.160***
	(0.100)	(0.051)	(0.098)	(0.052)
Governance	0.133	0.314	-0.184	0.221
	(0.243)	(0.207)	(0.254)	(0.189)
Legal origin (0/1)	0.323*		0.331*	
	(0.178)		(0.175)	
Common border (0/1)	0.110		0.183	
	(0.221)		(0.209)	
ln Distance	-0.427**		-0.361**	
	(0.173)		(0.169)	
Common cur. (0/1)	0.412*		0.465**	
	(0.228)		(0.221)	
GIIPSC (0/1)	-7.303***		-2.099***	
	(0.704)		(0.788)	
Home country FE	Yes	Yes	Yes	Yes
Host country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Home*host FE	No	Yes	Yes	Yes
R^2 adj.	52.3%	73.5%	52.6%	73.5%
# Obs.	7,142	7,132	7,142	7,132

Columns 2 and 4 show the regression results when country-pair fixed effects are included in the model. With the inclusion of country-pair fixed effects, the majority of the gravity variables – that are time-invariant country-pair variables – automatically drop from the model. While this specification is less insightful where it concerns the drivers of banks' cross-border positions, there is a lower risk of omitted variables. Model specification 2 is hence used for the construction of an instrument in section 3.4. In this specification the explanatory power of the model increases, and the (time-varying) bilateral trade variable still has a significant impact. The governance variable however remains statistically insignificant. More interestingly, the results in column 4 show that – in line with the result in column 3 – banks are more inclined to invest in countries that have a more similar GDP per capita. However, the coefficient loses some significance. Moreover, the coefficients for the other two dissimilarity measures are insignificant. In sum, we do not find evidence that banks are investing in dissimilar countries.

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 synchronised business cycles through similar production patterns (Imbs, 2014). Second, banks may have a tendency to operate in countries with which they are more familiar (and those countries are probably the more similar ones). Logically, expanding to another country, especially to a country that is not very familiar, will require monitoring. As such, there is a trade-off between diversification and monitoring (costs). Third, 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 more economically similar the countries may be (see also Goldberg, 2009). Lastly, other factors, such as distance may influence a bank's decision to invest in certain countries; banks may simply have a preference for investing in countries that are closer by.

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

3.4.1 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.[23]

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 of 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

[23] 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).

credit risk. They also differentiate between banking groups that are active in OECD countries only and those that have activities in at least 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. For Spanish banks, Argimón (2017) investigates the impact of internationalization on a bank's riskiness, and specifically focuses on decentralized multinational banks. She also finds that cross-border exposures to countries whose business and financial cycles are less than perfectly correlated with those of the home country generate more stability in the banking group.

In our paper we follow the approach taken by 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. But, we first 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 structural and dynamic dissimilarities in economic conditions between a bank's home and host country.

3.4.2 Methodology

3.4.2.1 Construction of the instruments

The relation between bank risk and geographical diversification may be endogenous with banks' foreign expansion decisions being related to its risk profile. For example, a bank with a relatively high risk profile may decide to go abroad to reduce its risk, implicating that geographic diversification may be driven by bank riskiness. Therefore, we apply an instrumental variables approach using two-stage least squares (2SLS). We use the estimates from the gravity model in section 3 to construct our instrument for geographical diversification. More specifically, we use the results from column 2 of Table 3.3. The (exponents of the) estimated log levels (here denoted as $x_{b,j,t}$) are used to construct the Herfindahl-Hirschmann Index ($HHI_{b,t}$) of geographic dispersion, which is our diversification variable. It is calculated as the sum of bank *b*'s squared exposures in different host countries *j* at time *t*;

$$HHI_{b,t} = \sum_{j=1}^{J} x_{b,j,t}^{2} \tag{2}$$

The index ranges from zero (perfect diversification) to one (all exposures in one country). The gravity model specification that is used for the construction of the instrument does not include any variables that could affect bank risk directly. Put differently, the included gravity variables – bilateral trade and host country's governance – are not expected to have a direct impact on banks' risk-return profile, but only do so via the diversification measure (exclusion restriction).

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 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 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 ($\overline{HHI}_{b,t}^{within}$) and between ($HHI_{b,t}^{between}$) component. The $HHI_{b,t}^{between}$ is the Herfindahl-Hirschmann Index of the foreign loans *between* similar and dissimilar countries for bank *b* at time *t*. This is written as follows:

$$HHI_{b,t}^{between} = (X_{b,t}^{dissim})^2 + (X_{b,t}^{sim})^2 \tag{3}$$

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

$$\overline{HHI}_{b,t}^{within} = \frac{1}{HHI_{b,t}^{between}} * [\sum_{m=1}^{M}(x_{b,m,t}^{dissim})^2 + \sum_{n=1}^{N}(x_{b,n,t}^{sim})^2] \qquad (4)$$

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 $X_{b,t}^{sim} = \sum_{n=1}^{N}(x_{b,n,t}^{sim})$. The product of these two subcomponents results in the Herfindahl-Hirschmann Index as expressed in (2):

$$HHI_{b,t} = HHI_{b,t}^{between} * \overline{HHI}_{b,t}^{within} \qquad (5)$$

We classify a country-pair as either similar or dissimilar as follows. We again use the three different specifications to measure how dissimilar a bank's home and host country are. That is, for each home country *i*, we consider the absolute difference between home country *i* and host country *j* in terms of i) GDP per capita ($GDPcapita_{|i-j|,t}$) ; ii) unemployment rate ($unemployment_{|i-j|,t}$) ; and iii) annual GDP growth ($GDPgrowth_{|i-j|}$). 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. And vice versa, similar countries have measures below the median. Thereby, 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. Again, the same estimations from the gravity model (Table 3.3, column 2) are used to construct these variables.

3.4.2.2 Model specifications

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

$$r_{b,t} = \alpha_b + \gamma_t + \beta_1 * (1 - HHI_{b,t}) + \sum_{k=5}^{K} \beta_k X_{b,t-1} + \varepsilon_{b,t} \tag{6}$$

where $\mathrm{r}_{b,\mathrm{t}}$ is either the natural logarithm of a bank's z-score, standard deviation of its return on assets (ROA) or its ROA at year *t* for bank *b*.[24] The z-score is defined as follows;

$$z - score_{b,t} = \frac{Leverage\ ratio_{b,t} + ROA_{b,t}}{\sigma(ROA_{b,t})} \tag{7}$$

[24] As the ROA can take on negative values, we compute the natural logarithm as ln ROA = ln(1 + ROA). We do not observe a ROA that is smaller than -1. Moreover, for robustness, we have also considered the Return on Equity (ROE) as a dependent variable. This however yields similar results and therefore, in the paper we focus on the ROA as a measure for profitability.

where a bank's leverage ratio ($Leverage\ ratio_{b,t}$) is measured by the bank's Tier 1 capital divided by its total assets. $ROA_{b,t}$ 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 ROA. 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. Since the standard deviation of a bank's ROA is autocorrelated within in a bank, we use standard errors clustered at the bank-level – i.e. robust standard errors in our fixed effect setting - to correct for this.

$HHI_{b,t}$ is the instrumented diversification measure. In the regression specification we subtract this number from one, such that the more geographically diversified a bank is, the higher the value of this variable. 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.

$X_{b,t-1}$ 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 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 capitalised 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.[25] 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 ($ROA_{b,t-1}$).

As a second step, and in order to control for the economic conditions of a country banks invest in, we insert the decomposition of the HHI measure into our baseline model (6). This results in:

$$r_{b,t} = \alpha_b + \gamma_t + \beta_1 * (1 - HHI_{b,t}^{between}) + \beta_2 * (1 - \overline{HHI}_{b,t}^{within}) + \sum_{l=5}^{L} \beta_l X_{b,t-1} + \varepsilon_{b,t} \quad (8)$$

3.4.3 Data source and summary statistics

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

[25] According to the definition from the SNL Financial Database.

to collect data on the economic and financial indicators. Table 3.4 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[26] 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 3.4. 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.

The final two columns of Table 3.4 provide the averages for a diversified and focused (i.e. less diversified) subsample of banks. Hence, in each year *t* from 2010 to 2017, 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) less volatile ROA; and iv) lower problem ratio.

[26] GIIPSC stands for Greece, Italy, Ireland, Portugal, Spain and Cyprus.

Table 3.4: Bank descriptive statistics (2010-2017)

This table shows descriptive statistics for the variables used in regressions (6) and (8) for all 61 European banks over the years 2010-2017. The seventh and eighth 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 sixth column provides the variable means for GIIPSC countries only.

						GIIPSC	Focus-ed	Diver-sified
	Mean	**Median**	**10%**	**90%**	**St. Dev.**	**Mean**	**Mean**	**Mean**
Tot. Assets (€ mrd)	515	264	116	1,308	522	353	375	696
Tier 1 leverage (%)	4.95	4.81	3.09	6.66	1.77	5.73	4.88	5.05
ROA (%)	0.001	0.003	-0.004	0.007	0.009	-0.031	0.004	0.002
St. Dev. ROA	0.003	0.001	0.000	0.006	0.004	0.005	0.003	0.002
Z-score	71.6	45.7	7.9	163.7	83.9	33.2	70.5	73.0
Problem ratio (%)	6.91	4.0	0.7	16.9	8.4	15.7	7.4	6.3
Cost-to-income (%)	62.1	61.8	44.3	81.4	21.7	63.2	60.4	64.2
1 – HHI	0.45	0.43	0.10	0.81	0.27	0.37	0.21	0.68
Non-int. income (%)	23.5	22.6	8.6	37.6	12.4	24.7	22.8	24.4

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.3.3.12 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 3.5 shows the average values of the two components of the diversification measure. Note that, at the 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 into countries with dissimilar economic conditions. Table 3.5 however shows that the diversification towards dissimilar countries (1-HHI between) is limited, and that the diversification within countries is greater.

Table 3.5: 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 three different measures.

	1-HHI within	**1-HHI between**
GDP per capita	0.419	0.065
Unemployment	0.342	0.196
GDP growth	0.379	0.137

Table A.3.3.13 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.

3.4.4 Results

3.4.4.1 Baseline model

As a first step, regression specification (6) is estimated, i.e. without controlling for whether banks expand into similar or dissimilar countries. Table 3.6 shows the regression results estimated by 2SLS. 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 coefficients for the diversification variable (*1-HHI*) in the first and second column indicate that the more internationally diversified a bank is, the higher its z-score and thus the healthier the bank. The coefficient of 3.536 in column 2 implies that in the case of a bank with a z-score of 65.4 (the average z-score of a bank in our sample) that is active in two countries and that expands its business to a third country (such that the diversification index increases from 0.5 to 0.67), the z-score will increase by 7.19 percent to 70.1. In other words, in this case the default risk decreases by around 7 percent. A bank's share of problem loans on its balance sheet, its size and its ROA significantly influence its z-score, where a higher amount of problem loans and a larger size results in a lower z-score and a higher ROA in a higher z-score, as expected. Only in the second column the Tier 1 leverage ratio shows the significant positive coefficient. While the coefficient for the cost-to-income ratio show the expected signs, the variable does not significantly contribute to our model.

Table 3.6: The impact of geographic diversification - 2SLS

This table shows the regression results from equation (6) over the period 2010-2017, estimated by 2SLS. The dependent variables are in the top row. The odd numbered columns contain the regression results including all banks, while the even numbered columns contain the results excluding banks from GIIPSC countries. We also report the estimated coefficients for the instrumental variable in the first stage regression and the F-test of the joint significance of instruments. 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						
1-HHI	3.536**	7.491***	-2.270	-8.395***	0.013	-0.001
	(1.411)	(2.753)	(1.996)	(2.571)	(0.013)	(0.014)
Control variables						
ln Total Assets (t-1)	-0.715*	-1.138**	0.556	1.129**	-0.012	-0.001
	(0.382)	(0.507)	(0.402)	(0.498)	(0.007)	(0.002)
Tier 1 leverage (t-1)	6.993	13.214***	1.207	-3.005	-0.048	-0.018
	(4.678)	(3.062)	(3.245)	(3.042)	(0.074)	(0.015)
ln Problem ratio (t-1)	-0.350***	-0.321***	0.267***	0.330***	0.001	-0.000
	(0.076)	(0.096)	(0.070)	(0.103)	(0.001)	(0.000)
ln ROA (t-1)	22.785***	69.961***	-24.15***	-64.87***		
	(5.497)	(15.958)	(6.733)	(15.993)		
Cost-to-income (t-1)	-0.200	-0.186	-0.005	-0.093	0.001	-0.000
	(0.226)	(0.308)	(0.270)	(0.289)	(0.002)	(0.001)
Share non-interest income (t-1)	-1.506	0.407	1.336	-0.012	-0.013	0.000
	(1.146)	(1.750)	(1.047)	(1.819)	(0.013)	(0.005)
	First stage results (dependent variable: 1-HHI)					
1-HHI predicted	0.721***	0.576***	0.730***	0.576***	0.709***	0.544***
	(0.162)	(0.107)	(0.163)	(0.107)	(0.166)	(0.126)
F-test stat	19.89	29.24	20.00	29.24	18.22	18.61
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Including GIIPSC	Yes	No	Yes	No	Yes	No
# Obs.	464	353	466	353	471	357

Second, the third and fourth column of Table 3.6 suggests that diversifying across borders benefits banks through a lower variability in their ROA, as indicated by the negative coefficient for the diversification measure *1-HHI*. This coefficient is only (highly) significant in case we exclude banks from GIIPSC countries, i.e. column 4. Regarding the control variables, a significant impact of a bank's problem loan ratio and its ROA on a bank's variability in ROA can be observed. Only in the fourth column does the size of a bank have a significant and positive impact, implying that larger banks – on average – have a more volatile ROA.

Third, the fifth and sixth column of Table 3.6 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 geographic diversification has no significant impact on a bank's ROA. Moreover, the coefficients for the control variables are also insignificant.

For all specifications, the first stage results – reported at the bottom of Table 3.6 – suggest that the instrumental variable, the predicted diversification measure, is closely associated with the real diversification measure. As expected, a higher (lower) level of a bank's predicted diversification implies a higher (lower) level of bank's actual diversification. The coefficient is close to one, and highly significant across all specifications. Moreover, the F-test of weak instruments in the first stage regression is always well above 10, implying that the model does not suffer from weak instrument bias.

In the next section, we run a similar model, but take into account the structural and dynamic dissimilarities in economic conditions between the home and host country. We thereby focus on the specifications excluding GIIPSC countries, given that banks from GIIPSC countries may – taking the sovereign debt crisis into account –distort the results to some extent. The F-test is more convincing, moreover, for the specifications where banks from GIIPSC countries are excluded.

3.4.4.2. Controlling for structural and dynamic dissimilarities

As a next step, we run equation (8), where the diversification measure is decomposed into the two components, i.e. the *1-HHI within* and *1-HHI between*. With this approach we are able to test under which conditions geographical diversification towards more dissimilar countries pays off. Table 3.7and Table 3.8 show the 2SLS regression results for a limited sample, i.e. excluding banks from GIIPSC countries, and Table A.3.14 and Table A.3.15 in the appendix show the same 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.[27]

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

Table 3.7: The impact of geographic diversification on banks' z-score (excl. GIIPSC) – 2SLS

This table shows the regression results from equation (8) over the period 2010-2017, estimated by 2SLS, and 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. We also report the estimated coefficients for the instrumental variable in the first stage regression and the F-test of the joint significance of instruments. 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		Unemployment		GDP growth	
	(1)		(2)		(3)	
Diversification						
1-HHI within	5.956**		6.850***		5.535***	
	(2.449)		(2.514)		(2.058)	
1-HHI between	4.512		5.385***		3.018**	
	(3.530)		(1.756)		(1.282)	
Control variables						
ln Total Assets (t-1)	-0.953**		-1.302**		-0.914**	
	(0.482)		(0.548)		(0.437)	
Tier 1 leverage (t-1)	13.520***		15.181***		13.976***	
	(3.089)		(3.505)		(3.138)	
ln Problem ratio (t-1)	-0.292***		-0.338***		-0.283***	
	(0.081)		(0.092)		(0.079)	
ln ROA (t-1)	68.014***		61.284***		70.436***	
	(16.472)		(17.153)		(15.711)	
Cost-to-income (t-1)	-0.230		-0.175		-0.266	
	(0.291)		(0.288)		(0.289)	
Share non-interest income (t-1)	0.244		0.783		0.404	
	(1.697)		(1.688)		(1.688)	
	First stage results					
	1-HHI within	1-HHI between	1-HHI within	1-HHI between	1-HHI within	1-HHI between
1-HHI within predicted	0.567***	-0.038	1.056***	-0.761***	1.036***	-0.68***
	(0.116)	(0.073)	(0.133)	(0.097)	(0.154)	(0.210)
1-HHI between predicted	-0.099	1.644***	-0.252*	1.254***	-0.010***	0.930***
	(0.206)	(0.190)	(0.149)	(0.130)	(0.119)	(0.197)
F-test stat	12.23	47.63	74.77	91.17	44.79	142.55
Bank FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
# Obs.	353		353		353	

Table 3.7 shows the impact of the two diversification components on a bank's z-score. The *1-HHI within* measures whether diversification in general pays off (be it in similar or dissimilar countries), whereas the *1-HHI between* measures whether diversification between similar and dissimilar countries is risk-reducing. The significant positive coefficients of *1-HHI within* in all columns indicate that international diversification in general improves a bank's z-score. Hence, in line with the findings in the previous section, geographical diversification is beneficial. The first column of Table 3.7 however shows that diversifying between similar and dissimilar countries (*1-HHI between*) will not further improve the z-score of a bank. By contrast, columns 2 and 3 show that banks that also diversify in the sense that they spread their activities between similar and dissimilar countries – and importantly; where the (dis)similarity is based on a dynamic indicator - significantly increase their z-score, thereby lowering their default risk.

For our analysis, it is important to note that banks with a similar diversification index $HHI_{b,t}$ can have different values for the distinct components $\overline{HHI}_{b,t}^{within}$ and $HHI_{b,t}^{between}$. Consider two banks (bank X and bank Y) that are both active in ten countries, and for the sake of simplicity, the investments in these ten countries are spread equally, i.e. the banks invest ten percent in each country. The $HHI_{b,t}$ equals 0.1 for both banks. Bank X invests only in countries that are economically similar to its home country. Its $HHI_{b,t}^{between}$ then equals 1, while its $\overline{HHI}_{b,t}^{within}$ is 0.1. Note that the product of these two components is equal to the bank's $HHI_{b,t}$. Bank Y invests in five dissimilar countries and five similar countries. Its $HHI_{b,t}$ is similar to the one of bank X and equals 0.1. However, its $HHI_{b,t}^{between}$ equals 0.5 and its $\overline{HHI}_{b,t}^{within}$ is 0.2. Again note that the product of these two components is equal to the bank's $HHI_{b,t}$ of 0.1. Hence, for bank X only the 1- $\overline{HHI}_{b,t}^{within}$ of 0.9 is relevant, while bank Y has a 1- $\overline{HHI}_{b,t}^{within}$ of 0.8 and a 1-$HHI_{b,t}^{between}$ of 0.5. Our findings show that in this case a bank that also diversifies its activities between similar and dissimilar countries – i.e. bank Y – has a higher z-score, ceteris paribus. Using the coefficients from column 2, the ln Z-score of bank Y is 33 percent higher than the one of bank X, all else equal.

To sum up, in general diversifying internationally will improve a bank's z-score and thereby reduces its default risk. Moreover, banks that also diversify into more dissimilar countries (with respect to the unemployment rates and GDP growth) experience an even higher beneficial impact from cross-border banking. Investing more in countries with a more dissimilar GDP per capita will however not add to the general beneficial impact from diversification. Hence, the difference between structural and dynamic (or cyclical) dissimilarities becomes apparent. The benefits from diversification stem from a different business cycle co-movement (dynamic) and not from different economic development levels (structural).

Table 3.8 shows the impact of the two diversification components on a bank's variability in ROA. The significant and negative coefficients of *1-HHI within* in all columns indicate that international diversification in general decreases a bank's variability in income. And similar to the results with the z-score as the dependent variable, the results show that banks can further reduce their risk by investing more in countries that have a lower business cycle co-movement with their home country.

Table 3.8: The impact of geographic diversification on banks' variability in ROA (excl. GIIPSC) – 2SLS

This table shows the regression results from equation (8) over the period 2010-2017, estimated by 2SLS, and for a subsample of banks, i.e. excluding from GIIPSC countries. The dependent variable is the natural logarithm of a bank's standard deviation of its ROA. We also report the estimated coefficients for banks the instrumental variable in the first stage regression and the F-test of the joint significance of instruments. 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	Unemployment	GDP growth
	(1)	(2)	(3)
Diversification			
1-HHI within	-6.928***	-7.418***	-6.511***
	(2.259)	(2.362)	(1.893)
1-HHI between	-4.649	-5.709***	-3.612***
	(3.103)	(1.679)	(1.128)
Control variables			
ln Total Assets (t-1)	0.957**	1.261**	0.909**
	(0.470)	(0.541)	(0.428)
Tier 1 leverage (t-1)	-3.316	-5.194	-3.935
	(2.927)	(3.254)	(3.002)
ln Problem ratio (t-1)	0.300***	0.341***	0.292***
	(0.089)	(0.096)	(0.086)
ln ROA (t-1)	-62.843***	-56.411***	-64.591***
	(15.953)	(16.851)	(15.615)
Cost-to-income (t-1)	-0.050	-0.085	-0.027
	(0.279)	(0.278)	(0.278)
Share non-interest income (t-1)	0.129	-0.394	0.040
	(1.760)	(1.751)	(1.755)

First stage results

	1-HHI within	1-HHI between	1-HHI within	1-HHI between	1-HHI within	1-HHI between
1-HHI within predicted	0.567***	-0.038	1.056***	-0.761***	1.036***	-0.684***
	(0.116)	(0.073)	(0.133)	(0.097)	(0.154)	(0.210)
1-HHI between predicted	-0.099	1.644***	-0.252*	1.254***	-0.010***	0.930***
	(0.206)	(0.190)	(0.149)	(0.130)	(0.119)	(0.197)
F-test stat	12.23	47.63	74.77	91.17	44.79	142.55

	(1)	(2)	(3)
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
# Obs.	353	353	353

Table A.3.14 and Table A.3.15 in the Appendix show the regression results for the full sample of banks, i.e. including the banks from GIIPSC countries. Table A.3.14 shows the impact of the two diversification components on the z-score, and the results are quite similar to those in Table 3.7 that focuses on the sample excluding GIIPSC countries. Table A.3.15 shows the impact of the two diversification components on the variability in ROA for the full sample of banks. In line with the results from the baseline in Table 3.6, diversification is not found to have an impact on the variability in ROA for the full sample. This means that for the full sample results, we cannot find evidence for a causal effect from diversification on bank risk as measured by the volatility in ROA. Note that this finding is only present when considering the full sample of banks, i.e. including the banks from GIIPSC countries. Hence, this finding may be driven by these banks and their highly volatile income after the crisis period.

To conclude, focusing on our subsample of banks, 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 ROA. Moreover, these benefits from diversification can be even higher when banks invest more in countries that differ more from their home country with respect to their phase in the business cycle. That is, additional benefits can be achieved by diversifying into countries with a different business cycle co-movement.

3.5 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 economically from their home country.

First, our results do not show any evidence that banks are inclined to invest more in dissimilar countries. Instead, we find that banks tend to invest significantly more in countries with an income per capita that is close to that in their home country. Banks may however invest cross-border for reasons other than diversification. For example, banks that are specialized towards a certain industry or business line may be induced to invest in more similar countries. Another reason why there may be a tendency to invest in similar countries is that banks may prefer to do business in a familiar environment, which is likely to arise in a more similar country. Logically, expanding to another country, especially to a country that is not very familiar, will require monitoring. As such, there is a trade-off between diversification and monitoring. Lastly, we find that bilateral trade is an important determinant for cross-border banking (whereby banks follow their clients), and the more countries trade with each other the more similar their economies may be.

Second, our results show that geographical diversification decreases bank risk. Next, we find that the beneficial impact from diversification can be higher when banks invest more in countries that have a lower business cycle co-movement with their home country. This result is therefore consistent with the view that diversification is risk-reducing, and that banks can diversify idiosyncratic risks away by investing in countries that have non-perfectly correlated business cycles. Investing more in countries with dissimilar economic development levels (i.e. GDP per capita) does not, however, add further to the general benefits of diversification. Moreover, we do not find a significant impact from cross-border banking on a bank's ROA.

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 stem from additional liquidity and capital requirements for cross-border subsidiaries, thereby negatively affecting cross-border activities.

3.6 Appendix

3.6.1 Data collection and sources

Link to the dataset

The dataset is published online and can be retrieved via the following link: http://www.bankinglibrary.com/e/fdz/IntBankLib/data/crossborderbanking.asp

Scope

We focus on the 61 largest European banks. These are banks with total assets of EUR 100 billion in either 2017 or 2010. Only the Belgian bank Dexia and the German bank WestLB have been left out: with the restructuring of Dexia in 2010 a large part of its portfolio went to (and 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 has significantly decreased its assets since then.

Data sources

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. Table A.3.9 in the Appendix contains an overview of the source(s) used by bank.

Approach

With our approach we aim to minimise any measurement errors that stem from not taking into account foreign exposures via branches and direct lending. Instead of relying on data of foreign subsidiaries, we decided to collect the data ourselves. Due to the absence of a standard reporting format some assumptions and simplifications had to be made. First, while some banks report their foreign exposures in loans or assets, other 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. Table A.3.9 in the Appendix shows the type (loans, assets or net income) of cross-border exposure used by a bank. The reason for our preference for loans and assets, is that these capture the real risk the bank is exposed to. Asset and loan exposures can be considered quite similar, i.e. most of the assets reported to a specific country will be invested in the economy via (loans granted by) banks, government etc: while income can be regarded as more different. However, for only three banks did we rely solely on net income. For some of the other banks, we use the reported net income (from the country-by-country report) in situations where a bank reports a less granular geographical split of its assets or loans (e.g. "assets in Africa"). In that case, we use the net income information from the country-by-country report to subdivide the total asset exposure to Africa (on the basis of net income) to different African countries listed in the country-by-country report. As such, we aim to minimise measurement errors that results from using different measurements across banks.

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 where we could not further subdivide these grouped exposures, we simply collected the exposures to groups of countries or continents. For the analysis, we defined country characteristics – such as GDP per capita or unemployment - at a group or continent level by taking the (GDP weighted) average of all countries belonging to that group or continent.

Third, the data collection resulted in an almost complete overview of the foreign exposures of the 61 European banks. There is a very small portion of foreign exposures – 3.6% of the total foreign exposures or 1.1% of the total assets – for which 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. Table A.3.9 below shows the percentage of total cross-border exposures per bank that could not be allocated to a specific country or region.

Table A.3.9 Data source and non-allocated data by bank

This table shows per individual bank the type of cross-border exposure and the source the data is based on as well as the percentage of total exposures that could not be allocated to a certain country or region. The following abbreviations are used:
Exposure: A = Assets, L = Loans, NI = Net Income
Source: AR = Annual Report, ST = Stress Test, CbC = Country-by-Country report

Name	Exposure	Source	Not allocated	Name	Exposure	Source	Not allocated
HSBC Holdings	L	AR	0.0%	Swedbank	A	AR	4.5%
BNP Paribas	L, NI	AR, ST	3.1%	Landesbank Baden-Württemberg	A	AR, ST	0.0%
Crédit Agricole Group	A, NI	AR, CbC	0.0%	La Banque Postale	L	AR	0.8%
Deutsche Bank	L, NI	AR, CbC	0.0%	Bayerische Landesbank	A	AR, ST	8.3%
Barclays	L, NI	AR, CbC	0.0%	Banco de Sabadell	L, A	AR	0.8%
Banco Santander	L, A	AR	11.0%	Bankia	A	AR	0.3%
Société Générale	A, NI	AR, CbC	0.0%	Erste Group Bank	A	AR	2.7 %
Groupe BPCE	A, NI	AR, CbC	0.0%	Raiffeisen Gruppe Switzerland	L	AR	0.0%
Royal Bank of Scotland Group	A	AR	0.0%	Nykredit Holding	L,A	AR, ST	0.0%
Lloyds Banking Group	A	AR, CbC	0.6%	Norddeutsche Landesbank Girozentrale	A	AR, ST	0.0%
UBS Group	L, NI	AR, CbC	0.0%	Belfius Banque	A	AR	2.2%

UniCredit	L, NI	AR, CbC	4.4%
ING Bank NV	A	AR	0.0%
Credit Suisse Group	L, A	AR	0.0%
Banco Bilbao Vizcaya Argentaria(BBVA)	A, NI	AR, CbC	0.0%
Crédit Mutuel Group	A, NI	AR, CbC	0.0%
Intesa Sanpaolo	L, NI	AR, CbC	0.0%
Coöperatieve Rabobank	L, NI	AR, CbC	0.0%
Nordea Bank	A, NI	AR, CbC	0.0%
Standard Chartered	A, NI	AR, CbC	0.0%
Commerzbank	A, NI	AR, CbC	3.6%
KfW Gruppe	L	AR	0.0%
Danske Bank	NI	AR	3.1%
Deutsche Zentral-Genossenschaftsbank	NI	AR, CbC	0.0%
Landesbank Hessen-Thüringen Girozentrale	NI	AR, CbC, ST	0.0%
Banca Monte dei Paschi di Siena	A, NI	AR, CbC	0.1%
Banco Popular Español	A	AR	0.0%
NV Bank Nederlandse Gemeenten	A	AR	0.0%
Zürcher Kantonalbank	A	AR	0.0%
NRW Bank	A	AR	8.1%
Raiffeisen Zentralbank Österreich	L	AR	1.7%
Bank of Ireland	A	AR	1.9%
OP Financial Group	A	AR	1.0%
Volkswagen Financial Services	A	AR	0.0%
Banco Popolare Società Cooperativa	A	AR	0.1%
Unione di Banche Italiane	A	AR	0.1%
SNS Reaal	L	AR	0.0%

ABN AMRO Group	A, NI	AR	0.0%
CaixaBank	A	AR	1.0%
Svenska Handelsbanken	A	AR	3.3%
Skandinaviska Enskilda Banken	A	AR	9.0%
DNB ASA	L	AR	0.0%
Nationwide Building Society	L, NI	AR, CbC	0.0%
KBC Group	A	AR	0.0%
National Bank of Greece	L, NI	AR, CbC	0.0%
DekaBank Deutsche Girozentrale	A	AR	0.5%
Allied Irish Banks	L	AR	1.6%
Caixa Geral de Depósitos	A	AR	0.0%
HSH Nordbank	A	AR, ST	0.0%
Landesbank Berlin	A	AR	3.3%

3.6.2 Remaining tables

Table A.3.10: Geographical distribution of assets per bank, 2017

Name	Total assets 2017 (in € bln)	Home	ROE	North America	South America	Asia	Africa	Oceania
HSBC Holdings	2,100.1	36.4%	3.2%	12.9%	0.5%	44.1%	0.2%	2.8%
BNP Paribas	1,960.3	32.0%	46.4%	12.3%	2.6%	6.1%		0.6%
Crédit Agricole Group	1,763.2	81.1%	11.5%	3.2%	0.1%	3.6%	0.5%	0.1%
Deutsche Bank	1,474.7	35.3%	21.8%	31.4%	1.4%	8.3%	0.5%	1.4%
Banco Santander	1,444.3	26.6%	43.0%	11.4%	19.0%			
Barclays	1,275.6	41.6%	20.5%	32.9%	0.1%	4.0%	0.8%	
Société Générale	1,275.1	72.9%	17.2%	4.4%	0.3%	3.4%	1.7%	
Groupe BPCE	1,259.9	90.9%	1.7%	4.8%	0.1%	1.3%	0.7%	0.5%
Lloyds Banking Group	914.1	96.5%	2.3%	1.2%				
ING Bank NV	846.3	28.6%	54.3%	5.1%	0.1%	7.4%	0.1%	4.5%
UniCredit	836.8	40.2%	56.6%	1.4%	1.4%	0.3%		
Royal Bank of Scotland Group	830.8	90.7%	3.8%	5.3%		0.2%		
Intesa Sanpaolo	796.9	83.7%	12.3%	1.3%	0.0%	1.4%	1.0%	
Crédit Mutuel Group	793.5	89.3%	7.9%	1.6%		1.2%		
UBS Group	782.5	32.8%	24.1%	33.5%	1.1%	8.5%		
Banco Bilbao Vizcaya Argentaria(BBVA)	690.1	49.2%	2.4%	25.4%	11.2%	11.9%		

Credit Suisse Group	680.5	30.4%	20.9%	39.9%	1.4%	7.5%		
Coöperatieve Rabobank	603.0	72.7%	6.7%	10.3%	3.0%	2.2%	0.1%	5.2%
Nordea Bank	581.6	28.7%	70.1%	0.6%	0.0%	0.4%		
Standard Chartered	552.6	18.4%	8.7%	7.1%	2.2%	62.5%	0.8%	0.1%
Deutsche Zentral-Genossenschaf tsbank	505.6	83.5%	13.4%	1.8%	0.1%	1.1%		
Danske Bank	475.4	53.8%	46.2%					
KfW Gruppe	472.3	81.0%	11.0%	1.0%	2.0%	3.0%	2.0%	
Commerzbank	452.5	52.7%	33.4%	6.9%		6.9%		
ABN AMRO Group	393.2	72.7%	16.6%	3.5%	1.9%	4.0%		1.3%
CaixaBank	383.2	79.3%	16.9%	0.4%	0.9%	3.2%	0.4%	
KBC Group	292.3	55.3%	40.2%	1.8%	0.1%	1.9%	0.3%	0.3%
Svenska Handelsbanken	281.5	58.9%	37.6%	3.5%				
DNB ASA	274.5	69.4%	22.1%	3.9%	2.1%	1.2%	0.5%	0.8%
Skandinaviska Enskilda Banken	260.4	66.5%	29.0%	2.7%		1.8%		
Nationwide Building Society	258.8	97.7%	2.3%					
Landesbank Baden-Württemberg	237.7	70.9%	19.7%	6.3%	0.6%	2.3%	0.1%	
La Banque Postale	231.5	98.8%	1.1%	0.1%		0.0%		
Swedbank	225.1	79.6%	18.2%	2.2%				
Banco de Sabadell	221.3	73.3%	17.6%	3.1%	6.0%			
Erste Group Bank	220.7	43.6%	55.6%		0.0%	0.4%	0.3%	

Bayerische Landesbank	214.5	80.3%	14.1%	4.7%	0.3%	0.5%	0.1%
Bankia	213.9	90.8%	8.7%	0.2%	0.2%		
Raiffeisen Gruppe Switzerland	194.6	95.0%	5.0%				
Nykredit Holding	191.6	95.0%	5.0%				
Belfius Banque	168.0	71.0%	27.0%	2.0%			
Norddeutsche Landesbank Girozentrale	165.4	86.1%	9.2%	1.6%	1.6%	1.6%	
Banco Popolare Società Cooperativa	161.2	95.2%	3.3%	0.7%	0.7%	0.1%	
Landesbank Hessen-Thüringen Girozentrale	158.3	78.0%	13.1%	9.0%			
Banco Popular Español	147.7	90.1%	7.2%	2.7%			
NRW Bank	147.6	70.9%	29.1%				
Zürcher Kantonalbank	140.0	88.2%	7.5%	2.5%	0.4%	1.3%	
NV Bank Nederlandse Gemeenten	140.0	82.8%	17.2%				
Banca Monte dei Paschi di Siena	139.2	95.1%	4.6%	0.4%		0.2%	
OP Financial Group	137.2	85.7%	12.8%	1.0%		0.5%	
Raiffeisen Zentralbank Österreich	135.1	19.9%	66.9%	1.5%		11.0%	
Unione di Banche Italiane	127.4	94.9%	3.2%	0.8%	0.8%	0.4%	
Bank of Ireland	122.6	69.2%	30.8%				

SNS REAAL	111.5	98.4%	1.6%				
DekaBank Deutsche Girozentrale	93.7	94.2%	5.8%				
Caixa Geral de Depósitos	93.2	73.0%	13.0%	1.7%	0.1%	7.2%	4.6%
Allied Irish Banks	90.1	80.1%	19.9%				
HSH Nordbank	70.4	61.7%	10.1%	9.5%	1.8%	13.4%	2.5%
Volkswagen Financial Services	69.0	54.7%	4.0%		10.5%	30.8%	
National Bank of Greece	64.8	87.5%	11.2%				0.8%
Landesbank Berlin	57.4	83.6%	14.6%	1.8%			

Note: The 2017-data was not for all banks available. In such a case, 2016 data is shown.

Table A.3.3.11: Correlation matrix: Gravity model

This table shows the correlation among the explanatory variables used in the gravity model specified in equation (1). The variables GDP growth, unemployment and GDP per capita are based on absolute values of the differences in these variables between the home country *i* and host country *j*.

	Common border	**Distance**	**Trade**	**Currency**	**GIIPSC**	**GDP growth$_{\lvert i-j \rvert}$**	**Unemploy-ment$_{\lvert i-j \rvert}$**	**GDP capita$_{\lvert i-j \rvert}$**	**Legal origin**	**Governance**
Common border	1									
Distance	-0.526	1								
Trade	0.364	-0.331	1							
Currency	0.432	-0.441	0.293	1						
GIIPSC	0.079	-0.136	0.152	0.430	1					
GDP growth	-0.115	0.173	-0.22	-0.099	0.049	1				
Unemployment	-0.081	0.186	-0.09	-0.023	0.115	0.106	1			
GDP capita	-0.222	0.291	-0.47	-0.299	-0.185	0.227	-0.091	1		
Legal origin	-0.089	0.062	-0.06	-0.008	0.024	0.054	0.009	0.056	1	
Governance	-0.259	-0.368	0.342	0.272	0.052	-0.264	-0.100	-0.758	-0.008	1

Table A.3.3.12: Descriptive statistics per year: Risk-return model

This table shows the descriptive statistics of our dataset of 61 banks for the years 2010 until 2017, 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**	**2016**	**2017**
Total Assets (in € mrd)	522	517	81	516	543	535	487	519	517	516	500
Tier 1 leverage (%)	1.77	1.44	1.04	4.41	4.38	4.63	4.97	4.98	5.49	5.56	5.90
ROA (%)	0.009	0.005	0.007	0.002	-0.002	-0.001	0.001	0.002	0.003	0.001	0.004
St. Dev. ROA	0.004	0.003	0.002	0.002	0.003	0.003	0.003	0.002	0.002	0.002	0.002
Z score	83.9	60.0	58.9	44.9	51.9	69.9	72.9	85.7	94.6	99.6	107.5
Problem ratio (%)	8.39	7.50	3.80	5.99	6.77	7.81	8.65	8.14	7.63	6.20	5.55
Cost-to-income (%)	21.7	14.7	16.0	59.0	62.4	70.2	60.2	61.5	61.2	64.5	61.3
1 – HHI	0.27	0.27	0.05	0.46	0.45	0.44	0.44	0.45	0.44	0.43	0.45
Non-interest income (%)	12.4	11.9	3.5	22.6	22.9	23.9	23.9	23.7	24.2	24.5	24.8

Table A.3.3.13: Correlation matrix: Risk-return model

This table shows the correlation among the explanatory variables used in the regression model specified in equation (6) and (8).

	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	-0.307	1							
ROA	0.119	0.042	1						
σ(ROA)	-0.122	0.122	-0.509	1					
Z-score	0.069	0.154	0.605	-0.934	1				
Problem ratio	-0.039	0.197	-0.357	0.613	-0.542	1			
Cost-to-income	0.155	0.043	-0.273	0.203	-0.160	0.208	1		
1 – HHI	0.490	0.076	0.194	0.004	0.057	0.004	0.056	1	
Non-interest income	0.218	-0.143	-0.065	0.092	-0.110	-0.028	0.375	0.081	1

Table A.3.14: The impact of geographic diversification on banks' z-score (incl. GIIPSC) – 2SLS

This table shows the regression results from equation (6) over the period 2010-2017, estimated by 2SLS. The dependent variable is the natural logarithm of a bank's standard deviation of its z-score. We also report the estimated coefficients for the instrumental variable in the first stage regression and the F-test of the joint significance of instruments. 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		Unemployment		GDP growth	
	(1)		(2)		(3)	
Diversification						
1-HHI within	2.627**		3.418***		2.889**	
	(1.292)		(1.265)		(1.295)	
1-HHI between	3.105		3.815***		1.986**	
	(2.104)		(0.901)		(0.927)	
Control variables						
ln Total Assets (t-1)	-0.593		-0.903**		-0.638*	
	(0.364)		(0.401)		(0.380)	
Tier 1 leverage (t-1)	6.663		7.749*		6.414	
	(4.753)		(4.086)		(4.825)	
ln Problem ratio (t-1)	-0.344***		-0.393***		-0.335***	
	(0.075)		(0.085)		(0.073)	
ln ROA (t-1)	22.478***		21.162***		23.553***	
	(5.457)		(5.226)		(5.509)	
Cost-to-income (t-1)	-0.228		-0.187		-0.208	
	(0.227)		(0.207)		(0.227)	
Share non-interest income (t-1)	-1.502		-1.190		-1.608	
	(1.155)		(1.148)		(1.168)	
			First stage results			
	1-HHI within	1-HHI between	1-HHI within	1-HHI between	1-HHI within	1-HHI between
1-HHI within predicted	0.809***	-0.094*	1.047***	-0.535***	1.007***	-0.46***
	(0.168)	(0.056)	(0.082)	(0.193)	(0.138)	(0.151)
1-HHI between predicted	-0.353	1.526***	-0.209*	1.126***	-0.46***	1.062***
	(0.230)	(0.367)	(0.107)	(0.184)	(0.108)	(0.142)
F-test stat	12.28	8.84	102.09	86.50	58.85	129.88
Bank FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
# Obs.	464		464		464	

Table A.3.15: The impact of geographic diversification on banks' variability in ROA (incl. GIIPSC) – 2SLS

This table shows the regression results from equation (6) over the period 2010-2017, estimated by 2SLS. The dependent variable is the natural logarithm of a bank's standard deviation of its ROA. We also report the estimated coefficients for the instrumental variable in the first stage regression and the F-test of the joint significance of instruments. 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	Unemployment	GDP growth
	(1)	(2)	(3)
Diversification			
1-HHI within	-0.254	-2.392	-1.550
	(2.917)	(1.791)	(1.566)
1-HHI between	-0.364	-3.265***	-1.638
	(1.229)	(1.138)	(1.004)
Control variables			
ln Total Assets (t-1)	0.075	0.759*	0.474
	(0.448)	(0.411)	(0.408)
Tier 1 leverage (t-1)	-5.214*	0.521	1.924
	(2.930)	(2.661)	(3.173)
ln Problem ratio (t-1)	0.232**	0.318***	0.262***
	(0.091)	(0.072)	(0.069)
ln ROA (t-1)	-21.258***	-22.235***	-24.707***
	(7.937)	(6.569)	(6.662)
Cost-to-income (t-1)	0.098	-0.025	0.028
	(0.294)	(0.239)	(0.259)
Share non-interest income (t-1)	0.239	0.991	1.134
	(1.208)	(1.020)	(1.035)

First stage results

	1-HHI within	1-HHI between	1-HHI within	1-HHI between	1-HHI within	1-HHI between
1-HHI within predicted	0.771***	-0.089	1.049***	-0.523***	1.015***	-0.457***
	(0.151)	(0.047)	(0.081)	(0.192)	(0.135)	(0.150)
1-HHI between predicted	-0.374	1.527***	-0.210**	1.215***	-0.130	1.055***
	(0.212)	(0.356)	(0.105)	(0.187)	(0.106)	(0.141)
F-test stat	13.14	9.22	108.58	80.48	61.84	108.66

	(1)	(2)	(3)
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
# Obs.	466	466	466

Chapter 4: The effects of liquidity regulation on bank assets and liabilities

Under Basel III rules, banks became subject to a liquidity coverage ratio (LCR) from 2015 onwards, to promote short-term resilience. Investigating the effects of such liquidity regulation on bank balance sheets, we find: (i) co-integration of liquid assets and liabilities, to maintain a minimum short-term liquidity buffer; and (ii) that adjustment in the liquidity ratio is skewed towards the liability side. This finding contrasts with established wisdom that compliance with the LCR is mainly driven by changes in liquid assets. Moreover, micro-prudential regulation has not prevented a pro-cyclical liquidity cycle in secured financing that is strongly correlated with leverage.[28]

JEL classification: E44, G21, G28.

Keywords: market liquidity, funding liquidity, liquidity regulation, liquidity coverage ratio, Basel III, banks, microprudential, macroprudential, co-integration, error correction models, leverage.

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4.1 Introduction

The Basel Committee on Banking Supervision (BCBS) has introduced a Liquidity Coverage Ratio (LCR) from 2015 onwards. It requires banks to hold a sufficient level of high quality liquid assets against expected net liquid outflows over a 30-day stress period, to promote short-term resilience (BCBS, 2009). The introduction of the LCR was motivated by the liquidity crisis of 2007-2008, which occurred in combination with a solvency crisis. In this context, our contribution addresses two questions: (*i*) what is the impact of a liquidity constraint such as the LCR on individual bank behaviour?; and (*ii*) what has been the role of liquidity regulation before, during and after the liquidity and solvency crisis of 2007-2008?

We study these questions by using a unique database for Dutch banks, which have been subject to liquidity regulation that is comparable to the Basel III's LCR since 2003. We can systematically track liquid assets, liabilities, and their ratio during the upswing and downswing of the financial cycle. Moreover, to investigate the link between liquidity and capital regulation, we collected bank level information on (core) capital, assets and risk weights.

On the first question – i.e. the impact of the LCR on bank behaviour – several studies assume that the causality runs from liabilities to assets. These studies find that banks adjust their assets in response to a negative funding shock (Berrospide, 2012; De Haan and van den End, 2013a and 2013b). An innovative element in our study is that we let the data determine the direction of causality. We argue that a constraint on the ratio between liquid assets and liquid liabilities implies that the two variables should be co-integrated, which is supported by our findings. The error correction regressions indicate that banks adjust their liquid liabilities

– and to a lesser extent their liquid assets – when the LCR is above its equilibrium value, while the adjustment is even more skewed towards the liability side when the LCR is below its equilibrium value. In line with this finding, we find that wholesale funding (with a high run-off rate in the denominator of the LCR) has been substituted by more stable deposits during the aftermath of the crisis.

To address the second question – i.e. the role of liquidity regulation – we take a macro-prudential perspective and investigate aggregate patterns in our variables before, during and after the crisis. Results indicate a strong increase in the levels of available and required liquidity (the constituent parts of the LCR) before the financial crisis and a strong decrease afterwards. This cycle in short-term assets and liabilities occurs mostly through secured financing. It is accompanied by increasing leverage during the upturn, and decreasing leverage during the downturn. This is in line with earlier results for the US on the link between liquidity and leverage (Adrian and Shin, 2010). Moreover, the LCR itself is strongly correlated with the leverage ratio and shows a pro-cyclical pattern. During increased risk-taking in the upturn of the financial cycle, 'cheaper' short-term wholesale funding (with a high run-off rate in the denominator of the LCR) is used to finance riskier and more profitable liquid assets (with a lower liquidity weight in the numerator), so that the LCR deteriorates. It is followed by de-risking and an increase in the LCR during the subsequent downturn. This finding of pro-cyclicality implies that banks' short-term liquidity buffers are at their lowest point when the crisis starts, exactly when they are needed the most. At the same time, regulatory risk-weighted capital requirements have not been a binding constraint, partly due to the pro-cyclicality of risk weights.

The rest of this paper is organised as follows. Section 2 presents our conceptual framework. Section 3 provides the estimation results on bank behaviour under a liquidity constraint. Section 4 investigates aggregate patterns for liquidity and solvency. Section 5 concludes.

4.2 Conceptual framework

The LCR is defined as a ratio with the numerator representing the amount of 'High Quality Liquid Assets' (HQLA), i.e. assets that can be easily and immediately converted into cash at little or no loss of value (BIS, 2013). Liquid assets primarily consist of cash, central bank reserves, and, to a certain extent, marketable securities, sovereign debt, and central bank debt.[29] The denominator is the net cash outflow within 30 days, which is the difference between outgoing and incoming cash flows.

The LCR is defined as:

$$LCR = \frac{High\ Quality\ Liquid\ Assets}{Cash\ outflows - Cash\ inflows} \tag{1}$$

where the cash outflows are subject to prescribed run-off rates and the cash inflows are subject to prescribed haircuts in order to assign these items a liquidity weight. The similarity between Basel III and the existing

[29] There are two categories of assets that can be included in the stock of HQLA: Level 1 assets can be included without a limit, while Level 2 assets can only comprise up to 40% of the stock. Level 1 assets are limited to cash, central bank reserves and marketable securities representing claims on or guaranteed by e.g. sovereigns, central banks, the BIS (with a 0% risk-weight under the Basel II Standardised Approach for credit risk). Sovereign or central bank debt can, under certain conditions (BIS, 2013), also be reported as Level 1 assets. Level 2 assets consist of other marketable securities, corporate debt securities and covered bonds that satisfy certain conditions. See BIS (2013) for a comprehensive definition of HQLA.

Dutch supervisory framework makes it possible to construct a comparable measure for the LCR; the Dutch Liquidity Coverage Ratio (DLCR).

In line with previous studies (e.g. Bonner, 2012; De Haan and Van den End, 2013a) the DLCR is defined as:

$$DLCR_{i,t} = \frac{AL_{i,t}}{RL_{i,t}} = \frac{\sum_j a_j \cdot Asset_{i,j,t} + \sum_k b_k \cdot Inflow_{i,k,t}}{\sum_l c_l \cdot Liability_{i,l,t} + \sum_m d_m \cdot Outflow_{i,m,t}} \tag{2}$$

where $AL_{i,t}$ and $RL_{i,t}$ stand for, respectively, available liquidity and required liquidity of bank *i* at time *t*. The variables a_j,b_k, c_l, and d_m represent the regulatory weights for the assets *j*, cash inflows *k*, liabilities *l*, and cash outflows *m*. Hence, available liquidity is defined as the weighted stock of liquid assets plus the weighted cash inflows scheduled within the coming month. The liquidity weight on assets is defined as 100 minus the haircut. These haircuts are determined by the supervisor and aim to reflect the lack of market liquidity in times of stress. Required liquidity is defined as the weighted stock of liquid liabilities plus the weighted cash outflows scheduled within the coming month. The liquidity weight on liabilities is defined as the run-off rate. These run-off rates aim to reflect the probability of withdrawal and hence the funding liquidity risk.

The LCR and the DLCR reflect the same regulatory philosophy and are very similar. The main differences are the regulatory weights. In particular, the stock of HQLA is more narrowly defined for the LCR than for the DLCR. For the latter, the haircuts and run-off rates were determined by the Dutch regulator under the 'Liquidity Regulation under the Wft', for the first time in January 2003.[30] There has been one structural change during the period under consideration. In May 2011, the Dutch Central Bank supplemented its existing rules with the 'Liquidity Regulation under the Wft 2011.[31] In part, the changes anticipated the new international rules, related to the Basel III requirements.

Given the similarity between the Dutch regulatory framework and the Basel III regulation, we will use the DLCR to study the effects of liquidity regulation on bank behaviour. To comply with the DLCR banks manage their balance sheet so that their available liquidity is larger than or equal to their required liquidity. To reduce the probability of non-compliance due to shocks in their liquidity position, banks aim for a positive margin between actual liquidity and required liquidity. However, a high liquidity buffer above the regulatory minimum is costly as less liquid assets (e.g. corporate bonds) and less liquid liabilities (e.g. short-term wholesale funding) might be more profitable. As a result of these two opposing forces, we expect banks to aim for a stable long-term relationship between available and required liquidity.

[30] The haircuts and run-off rates are available at: http://www.toezicht.dnb.nl/en/4/4/2/51-204136.jsp. Wft stands for "Wet op het financieel toezicht", the Dutch Law on Financial Supervision.
[31] The main change is a narrower definition of liquid assets; specifically, the haircuts for debt instruments issued by credit institutions and other institutions (e.g. corporate bonds) have been increased due to the perceived illiquidity of these assets under stressed markets. At the same time, the run-off rate for demand deposits has been decreased to reflect their observed stability during the crisis. Overall, the adjustments have led to more stringent liquidity standards.

Figure 4.1: Stylised bank balance sheet

	Balance sheet				
Liquid inflow → $\sum_k b_k \cdot Inflow_{i,k,t}$	Liquid assets	$\sum_j a_j \cdot Asset_{i,j,t}$	Liquid liabilities	$\sum_l c_l \cdot Liability_{i,l,t}$	→Liquid outflow $\sum_m d_m \cdot Outflow_{i,m,t}$
	Other assets		Other liabilities		

As both components of the DLCR belong to the same balance sheet (see Figure 4.1) there should be a relation between actual liquidity and required liquidity. This relation defines their co-movement over time, although the causality is unknown ex ante. We expect this long-term relationship partly to be determined by bank-specific characteristics, such as its size (e.g. whether it is seen as 'too big to fail') and its business profile. In sum, we hypothesise that the series for available and required liquidity are co-integrated with bank-specific equilibria.

4.3 Estimation results

4.3.1 Unit root tests and co-integration

To test this hypothesis, we use monthly data from the Dutch supervisory liquidity report over the period July 2003 until April 2013. The report includes detailed information on liquid assets and liquid liabilities at an individual bank level for all banks subject to the liquidity regulation. We use data for 59 banks for which the reported data are complete for the whole period under consideration.[32] Ideally our dataset would have been long enough to cover several financial cycles; however it gives us some comfort that our dataset covers at least the upswing and downswing of one financial cycle.

The long-run relationship between actual liquidity and required liquidity can only be estimated if the series are non-stationary and integrated at the same order. Given the expected heterogeneity in bank behaviour, we use a panel unit root test that allows for different individual fixed effects in the intercepts and slopes of the co-integration equation. Out of the full sample of 59 banks, the series actual liquidity and required liquidity are both integrated at order one for 41 banks (see Table 4.3.1 and Table 4.3.2).[33] Hence, we test for co-integration only for those banks. The results in Table 4.3.3 indeed strongly reject the null hypothesis of no cointegration against the alternative of cointegration for each individual bank.[34]

[32] The underlying data are confidential. Where we show estimation results for individual banks, we number them randomly so that results cannot be traced back to actual banks. Moreover, we only show aggregate data or estimation results and not the underlying data.
[33] The 18 banks for which we do not find cointegration are often (smaller) banks with some specific characteristics (e.g. foreign banks).
[34]We use Pedroni's (2001) co-integration test, since it allows for cross-sectional interdependence with different individual effects in the intercepts and slopes of the co-integration equation (i.e. a bank-specific long-run equilibrium).

Table 4.3.1: Panel unit root test

This table shows the results of the panel unit root test based on the Im-Pesaran-Shin (IPS) method, where the null hypothesis is that of a unit root. The appropriate number of lags is selected by Schwarz Information Criterion (SIC). The p-values are shown in parentheses. *** denotes the 1% significance level. Based on the results for the full sample, the dataset is limited to banks with time series that are integrated at order 1. The decision for exclusion is made based on the presence of a unit root at the 5% significance level (see Table 4.3.2).

	Actual Liquidity		Required Liquidity	
	Level	First differences	Level	First differences
Full Sample (59 banks)				
# Obs.	6808	6766	6788	6731
Test statistic	-6.653	-88.193	-9.522	-92.021
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Limited Sample (41 banks)				
# Obs.	4722	4710	4703	4691
Test statistic	-0.657	-72.827	1.076	-77.239
	(0.256)	(0.000)***	(0.859)	(0.000)***

Table 4.3.2: Intermediate unit root results

This table shows the individual Augmented Dickey Fuller (ADF) test results for all individual time series. The null hypothesis of a unit root (non-stationarity) is tested against the alternative that there is no unit root. The results in Table 4.3.1 show that the null hypothesis cannot be rejected for all 59 series. However, the intermediate ADF results indicate that most of the series suggest non-stationarity, meaning that the series are integrated at order 1 for 41 banks. The appropriate number of lags is selected by SIC. *, ** and *** denote 10%, 5% and 1% significance levels, respectively.

	Actual Liquidity		*Required Liquidity*			*Available Liquidity*		*Required Liquidity*	
Bank	**Prob.**	**Lag**	**Prob.**	**Lag**	**Bank**	**Prob.**	**Lag**	**Prob.**	**Lag**
1	0.44	0	0.46	0	31	0.62	1	0.00***	0
2	0.58	0	0.99	2	32	0.85	0	0.33	5
3	0.07	3	0.65	5	33	0.25	0	0.19	0
4	0.79	0	0.81	0	34	0.36	2	0.58	2
5	0.00***	1	0.00***	2	35	0.33	1	0.51	2
6	0.19	3	0.33	3	36	0.29	2	0.36	2
7	0.29	1	0.81	7	37	0.00***	0	0.00***	0
8	0.99	0	1.00	2	38	0.27	0	0.39	0
9	0.40	2	0.64	2	39	0.34	5	0.32	5
10	0.28	0	0.06*	0	40	0.07*	1	0.07*	1
11	0.24	2	0.13	2	41	0.30	1	0.87	1
12	0.38	4	0.51	4	42	0.62	1	0.64	1
13	0.61	0	0.55	0	43	0.29	6	0.54	4
14	0.57	3	0.82	3	44	0.34	2	0.39	2
15	0.00***	0	0.00***	0	45	0.00***	0	0.11	2
16	0.09	0	0.03**	2	46	0.01**	0	0.47	2
17	0.54	2	0.99	4	47	0.89	12	0.00***	0
18	0.99	9	0.85	2	48	0.59	2	0.19	1
19	0.30	2	0.35	0	49	0.00***	0	0.00***	0
20	0.00***	0	0.02**	1	50	0.31	1	0.75	1
21	0.68	0	0.72	5	51	0.46	0	0.03**	2
22	0.00***	0	0.00***	0	52	0.48	2	0.77	2
23	0.16	6	0.05	11	53	0.28	1	0.05**	1
24	0.00***	0	0.00***	0	54	0.12	0	0.12	1
25	0.12	1	0.71	1	55	0.03**	1	0.28	1
26	0.30	0	0.30	0	56	0.00***	0	0.00***	0
27	0.43	4	0.24	2	57	0.34	3	0.48	2

28	0.35	1	0.19	2	58	0.94	2	0.86	3
29	0.76	2	0.00***	6	59	0.63	1	0.18	2
30	0.01**	2	0.04**	2					

Table 4.3.3: Cointegration test results

This table shows the results of Pedroni's cointegration test. The null hypothesis of no cointegration is tested against the alternative that a cointegrating vector exists for each individual bank. This table shows panel statistics (left column) and group statistics (right column).[35] The appropriate number of lags for each individual time series is selected by SIC. p-values are in parentheses. *** denotes the 1% significance level.

	Within dimension			Between dimension	
Panel v-Statistic	9.764***	(0.000)	Group rho-statistic	-33.845***	(0.000)
Panel rho-Statistic	-14.877***	(0.000)	Group PP-statistic	-20.493***	(0.000)
Panel PP-statistic	-10.809***	(0.000)	Group ADF-statistic	-11.473***	(0.000)
Panel ADF-statistic	-10.781***	(0.000)			

4.3.2 Error Correction Model

Given the finding of co-integration at the individual bank level, the long-run equilibrium relationship can be estimated by Fully Modified Ordinary Least Squares (FMOLS) for heterogeneous co-integrated panels. The bank-specific long-run equilibrium relationship between actual liquidity and required liquidity is given by:

[35] The panel statistics approach pools over the 'within' dimension. It tests the null hypothesis that the first order autoregressive coefficient on the residuals is the same for each individual bank. The group statistics approach pools over the 'between' dimension. It allows the autoregressive coefficient to differ for each individual.

$$AL_{i,t} = \alpha_i^{AL} + \widehat{\beta}_{i,FMOLS}^{AL} RL_{i,t} + \varepsilon_{i,t} \tag{3}$$

where α_i^{AL}represents the individual fixed effects, and $\widehat{\beta}_{i,FMOLS}^{AL}$ is the FMOLS estimator correcting for heterogeneity and serial correlation by adjusting the initial OLS estimator.

The lagged residuals from equation (3) define the Error Correction Terms (*ECT*) in the following vector error correction model:

$$\Delta AL_{i,t} = \alpha_i^{AL} + \rho^{AL} ECT_{i,t-1}^{AL} + \gamma_i \Delta RL_{i,t-1} + u_{i,t}^{AL} \tag{4}$$

where α_i^{AL} represents the individual fixed effects, $\Delta AL_{i,t}$ represents the level change of actual liquidity from time t-*1* to time t, and ρ^{AL}represents the error correction speed of adjustment of actual liquidity. $\Delta RL_{i,t-1}$ is included to control for short-term adjustments, and $u_{i,t}^{AL}$ is the error term. The same approach can be applied for required liquidity. Then equation (3) and (4) will be replaced by, respectively (5) and (6):

$$RL_{i,t} = \alpha_i^{RL} + \hat{\beta}_{i,FMOLS}^{RL} AL_{i,t} + \varepsilon_{i,t} \tag{5}$$

$$\Delta RL_{i,t} = \alpha_i^{RL} + \rho^{RL} ECT_{i,t-1}^{RL} + \gamma_i \Delta AL_{i,t-1} + u_{i,t}^{RL} \tag{6}$$

To check for convergence to the long-run equilibrium the estimated speed of adjustment coefficient should show a negative sign. This so-called Engle and Granger (1987) two-step procedure is applied to make inferences about the direction of causality. Under this model, long-run causality is revealed by the statistical significance of the adjustment coefficient ρ^{AL}.

The results are shown in the first row of Table 4.3.4. These imply that when a bank moves away from its long-run equilibrium it adjusts both assets and liabilities, and that the adjustment is skewed towards the liability side of the balance sheet. That is, as the liquidity buffer is above (below) equilibrium, banks decrease (increase) their available liquidity and increase (decrease) their required liquidity. The estimated coefficient of -0.098 for available liquidity indicates that, after a shock to the long-run equilibrium, about 10% of this disequilibrium is corrected within one month through an adjustment in liquid assets. Likewise, the estimated coefficient of -0.221 for required liquidity indicates that about 22% of this disequilibrium is corrected within one month through an adjustment in liabilities. Given that required liquidity is determined by the weighted liabilities and cash outflows, the results indicate that banks adjust their funding mix - and to a lesser extent their portfolio allocation - when their liquidity position has changed.

Table 4.3.4: (Asymmetric) adjustment coefficients

This table shows the error correction terms from the Generalized Least Squares (GLS) results for the (Threshold) Error Correction Model for 41 banks over the period July 2003-April 2013 (4.749 observations). The heteroskedasticity of the error terms is corrected by using white robust standard errors and the standard deviations are displayed in parentheses. Cross-section weights are used and ** and *** denote 5% and 1% significance levels, respectively.

	Dependent variable			**Dependent variable**		
Symmetric	ΔAL	$\boldsymbol{\rho^{AL}}$	-0.098***	ΔRL	$\boldsymbol{\rho^{RL}}$	-0.221***
			(0.011)			(0.024)
Asymmetric	ΔAL	$\boldsymbol{\rho^{AL}_{\text{below}}}$	-0.059**	ΔRL	$\boldsymbol{\rho^{RL}_{\text{below}}}$	-0.314***
			(0.022)			(0.026)
	ΔAL	$\boldsymbol{\rho^{AL}_{\text{above}}}$	-0.129***	ΔRL	$\boldsymbol{\rho^{RL}_{\text{above}}}$	-0.142***
			(0.021)			(0.029)

A drawback of this first model is that it does not allow for asymmetric adjustment, i.e. it does not distinguish situations in which the liquidity buffer is above and below average. Banks may need to adjust more strongly when their DLCR falls below its long-run equilibrium and approaches the regulatory minimum. To allow for this asymmetry two dummy variables are introduced:

$$I^{AL}_{i,t} = \begin{cases} 1 \;\; if\; ECT^{AL}_{i,t-1} < 0 \\ 0 \;\; if\; ECT^{AL}_{i,t-1} \geq 0 \end{cases} \quad I^{RL}_{i,t} = \begin{cases} 1 \;\; if\; ECT^{RL}_{i,t-1} \geq 0 \\ 0 \;\; if\; ECT^{RL}_{i,t-1} < 0 \end{cases} \tag{6}$$

The asymmetric error correction model is estimated by:

$$\Delta AL_{i,t} = \alpha_i^{AL} + I_{i,t}^{AL}\rho_{below}^{AL}ECT_{i,t-1}^{AL} + (1 - I_{i,t}^{AL})\rho_{above}^{AL}ECT_{i,t-1}^{AL} + \sum_{j}^{L}\gamma_{i,j}\Delta RL_{i,t-j} + v_{i,t}^{AL} \qquad (7)$$

$$\Delta RL_{i,t} = \alpha_i^{RL} + I_{i,t}^{RL}\rho_{below}^{RL}ECT_{i,t-1}^{RL} + (1 - I_{i,t}^{RL})\rho_{above}^{RL}ECT_{i,t-1}^{RL} + \sum_{j}^{L}\gamma_{i,j}\Delta AL_{i,t-j} + v_{i,t}^{RL} \qquad (8)$$

where ρ_{below}^{AL} (ρ_{above}^{AL}) and ρ_{below}^{RL} (ρ_{above}^{RL}) represent the error correction speed of adjustment coefficients given that a bank is below (above) its average liquidity level.

The results in the second row of Table 4.3.4 suggest that the adjustment on the liability side becomes stronger when the DLCR is below its equilibrium. On average, 31% of the deviation from the long-run equilibrium is corrected within one month by a decrease in required liquidity. At the same time, adjustment on the asset side becomes slightly weaker and less significant, with only a 6% change in available liquidity. When shocks move the DLCR above its long-run equilibrium, banks decrease liquid assets and increase short-term liabilities. On average, shifts in liquid assets and liabilities both correct approximately 13-14% of the deviation from the long-run equilibrium.

4.3.3 Robustness Check

As indicated already, regulatory changes to the DLCR were introduced in May 2011. As this may lead to a structural break, and in order to exclude anticipation effects, we re-run the estimations for the period up to end 2010. Table 4.3.5 presents the results. The outcomes indicate an even stronger adjustment towards the liability side of the balance sheet.

Table 4.3.5: Robustness check

This table shows the Generalized Least Squares (GLS) results for the (Threshold) Error Correction Model for 41 banks over the period July 2003 - December 2010 (3.649 observations). The heteroskedasticity of the error terms is corrected by using white robust standard errors and the standard deviations are displayed in parentheses. Cross-section weights are used and ** and *** denote 5% and 1% significance levels respectively.

	Dependent variable			**Dependent variable**		
Symmetric	ΔAL	$\boldsymbol{\rho^{AL}}$	-0.106***	ΔRL	$\boldsymbol{\rho^{RL}}$	-0.292***
			(0.014)			(0.020)
Asymmetric	ΔAL	$\boldsymbol{\rho^{AL}_{\text{below}}}$	-0.095**	ΔRL	$\boldsymbol{\rho^{RL}_{\text{below}}}$	-0.357***
			(0.025)			(0.036)
	ΔAL	$\boldsymbol{\rho^{AL}_{\text{above}}}$	-0.119***	ΔRL	$\boldsymbol{\rho^{RL}_{\text{above}}}$	-0.215***
			(0.026)			(0.043)

4.3.4 Discussion of results

Our estimations indicate that a regulatory liquidity constraint influences bank behavior, and that Dutch banks primarily adjust their funding mix when their DLCR falls below its long-run equilibrium. This section briefly compares our results with the academic literature on the effects of liquidity regulation on bank behavior.[36]

[36] To save space, we focus only on studies based on econometric evidence, as it is closest to ours. In addition, there is a literature on the wider economic effects of liquidity regulation, which also focuses mainly on the asset side. Examples are King (2010), Perotti and Suarez (2010) and Wagner (2013). Other studies highlight that the LCR may provide incentives for increased reliance on central bank funding, among others EBA (2012), Ayadi et al. (2012) and Coeuré (2013). However, the data discussed in section 4.4 indicate that

Several authors investigate the effects of liquidity regulation on banks' liquid assets. De Haan and van den End (2013a) examine the liquidity management of Dutch banks. They model the stock of liquid assets as a function of the stock of liquid liabilities and the future cash inflows and outflows. A key finding is that banks keep liquid assets as a buffer against both the stock of liquid liabilities and net cash outflows. In another study, De Haan and van den End (2013b) find that in response to negative funding liquidity shocks, Dutch banks reduce wholesale lending, hoard liquidity in the form of liquid bonds and central bank reserves, and conduct fire sales of securities, especially equities.[37] Using data on US commercial banks, Berrospide (2012) studies the behaviour of banks' liquid assets as a function of banks' size, their capital ratio, their unused commitment ratio and their share of core deposits (as a proxy for the role of stable sources of funding). The author finds that stable sources of funding, such as deposits and bank capital, are key determinants of the holdings of liquid assets.

Overall, the econometric approach in the aforementioned studies relies on the assumption that banks adjust liquid assets in response to shifts in their funding profile. Hence, our finding that adjustment can also take place on the liability side of the balance sheet complements the existing literature. More recently, Banerjee and Mio (2018) point to the

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the reliance on central bank funding is limited for Dutch banks. Towards the end of the observation period, claims on the central bank increase markedly and outweigh reliance on central bank funding. This is consistent with the argument that the Netherlands was seen as a safe haven during the sovereign crisis of 2011-2012. A possible effect of liquidity regulation on central bank funding could therefore better be studied in countries where the reliance on central bank funding is higher.

[37] The authors suggest that the positive relation between equity holdings and secured funding could also reflect the use of equities in repos and securities lending transactions. When these activities are buoyant, banks' equity holdings are useful as collateral, while these become less useful when the secured funding market collapses.

effects of liquidity regulation on both assets and liabilities. Their study is closest to our approach. They find that banks that became subject to liquidity regulation significantly increased their share of HQLA. At the same time, banks also increased their share of domestic retail deposits, offset by a similar reduction in short-term wholesale funding and non-resident deposits. The main difference with our paper is that we study the adjustment to liquidity shocks after the regulation has been put in place, and that we rely on co-integration instead of regressions.

4.4 Aggregate data

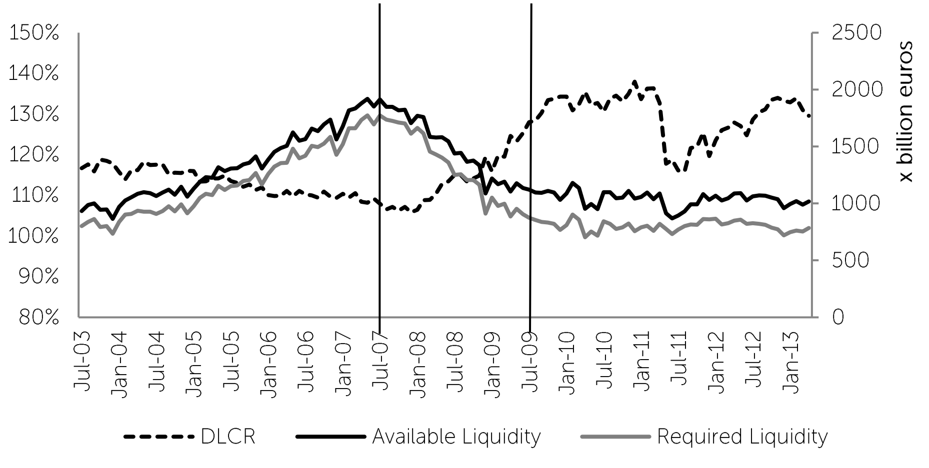
4.4.1 Patterns around the crisis

We now turn to the second question on the role of liquidity regulation before, during and after the liquidity and solvency crisis of 2007-2008. To do so, we shift focus from bank-level data towards aggregate patterns in the data for the Dutch banking sector as a whole. Figure 4.2 shows the average level of the DLCR for all banks in the sample and its development over time.

At the aggregate level, available liquidity always lies above required liquidity, so that the DLCR requirement is respected and minimum short-term liquidity buffers are maintained. As expected, available and required liquidity show strong co-movements, also at the aggregate level. Both series increase strongly in the run-up to the financial crisis, so that the aggregate balance expands strongly, and then decrease during the crisis. These large movements in available and required liquidity mainly cancel out in the ratio, but not fully. In the run-up to the crisis, required liquidity increases somewhat faster than available liquidity. As a result, the DLCR decreases gradually towards the direction of the regulatory minimum ratio of 1. During the crisis, required liquidity decreases more strongly than available liquidity, so that the DLCR shows a substantial increase. This suggests a pro-cyclical pattern of increased risk taking in the upswing of the financial cycle, i.e. a move towards 'cheaper' wholesale funding (with a high run-off rate in the denominator of the DLCR). It also suggests de-risking during the crisis, when wholesale funding dries up and needs to be substituted by more stable funding sources.

Figure 4.2: Dutch Liquidity Coverage Ratio (DLCR) and its components

The graph displays the aggregate level of liquidity of 59 Dutch banks for the period July 2003 until April 2013. The DLCR (left scale) is defined as the ratio of available liquidity over required liquidity. The available and required liquidity are given in billion euros (right scale) on a monthly basis.



The aggregate data contradict established wisdom that changes in liquid assets are driving the liquidity ratio. On the contrary, the DLCR decreases in the run-up to the financial crisis while the amount of liquid assets increases. The DLCR then strongly increases during the crisis, while liquid assets fall. Finally, the data show that the liquidity crisis of 2007-2008, characterised by a strong outflow of both liquid assets (decrease in available liquidity) and liabilities (decrease in required liquidity), is directly visible in the individual series, but not in the ratio, as it shows a substantial increase.

Unfortunately, the data do not include the run-up to the introduction of the liquidity regulation. This is a limitation of our study: we cannot make inferences on a possible level shift in liquid assets and liabilities due to the introduction of a binding liquidity ratio.[38] However, we do observe data around the regulatory changes of May 2011. Data show a fall in available liquidity, due to an increase in haircuts, that leads to a drop in the DLCR. This is followed by a gradual increase in the DLCR that is mostly driven by available liquidity, towards a similar level to that observed during October 2009 - May 2011.

4.4.2 Balance sheet composition

Figure 4.3-3.6 provide an overview of the shifts in total assets and liabilities for the Dutch banking sector as a whole, and total assets and liabilities weighted by their liquidity value (i.e. available and required liquidity). On the asset side, particularly secured wholesale lending, consisting of (reverse) repos and securities lending, increases steadily over 2003-2007, and then declines strongly during the crisis. As secured wholesale lending is defined as highly liquid, it accounts for most of the dynamics in available liquidity. Likewise, on the liability side, the strongest dynamics are observed in secured wholesale funding, which mainly consists of repos.

[38] For the UK, Banerjee and Mio (2014) find that an increase in liquid assets has been one of the effects of the introduction of liquidity regulation.

Moreover, over time, we observe a shift from wholesale funding towards retail demand deposits (with a low run-off rate). Overall, it appears that the liquidity components of the aggregate balance sheet reflect rapid balance sheet expansion and contraction over the financial cycle, driven by both secured funding and lending.

Figure 4.3: Breakdown of assets

This figure shows the aggregate asset allocation for the full sample of 59 banks over time, based on consolidated balance sheets.

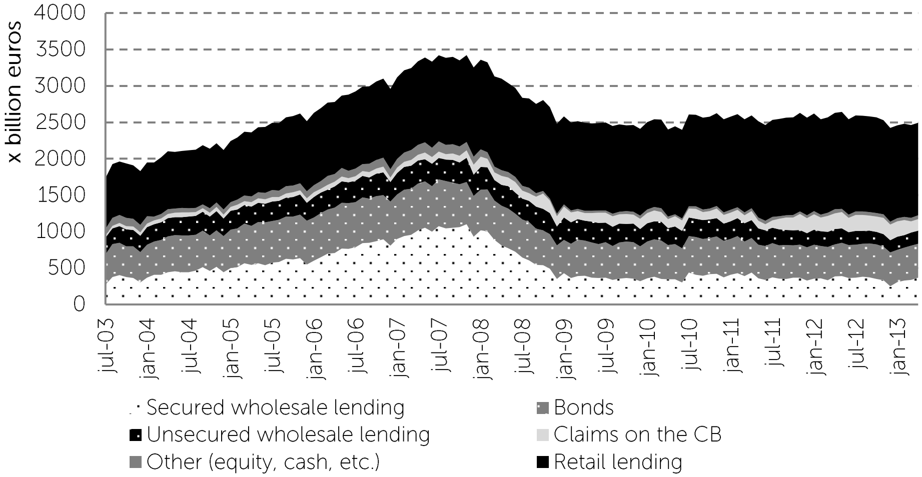


Figure 4.4: Breakdown of available liquidity (liquidity weighted assets)

This figure shows the aggregate asset totals weighted by their liquidity value for the full sample of 59 banks over time, based on consolidated balance sheets.

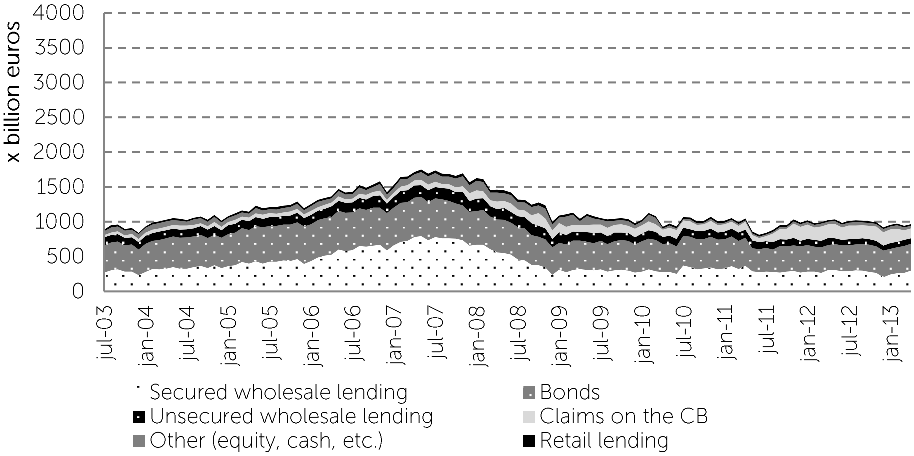


Figure 4.5: Breakdown of total liabilities

This figure shows the aggregate funding mix for the full sample of 59 banks over time, based on consolidated balance sheets, including off balance sheet items (therefore total liabilites exceeds the total assets in Figure 4.1).

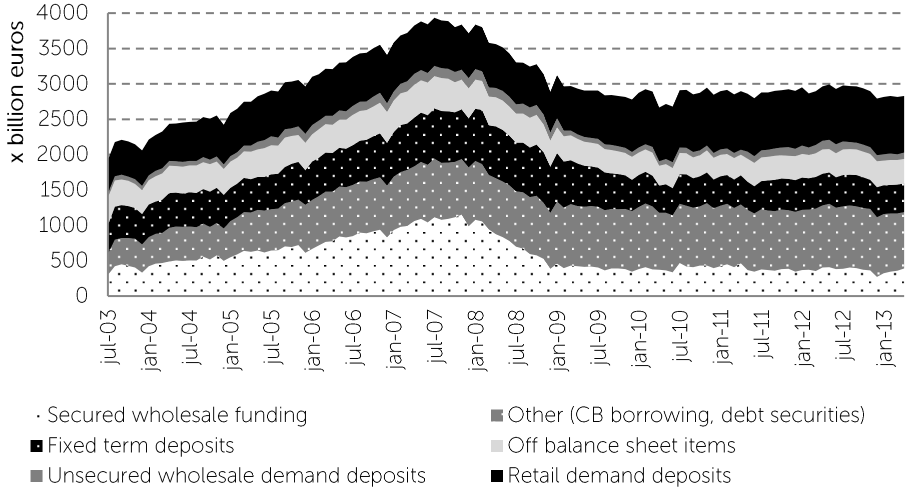
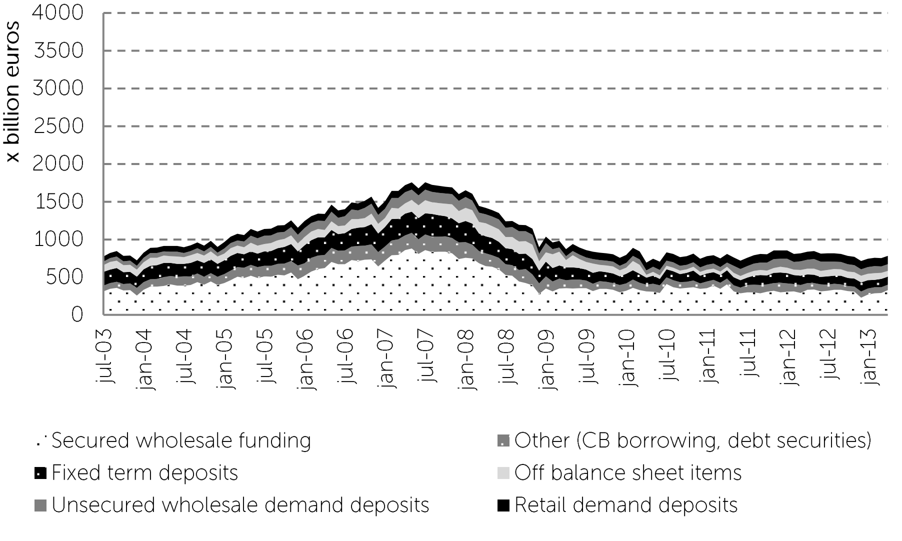


Figure 4.6: Breakdown of required liquidity (liquidity weighted liabilities)

This figure shows the aggregate liabilities weighted by their liquidity value for the full sample of 59 banks over time, based on consolidated balance sheets.



4.4.3 Discussion of results

From a microprudential perspective the liquidity rules appear to have been effective in the Dutch case, given that a minimum buffer of liquid assets has always been maintained to cover possible outflows, as captured by required liquid assets. At the same time, the liquidity regulation did not prevent a pro-cyclical liquidity cycle driven by secured financing. Our findings therefore provide empirical support to the 'consensus view' on systemic liquidity risk (Acharya et al., 2011). According to this view, microprudential measures such as the LCR help support stability, but are not sufficient. First, they focus on individual liquidity risk, but not on systemic liquidity risk. Second, they do not target liquidity risk in particular in securities financing transactions and derivatives. Third, they are not countercyclical.

Several authors have already pointed to the relevance of secured financing – and repos in particular – in explaining the build-up of risk prior to the financial crisis in the US, and contagion between institutions when this risk crystallised (e.g. Brunnermeier and Pedersen, 2009; Gorton and Metrick, 2012; Copeland et al., 2014). Our results point to the relevance of secured financing for European countries such as the Netherlands. Future research would be needed to provide further insights, especially on the role played by the type of collateral (such as asset backed securities versus government bonds) and the pattern of margins and haircuts that may have been driving fire sales during the crisis, which our dataset unfortunately does not provide. Such research could inform policy discussions on the use of through-the-cycle or countercyclical margins and haircuts on securities financing transactions, as currently discussed in international fora such as the Financial Stability Board (FSB, 2014).

A related approach points to the links between liquidity and leverage in the US context. Adrian and Shin (2010) suggest that financial market liquidity can be understood as the rate of growth of aggregate balance sheets. They argue that during the upswing of the financial cycle, asset prices increase so that capital increases and leverage falls.[39] This provides an incentive to financial institutions to use this 'excess capital' to maximise return on equity. They may therefore extend their balance sheet through borrowing funds to purchase assets, so that capital falls (and leverage increases) back to its previous level. This translates into pro-cyclical patterns in the size of banks' balance sheets. For US investment banks, Adrian and Shin (2010) present evidence for the expansion and contraction of balance sheets via repos (i.e. using purchased securities as collateral for the cash borrowing).[40] [41]

To investigate such a possible link between liquidity and leverage for Dutch banks, and with risk-weighted capital requirements more generally, we complemented our dataset with balance sheet data on risk weights, total assets and (core) capital.[42] Based on the possible link between liquidity and leverage, we expect a correlation between the cycle

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[39] Here leverage is defined as the ratio of total assets over capital.

[40] The Dutch banking sector is dominated by the largest three banks and therefore highly concentrated: the largest 3 banks account for around 75% of the total assets. These banks are universal banks: they combine traditional banking with a sizeable presence in securities markets. Our aggregate results therefore partly reflect the presence of these large banks in securities markets.

[41] Similarly, Geanakoplos (2010) points to pro-cyclical leverage driven by pro-cyclical margins and haircuts on collateral.

[42] The confidential data originates from the supervisory solvency reporting requirement. In contrast to the monthly reporting of liquidity data, the solvency data is reported quarterly. Besides that, and also in contrast to the liquidity data reporting, foreign branches with a parent company within the European Union are exempted from reporting, since the Dutch regulator plays no role in solvency supervision of these banks. Hence, data on both the solvency and liquidity position are available for 30 banks. However, these 30 banks still represent 90% of the total Dutch banking sector, based on 2013Q1 data and measured by total assets.

in available and required liquidity and the leverage ratio (defined here as equity over total assets). This occurs given that the series for available and required liquidity reflect debt-financed balance sheet expansion and contraction. All else equal (i.e. if equity would be constant) such a pattern would reflect pro-cyclical leverage. This pro-cyclical pattern of the leverage ratio is confirmed in Figure 4.7, which also highlights the strong correlation of the leverage ratio with the DLCR.

Given that liquidity problems often reflect underlying solvency problems (Admati and Hellwig, 2013), a link between liquidity ratios and risk-weighted capital ratios could also be expected. As shown in Figure 4.8, the correlation is indeed positive, but not as strong as for the leverage ratio. This difference can be explained by the pro-cyclical change in average risk weights during our sample period (Figure 4.9). As a result, risk-weighted capital requirements remained relatively stable above their regulatory minimum in the run-up to the crisis, despite increasing leverage. Further discussions on the performance of risk weights as *ex ante* and *ex post* measures of risk are subject to a separate literature, which is beyond the scope of this paper (see Le Lesle and Avramova, 2012).

Figure 4.7: Liquidity and leverage ratio[43]

This figure shows the weighted-average leverage ratio (left scale) and DLCR (right scale) for a sample of 30 banks on a quarterly basis for the period 2004Q1 – 2013Q1.

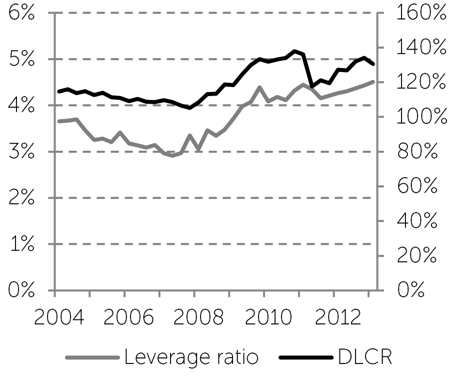


Figure 4.8: Liquidity and capital ratio[44]

This figure shows the weighted-average capital ratio (left scale) and DLCR (right scale) for a sample of 30 banks on a quarterly basis for the period 2004Q1 – 2013Q1.

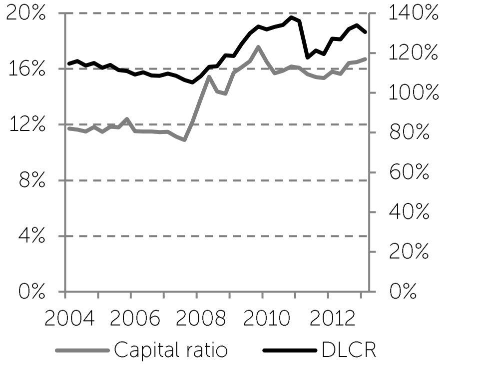
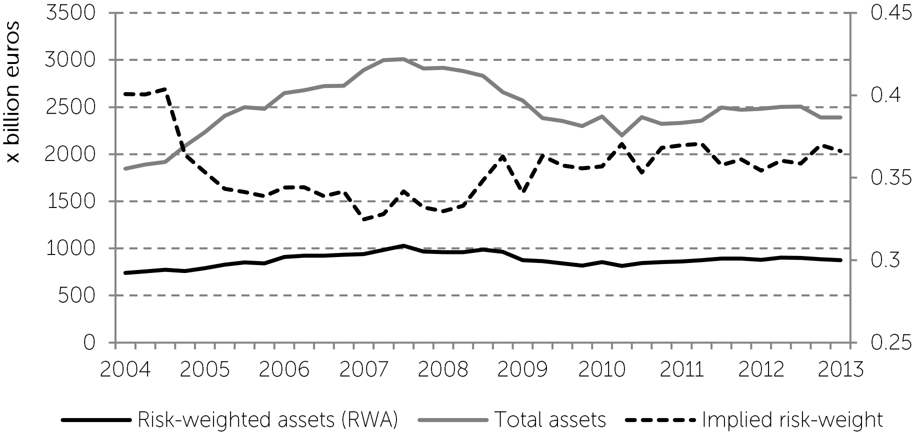


Figure 4.9: Risk weights

This figure shows the aggregate asset totals, risk-weighted assets, and the implied average risk weights (right scale) on a quarterly basis for the period 2004Q1 – 2013Q1.



[43] The leverage ratio is defined as total Tier 1 capital divided by total assets.
[44] The capital ratio is defined as the total eligible capital divided by total risk weighted assets (Basel definition).

Finally, our finding of a pro-cyclical pattern in the DLCR is in line with Goodhart et al. (2012). These authors argue that banks naturally have more liquid assets during booms than during busts, and that if a liquidity ratio is binding during a boom it will even be more restrictive during a bust, making it a pro-cyclical regulatory ratio. Therefore, the authors propose countercyclical haircuts (i.e. liquidity weights), so that the liquidity requirements become time-varying and the liquidity buffer can be released during times of financial stress.

4.5 Conclusion

The main implication of our study is that banks adjust their liquid liabilities, and to a lesser extent their liquid assets in response to shocks in their liquidity positions. In the Dutch case, liquidity regulation appears to have been effective from a micro-prudential perspective, but not from a macro-prudential perspective. While banks respect the minimum liquidity ratio, liquidity regulation has not prevented a pro-cyclical liquidity cycle in short-term secured financing that is strongly correlated with leverage. At the same time, the increase in leverage was not visible in the regulatory capital ratios. Hence, monitoring the risk-weighted capital requirements, or the LCR as a ratio, does not necessarily signal the build-up or materialisation of aggregate risks. It may need to be complemented by monitoring the LCR's constituent parts, both at an institutional level as well as for the banking sector as a whole, and interpreted against the background of movements in balance sheet size, leverage and the value of collateral.

Furthermore, and in line with previous research, our findings point to the significant role of secured financing for explaining the leverage and liquidity cycle. This calls for further research on the role played by the type of collateral, and the pattern of asset prices, margins and haircuts that may have been driving the liquidity cycle and fire sales during the crisis.

Chapter 5: Short-termism of long-term investors? The investment behaviour of Dutch insurance companies and pension funds

Countercyclical investment strategies of large institutional investors such as insurance companies and pension funds can support financial stability, while procyclical investment behaviour is considered as destabilising at a macro-level. Yet there is limited understanding of how insurance companies and pension funds invest during market shocks, such as the global financial crisis. Investigating the equity and fixed income portfolios of Dutch non-life insurers, life insurers and pension funds, we find evidence for procyclical behaviour by insurance companies (both life and non-life). For pension funds we find evidence for countercyclical behaviour during market upturns.[45]

JEL Classification: E44, G11, G22, G23

Keywords: macroprudential, investment behaviour, pension funds, insurance companies, procyclicality, global financial crisis.

[45] This chapter is co-authored with Sophie Steins Bisschop. We are grateful to Paul Witteman and Jasper de Boer for assistance with data collection. We thank Dirk Broeders, Tijmen Daniëls, Jon Frost, Leo de Haan, Arco van Oord, Robert Vermeulen, two anonymous referees and participants of the EIOPA Advanced Seminar on Quantitative Techniques for Financial Stability for valuable comments. Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank. The usual disclaimer applies.

5.1 Introduction

A question of long-standing interest to both academics and policy makers is whether institutional investors such as insurance companies and pension funds have a stabilising impact on financial markets. With rapidly growing assets under management, they have the potential to either stabilise or amplify swings in financial markets and the wider economy.

From a theoretical point of view, life insurers and pension funds are expected to act as shock absorbers in times of financial stress, as their long-term investment horizon enables them to endure short-term price movements. In contrast to for example banks and open-end mutual funds, insurers and pension funds do not face direct selling pressure as liabilities can not easily be withdrawn. Moreover, they often use rebalancing strategies. This implies 'buy low, sell high', i.e. selling off asset classes that are priced high and buying asset classes that are priced low. This also implies that the asset allocation remains relatively stable: when equities underperform fixed income, for example, investors buy more equities, keeping the total equity exposure at the level determined by the long-term strategic asset allocation strategy.

At a macro level, this rebalancing strategy could temper both upward and downward price movements, benefiting financial stability. In practice, however, institutional investors may decide not to apply rebalancing strategies, particularly in times of stress. During the global financial crisis, for example, many investors closed their positions in falling markets, further accelerating sharp price drops.

With assets under management of respectively 71% and 185% of Dutch GDP, insurers and pension funds are relevant from a systemic perspective. In this paper, we investigate whether they behave countercyclically by selling and buying in contrast to market movements, i.e 'buy low, sell high'. In addition, we also examine if they show asymmetric investment behaviour by reacting differently to market downturns compared to market upturns.

Using a unique dataset, we analyse Dutch insurers' and pension funds' investment behaviour over the last 10 years (2006Q1-2015Q4). This data set enables us to extract actual transactions excluding valuation effects. We contribute to the existing literature by focusing on actual transactions (not influenced by valuation effects) and by taking into account both equities and fixed income investments, thereby covering the majority of the balance sheet. Previous studies often focus on the asset allocation of one asset type. Moreover, we conduct this analysis for three sectors (non-life insurers, life insurers and pension funds) over a time period of ten years, covering both turbulent and more stable market circumstances.

Our results show that both non-life and life insurers behaved procyclically by selling (buying) equities in periods when equity prices were low (high). Non-life insurers showed stronger procyclical behaviour during the global financial crisis and during periods in which equities underperformed other assets, while life insurers showed stronger procyclical behaviour during periods when equities outperformed fixed income investments. For pension funds, we find some evidence for countercyclical investment behaviour during times of relatively tranquil market circumstances (i.e. non-crisis years) and during periods when equities outperform other assets.

The (investment) behaviour of large investors such as insurance companies and pension funds can have broader consequences for financial stability and the real economy.[46] Besides the impact of their investment decisions on market prices, they could also impact financial stability and the real economy through several other channels. Pension funds, for example, may curtail pension rights or increase contributions in times of stress. Several actions could occur at the same time, impacting the economy both positively and negatively. For example, when a pension fund with a funding position close to the required minimum faces falling equity prices, it may be encouraged to sell equity (which is valued using market value) to avoid curtailments or a rise in contributions in the short-run. Moreover, insurance companies could invest procyclically to avoid failure in the near future, thereby both negatively and positively affecting the real economy. This paper only focusses on the first impact channel by assessing whether insurance companies and pension funds have a stabilising or destabilising role in financial markets.[47]

The remainder of this paper is organised as follows. Section 5.2 presents our hypotheses and links to the relevant academic literature. Section 5.3 presents the data and research methodology. Section 5.4 presents the results of the regression analysis and section 5.5 concludes by exploring policy responses.

5.2 Hypotheses

5.2.1 Stabilizing role of institutional investors

Several studies analyse insurers' and pension funds' footprints in major

[46] See for example Joint FSF-CGFS working group (2009), Borio et al. (2010), or Claessens and Kose (2013) for an overview of the issues arising from procyclicality in the financial system.

[47] Besides, there are also studies on the impact of an institution's investment behavior on their own performance, see for example Blake et al. (1999), Daniel et al. (1998) and Brinson et al. (1991)

market events. They show mixed results, depending on the time period, geographical scope, and type of institutional investor. According to a study by the IMF (Papaioannou et al., 2013) US, Portugese and Spanish pension funds engaged in equity sell offs in 2007-2008, which could be considered as destabilising given the market circumstances at that time. On the other hand, pension funds in Norway, Italy, Poland, and Turkey reacted countercyclically by purchasing equity during the crisis and lowering the intensity of the purchases as markets recovered. Also focusing on the global financial crisis, the Bank of England (2013) concludes that pension funds invested countercyclically in the short run and procyclically in the medium run, but that the decision to sell equities was also triggered by the desire to structurally adopt safer investment strategies. Blake et al. (2015) analyse the behaviour of UK pension funds over a much longer time period (25 years) and conclude that they did not have a stabilising effect on markets, as they only applied rebalancing in the short run.

Compared to pension funds, there is somewhat more evidence for procyclical investment behaviour by insurance companies. Impávido and Tower (2009) point out that US life insurers contributed to the market crash in 2001-2003, i.e. the dotcom bubble, by selling equities in falling markets. During the global financial crisis they observe a similar pattern, albeit to a lesser extent. Rudolph (2011), however, does not find evidence for procyclical investment strategies of US life insurers in the longer run. His study shows that they kept their investment mix relatively stable over the period 2001-2011. The Bank of England (2013) finds a positive correlation between the equity investments of US, UK and French life insurers and stock market perfomance over the period 1996-2012. The authors do not draw strong conclusions from these findings due to data limitations and the fact that there was a structural shift towards more conservative asset allocations. The IMF (2016) concludes that lower-capitalised insurers were more prone to sell securities in 2008, but that overall U.S. life insurers acted countercyclically.

Regarding Dutch institutional investors, De Haan and Kakes (2011) investigate the investment behaviour of life and non-life insurers and pension funds before the financial crisis. They find that all three types of investors tend to be contrarian traders, especially pension funds. Bikker et al. (2010) confirm that pension funds invested countercyclically by partly rebalancing their portfolios in the time period 1999-2006. On average, about 39% of excess equity returns were rebalanced each quarter, leaving 61% of the portfolio for free float. With regard to the post-crisis period, in 2011 De Nederlansche Bank (2011) reported that Dutch pension funds were acting countercyclically by buying equities in falling markets at the start of the global financial crisis. For insurance companies the contrary was found by Houben and van Voorden (2014), who consider the equity investment behaviour of insurance companies during the crisis and show that when stock prices dropped, Dutch insurance companies actively decreased their exposure to equity markets, indicating procyclical behaviour. Moreover, Bijlsma and Vermeulen (2016), who consider the sovereign bond portfolio of Dutch insurers, find that during the height of the European sovereign debt crisis insurance companies engaged in procyclical investment behaviour by selling southern European assets.

In general, we expect that institutional investors have a stabalizing role on financial markets by rebalancing their portfolio in contrast to price movements. Formally, this can be expressed as hypothesis 1:

H1: Insurance companies and pension funds buy (sell) assets after market prices decrease (increase), i.e. 'buy low, sell high'

5.2.2 Differences in (non-) life insurers' and pension funds' investment behaviour

Non-life and life insurers and pension funds are all institutional investors and have commonalities, but differences between those three sectors also exist. For example, especially life insurers and pension funds have a long maturity of their liabilities and thus a long-term investment horizon, while non-life insurers are more concerned about the liquidity of their assets in the short-run. Gorter and Bikker (2013) examine the investment risk profile of pension funds and insurance companies, and find that pension funds take on board significantly more investment risk than insurers. Moreover, they also find that pension funds are more risk tolerant by rebalancing a larger fraction of their equity portfolio, both in bull and bear markets, whereas insurance companies rebalance in bull markets, but do not buy equities in bear markets to restore their equity allocation.

When comparing insurance companies and pension funds, it is also important to consider the regulatory framework applicable to both sectors.[48] Both sectors have to value their assets and liabilities based on market value – which can induce procyclical behaviour – but their liabilities are less sensitive to market circumstances as a consequence of the introduction of the ultimate forward rate. Also, both sectors can choose their investment portfolio as their asset allocation is not subject to

[48] For the period under consideration, Dutch insurers were subject to the European Solvency I Directive, while pension funds had to deal with a national regulatory framework.

hard limits, i.e. the 'prudent person' principle applies. One important difference is that pension funds literally can not go bankrupt. Besides that, pension funds have more recovery options, for example they can cut policyholders' benefits, or increase premiums. Hence, insurance companies may face more pressure on their business model in market downturns. In contrast to pension funds, insurers are also formally obliged to lower their risk profile of their investments or to attract additional capital in recovery periods, i.e. when their solvency position is below the regulatory minimum. Pension funds are not obliged to lower their risk profile, but they are not allowed to increase their risk profile during recovery.

In line with previous research and bearing in mind the regulatory framework, we expect to find stronger evidence for countercyclical behavior by pension funds compared to insurance companies. Moreover, we also hypothesise that non-life insurers are less countercyclical than life insurers, due to their shorter investment horizon. This is formalised in the two sub-hypotheses:

H2a: Pension funds show stronger countercyclical behavior than insurance companies

H2b: Life insurers show stronger countercyclical behavior than non-life insurers

5.2.3 Assymetric responses to market shocks

Pension funds and insurance companies may behave differently in turbulent times compared to relatively tranquil periods. A couple of studies find different investment behaviour of these investors during stressed circumstances, e.g. Impávido and Tower (2009) and Houben and van Voorden (2014) as referred to in section 5.2.1. Moreover, Bikker et al. (2010) highlight explicitly that pension funds reacted asymmetrically to market shocks: rebalancing was much stronger after negative equity returns. Since our study covers severe stress periods, we also test if we find stronger reactions after market downturns than market upturns. In line with the findings of Bikker et al. (2010), we expect that the equity buying and selling behaviour of insurance companies and pension funds may be different during periods of stress. This is formalised as hypothesis 3:

H3: Pension funds and insurance companies react asymmetrically to market shocks by reacting stronger to market downturns

5.3 Data and method

5.3.1 Dataset

We use an unique institution-specific database for Dutch insurance companies and pension funds over the period 2006Q1-2015Q4, covering both crisis and more tranquil periods.[49] Data is obtained from the non-supervisory statistics (balance of payment information), which contain detailed information on the holdings of equities and equity flows, i.e. real purchases and sales of equities corrected for valuation effects. Moreover, we collect supervisory data to control for institution specifics, such as the

[49] The underlying data are institution specific and therefore confidential. Hence, throughout the paper we show only aggregated data or estimation results.

solvency position.[50]

Data is collected for 10 non-life insurers, 8 life insurers and 29 pension funds, covering respectively 32%, 90%, and 74% of the Dutch sectors in terms of assets.[51] Insurance companies, both life and non-life, have assets under management of together around EUR 500 bln, or almost 80% of Dutch GDP, and EUR 28,000 per habitant (in 2015). Due to the compulsory company participation in industry-wide pension funds, Dutch pension funds have a larger amount of assets under management of about EUR 1,250 bln. This equals 185% of Dutch GDP or EUR 73,500 per inhabitant (in 2015).

Table 5.4.1 presents the descriptive statistics of our dataset. The size of the institutions included in the sample, measured by total assets, varies strongly. The right-skewed distribution indicates the presence of some relatively large institutions. Insurance companies, especially non-life, report quite high average solvency ratios of 244% and 400% for life and non-life insurers respectively (where the minimum requirement is 100%), although there is again a large variance across institutions. The average coverage ratio of pension funds equals 118%.

[50] For insurance companies only yearly data is available for the years 2006-2008, and 2015. Therefore, we interpolated this yearly data to construct quarterly data.
[51] We only include institutions for which the data is available for at least 10 consecutive quarters.

Table 5.4.1: Descriptive statistics

This table shows the descriptive statistics of our dataset over the period 2006Q1-2015Q4. It includes the average, median 10%- and 90% percentiles, and standard deviation of the key variables used in our regression analysis.

Non-life insurers	Mean	Median	10%	90%	St. Dev.
Rel. equity transactions (%)	-2.5%	0.0%	-18.9%	7.1%	19.7%
Rel. fixed income transactions (%)	0.6%	0.0%	-6.5%	8.7%	11.1%
Total assets (in € million)	2,774	2,292	630	6,588	2,186
Equity allocation (%)	4.3%	1.7%	0.0%	14.0%	6.1%
Fixed income allocation (%)	55.2%	63.2%	50.9%	86.2%	13.2%
Solvency ratio (%)	400%	289%	184%	518%	404%

Life insurers	Mean	Median	10%	90%	St. Dev.
Rel. equity transactions (%)	-3.5%	-0.8%	-15.7%	6.4%	13.2%
Rel. fixed income transactions (%)	0.5%	0.5%	-1.5%	3.9%	6.5%
Total assets (in € million)	35,975	36,627	3,347	70,135	24,834
Equity allocation (%)	5.8%	4.8%	1.1%	12.0%	4.1%
Fixed income allocation (%)	67.9%	67.6%	50.9%	86.2%	13.2%
Solvency ratio (%)	244%	233%	178%	333%	591%

Pension funds	Mean	Median	10%	90%	St. Dev.
Rel. equity transactions (%)	0.0%	0.4%	-8.1%	7.3%	11.4%
Rel. fixed income transactions (%)	1.7%	0.7%	-5.1%	8.6%	9.8%
Total assets (in € million)	21,950	6,820	2,077	37,560	49,589
Equity allocation (%)	26.9%	27.2%	6.5%	43.3%	13.9%
Fixed income allocation (%)	48.1%	50.2%	26.3%	66.3%	16.3%
Coverage ratio (%)	118%	112%	96%	146%	23%

The equity and fixed income allocation varies strongly across non-life insurers, life insurers and pension funds. In this study, the fixed income investments contain both bonds (all type of bonds, i.e. government bonds, corporate bonds, covered bonds etc.) and loans. The data clearly shows that pension funds invest relatively more in equities, which is in line with the finding of Gorter and Bikker (2013) that pension funds take on board significantly more investment risk than insurers. While aggregate information on the equity and fixed income allocation is informative in its own right, it is not useful for analysing procyclicality, since it does not correct for valuation effects. In other words, a rise in equity allocation could be driven by a positive market sentiment and/or an actual increase in shares. This study therefore focuses on the actual sales and purchases in equities and fixed income investments.

First, we consider the net amount of equities sold or bought expressed as a fraction of the total equities in the portfolio in the previous quarter *t-1*. This variable is the 'relative equity transaction'. Indicated by the negative mean and left-skewed distribution of this variable for both life and non-life insurers in Table 5.4.1, insurers were net equity sellers during our sample period. Pension funds, on the other hand, sold and bought on average about the same amount of equities as indicated by a mean of zero. Second, we construct a similar variable for the fixed income investments; the 'relative fixed income transaction'. The positive mean of this variable for all type of institutions indicates that pension funds and insurers on average bought fixed income investments over the years 2006-2015.[52]

5.3.2 Methodology

In order to empirically test our hypothesis we use the following baseline regression that we run for each type of investor (non-life insurer, life insurer, pension fund) separately:

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[52] While the investment data is quite granular, a disadvantage is that we can not trace all equity and fixed income holdings invested via investment funds. Especially pension funds invest a large part of their portfolio via investment funds. Yet for a couple of large pension funds – and thereby the majority of the investments via investment funds - we were able to match the investments via investment funds to the respective pension funds. Due to data availability we can only include this data from 2009Q2 onwards. A robustness check for the period 2009Q-2015Q4 does however reveal that the regression results for the data including and excluding investments via investment funds are rather similar.

$$\frac{T_{i,t}^{E}}{A_{i,t-1}^{E}} - \frac{T_{i,t}^{FI}}{A_{i,t-1}^{FI}} = \alpha_i + \beta_1 * (r_{i,t-1}^{E} - r_{i,t-1}^{FI}) + \beta_2 * \left(\frac{T_{i,t-1}^{E}}{A_{i,t-2}^{E}} - \frac{T_{i,t-1}^{FI}}{A_{i,t-2}^{FI}}\right) + \sum_{k=3}^{K} \beta_k X_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

The dependent variable $\frac{T_{i,t}^{E}}{A_{i,t-1}^{E}} - \frac{T_{i,t}^{FI}}{A_{i,t-1}^{FI}}$ measures the relative transaction difference defined as the relative equity transaction minus the relative fixed income transaction, whereas the relative transactions are defined as the net buying/selling in quarter *t* divided by the total holdings at *t-1* (as defined in the prevous section). In other words, this variable indicates whether an institution *i* actively increases or decreases its equity holdings relative to its fixed income investments. To correct for outliers we exclude observations of relative equity and fixed income transactions above 100% and below -100% (in total around 1% of all observations), as these transactions often concern a transfer of assets from or to investment funds. To control for serial correlation, we also include the lagged dependent variable, $\frac{T_{i,t-1}^{E}}{A_{i,t-2}^{E}} - \frac{T_{i,t-1}^{FI}}{A_{i,t-2}^{FI}}$.[53]

[53] The inclusion of this lagged dependent variable in a panel regression with cross-section fixed effects may create a bias (Nickell bias) if the time dimension (T) of the panel is relatively small when compared to the cross-section dimension. As the time dimension in our dataset is larger than the cross-section dimension for non-life insurers, life insurers as well as pension funds, the bias is less of an issue. Moreover, the bias, of size 1/T decreases with T. For robustness, we have also estimated the model using both the Arellano-Bond and the Blundell-Bond/Arellano-Bover estimator. Note that these alternative estimators are typically designed for datasets with a large cross-section dimension and small time dimension, and hence does not fit our dataset. While the coefficients keep their sign, the significance disappears. In this study, we present the OLS fixed effects estimations since i) the dynamic panel bias is less of an issue with our time dimension, and some studies (Roodman, 2006; Beck and Katz, 2011) argue that when T is large, or when T is 20 or more (Beck and Katz, 2011), the bias becomes small and OLS performs better than the alternatives; and ii) the alternative estimators are typically designed for situations with 'large N, small T'.

The variable α_i represents the individual fixed effect accounting for institution specific characteristics. $r^{E}_{i,t-1} - r^{FI}_{i,t-1}$ represents our main independent variable of interest, i.e. the return difference. This is defined as the net income stemming from equity investments by institution *i* in period *t* divided by the total equities in period *t-1* minus the reported net income on fixed income investments by institution *i* in period *t* divided by the total fixed income investments in period *t-1*. Hence, we test whether insurance companies and pension funds buy more (less) equities relative to fixed income investments when equity underperforms (outperforms) fixed income investments. In line with our first hypothesis we expect a negative coefficient for this variable, implying that institutions sell (buy) more equities compared to other (fixed income) assets when equity outperforms (underperforms), i.e. countercyclical behaviour.

$X_{i,t-1}$ includes institution specific control variables. The solvency position is included to control for the fact that institutions with higher capital buffers have more means to withstand market shocks. Moreover, pension funds with solvency positions that are close to the regulatory minimum, may not increase their risk profile while insurance companies are even obliged to lower their risk profile. Therefore, a positive coefficient is expected for this variable, as more solvent institutions have more means to withstand shocks and to take on more risk by buying equities. For pension funds, we also include a dummy variable that is equal to one if the actual equity allocation is below its strategic equity allocation. Every quarter, pension funds have to report their strategic and actual equity allocations to the supervisor. If the actual allocation lies below its strategic allocation a pension fund is expected to buy more equities relative to fixed income to bring its equity alloction closer to its strategic level and therefore we expect a positive coefficient for this variable. This control variable may also indicate pro- or countercyclical behaviour to a certain extent, as a deviation from the strategic equity allocation may be caused by price developments. However, this is only to a certain extent as pension funds may revise their strategic levels, and the study by Bikker et al. (2010) indeed shows pension funds' strategic levels follow stock market performance. Size is not included as a control variable, as the dependent variable – which is a relative one - does not depend on the size of an institution.

We also run the regression model with and without time fixed effects. Exclusion of time fixed effects allows us to verify if insurance companies and pension funds react to common shocks in the market, while the inclusion of time fixed effects allows us to test whether institutions' buying/selling decisions are influenced by small differences in their returns due to different equity and fixed income allocations.

A drawback of specification (1) is that it is symmetric, i.e. it does not distinguish between equity outperformance and underperformance. To test for assymetric investment behaviour, i.e. whether institutions rebalance more after market downturns compared to upturns, we also run the following regression:

$$\frac{T_{i,t}^{E}}{A_{i,t-1}^{E}} - \frac{T_{i,t}^{FI}}{A_{i,t-1}^{FI}} = \alpha_i + \beta_1 * (r_{i,t-1}^{E} - r_{i,t-1}^{FI}) * D_t^D + \beta_2 * (r_{i,t-1}^{E} - r_{i,t-1}^{FI}) * D_t^U + \beta_3 * \left(\frac{T_{i,t-1}^{E}}{A_{i,t-2}^{E}} - \frac{T_{i,t-1}^{FI}}{A_{i,t-2}^{FI}}\right) + \sum_{k=4}^{K} \beta_k X_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

where D_t^D and D_t^U represent two dummy variables, respectively denoting the downturn and upturn of the financial markets. We distinguish two for the market situation. The first is based on whether the equities underperform (downturn) or overperform (upturn) relative to fixed income. The second is based on whether there is a crisis period 2007Q3-2009Q2 (downturn) definitions or not (upturn). Hence, the latter verifies if there is a stronger relationship between investment behaviour and performance during the global financial crisis.

5.4 Results

Table 5.4.2 shows the results of our baseline regression model. The first two columns present the regression outcomes for non-life insurers. The model including time fixed effects - presented in column 1 – displays no significant impact of equity under- or outperformance on the investment behaviour. However, with the exclusion of the time fixed effects in column 2, the significant and positive coefficient for the return difference variable indicates that non-life insurers react procyclically to common market movements. If the return on equity is lower (higher) than fixed income, non-life insurers decrease (increase) their equity investments by selling relatively more equities than other (fixed income) assets. Moreover, in this specification, the coefficient for the solvency position is positive and significant, as expected.

Columns 3 and 4 show the regression output for life insurance companies. The results are similar to the results for non-life insurers. However, the coefficient for the return difference variable is somewhat lower than for non-life insurers. Hence, also for life insurance companies we do find some evidence for procyclical behaviour.

The results for pension funds are reported in columns 5 and 6. None of the variables show a significant coefficient. As stated before, there is a large variance in size among the pension funds in our sample, and these unweighted regressions assume equal informational value to each observation of a pension fund, irrespective of its size. Therefore, we also run regressions where we weigh each institution (insurer or pension fund) according to its size as measured by its total assets. Such weighted regressions yield results that are more in line with economic reality.

Table 5.4.2: Baseline regression model (unweighted)

This table shows the baseline regression results from equation (1) over the period 2006Q1-2015Q4 for non-life insurers, life insurers and pension funds separately. The dependent variable is an institution's relative transaction difference, i.e. the net sales/purchases of equities in time *t* divided by the total equity holdings at time *t-1* minus the net sales/purchases of fixed income investments in time *t* divided by the total fixed income investments at time *t-1*. Standard errors are clustered at the institution level, and reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	Non-life insurers		Life insurers		Pension funds	
	(1)	(2)	(3)	(4)	(5)	(6)
Return difference (-1)	0.202	0.271**	0.082	0.117**	-0.076	-0.063
	(0.132)	(0.118)	(0.072)	(0.039)	(0.056)	(0.042)
Relative transaction difference(-1)	0.168**	0.190**	0.172***	0.169**	-0.017	-0.031
	(0.073)	(0.064)	(0.047)	(0.071)	(0.045)	(0.044)
Solvency (-1)	-0.000	0.006***	0.043**	0.030**	0.041	0.008
	(0.006)	(0.002)	(0.012)	(0.010)	(0.034)	(0.022)
Strategic dummy (-1)					0.015	0.016
					(0.012)	(0.010)
# Obs.	232	232	284	284	1,073	1,073
R^2	25.4%	12.7%	24.6%	8.1%	7.8%	2.6%
R^2 adj.	4.8%	7.9%	9.2%	4.8%	1.4%	0.0%
Time FE	Yes	No	Yes	No	Yes	No
Institution FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5.4.3 shows the weighted regression results. For pension funds, the results in columns 5 and 6 show that the coefficient for the return difference variable remains insignificant. However, the explanatory power of the model improves somewhat, and the coefficients for the strategic dummy variable are now positive and significant. This is in line with our expectation that pension funds with an equity allocation that is below its strategic level will increase their equities relative to fixed income. This is also a slight indication for countercyclical investment behaviour. The weighted regression results reveal that the buying and selling behaviour of pension funds can be better explained by the larger pension funds. Moreover, the significant coefficient for the strategic dummy in these weighted regressions implies that only the larger pension funds rebalance in line with their strategic allocations.

The evidence for procyclical behaviour by non-life insurance companies is even more confirmed by the weighted regression results. Both specifications, with and without time fixed effects, show a significantly positive coefficient for the return difference variable. For life insurers, the return difference variable is not significant anymore, indicating that probably mainly the smaller life insurance companies invest in a more procylical way.

Table 5.4.3: Baseline regression model (weighted)

This table shows the baseline regression results from equation (1) over the period 2006Q1-2015Q4 for non-life insurers, life insurers and pension funds separately. The size of an institution in assets determines the weight in the regression model. The dependent variable is an institution's relative transaction difference, i.e. the net sales/purchases of equities in time *t* divided by the total equity holdings at time *t-1* minus the net sales/purchases of fixed income investments in time *t* divided by the total fixed income investments at time *t-1*. Standard errors are clustered at the institution level, and reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	Non-life insurers		Life insurers		Pension funds	
	(1)	(2)	(3)	(4)	(5)	(6)
Return difference (-1)	0.276**	0.358**	0.002	0.093	-0.089	-0.207
	(0.107)	(0.146)	(0.071)	(0.060)	(0.087)	(0.132)
Relative transaction difference(-1)	0.163***	0.202***	0.150*	0.137	0.009	-0.001
	(0.042)	(0.040)	(0.069)	(0.077)	(0.029)	(0.027)
Solvency (-1)	-0.005	0.007***	0.052***	0.040**	0.006	-0.013
	(0.008)	(0.001)	(0.010)	(0.014)	(0.084)	(0.029)
Strategic dummy (-1)					0.033***	0.029***
					(0.010)	(0.010)
# Obs.	232	232	284	284	1,073	1,073
R^2	26.5%	10.8%	31.3%	8.5%	26.6%	3.5%
R^2 adj.	6.2%	5.9%	17.2%	5.1%	21.5%	0.5%
Time FE	Yes	No	Yes	No	Yes	No
Institution FE	Yes	Yes	Yes	Yes	Yes	Yes

To conclude, we do find an indication for procyclical investment behaviour by insurance companies, while for pension funds we find that mainly the larger pension funds apply rebalancing to bring back their equity allocation to their strategic level. However, we do not find any direct response in their investment behaviour stemming from return differences between equities and fixed income. At least, we do not find evidence for pension funds behaving procyclical The larger coefficients for non-life insurers compared to life insurers are an indication for our second hypothesis that non-life insurers react more procyclically to market circumstances than life insurers. Lastly, the fact that insurers respond to common market shocks, may indicate that equity market movements could trigger herding behaviour.[54]

In the paper we only show the results of the regression model including a one-quarter lag of the return difference. We have also tested the robustness of the results under different specifications of the return difference variable. Hence, we did estimate the regressions using two-quarter lags, four-quarter lags and up to four lags of the return difference variable. The results (not shown here) confirm procyclical behaviour by both non-life and life insurers, as all significant coefficients for the return difference variable have a positive sign. Moreover, for pension funds we find significantly negative coefficients for the second and fourth lag, indicating countercyclical behaviour.

Table 5.4.4 shows the outcomes from the asymmetric regression equation (2). For non-life insurers, the positive and significant coefficients in columns 2 and 4 reveal that non-life insurers show stronger procyclical investment behaviour during market downturns, i.e. during the global financial crisis and when equity underperformed fixed income investments. However, the difference between the coefficients for crisis versus non-crisis periods, and periods of equity outperformance versus equity underperformance is not significant. The solvency variable shows the expected and positive significant coefficient. In line with the baseline regression results, no significant results can be found for the regression specifications including time fixed effects. When the weighted regression results in Table 5.4.5 are considered the results are quite similar, except that – and similar to the baseline specifications – the coefficients for the

[54] Herding behaviour occurs if institutions unintentionally have similar investment strategies. See for example Scharfstein and Stein (1990), or more recently Broeders et al. (2016) for a study on herding behavior by pension funds.

return difference variable in the model including time fixed effects become statistically significant. In contrast to the unweighted regression results, the weighted regression results in column 3 now point to procyclical behaviour during non-crisis times (and not during crisis periods), as indicated by the slightly significant coefficient.

Regarding life insurers, the results in Table 5.4.4 suggest that life insurers' procyclical investment behaviour is stronger when equities outperform other assets. In contrast to the results for non-life insurers, when equities perform well, life insurers tend to increase their equity holdings relative to fixed income. Moreover, the difference between the coefficients for equity underperformance and equity outperformance is statistically significant. We do however not find evidence for stronger reactions to price movements during crisis periods and the coefficients in column 8 are just not significant anymore. The weighted regression results in Table 5.4.5 are in line with the unweighted results for life insurers.

For pension funds, the results in columns 10 and 12 of Table 5.4.4 now show some evidence for countercyclical behaviour by pension funds. The significantly negative coefficients indicate that pension funds invest contrary to price movements during non-crisis periods and when equities outperform fixed income investments. However, no significant results can be found in the model without time fixed effects, i.e. columns 9 and 11. Moreover, the strategic dummy is only significantly positive in column 10. The weighted regression results in columns 10 and 12 of Table 5.4.5 confirm the finding of countercyclical investment behaviour by pension funds during market upturns. Moreover, - and in line with the weighted regression results from the baseline specification - the strategic dummy variable is high significant across all specifications.

Table 5.4.4: Asymmetric regression model (unweighted)

This table shows the baseline regression results from equation (2) over the period 2006Q1-2015Q4 for non-life insurers, life insurers and pension funds separately. The dependent variable is an institution's relative transaction difference, i.e. the net sales/purchases of equities in time *t* divided by the total equity holdings at time *t-1* minus the net sales/purchases of fixed income investments in time *t* divided by the total fixed income investments at time *t-1*. Standard errors are clustered at the institution level, and reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	Non-life insurers				Life insurers				Pension funds			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Performance dummies		*Crisis dummies*		*Performance dummies*		*Crisis dummies*		*Performance dummies*		*Crisis dummies*	
Return difference (-1) *crisis(-1)			0.582	0.838***			0.102	0.131			-0.037	-0.038
			(1.188)	(0.232)			(0.097)	(0.101)			(0.204)	(0.114)
Return difference (-1) *no crisis(-1)			0.182	0.130			0.074	0.110			-0.078	-0.069*
			(0.129)	(0.104)			(0.082)	(0.084)			(0.059)	(0.040)
Return difference(-1) * equity underperf. (-1)	0.267	0.395***			0.037	-0.018			-0.051	-0.021		
	(0.166)	(0.134)			(0.071)	(0.075)			(0.061)	(0.052)		
Return difference(-1) * equity outperform.(-1)	0.095	0.076			0.222	0.375**			-0.259	-0.202*		
	(0.387)	(0.241)			(0.157)	(0.142)			(0.220)	(0.117)		
Relative transaction difference(-1)	0.167**	0.185**	0.169**	0.165**	0.164**	0.151**	0.173**	0.170***	-0.016	-0.029	-0.016	-0.031
	(0.082)	(0.071)	(0.080)	(0.072)	(0.068)	(0.062)	(0.068)	(0.060)	(0.044)	(0.044)	(0.045)	(0.044)
Solvency (-1)	0.000	0.005	0.000	0.006	0.042*	0.033**	0.043*	0.029**	0.039	-0.003	0.042	0.009
	(0.010)	(0.007)	(0.010)	(0.007)	(0.022)	(0.014)	(0.021)	(0.013)	(0.035)	(0.023)	(0.034)	(0.022)
Strategic dummy (-1)									0.016	0.018*	0.015	0.016
									(0.012)	(0.010)	(0.012)	(0.010)
# Obs.	232	232	232	232	284	284	284	284	1,073	1,073	1,073	1,073
R^2	25.3%	13.0%	25.5%	14.3%	24.9%	9.2%	24.6%	8.1%	7.8%	2.8%	7.8%	2.6%
R^2 adj.	4.1%	7.7%	4.4%	9.2%	9.1%	5.4%	8.8%	4.4%	1.2%	0.0%	1.3%	0.0%
Time FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P(Equality of coefficients)	0.609	0.316	0.665	0.166	0.343	0.054*	0.875	0.892	0.386	0.202	0.851	0.789

Table 5.4.5 Asymmetric regression model (weighted)

This table shows the baseline regression results from equation (2) over the period 2006Q1-2015Q4 for non-life insurers, life insurers and pension funds separately. The size of an institution in assets determines the weight in the regression model. The dependent variable is an institution's relative transaction difference, i.e. the net sales/purchases of equities in time *t* divided by the total equity holdings at time *t-1* minus the net sales/purchases of fixed income investments in time *t* divided by the total fixed income investments at time *t-1*. Standard errors are clustered at the institution level, and reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% levels.

	Non-life insurers				Life insurers				Pension funds			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Performance dummies		*Crisis dummies*		*Performance dummies*		*Crisis dummies*		*Performance dummies*		*Crisis dummies*	
Return difference (-1) *crisis(-1)			0.969	0.884**			-0.046	0.165			-0.842	-0.593
			(0.757)	(0.372)			(0.163)	(0.146)			(0.501)	(0.357)
Return difference (-1) *no crisis(-1)			0.233*	0.180			0.013	0.075			-0.065	-0.090*
			(0.118)	(0.117)			(0.087)	(0.067)			(0.089)	(0.052)
Return difference(-1) * equity underperf. (-1)	0.427*	0.542**			-0.027	-0.021			-0.087	-0.057		
	(0.211)	(0.230)			(0.054)	(0.067)			(0.075)	(0.104)		
Return difference(-1) * equity outperform.(-1)	0.087	0.103			0.205	0.376**			-0.093	-0.638***		
	(0.179)	(0.120)			(0.218)	(0.127)			(0.467)	(0.203)		
Relative transaction difference(-1)	0.163***	0.200***	0.163***	0.183***	0.146*	0.123	0.148*	0.139	0.009	0.014	0.003	0.008
	(0.041)	(0.042)	(0.042)	(0.044)	(0.066)	(0.081)	(0.065)	(0.075)	(0.035)	(0.026)	(0.029)	(0.019)
Solvency (-1)	-0.005	0.006***	-0.005	0.006***	0.050***	0.043**	0.052***	0.039**	-0.001	-0.035	0.001	-0.026
	(0.008)	(0.001)	(0.008)	(0.001)	(0.011)	(0.015)	(0.010)	(0.013)	(0.089)	(0.031)	(0.084)	(0.035)
Strategic dummy (-1)									0.035***	0.033***	0.033***	0.028***
									(0.011)	(0.011)	(0.010)	(0.010)
# Obs.	232	232	232	232	284	284	284	284	1,073	1,073	1,073	1,073
R^2	26.6%	11.3%	26.8%	12.4%	31.5%	9.5%	31.3%	8.6%	26.6%	4.6%	26.9%	5.3%
R^2 adj.	5.8%	5.9%	6.1%	7.2%	17.0%	5.7%	16.9%	4.9%	21.4%	1.5%	21.7%	2.2%
Time FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P(Equality of coefficients)	0.362	0.205	0.369	0.102	0.226	0.061*	0.774	0.626	0.989	0.001*	0.127	0.154

5.5 Conclusion and policy implications

With large amounts of assets under management, insurance companies and pension funds can either amplify or stabilise market movements. Our analysis shows evidence for procyclical investment behaviour by insurance companies, both life and non-life insurers. Non-life insurers show stronger procyclical behaviour during the global financial crisis and during periods in which equities underperformed other assets. Contrary, life insurers show stronger procyclical behaviour during periods when equities outperformed fixed income investments. For pension funds, we do find some evidence for countercyclical behaviour, but only in non-crisis periods and when equity outperforms fixed income investments (i.e. market upturns). The nature of the business models can explain the different findings. In general, insurance companies may face more (regulatory) pressure on their business model in market downturns, and non-life insurers have a higher demand for liquid assets due to their shorter maturity of their liabilities.

Procyclical investment behaviour could be harmful for the stability of the financial system, meaning that there could be a role for policy. Since the global financial crisis, policy measures are even more focussed on improving the resilience of the overall financial system. This holds particularly for the banking sector, for which a macroprudential framework has been established. Expanding this framework beyond the banking sector is currently an important topic on the agenda of international policy makers.

In this context, policy makers may also want to focus on discouraging procyclical investments by large institutional investors. In doing so, there has to be a well-balanced trade-off between macro and microprudential objectives. From a macro perspective, for example, the system benefits from regulatory flexibility in times of stress, since it enables countercyclical investment behaviour. However, this may not desirable from a micro perspective, particularly not if institutions are coping with solvency problems. For some elements of regulation, the macro micro trade-off is easier to make than for others. While mark-to-market valuation forces institutions to be more concerned with short-term market movements, it is an important condition for proper risk management. Therefore, the alternative of having no mark-to-market valuation could be worse.

One measure that could be desirable from both a macro and micro perspective is the building up of extra buffers during good times which can be drawn down to withstand shocks during bad times. This measure has already been implemented for the banking sector (countercyclical buffer and conservation buffer), and could be extended to other sectors, as it increases an institution's capacity to act as a shock absorber in times of stress. Hence, this topic could be further explored in current policy discussions on improving the resilience of both institutions and the overall financial system.

Samenvatting (summary in Dutch)

De titel van dit proefschrift is "Over natuurlijke cycli in de financiële wereld; de rol en impact van financiële instellingen". Een cyclisch patroon kenmerkt zich door een periode van sterke economische groei (de '*boom*'), gevolgd door een krimp, die in een extreem geval kan uitmonden in een recessie (de ' *bust*'). Over het bestaan van zulke *boom-bust* patronen in de financiële wereld is er consensus; deze hebben we gezien in bijvoorbeeld de aandelen-, krediet- en huizenmarkt. De cycli in verschillende markten hangen bovendien vaak met elkaar samen; zo zijn cycli in de krediet- en huizenmarkt sterk met elkaar gecorreleerd (Claessens et al., 2011a). Daarbij is er ook een samenhang met de algemene conjunctuurcyclus (Claessens et al., 2011b). Een periode van economische neergang- veelal uitgedrukt in het BBP van een land – wordt versterkt door een verstoring in financiële markten, en vice versa. Dit hebben we bijvoorbeeld gezien in de afgelopen financiële crisis van 2007-2009.

Over de oorzaak van deze cycli is echter beduidend minder overeenstemming. Zo zijn er stromingen die neergangen toeschrijven aan exogene schokken (zie voor een overzicht; Zarnowitz, 1985; 1999). In toenemende mate, en vooral na de financiële crisis van 2007-2009, is er aandacht voor endogeniteit. Deze gedachte vindt zijn oorsprong in de theorie van Minsky (1977). Financiële instabiliteit wordt niet gedreven door exogene schokken, maar is het gevolg van een onevenwichtige economische expansie en (te) hoge kredietgroei. Met andere woorden; het financiële systeem zelf creëert bubbels, die op termijn onhoudbaar zijn en zullen knappen. Een soort natuurlijk terugkerend fenomeen.

Tekenend daarbij is dat in perioden waarin een lage-risico omgeving wordt verondersteld ("want alles gaat goed") juist nieuwe risico's worden opgebouwd. Ook over de financiële crisis van 2007-2009 kan worden gezegd dat deze – in ieder geval grotendeels – zijn oorsprong had in de financiële sector.

Dit proefschrift onderzoekt de rol van en de impact voor verschillende financiële instellingen bij deze cyclische patronen. De endogeniteitstheorie impliceert dat financiële instellingen – als belangrijk onderdeel van het financiële systeem - namelijk ook bijdragen aan deze cycli. Anderzijds hebben dergelijke cyclische patronen, met name in het extreme geval van crises, niet alleen grote gevolgen voor de economie en huishoudens en bedrijven, maar zijn financiële instellingen ook onderhevig aan deze cycli. En in dit proefschrift wordt ook onderzocht of financiële instellingen ook juist niet baat kunnen hebben bij het bestaan van cycli. Hieronder worden per hoofdstuk de bevindingen beschreven.

Hoofdstuk 2 focust specifiek op de kredietcyclus. Zoals hierboven gesteld voedt een forse opbouw van krediet een onevenwichtige groei. Dit hoofdstuk gaat in op hoe een dergelijke kredietcyclus - met een *boom* en *bust* in het krediet - tot stand komt, en kijkt specifiek naar de rol van buitenlands gefinancierd krediet. Banken in een land zijn in zekere mate gelimiteerd in het verstrekken van krediet. In een simpel voorbeeld kan er niet meer krediet worden verstrekt dan een bank aan spaargelden op de balans heeft staan. Dat er binnen een land toch meer krediet kan worden verleend dan de som van het totale spaargeld in een land, komt enerzijds door het bestaan van buitenlandse banken. Buitenlandse banken kunnen hun buitenlandse spaargelden gebruiken om elders – ongeacht of zij zich in dat land vestigen of niet – krediet te financieren. Een andere reden waardoor het totale krediet in een land groter kan zijn dan de som van binnenlandse spaargelden is doordat banken zelf geld lenen bij andere buitenlandse banken. Banken zijn dan actief op de zogeheten interbancaire markt. Het geld dat zij daar lenen kan worden omgezet in krediet binnen hun land. We spreken dus van buitenlands gefinancierd krediet in een land als dat krediet met buitenlandse gelden wordt gefinancierd. Buitenlands gefinancierd krediet is niet hetzelfde als krediet van een buitenlandse bank. Krediet van een buitenlandse bank dat is gefinancierd met spaargelden binnen het land waar het krediet wordt uitgezet, is geen binnenlands gefinancierd krediet (het is immers gefinancierd met binnenlandse spaargelden).

Veel studies focussen op de rol van het krediet van buitenlandse banken in de kredietcyclus (zie bijvoorbeeld Crystal et al., 2001; de Haas and van Lelyveld, 2006). In hoofdstuk 2 ligt de focus op buitenlands gefinancierd krediet, omdat wordt verondersteld dat juist dit type krediet kwetsbaarheden meebrengt. Immers, in een situatie waarin de totale schulden (krediet) van huishoudens en bedrijven in een land groter zijn dan de spaargelden is er een grote schuldlast, hetgeen zorgt voor kwetsbaarheden in economisch mindere tijden. Daarbij wordt ook verondersteld dat juist het buitenlands gefinancierd krediet het cyclische patroon in krediet versterkt. Naast dat het groeipotentieel van buitenlands gefinancierd krediet in een *boom* minder gelimiteerd is, doordat deze niet afhankelijk is van de beschikbare spaargelden, kan de interbancaire geldmarkt – en daarmee een financieringsbron van buitenlands gefinancierd krediet - in een *bust* opdrogen. Dit versterkt de cyclus. Een aantal recente studies van de *Bank for International Settlements* (zie bijvoorbeeld Borio et al. (2011), Avdjiev et al. (2012); Ehlers and McGuire (2017)) focust op buitenlands gefinancierd krediet, en suggereert dat dit type krediet een grote rol speelt bij het verklaren van de hoge kredietgroei in de jaren voorafgaand aan de financiële crisis van 2007-2009.

Middels het analyseren van kredietcycli in 41 verschillende landen over de periode 1985k1-2015q4 onderzoekt dit hoofdstuk of buitenlands gefinancierd krediet een rol speelt in *booms* en *busts* in krediet. De resultaten in hoofdstuk 2 suggereren dat buitenlands gefinancierd krediet inderdaad een rol speelt in *booms* in krediet. Een *boom* wordt namelijk geassocieerd met een stijging in de hoeveelheid buitenlands gefinancierd krediet als onderdeel van het totale krediet. Opmerkelijk is dat de periode kort vóór de *boom* juist wordt gekenmerkt door een stijging in het binnenlands gefinancierde krediet. Dit suggereert dat vóór de boom binnenlands gefinancierd krediet in een groeiende kredietbehoefte kon voorzien, maar dat door een grote en aanhoudende vraag naar krediet tijdens een *boom* buitenlands gefinancierd krediet nodig was. De resultaten duiden niet op een verband tussen het buitenlands gefinancierde krediet en het bestaan van *busts* in krediet.

De resultaten uit Hoofdstuk 2 raken aan beleidsdiscussies over globalisatie. De laatste decennia is liberalisatie de trend geweest, en dit heeft geleidt tot een toenemende mate van globalisering in de financiële wereld. Globalisatie biedt zeker voordelen, zoals groeikansen voor opkomende markten en meer financieringsmogelijkheden (toegang tot buitenlands gefinancierd krediet). Hoofdstuk 2 laat echter zien dat globalisatie, en een grotere afhankelijkheid van buitenlandse financiering, ook kan bijdragen aan *boom-bust cycles* in krediet. Daarbij heeft globalisatie als gevolg dat economieën steeds meer verweven raken;

booms en *busts* vinden dan op dezelfde momenten plaats. Dit bleek ook uit Hoofdstuk 2. Dit geldt niet alleen voor de kredietcyclus. Ook de samenhang in conjunctuurcycli tussen landen is in de afgelopen jaren van globalisatie alleen maar sterker geworden (Claessens et al., 2011a). Toch is die samenhang – ofwel correlatie – tussen landen nooit helemaal perfect. En die niet perfectie correlatie in cycli tussen landen biedt juist perspectieven voor het verlagen van risico's door geografische diversificatie; daarover gaat Hoofdstuk 3.

In het algemeen kan diversificatie leiden tot een daling van risico's (Markowitz, 1952); het bekende "niet op één paard wedden" gaat hier op. Hoofdstuk 3 veronderstelt dat banken hun risico's kunnen verkleinen, en hun risico-rendementsprofiel kunnen verbeteren, door geografische diversificatie. Ofwel, door hun activiteiten niet te beperken tot één land. Een belangrijke voorwaarde hierbij is dat er een niet-perfecte correlatie moet bestaan in de economische omstandigheden tussen de landen waar de bank actief is (Levy and Sarnat, 1970). In het meest extreme geval; een bank die zich in twee landen vestigt, zal er baat bij hebben als deze landen niet tegelijk een crisis meemaken. De bank kan in dat geval financiële klappen als gevolg van een crisis in het ene land compenseren met een blijvende stroom aan inkomsten uit het andere land.

Hoofdstuk 3 onderzoekt of geografische diversificatie positief uitpakt voor het risico-rendementsprofiel van een bank. De resultaten suggereren dat banken hun risico kunnen verlagen door hun activiteiten geografisch te spreiden. Het hoofdstuk laat verder zien dat de positieve effecten van geografische diversificatie hoger zijn als banken zich vestigen in landen met een economische cyclus die afwijkt van die van het thuisland van de bank. Uit het onderzoek komt echter geen bewijs dat geografische diversificatie ook het rendement van een bank kan verhogen. Hoofdstuk 3 gaat ook na of banken ook daadwerkelijk op deze wijze hun risico's diversifiëren door actief te zijn in landen met verschillende economische omstandigheden. De resultaten suggereren echter dat banken voornamelijk actief zijn in landen die in economisch opzicht juist lijken op hun thuisland. Dit impliceert dat landen dus niet volledig gebruik maken van de risico-reducerende voordelen die geografische diversificatie biedt.

Zoals gezegd leidt globalisering tot meer verwevenheden tussen banken en economieën. De financiële crisis van 2007-2009 heeft laten zien dat een te grote verwevenheid tot problemen kan leiden op het moment dat het vertrouwen van instellingen in elkaar wegvalt. Toen bleek namelijk dat de interbancaire geldmarkt in mindere tijden een onzekere bron van financiering is. Onder andere doordat het vertrouwen in deze markt wegviel, en banken elkaar geen geld meer wilden lenen, kwamen banken in liquiditeitsproblemen. In reactie hierop is er in 2015 – met de introductie van het nieuwe regelgevend kader Bazel III – liquiditeitsregelgeving geïntroduceerd. In Nederland is vergelijkbare liquiditeitsregelgeving op nationaal niveau al eerder, in 2003, ingevoerd. Een belangrijk onderdeel van deze regelgeving is dat banken zich moeten houden aan een liquiditeitsratio. Dit impliceert dat banken tegenover hun liquide verplichtingen voldoende liquide activa dienen aan te houden. Hoofdstuk 4 onderzoekt op basis van de Nederlandse data de impact van liquiditeitsregelgeving voor individuele banken, en gaat na wat de rol van liquiditeitsregelgeving over de kredietcyclus en gedurende de financiële crisis van 2007-2009 was.

Terwijl veel studies ervan uit gaan dat banken die in liquiditeitsproblemen komen aanpassingen doen in hun activa (Berrospide, 2012; De Haan and van den End, 2013a and 2013b), maakt Hoofdstuk 4 geen gebruik van deze veronderstelling. De bevindingen uit Hoofdstuk 4 laten allereerst zien dat banken ingeval van een negatieve schok in hun liquiditeitsratio, allereerst hun liquide verplichtingen (passiva) aanpassen. Dit suggereert dat banken hun (liquide en meer instabiele) interbancaire financiering inruilen voor meer stabielere spaargelden. Op microniveau – het niveau van een bank - kan dus worden gezegd dat de liquiditeitsregels 'werken'; bij een negatieve schok in hun liquiditeitsratio worden banken getriggerd actie te ondernemen.

Op macroniveau – als wordt gekeken naar het totaal van liquide activa en passiva van alle banken – is er echter een procyclisch patroon in liquiditeit zichtbaar. De resultaten wijzen op een grote toename in liquiditeit vóór de financiële crisis van 2007-2009, en op een forse afname daarna. De resultaten wijzen er ook op dat deze liquiditeitscyclus sterk samenhangt met de *leverage* cyclus, in lijn met de bevindingen van Adrian and Shin (2010) voor de US. Deze cycli kenmerken zich door een toenemend gebruik van de interbancaire geldmarkt (met name gedekte marktfinanciering) door banken in economisch goede tijden. Het geld dat zij hier ophalen wordt geïnvesteerd in liquide activa, waarmee in betere tijden relatief hoge winsten - maar tegen een hoog risico - kunnen worden behaald. In de periode waarin lage risico's worden verondersteld worden nu nieuwe (liquiditeit)risico's genomen en opgebouwd. En in economisch mindere tijden wordt de liquiditeit in hetzelfde rappe tempo afgebouwd. Dit procyclische patroon in liquiditeit impliceert ook dat de liquiditeitsbuffers van banken het laagst zijn in de periode waarin deze juist het hardst nodig zijn.

De liquiditeitscyclus, met het massaal aan- en verkopen van liquide activa in respectievelijk goede en slechte tijden, heeft ook gevolgen voor de financiële markten. Als alle banken op hetzelfde moment van hun (liquide) activa af moeten, dan heeft dit gevolgen voor de prijzen van aandelen en obligaties. De liquiditeitscyclus kan dan de financiële markt cyclus beïnvloeden.

Hoofdstuk 5 focust op de financiële markt cyclus en onderzoekt de rol van pensioenfondsen en verzekeraars hierin. Pensioenfondsen en verzekeraars beheren voor hun klanten – pensioendeelnemers en polishouders – een behoorlijke bulk geld. In Nederland is hun vermogen goed voor respectievelijk 185% en 71% van het BBP. Het vermogen dat zij beheren wordt grotendeels geïnvesteerd in aandelen en obligaties, en daarmee zijn pensioenfondsen en verzekeraars grote spelers op de financiële markten. Hun beleggingsgedrag kan de financiële markt zodoende beïnvloeden. In theorie wordt gesteld dat het beleggingsgedrag van pensioenfondsen en verzekeraars een stabiele werking heeft op de markt. Dit komt doordat zij aan '*rebalancing*' doen. Zij kopen activa die laaggeprijsd zijn, en verkopen activa die hooggeprijsd zijn. Door deze '*buy low, sell high*' strategie blijft de activa-allocatie in stand. Deze *rebalancing* strategie kan een stabiliserende werking hebben op de markt doordat deze contra-cyclisch is; '*buy low, sell high*' impliceert namelijk dat pensioenfondsen en verzekeraars doorgaan met het kopen van activa tijdens economisch mindere tijden, en vice versa.

Doordat zij door hun bedrijfsmodel een lange-termijn visie hebben, zijn zij – minder dan andere partijen, zoals banken – ook minder genoodzaakt om op korte termijn te activa verkopen.

Door het beleggingsgedrag in aandelen van Nederlandse pensioenfondsen en verzekeraars over de periode 2006-2015 te analyseren, wordt onderzocht of deze partijen tijdens de periode rondom de financiële crisis van 2007-2009 daadwerkelijk een contra-cyclische werking hadden op de aandelenmarkt. Voor pensioenfondsen duiden de resultaten inderdaad op contra-cyclisch beleggingsgedrag. De resultaten suggereren echter dat verzekeraars, zowel levensverzekeraars alsook niet-levensverzekeraars, procyclisch hebben belegd. De verschillen in beleggingsgedrag tussen verzekeraars enerzijds en pensioenfondsen anderzijds kunnen worden verklaard door verschillen in hun bedrijfsmodel en het regelgevend kader. Pensioenfondsen hebben simpelweg meer herstelmogelijkheden; zij kunnen de pensioenpremies verhogen, afzien van indexatie, en – in het meest verregaande geval – korten. Verzekeraars hebben deze mogelijkheden niet, en zijn daardoor eerder genoodzaakt om over te gaan tot de verkoop van activa, waaronder aandelen, in economisch mindere tijden. Het procyclische beleggingsgedrag door deze partijen versterkt de cyclus in aandelenprijzen, en dit pakt op macroniveau ongunstig uit.

Summary

The title of this dissertation is “On the cyclical nature in finance; the role and impact of financial institutions”. A cyclical pattern is characterised by a period of strong economic expansion (‘boom’), followed by a period of detraction, that can even result in a recession (‘bust’). We have seen these boom-bust patterns in, for example, the equity, credit and housing market. Financial cycles in different markets are often synchronised; strong interlinkages exist between, for example, credit and housing market cycles (Claessens et al., 2011a). And financial cycles are also found to have a relation with the business cycle (Claessens et al., 2011b). A period of economic downturn –measured by a country’s GDP – intensifies financial market disruptions, and vice versa. We have observed this during the recent global financial crisis of 2007-2009.

There is however less consensus on the underlying causes of certain cycles. Some theories point to exogenous factors as an important driver of downturns (Zarnowitz, 1985;1999). Especially since the global financial crisis of 2007-2009, there is an increasing attention for endogeneity. The principle of endogeneity actually goes back to Minsky (1977). Following his ‘financial instability theory’, financial fluctuations are not the result of exogenous shocks, but rather the consequence of unsustainable economic expansion and growing indebtedness. Put it differently; the financial system itself creates bubbles, which will result in unsustainable situations, and, ultimately, the bubble will burst. In that sense, we can speak of a kind of natural phenomenon. During periods that are perceived to be less risky (“because everything goes so well”) risks are

built up. The global financial crisis of 2007-2009 is also seen as an event that - at least partially - originated within the financial system.

This dissertation investigates the role and impact of financial institutions over the financial cycle. The theory of endogeneity implies that financial institutions – as major players within the financial system – also contribute to the cyclicality in the system. And such cyclical patterns, especially in the extreme case of a crisis, do not only have large consequences for the economy, and households and businesses, but financial institutions will also be impacted by these. Not only in a negative way. This dissertation, for example, also analyses whether financial institutions can benefit from non-perfectly synchronised cycles. Below, I will summarise the individual chapters.

Chapter 2 focuses on the credit cycle, and investigates how such a cycle – with a boom and a bust in credit – originates. Thereby, it focuses specifically on the role of foreign funded credit. Banks in a country are more or less limited in the amount of credit they can grant to households and businesses. In a very simplified manner: banks cannot grant more credit than they hold deposits. Within a country, the total credit can however exceed the total amount of domestic deposits held at banks. On the one hand, this is the result of foreign banks being active in the country. Foreign banks can use their (foreign) deposits to lend money elsewhere, irrespective of whether they settle in that country or not. Yet another reason why the total amount of credit in a country may exceed the total amount of domestic deposits is the usage of interbank credit by banks. Besides collecting deposits, banks can obtain funding from other banks via the interbank market. The money they borrow from the interbank market will be converted into domestic credit. Foreign funded credit is thus defined as the credit in a country that is funded with foreign money. Do note that foreign funded credit is not exactly similar to credit from foreign banks. Credit from foreign banks that is funded by domestic deposits does not belong to foreign funded credit, as it simply is domestically funded.

Many studies focus on the role of credit from foreign banks in the credit cycle (see, for example, Crystal et al., 2001; de Haas and van Lelyveld, 2006). Chapter 2 focuses on foreign funded credit, because it is assumed that especially this type of credit may create vulnerabilities. A situation in which the total debt (credit) to households and corporations is larger than their total deposits implies a higher indebtedness of these parties, resulting in increased vulnerabilities during economic reversals. It is also assumed that foreign funded credit is potentially more procyclical. During a boom, the growth potential of foreign funded credit is higher than domestically funded credit since it is less restricted by, for example, the domestic deposit base. During a bust, however, foreign funded credit may decline at the same high speed since the interbank market, an important funding base of foreign funded credit, may dry up. A couple of recent studies by the Bank for International Settlements (see, for example, Borio et al. (2011); Avdjiev et al. (2012) and Ehlers and McQuire (2017)) focus on foreign funded credit, and suggest that especially this type of credit contributed to the high credit growth during the years preceding the global financial crisis of 2007-2009.

By analysing credit cycles in 41 countries over the period 1985q1-2015q4, this chapter investigates if foreign funded credit plays a role in booms and bust in credit. The results suggest that it does so in the case of credit booms, since these are associated with an increase in foreign funded credit relative to domestically funded credit. This relationship is found for cycles in both emerging and developed economies and for business as well as for household credit cycles. Interestingly, the period preceding a boom is characterised by an increase in domestically funded credit, relative to foreign funded credit. This suggests that before the boom domestically funded credit is able to fulfil the increased demand for credit, but that the large and ongoing credit needs cause a substitution of domestic credit by foreign funded credit. The results do not suggest any relation between foreign funded credit and credit busts.

The results of Chapter 2 contributes to policy discussion on globalisation. Over the last decennia there has been a trend towards liberalisation, and this has led to increased financial globalization. Globalisation provides opportunities, such as growth opportunities for emerging countries and access to new funding sources, for example via foreign funded credit. Chapter 2 however also shows that globalisation, via an increased reliance on foreign funded credit, may contribute to boom-bust cycles in credit. Globalisation also leads to more synchronized economies; as a consequence booms and busts in different countries occur more and more simultaneously. This was also shown in Chapter 2. This is not only the case for the credit cycle. Also business cycles have become more synchronized across countries as a consequence of ongoing globalization (Claessens et al., 2011a). Business cycles are however never perfectly synchronized or correlated. This non-perfect correlation in cycles offers opportunities for risk diversification by banks. This is what Chapter 3 is about.

In general, diversification has the potential to reduce risk (Markowitz, 1952). It is about spreading risks ("don't put all your eggs in one basket"). Chapter 3 assumes that banks can reduce their risk, and improve their risk-return profile, by geographical diversification. In other words, banks should not limit their activities to one country. An important condition is the existence of a non-perfect correlation in economic conditions in countries in which the bank conduct business (Levy and Sarnat, 1970). In the most extreme case; a bank that is active in two countries will benefit in case these countries will not experience economic difficulties at the same time. In that case, the bank can compensate financial difficulties in one country by ongoing business in the other country.

Chapter 3 first analyzes whether geographical diversification is beneficial. The results show that geographical diversification by banks can reduce their risk and even more so if banks diversify into countries with an economic cycle that differs from the one of their home country. The results do however not point to any relation between geographical diversification and increased returns. Chapter 3 also investigates whether banks do actually diversify into economically dissimilar countries. The results however suggest that banks mainly invest in countries that are more similar to their home country. Banks do thus not fully utilise the diversification opportunities.

Globalisation does not only results in more synchronized economies, but also leads to increased interconnectedness within the financial system and between financial institutions. The financial crisis of 2007-2009 has shown that the latter can lead to contagion risks in stressed markets. The interbank market turned out to be a less stable source of funding, causing liquidity problems at multiple institutions at the same time. During times of decreased market confidence, as a result of increasing losses in the subprime mortgage market in 2007, the trust of banks in one another dropped. Banks were less willing to lend money to each other, the interbank market dried up and as a consequence, banks were facing liquidity issues. In response to what happened, the new regulatory framework Basel III – that was implemented in 2015 – also introduced liquidity regulation. In the Netherlands a very similar form of liquidity regulation was already introduced at the national level in 2003. An important element of this regulation is that banks have to meet a liquidity coverage ratio. This implies that banks should hold sufficient liquid assets against their short-term (liquid) liabilities. Based on data on Dutch banks, Chapter 4 investigates the impact of liquidity regulation on individual bank balance sheets, and analyses the role of liquidity regulation over the credit cycle, covering the global financial crisis of 2007-2009.

While many studies implicitly assume that banks that are facing liquidity issues will adjust their (liquid) assets (Berrospide, 2012; De Haan and van den End, 2013a and 2013b), Chapter 4 doesn't do so. The findings of Chapter 4 first of all suggest that in case of a negative shock to their liquidity ratio, banks adjust their liabilities. This suggests that banks substitute their (more liquid and unstable) wholesale funding by more stable deposits. The findings also show that, from a microprudential perspective – i.e. the level of an individual bank - the liquidity rules appear to have been effective, given that a minimum buffer of liquid assets has always been maintained to cover possible outflows.

At the macrolevel – considering the total amount of liquid assets and liabilities of all banks –a procyclical pattern in liquidity is however observed. The results point to a large increase in liquidity during the run-up to the global financial crisis, followed by a sharp decrease afterwards. The results suggest that this cycle in liquidity strongly correlates with the leverage cycle, in line with the findings for the US, by Adrian and Shin (2010). These cycles are characterised by an increased reliance on the interbank market, especially secured funding, during good times. Banks use this funding to invest in liquid – but more risky – assets. Hence, in line with the theory of Minksy (1977); during times in which the perceived risk is low, new risks are built up. During economic reversals however, there is a rapid decrease in liquidity. This procylical pattern in liquidity also implies that banks' liquidity buffers are at the lowest level when needed the most.

The liquidity cycle, with the massive buying and selling of liquid assets in respectively good and bad times, will also have an impact on financial markets. In case many banks have to sell their (liquid) assets at the same this will ultimately impact equity and bond prices. The liquidity cycle may thus impact the financial market cycle.

Chapter 5 focuses on the financial market cycle and, more specifically, investigates the role of pension funds and insurance companies. Pension funds and insurance companies have large assets under management. In the Netherlands, their assets under management respectively represent 185% and 71% of the Dutch GDP. The majority is invested in equities and bonds. Pension funds and insurance companies are therefore seen as important players in the financial markets, as their investment behavior may either stabilise or amplify financial market movements. Theoretically, pension funds and insurance companies are seen as financial market stabilisers, as they often apply a rebalancing strategy. This implies 'buy low, sell high', i.e. selling off asset classes that are priced high and buying assets classes that are priced low. This strategy is regarded as a stabilizing one since it works in a countercyclical manner. 'Buy low, sell high' also implies that pension funds and insurance companies continue buying during economic slowdowns, i.e. times when prices are low, and vice versa.

By investigating the equity investment behavior of Dutch pension funds and insurance companies over the period 2006-2015, Chapter 5 analyses whether the investment behavior of these parties had a countercyclical impact on the financial markets. For pension funds, the results indeed suggest countercyclical investment behavior. It is however found that insurers, both life and non-life, acted in a procyclical manner. The differences between pension funds and insurance companies may be explained by the nature of their business models, and the regulatory frameworks. Pension funds simply have more recovery options; they can for example increase premiums or apply benefit reductions. Insurance companies do not have these options and therefore face more pressure to sell assets, of which equities, during downturns. At macro level, their procyclical behavior is undesirable, since it intensifies the cyclicality in financial markets.

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Patty Duijm (1990) holds a bachelor's degree in Economics and Business Economics from the VU University Amsterdam, where she graduated in 2011. She continued her studies with a pre-master in Econometrics at the Erasmus University Rotterdam to prepare for a master degree in econometrics. In that year she was awarded the Duisenberg School of Finance scholarship which allowed her to start the M.Sc. Risk Management there.

After graduating in 2013 Patty joined the De Nederlandsche Bank as an economist at the Financial Stability Division. In 2015, during her time at De Nederlandsche Bank, she started as a part-time Ph.D. student at the Rotterdam School of Management (Erasmus University). Her research interests include financial cycle theory, the impact of policy reforms on financial institutions, international banking and risk diversification. In 2017 she moved to the Supervisory Policy Department on Insurance Companies as an economist/policy advisor, where she is currently working.

Portfolio

Publications in refereed journals

Jon Frost, Patty Duijm, Clemens Bonner, Leo de Haan, Jakob de Haan (2019). International Lending of Dutch Insurers and Pension Funds: the Impact of ECB Monetary Policy and Prudential Policies in the Host Country. *Open Economics Review, 1-12*. Link

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Work in progress

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