UNIVERSITY OF SOUTHAMPTON

FACULTY OF BUSINESS, LAW AND ART

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The implications of the complexity of banks on M&As, non-traditional banking activities and corporate governance: evidence from the US banking sector

by

Daniel Mayorga Serna

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ABSTRACT

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MANAGEMENT

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THE IMPLICATIONS OF THE COMPLEXITY OF BANKS ON M&As, NON-TRADITIONAL BANKING ACTIVITIES AND CORPORATE GOVERNANCE: EVIDENCE FROM THE US BANKING SECTOR

Daniel Mayorga Serna

This thesis focuses on the study of the complexity of entities in the US banking sector. To this end, three lines of research are pursued in this thesis. We start with an investigation analysing the importance of strategic fit for post-M&A performance, which is one of the necessary prior steps for a financial institution to become complex. Second, we extend our investigation to analyse the effectiveness of the Dodd-Frank Act. 2010 to control the risk and non-traditional banking activities of complex bank holding companies. This law is considered one of the main avenues for the US government to control the continuously growing complexity of financial institutions. Lastly, we explore the influence of the complexity of banks on the composition of their board according to the degree of busyness of board members in terms of sitting on other boards.

Using different econometric approaches and different samples, we present robust evidence for several findings. Firstly, strategic fit plays a key role as a performance enhancing factor for banks that decide to expand their market and/or diversify their products portfolio through pursuing merger deals. The subsequent analysis finds that the Dodd-Frank Act. 2010 has distinct effects on the risk and non-banking activities among the different types of complex BHCs. Moreover, we present differences between large and consolidated BHCs in their "shadow" banking activities following the enactment of this law. Furthermore, we observe that banks continue increasing their proportions of independent directors. However, banks require independent board members with fewer commitments from outside boards. Lastly, the busyness degree of the executive board members is related to the organisational complexity between banks and their subsidiaries.

The empirical results give rise to numerous important policy implications. The supervision of a proper degree of strategic fit in key aspects between merging entities before a merger approval might increase the probability to achieve positive post-mergers outputs and reduce early bailouts that affect local economies. Furthermore, the recent re-regulatory changes have achieve to partially increase the stability of BHCs in which policy makers should consider the nature of complexity to have a better control of their risk, especially placing limits on their risky non-traditional banking activities. Finally, it has highlighted the importance of laws, related to the appointment of the board members, to take into account the individual complexity of each banking institution

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DECLARATION OF AUTHORSHIP

I, ***Daniel Mayorga Serna*** declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

The implications of the complexity of banks on M&As, non-traditional banking activities and corporate governance: evidence from the US banking sector

I confirm that:

This work was done wholly or mainly while in candidature for a research degree at this University;
Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
Where I have consulted the published work of others, this is always clearly attributed;
Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
I have acknowledged all main sources of help;
Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
None of this work has been published before submission

Signed: ....

Date: ....

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Southampton, 18th January 2017

Daniel Mayorga Serna

Chapter 1: Introduction

1. Introduction

1.1 Aims

This thesis aims to offer new insight into the complexity of institutions in the US banking sector. To this end, it provides as the first analysis an investigation of the importance of strategic fit in M&As to achieve positive post-merger outputs. Then, it unveils how the recent re-regulatory change after 2010 affects risk and non-banking activities for complex entities. Lastly, it assesses the involvement of directors on the boards of complex Bank Holding Companies, according to their degree of busyness from their work on other boards.

1.2 Overview

1.2.1. The deregulation process in the U.S. banking sector

Two main de-regulation changes are considered the most relevant for the analysis in the complexity of financial institutions in the U.S. Firstly, the passage and implementation of the Riegle–Neal Act. enacted in 1994 allowed banks to expand their branching network outside their home state (Heffernan, 2005). This law provides 36 U.S. States to gradually reduce their regional interstate banking restrictions and to eliminate any limits by 1997 (Becher and Campbell, 2005). This delay in the law was granted to protect their local financial markets and to be prepared to compete with the large out-of-state institutions (Johnson and Rice, 2007). This change in the law triggered a massive merger activity inside and outside States, in which large financial corporations wanted to enter into new markets to achieve economies of scope or scale (Stiroh and Rumble, 2006).

Secondly, the GLBA Act in 1999 intensified this process by reducing the remaining barriers between investment banking and commercial banking in which the BHCs were allowed to offer specialized investment services and products to their customers through one of their holding non-bank affiliates (Copeland, 2012). Then, banks were able to acquire or set up non-bank subsidiaries as well as to become an FHC in order to maintain the control of these entities through the same holding (Heffernan, 2005).

There is still no consensus about whether this period of branching de-regulation had a positive or negative impact on banks (Kolaric and Schiereck, 2014). Scholars show how banks that expand geographically by acquiring or setting up new branches or subsidiaries have an advantage to diversify their portfolio with more variety and higher quality of financial products (Goetz 2014). Others studies argue that intrastate mergers achieve greater benefits comparing with interstates mergers (Becher and Campbell, 2005).

The complexity of financial institutions has increased remarkably over the last two decades. The de-regulation process during the 1990's enabled banks to expand their branching networks, as well as to enter into new markets (Berger *et al.*, 1999). During this period banks had the opportunity to grow through merging with entities inside or outside their home markets. Thus, the decision to engage in a merger deal with the most suitable partner in order to increase merger success became an important issue for banks (Wheelock and Wilson, 2004). Even though, the prior banking literature has tried to explain merger success through quite different approaches (DeYoung *et al.*, 2009), only a few studies analyse how the fitting degree of different features between partner banks can achieve positive post-merger outputs (Kolaric and Schiereck, 2014). This thesis provides more insights on this topic by borrowing a concept from the strategic management literature to illustrate how strategic fit in key important features from the merger deal can enable acquirer banks to increase the probability of achieving merger success.

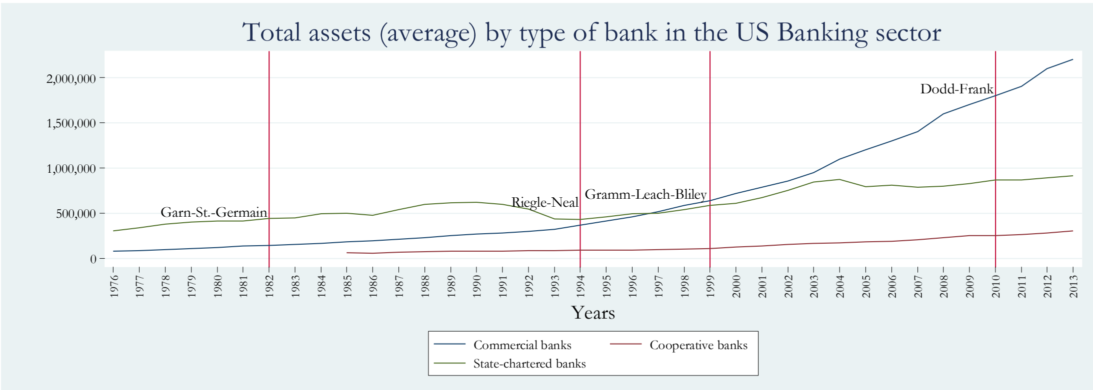
This de-regulation process affects the organizational structure of US banks considerably, especially when they are permitted to integrate non-bank entities into their holdings (Cetorelli *et al.*, 2014). At the same time, the financial products and services of banks have become more sophisticated in order to satisfy the risk appetite of the market. Following this, banks have found ways to obtain additional liquidity through these financial products which are different from their traditional banking sources. This encouraged banks to increase their non-traditional financial activities, especially through their recently acquired non-bank subsidiaries, commonly known as "shadow banking activities" (Pozsar *et al.*, 2013). These shadow banking activities are considered to be one of the main triggers of the financial crisis of 2007. As a result, the US government enacted the Dodd-Frank Act. in 2010 in order to set boundaries to the non-banking activities that banks engage in with their non-bank subsidiaries (Lippe *et al.*, 2015). This thesis extends previous research to evaluate the effectiveness of this recent re-regulatory change to control for the risk in complex US BHCs. Moreover, this thesis shows that the effects of the Dodd-Frank Act. reduce the shadow banking activities between complex banks and their non-bank subsidiaries.

Furthermore, during this period of deregulatory and re-regulatory changes, prior studies point out that the role of the bank boards is important to control the growing complexity of financial institutions (De Andres and Vallelado, 2008). Thus, banks may modify their board composition, not only to fulfil regulatory requirements, but also to receive more effective advice and monitoring services, especially from the independent members of the board. This valuable service from their board members is needed to fully understand the sophisticated financial activities which banks decide to engage in, as well as to give insights into other industries that banks are involved in. However, prior research does not analyse why this phenomenon differs for complex and non-complex entities, or it is focused only on the largest and complex entities from the US banking sector (John *et al.*, 2016). This thesis aims to expand the knowledge about how complex US BHCs appoint board directors according to their degree of busyness derived from serving other boards. Finally, public policy implications of the findings of this study are discussed in each of the three distinctive lines of research presented in this thesis.

1.2.2. Market structure

The structure of the market of the US banking sector during the last two decades has undergone considerable changes. Figure 1.1 shows trends for the average of total assets of the commercial banks, the cooperative banks as well as the state-chartered banks which are the most representative types of entities from the US banking sector. This Figure shows that during the 1970's and 1980's the average of total assets for the three types of entities show a consistent behaviour. During this period the state-chartered banks maintain higher total assets compared with the commercial banks. However, after the de-regulatory change of 1994, the total assets of the state-chartered entities fall while the total assets of commercial banks show a constant increase. After the Gramm-Leach-Bliley of 1999, the cooperative banks and the state-chartered entities show a steady rise in their total assets for ten years, while the total assets of commercial banks have constantly increased after the release of the limits on the non-traditional banking activities. This growth in the total assets of commercial banks continues after the Dodd-Frank Act of 2010, while for the cooperative and state-chartered banks their total assets maintain a steady course for the years following this law.

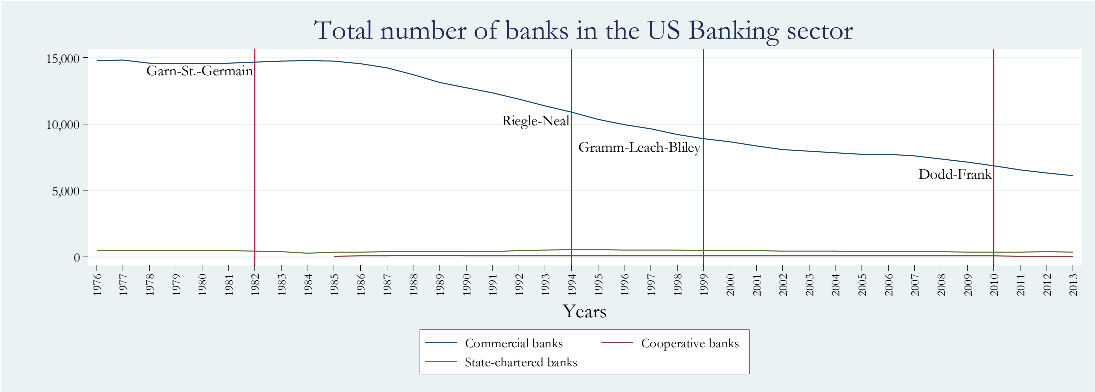
Figure 1.1.



Data source: Wharton Research Data Services, on the bank regulatory section, last access January 2nd 2017

Regarding the number of entities, Figure 1.2, in the next page, shows trends for these types of banks. This Figure reveals that the number of commercial banks is considerably higher comparing with the state-chartered banks and cooperative banks. The number remains steady until mid-1980's, when this type of bank begin a decline that continues for the 1990's and 2000's. As a result, the number of commercial banks drops from 14,790 entities in 1976 to 6,095 at the end of 2013. Regarding the state-chartered banks, they show a steady decline in number starting with 481 and dropping to 367 entities during the same period. Meanwhile, the number of cooperative banks is only 19 in 1985 and increases to 53 institutions.

Figure 1.2



Data source: Wharton Research Data Services, on the bank regulatory section, last access January 2nd 2017

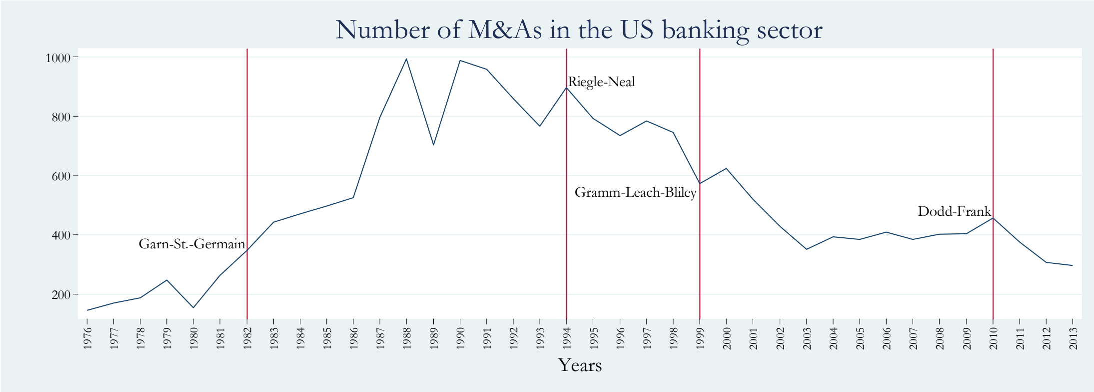
This analysis reveals that the number of commercial banks has dramatically reduced, which are the most representative banks in the US banking sector. However, their total assets have increased exponentially, especially after the de-regulatory changes of the 1990's and continues after the re-regulatory change of 2010. This shows that the growing market is concentrated in a fewer number of entities in which banks increase were allowed to increase their non-traditional banking activities and to consolidate their branching network during this period of time.

1.2.3. Merger activity

According to the Federal Reserve Bank of Chicago's website.[1] There were 19,776 mergers in the US banking sector from 1976 to 2013. Figure 1.3 depicts the trends of the total mergers. This figure shows that the number of M&As in the US banking sector increase markedly during the late 1970's and 1980's reaching to a peak of 994 deals in 1988 but fall dramatically in the following year and then showing a recovery in 1990. Then, there is a steady decline that continues until the Riegle-Neal Act. was enacted in 1994, in which mergers reach a new peak. This period of constant fluctuation might be the result of the savings and loan crisis that took place during the 1980's and at the beginning of the 1990's. From 1994 to 1999 mergers fall gradually and after the Gramm-Leach-Bliley Act. in 1999, mergers grew slightly but then continue constantly declining until 2005 in which there was a steady fluctuation. Then mergers rise slightly in 2010 when the Dodd-Frank was enacted followed by another steady decline that continues until 2013. This analysis shows that the branching de-regulation of 1994 is the continuation of the consolidation process that has already started in the banking sector in the years prior the enactment of the Riegle Neal Act. 1994.

[1] https://www.chicagofed.org/banking/financial-institution-reports/merger-data, last access August 11th 2016.

Figure 1.3

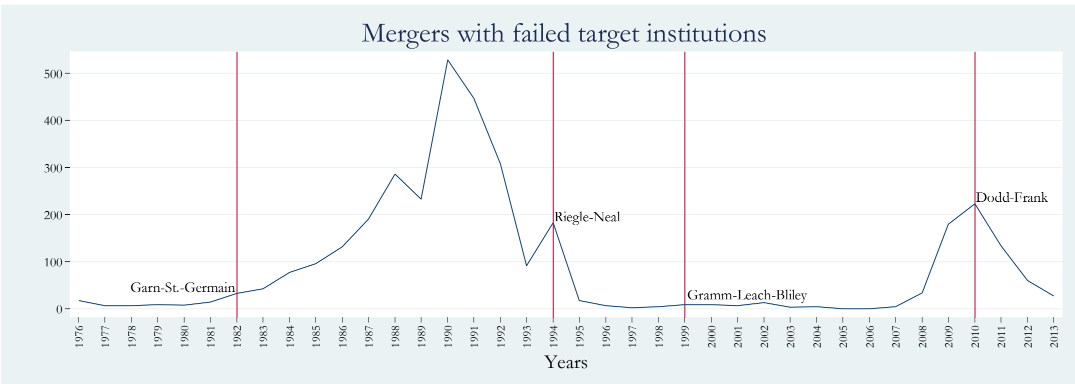


Data source: Federal Reserve Bank of Chicago.

During this time period we can recognize two main types of mergers: the assisted and the unassisted mergers. The first type is related to mergers in which the banking authorities rescue failed banks through merging them with healthy banks, preferably from the same local market to minimize the impact on depositors and borrowers in the local economy. The second type of mergers is when two different entities merge and do not need any support from the regulator to accomplish the merger (Wheelock, 2011).

Regarding the mergers in which the target institution is a failed institution, Figure 1.4 shows the trend for this type of merger from the years 1976 to 2013. This chart reveals that this type of deal increase steeply throughout 1981 to 1987 with a slight drop in 1988 and then increase dramatically reaching a peak of 528 mergers in 1990, followed by a sharp decline until 1993. This period of high fluctuation might be the result of the greater number of failed savings and loans institutions that were rescued during this period. Then, there is a recovery in 1994 with the enactment of the Riegle-Neal Act., showing another sudden drop to fifteen deals for the following year. Mergers remain steady from 1996 to 2007 in which the average number of mergers with failed institutions is five. However, these type of mergers grow markedly again reaching two hundred and twenty-three deals in 2010 and decline sharply after the Dodd-Frank Act. showing only twenty-seven mergers with failed entities in 2013.

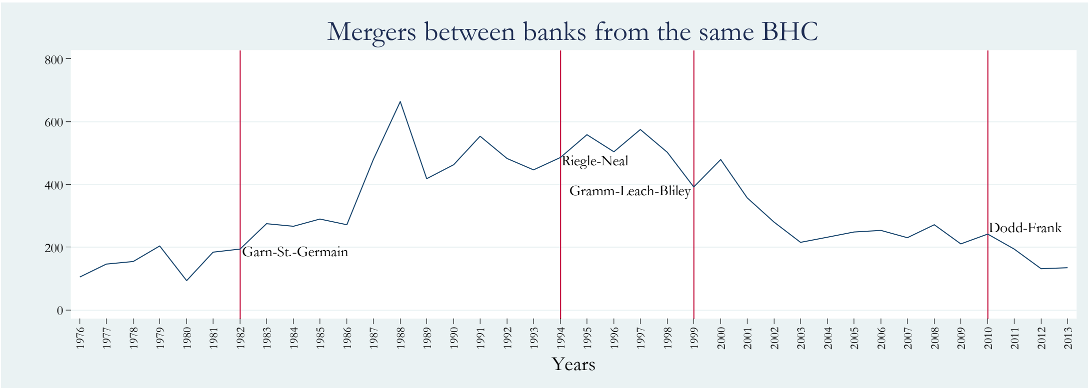
Figure 1.4



Data source: Federal Reserve Bank of Chicago.

Among the unassisted mergers are mergers between entities from the same BHC, and the trend for these mergers is shown in Figure 1.5 below. These mergers show a steady growth during the 1970's and 1980's reaching a peak of six hundred and sixty-four in 1988 followed by a steep decline in the following year. There is a constant fluctuation during the 1990's and after 2000 these mergers decline gradually until 2003 after which they remain steady. Finally, after the Dodd-Frank Act. in 2010 mergers between partners from the same parent BHC decline again and in 2013 we observe only one hundred and five deals. The increase shown in 2000 might be the result of the mergers between banks and their non-bank subsidiaries, which had been approved after the enactment of the Gramm-Leach-Bliley in 1999.

Figure 1.5



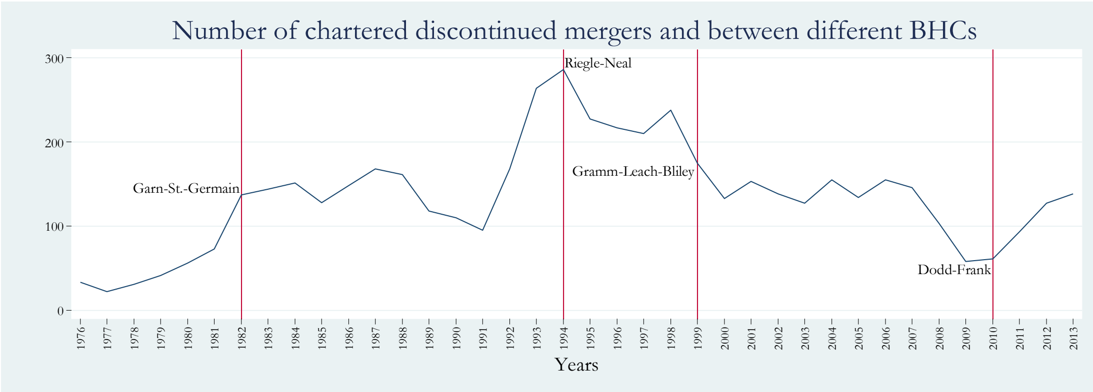
Data source: Federal Reserve Bank of Chicago.

Another type of merger that we identify is the chartered discontinued merger[2] and mergers between partner banks with different holding companies, which are displayed in Figure 1.6, in the next page. These types of mergers reach a peak in the years 1994 to 1998 followed by a slight decline in the next year. From 2000 to 2007 these mergers show a steady fluctuation. Moreover, despite their decrease due to the last financial crisis from late 2007, recent trends show signs of an upturn in the number of mergers that is seen as part of an ongoing consolidation process (Adams, 2012b).

This graphic representation strongly indicates that mergers between healthy institutions from different holding companies have a more steady behaviour comparing with the other types of mergers especially after the Riegle_Neal Act in 1994. This provides evidence that financial institutions continue looking to merge with other entities to expand into other markets or to diversify their product portfolio (Kolaric and Schiereck, 2014).

[2] For details about Federal Reserve merger code definitions see Appendix 1.A.

Figure 1.6



Data source: Federal Reserve Bank of Chicago.

1.2.4. Corporate governance practices

Regarding the corporate governance practices of banks, prior literature have pointed out the differences between financial and normal entities (Adams and Mehran, 2012). One of the most common differences is that banks require larger boards with more independent board directors sitting on them. Researchers find that banks require higher levels of advice from their outsiders because they have valuable knowledge from other sectors because they have experience of other boards (John *et al.*, 2016). This allows them to fully understand the financial activities that nowadays banks to engage in. Especially after the removing of the limits between the traditional and non-traditional activities in which banks have increased considerably the complexity of their financial activities. However, these directors are usually considered busy due to the number of commitments they have with other boards (Jiraporn *et al.*, 2009). In this way, prior literature has analysed how their busyness degree can affect either the performance (Belkhir, 2009) or the risk of the financial entities (Berger *et al.*, 2014).

Moreover, the busyness of the board of directors is not exclusive to outsiders in which insider directors can also be considered busy directors. Some BHCs might have different boards inside the holding to fulfil banking authorities, and banks might require that their key directors, such as the CEO or CFO, to be seated on the board of their subsidiaries. This will enable the main board to have insider board members that can understand the internal organizational complexity between the parent holding and its affiliates and thus control for risk (Elyasiani and Zhang, 2015).

1.3 Structure of the thesis

This thesis is structured around the involvement of complex banks from three distinctive perspectives. To achieve this, an individual chapter is devoted to each of the three different lines of research. What is common between these chapters is that all are focused on the US banking sector and analyse one aspect in which complex entities may be involved.

Chapter 2 contains the first analysis of this thesis, showing the relationship between strategic fit and M&As, in which the latter are considered to be one of the previous steps for banks to become complex institutions. Chapter 3 aims to analyse the extent to which the recent re-regulatory changes have reduced risk exposure and non-traditional activities (or shadow banking activities) for a sample of 129 complex institutions and 938 non-complex large US BHCs. Chapter 4 takes a different approach to analysing the complexity of the BHCs and focuses on corporate governance. Chapter 5 provides an overall summary of this thesis and underlines the important policy implications emerging from it. It also shows the limitations of the presented research and highlights possible future avenues for research. The subsequent section presents a brief summary of each chapter.

1.3.1. Chapter 2: How important is strategic fit for post-M&A performance in the US banking sector?

This chapter presents an empirical study of the relationship between strategic fit and M&A. Despite a great number of studies having focused on analysing the factors to achieve merger success, little research can be found in the banking literature on the role of strategic fit for post-merger performance (Kolaric and Schiereck, 2014). Furthermore, prior studies analyse only one of the main sources of strategic fit, either similarities or complementarities (Altunbaş and Marqués-Ibañez, 2008; Kim and Finkelstein, 2009). Chapter 1 shows how the combination of complementarities and similarities in key aspects of merger deals have an effect on post-merger performance. Using the Generalized Linear Model (GLM) approach, this chapter presents robust evidence that complementarities in the loan portfolio affect post-merger performance. However, higher levels of complementarities in the loan market between partner banks can also affect it. Furthermore, we find that differences in non-performing loans and cost control strategies can enhance post-M&A performance. Meanwhile, only similarities in liquidity levels between merging banks can achieve positive merger outputs. Additionally, several robustness checks are presented in this chapter to verify the validity of these findings, in which results remain robust for all of them. This chapter concludes that banking authorities might consider the degree of strategic fit between partner banks before the approval of their merger deal in order to increase their probability of obtaining positive merger outputs, not only in the short-term, but also to be maintained for the medium and long-terms periods.

1.3.2. Chapter 3: Did the Dodd-Frank Act. 2010 enhance the risk exposure of complex bank holding companies in the US?

Chapter 3 examines the impactof Dodd-Frank Act. 2010 on risk-taking behaviour of complex BHCs. The Dodd-Frank Act. 2010 aims to reduce the increasing complexity of financial institutions through controlling for their non-traditional banking activities with their non-bank subsidiaries. Therefore, the main objective of this chapter is to analyse whether and to what extent this re-regulatory change has effectively decreased the risk exposure of complex financial entities, as well as their activities with non-bank subsidiaries. To accomplish this aim, a balanced dataset of

BHCs is selected, covering a three-quarter window for the pre- and post-periods of the Dodd-Frank Act. This enables the researcher to observe the effectiveness of the recent re-regulatory change between the treatment group of the sample composition by complex entities and the control group composition by non-complex entities. Results of this chapter show that complex entities, classified as credit-extending-activities, enhance their risk exposure and reduce their income derived from non-bank subsidiaries. Meanwhile, entities with supervisory judgement classification improve bank stability and at the same time reduce investments to their non-bank affiliates. In contrast, complex banks with management-factors classifications are the only ones to increase their investments in their non-banks subsidiaries. Lastly, no evidence is found that this law affects the other types of complex institutions, such as non-bank-financial institutions and institutions with high-risk-activities. These results show that the recently re-regulatory changes had the expected effect on some of the types of complex BHCs. This chapter shows that future changes in regulation should consider the inclusion of all types of complex entities in order effectively enhance risk exposures, as well as to control for the non-banking activities that complex entities decide to engage in.

1.3.3. Chapter 4: The impact of complexity in US bank holding companies on corporate governance.

Chapter 4 makes a contribution to the corporate governance literature by examining the behaviour and involvement of the board of directors in complex US BHC. Results from the fractional response model show that complex entities are negatively related to the proportion of board members without any other directorship, while it is positive for the proportion of directors that are sitting on other boards. Furthermore, this analysis finds that complex institutions are reducing their proportion of independent board members that maintain three or more outside directorships and replacing them with independent directors with fewer than three. In the case of the executive directors and using the whole sample, the study finds that complex entities require higher proportions of executive board members that are sitting on up to two outside boards. However, for the largest complex institutions that maintain their complexity indicator and survive during the time span of this analysis show higher proportions of executive directors with three of more directorships. These findings support the idea that laws aimed to regulate the appointment of independent directors in bank boards to maintain independence from bank managers might consider the busyness degree of outsiders from other boards in order to receive proper advisory and/or supervisory support from them.

1.3.4. Chapter 5: Summary, conclusions and future research.

Chapter 5 contains a global summary and the concluding remarks of this thesis. Furthermore, this chapter mentions the limitations of this work as well as avenues for future research.

Chapter 2: How important is strategic fit for post-M&A performance in the US banking sector?

How important is strategic fit for post-M&A performance in the US banking sector?

Abstract

Motivated by the ongoing increase in M&As in the financial services sector, this chapter analyses how the two main sources of strategic fit – similarities and complementarities – affect post-merger performance. Using samples from the US banking industry with different time windows before and after a merger deal (two, three and four years), we compare the effects of strategic fit through time. Our findings show that complementarities in the loan portfolio have a double effect. On the one hand, differences in loan portfolio composition between merging banks result in better post-merger performance. On the other hand, greater differences between their aggregate loan markets erode post-merger performance. Furthermore, we show that dissimilarities in efficiency levels between partner banks enhance performance only for the short and medium terms. Finally, we show that differences in non-performing loan ratios and similarities in liquidity ratios between merging banks boost bank performance for all the time windows.

JEL classification: G21, G34

Keywords: Banking, mergers and acquisitions, strategic fit, strategic similarity, strategic complementarity, corporate strategy.

2. How important is strategic fit for post-M&A performance in the US banking sector?

2.1 Introduction

Over the last two decades, M&A's in the US financial sector have attracted the attention of a broad number of scholars (DeYoung *et al.*, 2009; Kolaric and Schiereck, 2014). Mergers have played a part in the ongoing decline in the number of commercial banks and savings institutions in the US, from 9,529 in 1996 to only 6,692 by the start of 2014 (FDIC, 2014). This significant decline of 30% is considered part of a consolidation process that encourages banks to merge either to increase their market power or enter new markets to achieve economies of scale or scope (Wheelock, 2011). Furthermore, banks which merge many times can become big enough to gain greater influence in their local markets and receive preferential treatment from State governments and regulators to avoid systemic risk affecting depositors, creditors and shareholders (Kaufman, 2015). Additionally, mergers contribute to increasing the complexity of financial institutions when banks decide to expand into non-traditional banking activities through acquiring specialized financial affiliates (Cetorelli *et al.*, 2014).

In order to achieve a better understanding of bank merger strategies, previous studies have investigated how strategies to expand geographically and to diversify products enables positive merger outputs (Kolaric and Schiereck, 2014).

Focusing on performance (DeLong, 2001; Becher and Campbell, 2005) find that strategic fit between acquirer and target bank enhances post-merger performance because it mitigates management incompatibilities, integration problems and cultural differences that have adverse effects on M&A performance (Chatterjee *et al.*, 1992; Laamanen and Keil, 2008; Stahl and Voigt, 2008). A higher level of strategic fit allows merged banks to combine their resources in the most appropriate manner according to their individual capabilities and features to achieve positive merger outputs (Lubatkin, 1983; Singh and Zollo, 1999; Homburg and Bucerius, 2006). Strategic fit takes place during the pre-merger phase, and it is classified into similarities and complementarities (Bauer and Matzler, 2014). The first of these concepts is when partner institutions have similar resource allocations that create unique synergies which cannot be easily replicated by other merging institutions (Harrison *et al.*, 1991), while the second concept is related to the creation of synergies through differences in resources between partner banks that either institutions cannot achieve alone, and is not feasible through other merger deals (Harrison *et al.*, 2001; Bauer and Matzler, 2014).

So far, there has been little attention on strategic fit in the banking industry (Kolaric and Schiereck, 2014). To date, there are only a few studies related to strategic fit in the US banking sector (Ramaswamy, 1997; Kim and Finkelstein, 2009) and one study on the EU banking sector (Altunbaş and Marqués-Ibañez, 2008). Previous papers have only focused on one aspect, be it complementarities in resources and capabilities (Krishnan *et al.*, 1997; Sarkar *et al.*, 2001) or similarities in key strategies such as cost control, capital, requirements, liquidity, credit risk, among others (Lubatkin, 1987; DeLong, 2001).

To the best of our knowledge, there is no research that encompasses both the analysis of similarities and complementarities in the same study to understand how these two sources of strategic fit interact to enhance M&As' post-merger performance. The main reason to study both sources of strategic fit is because, in any merger deal, partner banks always share similarities as well as complementarities in their resources, knowledge, and/or capabilities that might affect the performance of the resulting bank. Thus, the analysis of both sources will allow us to observe which combination of complementarities and similarities enable banks to achieve the most suitable amalgamation of their combining resources in order to obtain positive merger performance. While prior research that focuses on just one of them, are only capturing part of this amalgamation between merging entities.

This study aims, therefore, to cover this gap by investigating how and to what extent similarities and complementarities in the lending strategies of merging banks have an impact on post-merger performance. Second, unlike previous studies we use three different time-window samples to depict the short-, medium- and long-term periods of the mergers in order to compare the behaviour of complementarities and similarities to achieve positive merger outputs. In addition, we use a very large US mergers sample for the years 1994 to 2013. Next, we consider intra-State mergers and inter-State mergers[3] with a variety of banks of all sizes[4] and from forty-four States compared to previous studies that only consider intra-State mergers from twenty States for a one year time period (Ramaswamy, 1997). Furthermore, we create a unique cross-sectional sample with mergers that do not overlap or are influenced by previous or subsequent mergers during the time window selected for each sample. Finally, from a methodological viewpoint, we use different econometric approaches, Generalized Linear Model (GLM) and Ordinary Least Squares (OLS), to verify the consistency of our results.

For this study, we combine bank financial reports obtained from the Federal Deposit Insurance Corporation (FDIC) with mergers data from the Federal Reserve Bank of Chicago. The US financial sector is ideal to conduct our study for the following three reasons: firstly, because of the

[3] Inter-State (intra-State) mergers are mergers where partner banks are not (are) in the same State.
[4] The classification of bank size is as follow: large banks have total assets > 1 billion US dollars, medium size banks as 1 billion US dollars > total assets > 300 million US dollars and small banks have total assets < 300 million US dollars. Note that previous literature only classify banks as large (more than 1 billion) and small (less than 1 billion) and there is no explicit classification for medium size banks (Berger *et al.*, 2005). However it has been shown that small banks with less than 300 million US dollars might have a different cost structure and branching network (Berger *et al.*, 1987; Berger and Humphrey, 1993). Thus, we consider as medium size entities banks with more that 300 million dollars but less than 1 billion as total assets.

number of mergers and acquisitions over the last twenty years; secondly, our samples contain inter-State and intra-State mergers made by banks of all different sizes; lastly, complete information about the mergers and relevant accounting data is available.

Our first empirical finding is that merging banks with differences in their loan portfolios achieve positive post-merger performance not only in the two-year window but also in the three- and four-year windows. However, we find that differences in the aggregate loan market between merging banks have a significant adverse effect on merger performance for the three- and four-year windows. This means that intra-State mergers create merger value compared with out-of-State mergers. Moreover, we find that differences in the management of doubtful loans have a consistent and positive effect on post-merger performance for all the samples used in this study. This finding suggests that acquirer banks decrease their credit risk through merging with banks that have different control strategies for non-performing loans. Furthermore, we find that differences in efficiency levels enhance only for the two- and three-year windows. This finding shows that dissimilarities in cost control strategies between conjoining banks can achieve positive post-merger performance for the short and medium terms. Meanwhile, we find that differences in liquidity levels between partner banks can have a negative effect on merger performance for all the time-year windows. Nonetheless, when we select only intra-State mergers from our samples, we observe that mergers with similarities in liquidity levels achieve positive post-merger performance only for the two-year window.

We also conduct robustness checks. Firstly, we conduct a robustness test in which we only consider intra-mergers in our sample, to assess for different behaviour in the estimates of our variables between outputs obtained using our entire samples and a sub-sample of mergers where merging banks are located in the same US State. Next, we rerun our model by excluding Texas and Illinois, which account for almost twenty percent of all observations. Thirdly, we remove from our samples all mergers where the acquirer is a large bank. Fourthly, we re-run our main model but now with the disaggregated ratios of liquidity and non-performing loans in order to observe which of the partner banks influence more the post-merger performance. Finally, we run our main model using OLS to observe any differences between the outputs obtained using GLM regressions. Our main results are robust to all these checks.

Organization of this chapter is as follows: Section 2 gives a brief overview of the literature; Section 3 provides details of the methodology and data used to conduct this study; Section 4 presents our findings; Finally, Section 5 concludes.

2.2 Literature review

Over the last decades, there has been a proliferation of studies which have examined the effect of geographic and product strategy on bank post-merger performance (Elsas *et al.*, 2010; Bandelj, 2014; Meslier *et al.*, 2016). The majority of these studies focus on the US or European countries (Kolaric and Schiereck, 2014). The prevailing view is that banks that geographically consolidate their market share through M&As achieve a higher performance than banks that are more diversified.

Regarding studies from the European banking sector, there is still, no general consensus about whether cross-border mergers achieve greater positive merger outputs compared with their domestic counterparts. Vander Vennet (1996) finds that only cross-border mergers achieve efficiency improvement. However, only those domestic deals where merging banks have equal size can positive merger outputs be reached. Using a sample of four hundred and ninety-two takeovers, he examines the effects on bank performance effects between European financial institutions over the period 1988-1993. He argues that banks pursue domestic mergers only as a defensive strategy, in which bank managers are pushed to maximise banks size to avoid being acquired by their competitors. Only domestic mergers in which partner banks are similar in size gain positive post-merger performance. Hagendorff *et al.* (2008) find that cross-border mergers in which target banks are located in economies with a lower protection for investors (most of them EU countries) achieve higher post-merger returns comparing with mergers where the target entity is located in countries with a strong protection for investors (such as the US). On the opposite side, Cybo-Ottone and Murgia (2000) find that mergers with foreign entities do not achieve positive stock market valuation after the announcement of a merger deal. Their sample consists of European merger deals from 1998 to 1997.

A similar picture can be obtained from US studies. Deng and Elyasiani (2008) find a closer relationship between the degree of geographic diversification and bank risk in terms of distance between bank headquarters and their subsidiaries. They collect a sample of five hundred and five listed BHCs from the US. They find that geographic diversification can help to reduce risk, however longer distances diminish this. However, Goetz *et al.* (2013) find that inter-State mergers erode banks valuation. They argue that banks that pursue inter-State deals to expand geographically, increase their lending to their foreign subsidiaries but their non-performing loans also increase which affect negatively entities value. A more recent study conducted by (Meslier *et al.*, 2016) compares intra-State and inter-State mergers between large and small entities. They use a sample of US BHCs from 1994 to 2008 and show that small banks benefit in terms of risk when they diversify through intra-State mergers while large banks are more likely to reduce risk if they pursue inter-State deals.

As regards to portfolio strategies, there has been little agreement on whether banks should specialize (focus) or expand (diversify) their financial services and products. Some studies claim that mergers where acquirer banks pursue specialization in their loan portfolio achieve greater post-merger performance (Kolaric and Schiereck, 2014). For example, Beitel *et al.* (2004) analyse the announcement effects of European merger deals and argue that diversified mergers which have lower correlations between bidder and target bank in different key factors such as product/activity focus, growth focus, cost efficiency, among others have a negative effect on shareholder wealth. Recently, Zhang (2014) using a sample dataset of U.S. bank takeover bids finds that acquirer banks which merge following their original business line achieve greater cumulative abnormal returns (CARs) compared to institutions which merge and diversified their activities. Related to research that supports diversification strategies, Filson and Olfati (2014) find that US bank holding company mergers which pursue diversification into specialized financial products such as investment banking, securities brokerage and insurance after the approval of the Gramm-Leach-Bliley Act. in 1999, show positive CARs. Further, Elsas *et al.* (2010) using a sample of large banks from nine developed countries, find that banks which diversify their revenues through non-interest income increase their market value.

Studies exist in the literature that analyse for both, product and geographic diversification strategies through mergers in the banking sector. DeLong (2001) presents one of the most relevant studies from the US. He uses a sample of two hundred and eight mergers between traded entities from 1998 to 1996. He finds that mergers where partner banks share a similar activity (products) and also similar geographically, enhance stockholder value by three percent.

Studies of strategic fit with a focus in the banking sector are scarce. The first paper is by Ramaswamy (1997), who conducts a study of 46 mergers that took place in 1987 in twenty US States. He assess five key areas: market coverage, marketing activity (marketing expenditures to revenues), risk propensity (core capital to loans outstanding), operational efficiency (overhead expenditure to total revenue) and client mix (business loans to consumer loans). He finds that dissimilarities between bidder banks and target banks in four of these features do not improve performance measured by return on assets (ROA). Only market coverage was positive but not significant and only similarities in key strategic variables between merging banks improve post-merger performance.

Another relevant study is Altunbaş and Marqués-Ibañez (2008), who analyse similarities using a dataset consisting of 207 domestic mergers and 55 cross-border mergers in the EU that occurred between 1992 and 2001. Using change in Return on Equity (ROE) as a performance measure, they find that differences between merging banks in capitalisation (total capital to total assets), other expenses (other expenses to total assets), off-balance sheet activities (off-balance income to total assets) and liquidity (liquid assets to total deposits) have positive effects on performance for domestic mergers. Meanwhile, for cross-border mergers dissimilarities in ratios like credit risk (loan loss provisions to net interest revenues), loan ratio (total loans to total assets) and diversity of earnings (other operational income to total assets) create benefits for the resulting bank. They conclude that only close relatedness between merging institutions can enhance M&A performance.

The only relevant study related to strategic complementarities in US banking is conducted by Kim and Finkelstein (2009) They carry out an event study using a sample of publicity traded banks and bank holding companies from the U.S. with 2,204 mergers made by 501 acquiring banks that occurred between 1989 and 2001. As a performance measure, they calculate the CARs of the market price from the bidder bank five days before and five days after the merger deal announcement. They find a positive relationship between complementarities in the loan portfolio and post-merger performance. Moreover, there is a negative interaction between the concentration strategies of the acquiring banks and complementarities in the loan portfolio. Additionally, they investigate for complementarities between the aggregate market loans portfolio of the merging banks and they find a negative relation with merger performance. They conclude that complementarities are relevant antecedents to achieve positive post-merger performance. Table 2.1, below, presents a descriptive overview of the main characteristics and sample selection of these studies.

Table 2.1. Descriptive overview of prior research

Main characteristics

Reference (year)	Type of Study	Performance measure	Type of Strategic fit assessed	index distance	Period	Sample Size
Ramaswamy (1997)	Efficiency study	ROA	Similarities	Euclidean	1987	46
Kim and Finkelstein (2009)	Event study	CAR	Complementarities	Mahalanobis	1989-2001	2204
Altunbaş et al. (2008)	Efficiency study	ROE	Similarities	Euclidean	1992-2001	262

Sample selection

Reference (year)	Data window	Source	Type of Institutions
Ramaswamy (1997)	The difference between three years acquirer's ROA revenue weighted average after merger minus three years ROA's revenue weighted sum of the merged banks previous to the merger deal. Banks that were involved in more than one merger in this period were excluded.	Federal Deposit Insurance Corporation (FDIC), The Bank Quarterly and Statewide annual reports of banks published by Sheshunoff Information Services and the Data Book (FDIC publication).	FDIC member banks from the United States.
Kim and Finkelstein (2009)	CAR five days before and five days after the announcement.	SNL Financial's DataSource; Centre for Research in Securities Pricing and Federal Reserve Board.	Traded banks and bank holding companies from U.S.
Altunbaş et al. (2008)	Two years acquirer's ROE weighted average after merger minus the ROE's weighted sum of merged banks previous to the merger deal. Banks that were involved in another merger during the three years prior to the merger deal were excluded.	SDC Platinum database from Thomson Financial and Bank Scope database of Bureau Van Dijk.	Commercial banks from the European Union.

Whereas, Kim and Finkelstein (2009) only look at complementarities in their analysis, they argue that future studies should incorporate both complementarities and similarities. In this chapter, we analyse both of the aspects of strategic fit in merging institutions. We specifically provide nuanced evidence on how and to what extent banks can enhance their performance in the post-merger period by merging partners with differences in the loan portfolio and non-performing loans ratio, as well as similarities in liquidity levels.

So far, the existing literature does not provided a complete understanding if a suitable combination of complementarities and similarities of resources in a merger deal enable partners to achieve positive post-mergers performance on the resulted entities. Scholars recognize that every merger deal might contain both types of strategic fit and more studies are needed in order to fully understand the advantages to achieve a perfect amalgamation between partner banks (Kim and Finkelstein, 2009). Additionally, no prior studies properly discuss the advantages for banking authorities to consider complementarities as well as similarities in the approval of a merger deal in order to increase their merger success, avoiding premature bailouts that affect local economies.

This chapter shows several contributions to the existing literature. Firstly, it is the first study that analyses complementarities and similarities in the same study, while previous focus only on one of them. Secondly, this study uses a larger cross-sectional sample covering twenty years of data, comparing with Ramaswamy(1997) which focuses on the US banking sector that includes mergers taken from only one year (1987). Thirdly, this research uses a unique dataset that contains information for mergers that do not overlap with any prior or subsequent mergers allowing us to observe mergers in isolation. This is needed to accurately assess the strategic fit of the mergers, in which the existing banking literature relating to strategic fit do not properly isolate mergers in their samples and their results can be influenced by other prior or subsequent mergers. Lastly, this study considers three different time windows in order to compare the effects of strategic fit on post-merger performance in the short-, medium- and long-terms. Again, previous research have focused their main analysis on only one of them (Ramaswamy, 1997; Altunbaş and Marqués-Ibañez, 2008; Kim and Finkelstein, 2009).

2.3 Methodology

2.3.1 Data description

The dataset we build contains cross-sectional data which is drawn from two different sources. Firstly, accounting data was collected from Call Reports. This dataset includes information from all the FDIC insured financial institutions, which is recorded quarterly according to the reporting form FFIEC 031. Secondly, merger deals are obtained from the merger file available on the Federal Reserve Bank of Chicago's website.[5]

Criteria for selecting mergers were as follows: the time framework chosen was from 1994 to 2013 which resulted in 10,258 mergers. The reason for selecting this period of time is that it covers two important de-regulatory changes: the first is the relaxation in the rules on branching networks through the implementation of the Riegle-Neal Inter-State Banking and Branching Efficiency Act. in 1994 (Becher and Campbell, 2005); the second is the reduction of barriers between commercial banking and specialized financial activities through the passage of the Gramm-Leach-Bliley Act. in 1999 (Heffernan, 2005; Asaftei, 2008). Further, it covers the financial crisis from 2008 and re-regulatory changes in the Dodd-Franck Act. in 2010 that diminish merger activity. In order to analyse similarities and complementarities over the long run, we selected samples of two-, three- and Four-year windows. Therefore, mergers from 1994 to 1996 and 2012 to 2013 were excluded for the two-year sample, as well as 1994 to 1996 and 2011 to 2013 for the three-year sample and finally 1994 to 1997 and 2010 to 2013 were dropped from the four-year sample.

Our eligibility criteria require mergers where bidder banks acquire the totality of a healthy bank. Thus, mergers with failed banks, banks receiving government assistance and target banks that have not transferred the total of their assets to the survivor bank were removed.[6] In addition, we did not consider mergers between partners from the same bank holding company due to the fact that similarities or complementarities are unlikely to describe the real reason of the merger deal. In addition, we select only mergers where both institutions report their financial information through the Call Reports which is our main accounting data source. Furthermore, we select mergers in which bidder and target banks are not involved in any other merger deal in a time framework of three years before and three years after the merger deal for the two-year sample, four years for the three-year sample and five years for the four-year window sample. This allows us to isolate the effects of similarities and complementarities for each merger without any influence from previous or subsequent mergers.[7] Lastly, mergers that took place in U.S. territories were removed, such as Puerto Rico and Hawaii among others due to their local markets being different comparing with those in any other US State. Accordingly, our final samples for two-, three- and four-year horizon

[5] https://www.chicagofed.org/banking/financial-institution-reports/merger-data, last access August 11th 2016

[6] The merger code selected to cover this criteria is 1 = charter discontinued according to the mergers code definitions. For details see Appendix 1.A.

[7] We notice that in most of the cases the date in which the mergers were authorized by the FDIC showed in the annual report is not the same date in which these mergers appear in the list of the mergers. And for some mergers, these dates sometimes differ by almost one year. Furthermore, this gap enable us to isolate a single merger and avoid other influences from the pre- and post-phases, such as anticipation of the market for future benefits from the merger which can impact temporary the capital ratios of the merging banks (Dosoung and Philippatos, 1983; Lubatkin, 1987).

were 276, 189 and 144 mergers respectively. Table 2.2, below, displays summary details of our sample selection.

Table 2.2. Sample selection criteria

	Time window	Two-year 1996 to 2011	Three-year 1997 to 2010	Four-year 1998 to 2009
1	Total number of mergers between banks excluding all corporate reorganizations and mergers including failed banks. (Call Reports must be available for both parties).	1,738	1,521	1,312
2	We exclude mergers where acquirer banks and/or target banks are involved in mergers up to 3 years before (4 years before, 5 years before). Also we exclude mergers where the acquirer bank is involved in a subsequent merger up to 3 years after (4 years after, 5 years after).	278	189	144
3	We exclude all mergers in US territories (Puerto Rico and Hawaii).	276	189	144
	Final Sample	**276**	**189**	**144**

Note: These criteria are necessary to enable us to examine with precision the effects of a single merger in isolation. Source: Federal Reserve Bank of Chicago.

Note, that these time-year windows contain the complete mergers that fulfil all the needed criteria in order to observe each merger deal in total isolation. In this way, we will be able to properly measure similarities and complementarities without any influence from a previous or subsequent merger that partner banks decide to engage with other entities. It is important to mention that the criteria for our sample selection eliminates serial acquirers as these types of entities engage in several merger deals over a short period, in which is not possible to fully isolate the effect on the performance for each of the merger deals. As a result, our final sample for the two-year window contains 264 bidder banks that appear only once, and six acquirers that show two mergers. Furthermore, the year that presents the most mergers is 1999 with 26, followed by 2007 and 2008 both with 24, and lastly 2004 with 23 merger deals. Additionally, the US State that has the most bidder and target banks is Texas with 56 banks, followed by Illinois with 51.

Table 2.3, in the next page, shows the composition of the time-window samples by bank size. It indicates that for most of the mergers in the two-year window, small banks represent 97% of the target banks while for acquirer banks this percentage is 67%. As expected, the acquirer banks tend to be large and medium sized entities whereas target banks tend to be smaller sized entities. Finally, the number of large acquirer entities reduce drastically in number for the three- and four-year windows.

Table 2.3. Mergers by bank size

Total assets	Large banks >$1 billion	Medium banks <$1 billion > $300 million	Small banks < $300 million	Total
Target banks				
Two-year window	2	6	268	**276**
Three-year window	0	5	184	**189**
Four-year window	0	3	141	**144**
Acquirer banks				
Two-year window	15	77	184	**276**
Three-year window	4	55	130	**189**
Four-year window	3	41	100	**144**

Continuing with our analysis of the composition of our sample, Table 2.4 displays the number of BHCs represented by the banks in our sample, according to the number of merger deals that the BHCs show in each time-year window. It also presents the banks that are not part of any BHC at the time of the merger deal. This table reveals that the majority of the acquirer banks are part of a BHC and only three of them do not belong to any BHC. Furthermore, most of the BHC of the sample are represented by only one merger deal, whereas 11 BHCs shows two or three merger deals for the two-year window, and 5 and 1, for the three- and four-year window, respectively. Meanwhile, the majority of the target banks do not belong to any BHCs in which only 39 of them have a BHC for the two-year window, as well as 28 and 24 for the three- and four-year window respectively. Note that in this case only one BHC is present in two merger deals in all the time-year windows. This analysis shows that most of the merger deals selected for our sample are between acquirer banks that are part of a BHC and independent banks that do not belong to any BHC. Additionally, most of the BHCs from both partner banks only engage in one merger deal during all the time-year windows. This can be interpreted as most of the merger deals from our samples are not influenced by the decision of their parent BHCs to engage in more than one merger deal.

Table 2.4. Number of banks within BHC involved in mergers for our sample

	Time window		
	Two-year	**Three-year**	**Four-year**
Acquirer Banks			
One merger	249	175	140
Two mergers	9	4	1
Three mergers	2	1	0
Total number of acquirer BHCs:	**260**	**180**	**141**
Acquirer banks without a BHC:	**3**	**3**	**2**
Target Banks			
One merger	39	28	24
Two mergers	1	1	1
Total number of target BHCs:	**40**	**29**	**25**
Target banks without a BHC:	**235**	**159**	**118**

2.3.2 Empirical strategy

Our model to assess the effects of strategic fit on M&A post-performance takes the following form:

$$\Delta \Pi_{it} = \alpha + \beta_1 co_{it} + \beta_2 si_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it} \tag{1}$$

Where:

$\Delta \Pi_{it}$ = Change in performance (ROA, ROE) of the merger i at the time window t (two-year, three-year or four-year). This is calculated as the average of the post-M&A performance ratio, minus the sum of the average of the performance ratios for the merging banks in the pre-merger phase.

co_{it} = Complementarity variables between merging banks in their loan portfolios and between their loan market portfolio.

si_{it} = Similarity variables between joining banks in key features such as doubtful loans, liquidity and cost structure.

$X_{i,t}$ = Control variables such as relative size, type of entity as well as merger experience of the acquirer.

δ = Fixed-effects dummy variables.

ε_{it} = Error term of the equation.

We include fixed effects dummies to control for unobserved heterogeneity at the year level, such as regulatory changes and crises during the time span of our sample. Similarly, we include State fixed dummies in order to control for differences in GDP and demand for loans between the different US States in our sample. For our main analysis, we run this model applying the Generalized Linear Model (GLM) approach (Papke and Wooldridge, 2008). Finally, we make use of robust-standard-errors. The use of robust standard errors enables us to better control for large outliers and observations with large leverage values in our time window samples (Cameron and Miller, 2015).

2.3.3 Variables definition

Following Ramaswamy (1997) and Altunbaş and Marqués-Ibañez (2008), we use ROA and ROE ratios as performance measures. We calculate these two ratios for the pre-merger and post-M&A phases. In particular, for the pre-merger phase, we compute the mean of the variables for the merging banks for four years, three years and two years depending on the window we have considered for our analysis. For post-M&A performance, we follow the same procedure for the acquiring bank. We then calculate the changes in performance (ΔROA/ ΔROE) as the difference between ROA and ROE during the pre-merger and post-M&A phases. We employ this procedure for all the other variables included in the model.

We consider two complementarity variables in our model: *Loan composition* and *Loan market composition*. In terms of product strategy, loan composition reflects the core of banking activities and should account for the largest portion of total assets (Kim and Finkelstein, 2009). Therefore, we devote our attention to the analysis of loan composition rather than focusing on other type of earning assets. In particular, *Loan composition* measures the strategic complementarity in loan portfolios and loan markets between merging banks. Following Huang (2008) we use the Pearson correlation coefficient r:

$$r = \frac{\sum(x_{i,t} - \overline{x_{i,t}})(y_{i,t} - \overline{y_{i,t}})}{\sqrt{\sum(x_{i,t} - \overline{x_{i,t}})^2 \sum(y_{i,t} - \overline{y_{i,t}})^2}} \tag{2}$$

where x and y are the average loan composition of partner banks in the merger i at the time window t, up to two, three or four years before the merger according to the window of analysis we have used. For the concerns of this study, a negative Pearson correlation coefficient close to -1 indicates high complementarities between the loan portfolios of the two merging banks. If this value is close to 1, this means that merging banks have a similar loan portfolio. The loan portfolio classification used to assess complementarities is the following:

1. Commercial loans as a % of total loans and leases.

2. Residential loans as a% of total loans and leases.

3. Agricultural loans as a % of total loans and leases.

4. Other real estate loans as a % of total loans and leases.

5. Consumer loans as a % of total loans and leases.

6. Other minor loans and leases as a % of total loans and leases.

This portfolio classification is shown in the FFIEC 031 reporting form from Call Reports for the year 2013. To maintain this classification for all the time span of our sample, we conducted a mapping for the accounting codes available on the Call Reports and need to obtain the same classification for all the previous years to 2013.[8] Previous literature shows that the relationship between performance and complementarities in the loan portfolio is negative. This means that banks with differences in loan composition are able to enhance their post-M&A performance (Kim and Finkelstein, 2009).

[8] Appendix 2.A provides details of the accounting codes from Call Reports for the loan portfolio.

Next, we include *Loan market composition* in our model to take account of the differences in the loan market composition between the bidder and target bank. To this aim we use the total amount of each type of loans shown in the period prior the merger deal and we build a matrix that represents the loan portfolio compositions of each partner bank for the two, three or four year time-window, respectively. Then, to calculate the Mahalanobis distance (MAHAD) we use the following formula:

$$MAHAD = \sqrt{\begin{matrix}(L_{x_{i,t}} - L_{y_{i,t}})^T, \\ W^{-1}(L_{x_{i,t}} - L_{y_{i,t}})\end{matrix}}$$

where $L_{x_{i,t}}$ is the matrix of the aggregate loan portfolio of the acquiring banks, $L_{y_{i,t}}$ represents the matrix of the aggregate loan market portfolio of the target banks and W^{-1} is the inverse of the pooled covariance matrix of the merger i at the time window t before the merger up to two, three or four years according to the analysis window we have used. This formula allows us to obtain a distance between the two mixtures of products of the portfolio between the partner banks as represented through their matrices. This distance also considers the correlation between the different types of loan products. This means that a loan category in not totally independent from all the other categories of loans. Kim and Finkelstein (2009) argue that, for example, real estate loans have a higher correlation with consumer loans from the same loan portfolio, whereas real estate loans might have a lower correlation with other types of loans such as foreign government loans.[9] Furthermore, this measure considers the variance-covariance matrix, that allows us to obtain a distance which is built by a multiple or partial overlapping between the different types of loans of the portfolios from the merging banks (Berry *et al.*, 2010). Thus, by using this measure it is possible to capture not only the similarities but also the differences between partner banks, in obtaining an accurate measure of complementarity in their loan portfolio composition (Kim and Finkelstein, 2009).

The Mahalanobis distance in the loan market portfolio can take any positive value: if this number is higher, it means that the differences between loan markets from partner banks is higher, while these differences are lower if this measure is close to zero. Note that this measure only applies for the inter-State mergers from our sample. In the case of intra-State mergers, this index takes the value of zero as both target and acquirer share the same loan market. In accordance with Kim and Finkelstein (2009), we expect to find a negative relationship between the change in performance and market complementarity.

Following Drazin and Ven (1985), Ramaswamy (1997) and Altunbaş and Marqués-Ibañez (2008), we use the Euclidean distance metric to calculate the similarities between the risk profile and cost strategy of merging banks. Euclidean distance is calculated as follows:

[9] It is important to mention that for our classification of the different types of loans of the loan portfolio, real estate loans are included into residential loans classification, whereas loans to foreign governments are included into the other minor loans and leases category.

$$si_{it} = \sqrt{(x_{it} - y_{it})^2} \tag{4}$$

where si_{it} is the similarity index and x_{it} and y_{it} are the average ratio values of the risk and cost efficiency measures for the bidder bank and the target bank. We calculate the average of these variables for two, three and four years, according to our window of analysis. In particular, *Liquidity* is the ratio between liquid assets to total deposits and federal funds purchased and securities sold. Then, we calculate *Non-performing loans* as non-accrual loans to total interest income. In line with previous studies (e.g. Altunbaş and Marqués-Ibañez, 2008) we expect to find that differences in this ratio have a negative effect on post-M&A performance. Finally we control for banks efficiency calculated as the ratio of total costs (interest expenses plus non-interest expenses) to income (interest income plus non-interest income). Consistent with previous studies in banking, we expect to find cost to income ratio, *Efficiency*, negatively correlated to performance. [10]

Finally, following Kim and Finkelstein (2009) we include three control variables relative to the deal characteristics: *Relative Size, Type of entity* and *Experience*. *Relative Size* is calculated as the amount of the target's total assets divided by the acquirer's total assets. Previous studies have found that the greater the difference in size between bidder and target, the better the performance that can be achieved in the post-M&A period (Laamanen and Keil, 2008). However, the strategic fit literature from the banking industry shows mixed results. Kim and Finkelstein (2009) argue that there is a negative relationship between relative size and performance. In contrast, Altunbaş and Marqués-Ibañez (2008) find a negative relationship between size and post-M&A performance for domestic mergers but a positive relationship for cross-border mergers. They argue that cross-border acquirers pursue increasing revenues by acquiring a bigger target. We then control for *Entity type*. In particular, we include a dummy variable that takes the value of 1 if both merging banks are the same type of entity, 0 otherwise.[11] Lastly, we take into consideration the possibility that the acquirer bank has been involved in other M&As. In this case, banks could be more flexible and adapt better to a new business environment, and thus increasing the probability of acquisition success (Kim and Finkelstein, 2009). In particular, we makes use of a dummy variable, *Experience*, which takes the value of 1 if acquirer has previous mergers experience, 0 otherwise.[12]

Descriptive statistics of the variables are displayed in Tables 2.5 and 2.6. Table 2.5 shows the main statistics measures, while Table 2.6 reports the correlation matrix. Table 2.5 indicates, that in terms

[10] The level of capitalization is not significant in any of our specifications. We run a t-test (see Appendix 2.C) to verify whether there are significant differences in the level of capital between target and acquiring banks for all the windows included in our analysis. All the results show that the mean difference between the two groups of banks is insignificant. A possible explanation for this result is that we consider only healthy banks in our sample. We therefore decide to drop this variable from our analysis.

[11] We use the code RSSD9331 from Call Reports that contains the classification for all the financial entities. Our sample only considers entities classified as commercial banks, State-chartered savings banks, as well as cooperative banks.

[12] For details related to the definition of the variables see Appendix 2.B.

of total assets, acquirer entities are around five times larger than target entities. The mean of the *Loan composition* variable depicts a positive value of .6; this shows that, in average, the merging banks from the sample have a similar composition in their loan portfolio, according to the loan portfolio classification as shown on page 28. Furthermore, the mean of the *Loan market composition* variable is small; this can be interpreted as most of the mergers from the sample are intra-State mergers. Lastly, in Table 2.6 it can be observed that there are no high correlations between the independent variables hence no multicollinearity problems.

Table 2.5. Descriptive statistics

Variables	N	Mean	SD	Min	Max
ΔROE	276	.017	.06	-.18	.48
ΔROA	276	.0012	.0044	-.015	.03
Loan composition	276	.6	.42	-.77	1
Loan market composition	276	7.3	29	0	273
Efficiency	276	.13	.15	.0013	1.8
Efficiency acquirer	276	.76	.089	.33	1.2
Efficiency target	276	.85	.17	.54	2.5
Liquidity	276	.23	.62	.0004	9.9
Liquidity acquirer	276	.4	.23	.074	3.1
Liquidity target	276	.49	.62	.065	10
Non-performing loans	276	.0061	.012	0	.17
Non-performing loans acquirer	276	.0044	.0057	0	.034
Non-performing loans target	276	.0067	.013	0	.17
Relative Size	276	.4	.41	.0071	3.5
Total assets acquirer (in '000)	276	768,756	6,265,589	5,035	101,600,000
Total assets acquirer(log)	276	12	1.2	8.6	18
Total assets target (in '000)	276	142,026	1,041,346	2,377	17,055,669
Total assets target(log)	276	11	1	7.7	16
Type of entity	276	.92	.28	0	1
Experience	276	.33	.47	0	1

Note: ΔROE and ΔROA are respectively the change of ROE and ROA at the time window t (two-, three- or four-years). We calculate them as the average of the post-merger performance ratios from acquirer minus the average of the performance ratios from partner banks in the pre-merger phase. *Loan composition* measures the strategic complementarity in loan portfolios while *Loan market composition* measures the differences in the loan market composition between the acquiring bank and target bank. *Liquidity* is the ratio between liquid assets to total deposits and federal funds purchased and securities sold. *Efficiency* is the ratio of interest expenses plus non-interest expenses divided by interest income plus non-interest income. *Non-performing Loans* is the ratio between nonaccrual loans and lease financial receivables divided by total interest income. We use the Euclidean distance to measure the similarity between acquirer and target in terms of *Liquidity*, *Efficiency*, and *Non-performing Loans*. *Relative Size* is calculated as the amount of the target's total assets divided by the acquirer's total assets. *Type of entity* is a dummy variable that takes the value of 1 if both merging banks are classified as the same entity, 0 otherwise. *Experience* is a dummy variable that takes the value of 1 if the acquiring bank has previous merger experience, 0 otherwise.

Table 2.6. Correlation matrices for the samples

Panel A. Correlation matrix for Change in ROE

		1	2	3	4	5	6	7	8	9
1	Change ROE	1.00								
2	Loan composition	-0.20	1.00							
3	Loan market composition	-0.01	0.02	1.00						
4	Efficiency	0.33	-0.23	0.09	1.00					
5	Liquidity	0.02	-0.12	0.16	0.65	1.00				
6	Non-performing loans	0.33	-0.01	0.01	0.28	-0.02	1.00			
7	Size	-0.20	0.12	-0.06	-0.13	-0.07	-0.04	1.00		
8	Type of entity	0.02	-0.10	0.08	-0.05	0.03	-0.12	0.14	1.00	
9	Experience	0.03	-0.06	-0.01	-0.07	-0.03	-0.09	-0.24	0.05	1.00

Panel B. Correlation matrix for Change in ROA

		1	2	3	4	5	6	7	8	9
1	Change ROA	1.00								
2	Loan composition	-0.26	1.00							
3	Loan market composition	0.02	0.02	1.00						
4	Efficiency	0.53	-0.23	0.09	1.00					
5	Liquidity	0.16	-0.12	0.16	0.65	1.00				
6	Non-performing loans	0.37	-0.01	0.01	0.28	-0.02	1.00			
7	Size	-0.27	0.12	-0.06	-0.13	-0.07	-0.04	1.00		
8	Type of entity	-0.03	-0.10	0.08	-0.05	0.03	-0.12	0.14	1.00	
9	Experience	-0.01	-0.06	-0.01	-0.07	-0.03	-0.09	-0.24	0.05	1.00

Note: ΔROE and ΔROA are respectively the change of ROE and ROA at the time window t (two-, three- or four-years). We calculate them as the average of the post-merger performance ratios from acquirer minus the average of the performance ratios from partner banks in the pre-merger phase. *Loan composition* measures the strategic complementarity in loan portfolios while *Loan market composition* measures the differences in the loan market composition between the acquiring bank and target bank. *Liquidity* is the ratio between liquid assets to total deposits and federal funds purchased and securities sold. *Efficiency* is the ratio of interest expenses plus non-interest expenses divided by interest income plus non-interest income. *Non-performing Loans* is the ratio between nonaccrual loans and lease financial receivables divided by total interest income. We use the Euclidean distance to measure the similarity between acquirer and target in terms of *Liquidity*, *Efficiency*, and *Non-performing Loans*. *Relative Size* is calculated as the amount of the target's total assets divided by the acquirer's total assets. *Type of entity* is a dummy variable that takes the value of 1 if both merging banks are classified as the same entity, 0 otherwise. *Experience* is a dummy variable that takes the value of 1 if the acquiring bank has previous merger experience, 0 otherwise.

2.4 Results

2.4.1 Main Results

To begin our regression analysis, we estimate our model (1) using GLM regressions. Table 2.7, on the page 34, shows outputs for this analysis. Note our variable to depict complementarities on *loan composition* between merging banks is negative and significant for all the window samples. This finding shows that complementarities in loan portfolios between conjoining banks achieve positive post-merger performance in the short, medium and long-term. This is in line with the diversification theories exposed by previous research in which banks that expand their product range achieve better post-merger performance (Elsas *et al.*, 2010). Furthermore, compared with the previous banking literature which assesses for strategic complementarities in a short period of time, five days before and after the merger announcement (Kim and Finkelstein, 2009), we find that the benefits of complementarities in loan portfolio between partner institutions can be maintained up to four years after the merger deal. Additionally, the coefficients for the change in ROE are higher suggesting that differences in the loan portfolio between partner banks are more sensible in terms of ROE.

Related to complementarities in the *loan market composition* between merging banks, it shows negative for all the columns, but this is only significant for the three-year window and for the four-year sample in both measures of performance. The coefficient for this variable is not significant for the short-term window. This means that higher differences between the loan market of the partner banks affect negatively the post-merger performance. This finding suggests that banks can reduce losses by focusing on mergers deals where partner banks are from the same US State which compete in the same loan market. While bank mergers which take place in different loan markets can affect negatively merger performance especially for the medium- and long-term. This supports the financial literature which shows that inter-State mergers are negative enhancing for post-merger outputs (Trift and Scanlon, 1987; Toyne and Tripp, 1998). Note that this variable shows a small coefficient for all columns, which might be because the composition of our window samples is composed of more intra-mergers than inter-mergers.

For the variables that depict similarities on key financial aspects of the merger, we find that differences in terms of *efficiency* between the merging banks lead to an improvement of performance especially for the two-year and three-year window. However, such an effect disappears in the long term in this way indicating potential difficulties of integrating banks with different cost structures.

As regard the coefficients of *liquidity* are negative for all the window samples. This means that after the merger deal it might be difficult to fully integrate entities with heterogeneous liquidity structures which deteriorate performance. (Altunbaş and Marqués-Ibañez, 2008).

Meanwhile, the variable to depict strategic fit on *non-performing loan* ratios between partner entities, shows positively related to the change in performance for all the columns. The coefficient for this variable is significantly related to ROA for all the samples, however in terms of ROE is only significant for the medium- and long-term samples. This result implies that differences in strategies to manage doubtful assets between conjoining banks maintain a positive effect on performance up to four years after the merger. Note that the regressions for the change in ROE depict a greater magnitude for the coefficients in this variable, which shows differences in the control for their nonaccrual loans is more significant when performance is measured in terms of ROE. This is in line with previous literature in which Altunbaş and Marqués-Ibañez (2008) find that differences in a similar ratio (loan loss provisions to net interest revenues) are performance enhancing. This can be interpreted as synergies are created when partner banks share complementary knowledge to control for doubtful assets which improve performance of the resulting bank (Tanriverdi and Venkatraman, 2005).

As expected, we find *relative size* is negative and significant for the two-year and Four-year window. This is line with the literature (Beitel *et al.*, 2004; Laamanen and Keil, 2008), however, it is at odds with Gupta and Misra (2007) who argue that higher relative size in a bank merger deal enhances positive merger outputs.

Moreover, we find that merging banks with the same *type of entity* can benefit post-merger performance but only in the short term window. Lastly, we do not find evidence that mergers in which the acquirer has previous merger *experience* affect the change in merger performance.

Table 2.7. The impact of similarities and complementarities on M&A performance

	Two-year window		Three-year window		Four-year window	
	ΔROE	**ΔROA**	**ΔROE**	**ΔROA**	**ΔROE**	**ΔROA**
Loan composition	-0.014	-0.0012*	-0.024**	-0.0024***	-0.021**	-0.0020**
	(0.008)	(0.001)	(0.009)	(0.001)	(0.007)	(0.001)
Loan market composition	-0.000030	-0.0000019	-0.00032**	-0.000028*	-0.00040**	-0.000034*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Efficiency	0.15***	0.016***	0.099**	0.014***	0.017	0.0013
	(0.031)	(0.003)	(0.034)	(0.004)	(0.044)	(0.004)
Liquidity	-0.023***	-0.0017***	-0.015*	-0.0030***	-0.0076	-0.0030***
	(0.006)	(0.000)	(0.007)	(0.001)	(0.007)	(0.001)
Non-performing loans	1.00	0.068*	3.37***	0.17***	3.14***	0.16***
	(0.766)	(0.029)	(0.336)	(0.029)	(0.288)	(0.031)
Relative Size	-0.018*	-0.0019*	-0.017	-0.0012	-0.042***	-0.0035***
	(0.008)	(0.001)	(0.009)	(0.001)	(0.008)	(0.001)
Type of entity	0.026**	0.0013*	-0.00084	-0.00026	0.0023	-0.00022
	(0.009)	(0.001)	(0.010)	(0.001)	(0.010)	(0.001)
Experience	0.000056	-0.00040	0.0055	-0.00022	-0.0082	-0.00066
	(0.007)	(0.000)	(0.008)	(0.001)	(0.007)	(0.001)
Constant	-0.023	-0.00025	-0.0071	0.0010	0.035	0.0037
	(0.024)	(0.002)	(0.021)	(0.002)	(0.024)	(0.002)
Years FE	Yes	Yes	Yes	Yes	Yes	Yes
Target State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276	276	189	189	144	144

Note: ΔROE and ΔROA are respectively the change of ROE and ROA at the time window t (two-, three- or four-years). We calculate them as the average of the post-merger performance ratios from acquirer minus the average of the performance ratios from partner banks in the pre-merger phase. *Loan composition* measures the strategic complementarity in loan portfolios while *Loan market composition* measures the differences in the loan market composition between the acquiring bank and target bank. *Liquidity* is the ratio between liquid assets to total deposits and federal funds purchased and securities sold. *Efficiency* is the ratio of interest expenses plus non-interest expenses divided by interest income plus non-interest income. *Non-performing Loans* is the ratio between nonaccrual loans and lease financial receivables divided by total interest income. We use the Euclidean distance to measure the similarity between acquirer and target in terms of *Liquidity*, *Efficiency*, and *Non-performing Loans*. *Relative Size* is calculated as the amount of the target's total assets divided by the acquirer's total assets. *Type of entity* is a dummy variable that takes the value of 1 if both merging banks are classified as the same entity, 0 otherwise. *Experience* is a dummy variable that takes the value of 1 if the acquiring bank has previous merger experience, 0 otherwise. The regressions include year-fixed effects, State fixed effect and robust standard errors. Standard errors are reported in parentheses. *p<0.1, **p<0.05, ***p<0.01.

It is important to mention that we conduct additional analysis to those previously mentioned. However, these are not included because results are not significant comparing with those obtained using our model (1). We include as control variables a measure for the market share of the bidder and target entities as well as the concentration in loan portfolio of both partner banks in terms of HHI but none of them have significance in our model. Furthermore, we include GDP of the US States and other macroeconomic variables that might affect merger activity in certain States. Nevertheless, we decide to include State fixed effects to capture all these economic aspects. Similarly, we include a dummy variable for regulatory changes and crisis that took place during the time span of our sample, but again we include year fixed effects that help us to capture these events.

2.4.2 Robustness checks

Analysing Strategic fit for only intra-State mergers

For our first robustness test, we focus solely on intra-State mergers as inter-State merges can be driven by different economic motivations (Berger, 1998; Kolaric and Schiereck, 2014). For example, Becher and Campbell (2005) maintain that intra-State mergers can be associated with the reduction of costs related to overlapping operations, while inter-State mergers can be motivated by economies of scale and diversification benefits. Table 2.8, below, shows outputs for these regressions. For this case, the most relevant differences we find with previous results is that *loan composition* in no longer significant for the two-year window and *liquidity* is only positive and significant for the short-term window. The rest of the coefficients from the other variables show similar results to those presented in the previous analysis. We can conclude that for mergers that took place in the same State where partner banks are located, similarities in their *liquidity* together as well as differences in their *non-performing loans* and *efficiency* ratios, an together with complementarities in their loan composition are required to generate positive merger outputs for the short term window. However, we do not find evidence that similarities in liquidity enhance merger performance for the medium and long term. Only complementarities and differences enable merging banks to achieve positive post-merger performance for the medium and long windows.

Table 2.8. The impact of similarities and complementarities on M&A performance: only intra-State mergers

	Two-year window		Three-year window		Four-year window	
	ΔROE	**ΔROA**	**ΔROE**	**ΔROA**	**ΔROE**	**ΔROA**
Loan composition	-0.014	-0.0011	-0.023*	-0.0020**	-0.020**	-0.0018**
	(0.008)	(0.001)	(0.009)	(0.001)	(0.008)	(0.001)
Efficiency	0.16***	0.016***	0.098**	0.013***	0.040	0.0032
	(0.035)	(0.003)	(0.031)	(0.003)	(0.048)	(0.004)
Liquidity	-0.015	-0.0017*	0.019	0.00082	0.016	0.000072
	(0.014)	(0.001)	(0.014)	(0.001)	(0.010)	(0.001)
Non-performing loans	0.93	0.068*	3.40***	0.17***	3.10***	0.16***
	(0.730)	(0.028)	(0.345)	(0.030)	(0.297)	(0.029)
Relative Size	-0.020*	-0.0021**	-0.018	-0.0012	-0.045***	-0.0037***
	(0.008)	(0.001)	(0.009)	(0.001)	(0.008)	(0.001)
Type of entity	0.025**	0.0013*	-0.00062	-0.00017	0.0075	0.00030
	(0.009)	(0.001)	(0.010)	(0.001)	(0.009)	(0.001)
Experience	0.0040	-0.00015	0.011	0.00015	-0.0065	-0.00073
	(0.008)	(0.000)	(0.008)	(0.001)	(0.007)	(0.001)
Constant	-0.044*	-0.0020	-0.031	-0.0016	0.016	0.0015
	(0.021)	(0.002)	(0.023)	(0.003)	(0.025)	(0.002)
Years FE	Yes	Yes	Yes	Yes	Yes	Yes
Target State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	251	251	171	171	127	127

Note: ΔROE and ΔROA are respectively the change of ROE and ROA at the time window t (two-, three- or four-years). We calculate them as the average of the post-merger performance ratios from acquirer minus the average of the performance ratios from partner banks in the pre-merger phase. *Loan composition* measures the strategic complementarity in loan portfolios while *Loan market composition* measures the differences in the loan market composition between the acquiring bank and target bank. *Liquidity* is the ratio between liquid assets to total deposits and federal funds purchased and securities sold. *Efficiency* is the ratio of interest expenses plus non-interest expenses divided by interest income plus non-interest income. *Non-performing Loans* is the ratio between nonaccrual loans and lease financial receivables divided by total interest income. We use the Euclidean distance to measure the similarity between acquirer and target in terms of *Liquidity*, *Efficiency*, and *Non-performing Loans*. *Relative Size* is calculated as the amount of the target's total assets divided by the acquirer's total assets. *Type of entity* is a dummy variable that takes the value of 1 if both merging banks are classified as the same entity, 0 otherwise. *Experience* is a dummy variable that takes the value of 1 if the acquiring bank has previous merger experience, 0 otherwise. The regressions include year-fixed effects, State fixed effect and robust standard errors. Standard errors are reported in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Removing States with merger concentrations

Our second robustness check is to assess if the removal of States with a high concentration of mergers from our samples affects our results. We exclude all mergers where the acquirer banks are based in either Texas or Illinois which represent almost twenty percent of the total samples. To fulfil this part of our analysis we remove fifty-four, thirty-eight and thirty-one mergers for the two-, three- and four-year samples, respectively and rerun the regressions using model (1). Table 2.9, below, depicts the output of these regressions showing similar results for the variables that depict strategic fit between merging banks. In general terms, we find that this output shows similarity with that displayed in our previous analysis but with higher levels of significance for the coefficients and with some slight differences especially in terms of ROE for some time-window samples.

Table 2.9. The impact of similarities and complementarities on M&A performance: excluding Texas and Illinois

	Two-year window		Three-year window		Four-year window	
	ΔROE	ΔROA	ΔROE	ΔROA	ΔROE	ΔROA
Loan composition	-0.022*	-0.0018**	-0.049***	-0.0040***	-0.042***	-0.0028**
	(0.010)	(0.001)	(0.010)	(0.001)	(0.010)	(0.001)
Loan market composition	-0.000080	-0.0000033	-0.00040***	-0.000035***	-0.00058***	-0.000049***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Efficiency	0.15***	0.017***	0.097**	0.013***	0.016	-0.000011
	(0.033)	(0.002)	(0.033)	(0.004)	(0.059)	(0.006)
Liquidity	-0.024***	-0.0019***	-0.019**	-0.0032***	-0.011	-0.0030***
	(0.005)	(0.000)	(0.007)	(0.001)	(0.009)	(0.001)
Non-performing loans	3.02**	0.17***	3.37***	0.20***	3.20***	0.19***
	(1.022)	(0.048)	(0.443)	(0.032)	(0.378)	(0.029)
Relative Size	-0.023**	-0.0021*	-0.020**	-0.0012	-0.050***	-0.0040***
	(0.008)	(0.001)	(0.008)	(0.001)	(0.011)	(0.001)
Type of entity	0.014	0.00079	0.0029	-0.00014	0.0050	-0.000028
	(0.009)	(0.001)	(0.011)	(0.001)	(0.012)	(0.001)
Experience	-0.0025	-0.00048	0.00066	-0.00035	-0.016*	-0.00094
	(0.007)	(0.000)	(0.008)	(0.001)	(0.006)	(0.001)
Constant	-0.020	-0.00013	-0.0061	0.0013	0.039	0.0046*
	(0.023)	(0.002)	(0.022)	(0.002)	(0.023)	(0.002)
Years FE	Yes	Yes	Yes	Yes	Yes	Yes
Target State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	222	222	151	151	113	113

Note: ΔROE and ΔROA are respectively the change of ROE and ROA at the time window t (two-, three- or four-years). We calculate them as the average of the post-merger performance ratios from acquirer minus the average of the performance ratios from partner banks in the pre-merger phase. *Loan composition* measures the strategic complementarity in loan portfolios while *Loan market composition* measures the differences in the loan market composition between the acquiring bank and target bank. *Liquidity* is the ratio between liquid assets to total deposits and federal funds purchased and securities sold. *Efficiency* is the ratio of interest expenses plus non-interest expenses divided by interest income plus non-interest income. *Non-performing Loans* is the ratio between nonaccrual loans and lease financial receivables divided by total interest income. We use the Euclidean distance to measure the similarity between acquirer and target in terms of *Liquidity*, *Efficiency*, and *Non-performing Loans*. *Relative Size* is calculated as the amount of the target's total assets divided by the acquirer's total assets. *Type of entity* is a dummy variable that takes the value of 1 if both merging banks are classified as the same entity, 0 otherwise. *Experience* is a dummy variable that takes the value of 1 if the acquiring bank has previous merger experience, 0 otherwise. The regressions include year-fixed effects, State fixed effect and robust standard errors. Standard errors are reported in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Removing large acquirers

For our third robustness check, we drop mergers where the acquirer is a large bank. These type of mergers might have different behaviours due to the fact that high and complex financial institutions face more bureaucratic procedures and politics that might affect the amalgamation of the strategies with the target institution affecting its performance (DeYoung *et al.*, 2004). For this robustness check, we detect fifteen, four and three mergers where the acquirer is a large bank for the two-, three- and Four-year windows. Note that our samples do not contain a higher number of large banks as acquirers or neither as targets. This is because most of them have overlapping mergers in the time framework of our analysis and are thus excluded. Table 2.10, below, displays these outputs; again we obtain similar results to those shown in Table 2.7, on page 34, for our variables that measure for strategic fit between merging institutions.

Table 2.10. The impact of similarities and complementarities on M&A performance: excluding large acquiring banks

	Two-year window		Three-year window		Four-year window	
	ΔROE	**ΔROA**	**ΔROE**	**ΔROA**	**ΔROE**	**ΔROA**
Loan composition	-0.013	-0.0011	-0.023**	-0.0023***	-0.020**	-0.0019**
	(0.008)	(0.001)	(0.009)	(0.001)	(0.007)	(0.001)
Loan market composition	-0.000020	0.00000081	-0.00034**	-0.000030**	-0.00040**	-0.000033*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Efficiency	0.14***	0.016***	0.087*	0.013**	-0.0082	-0.00085
	(0.037)	(0.003)	(0.035)	(0.004)	(0.040)	(0.004)
Liquidity	-0.020**	-0.0017***	-0.014*	-0.0029***	-0.0039	-0.0027***
	(0.007)	(0.000)	(0.007)	(0.001)	(0.007)	(0.001)
Non-performing loans	1.06	0.069*	3.43***	0.18***	3.14***	0.16***
	(0.776)	(0.029)	(0.344)	(0.030)	(0.302)	(0.032)
Relative Size	-0.016*	-0.0013*	-0.018*	-0.0013	-0.043***	-0.0036***
	(0.008)	(0.001)	(0.009)	(0.001)	(0.008)	(0.001)
Type of entity	0.032**	0.0015*	0.0078	0.00030	0.0084	0.00015
	(0.010)	(0.001)	(0.011)	(0.001)	(0.009)	(0.001)
Experience	0.0022	-0.00018	0.0044	-0.00033	-0.012	-0.0010
	(0.008)	(0.000)	(0.009)	(0.001)	(0.007)	(0.001)
Constant	-0.032	-0.00073	-0.017	0.00038	0.028	0.0031
	(0.025)	(0.002)	(0.021)	(0.002)	(0.024)	(0.002)
Years FE	Yes	Yes	Yes	Yes	Yes	Yes
Target State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	261	261	185	185	141	141

Note: ΔROE and ΔROA are respectively the change of ROE and ROA at the time window t (two-, three- or four-years). We calculate them as the average of the post-merger performance ratios from acquirer minus the average of the performance ratios from partner banks in the pre-merger phase. *Loan composition* measures the strategic complementarity in loan portfolios while *Loan market composition* measures the differences in the loan market composition between the acquiring bank and target bank. *Liquidity* is the ratio between liquid assets to total deposits and federal funds purchased and securities sold. *Efficiency* is the ratio of interest expenses plus non-interest expenses divided by interest income plus non-interest income. *Non-performing Loans* is the ratio between nonaccrual loans and lease financial receivables divided by total interest income. We use the Euclidean distance to measure the similarity between acquirer and target in terms of *Liquidity*, *Efficiency*, and *Non-performing Loans*. *Relative Size* is calculated as the amount of the target's total assets divided by the acquirer's total assets. *Type of entity* is a dummy variable that takes the value of 1 if both merging banks are classified as the same entity, 0 otherwise. *Experience* is a dummy variable that takes the value of 1 if the acquiring bank has previous merger experience, 0 otherwise. The regressions include year-fixed effects, State fixed effect and robust standard errors. Standard errors are reported in parentheses. *p<0.1, **p<0.05, ***p<0.01.

Analysis using separated ratios between merging banks

For our fourth robustness test, we estimate our model (1) but now include the variables that depict similarities such as *efficiency*, *liquidity* and *non-performing loan* ratios separated between acquirer and target banks as well as their size in terms of total assets. It is important to mention that in this part of our analysis we do not show separate values for the variables of complementarities due to the fact that *loan composition* and *loan market composition* cannot be disaggregated between partner banks. Table 2.11, on page 38, shows outputs for this set of regressions. The coefficients for the *loan composition* variable continue being negative and significant but only for the medium term sample while complementarities in *loan market composition* continue being negative and significant for the three- and four-year window sample. Meanwhile, for the disaggregated *liquidity* variable, it can be seen to be negative for the target bank in all the samples while it is positive for the acquirer bank for the medium-term window. Furthermore, we observe that the efficiency ratio from the acquirer affects negatively performance for the medium-term window while the efficiency ratio from the target enhance performance for the short and medium-term windows. Moreover, the non-performing loans ratio is only positive and significant for the target side and again negative for the acquirer for the two-year sample. As expected, the total assets of target banks show negative and meaningful values for all time-windows, while for acquirer banks is positive and meaningful only for the Four-year window. We conclude that liquidity levels and larger size of target banks have a harmful effect on the change in performance. However, this adverse effect can be lightened by their strategies to control for doubtful loans as well as size from acquirer entities and the efficiency strategies from target entities in order to achieve positive post-merger performance.

Table 2.11. The impact of similarities and complementarities on M&A performance: separated ratios for acquiring and target banks

	Two-year Window		Three-year Window		Four-year Window	
	ΔROE	**ΔROA**	**ΔROE**	**ΔROA**	**ΔROE**	**ΔROA**
Loan composition	-0.012	-0.00074	-0.022*	-0.0021**	-0.0098	-0.0011
	(0.009)	(0.001)	(0.010)	(0.001)	(0.007)	(0.001)
Loan market composition	-0.000055	-0.000006	-0.00038***	-0.00003**	-0.0005***	-0.00004*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Efficiency acquirer	-0.050	-0.0057	-0.086*	-0.0092**	-0.014	-0.0012
	(0.031)	(0.003)	(0.038)	(0.003)	(0.038)	(0.004)
Efficiency target	0.11**	0.014***	0.059	0.011***	0.050	0.0048
	(0.037)	(0.003)	(0.039)	(0.003)	(0.033)	(0.003)
Liquidity acquirer	0.0035	0.00011	0.022	0.0035*	-0.022	-0.00028
	(0.011)	(0.001)	(0.016)	(0.002)	(0.019)	(0.002)
Liquidity target	-0.022**	-0.0015***	-0.017**	-0.0031***	-0.026***	-0.0042***
	(0.007)	(0.000)	(0.006)	(0.001)	(0.007)	(0.001)
Non-perf. loans acquirer	-1.30	-0.048	-2.25*	-0.097	-0.41	0.0045
	(0.728)	(0.047)	(0.947)	(0.065)	(1.032)	(0.071)
Non-perf. loans target	1.15	0.070**	2.78***	0.12***	2.59***	0.13***
	(0.656)	(0.023)	(0.402)	(0.027)	(0.390)	(0.037)
Size acquirer(log)	0.0035	0.00067	0.0064	0.00050	0.018***	0.0015**
	(0.005)	(0.000)	(0.005)	(0.000)	(0.005)	(0.000)
Size target(log)	-0.016***	-0.00072*	-0.020***	-0.0012**	-0.023***	-0.0015**
	(0.005)	(0.000)	(0.005)	(0.000)	(0.006)	(0.001)
Type of entity	0.028*	0.00095	0.0021	0.00020	0.0051	0.00023
	(0.011)	(0.001)	(0.012)	(0.001)	(0.009)	(0.001)
Experience	0.0049	-0.00026	0.0051	0.00011	-0.0082	-0.00063
	(0.008)	(0.001)	(0.008)	(0.001)	(0.007)	(0.001)
Constant	0.057	-0.0069	0.15	0.0064	0.028	-0.0018
	(0.091)	(0.008)	(0.115)	(0.008)	(0.086)	(0.008)
Years FE	Yes	Yes	Yes	Yes	Yes	Yes
Target State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276	276	189	189	144	144

Note: ΔROE and ΔROA are respectively the change of ROE and ROA at the time window t (two-, three- or four-years). We calculated them as the average of the post-merger performance ratios from acquirer minus the average of the performance ratios from partner banks in the pre-merger phase. *Loan composition* measures the strategic complementarity in loan portfolios while *Loan market composition* measures the differences in the loan market composition between the acquirer bank and target bank. We use the Mahalanobis distance measure to calculate the level of complementarity for *Loan composition* and *Loan market composition* between the acquirer and target banks. *Liquidity* is the ratio between liquid assets to total deposits and federal funds purchased and securities sold. *Efficiency* is the ratio of interest expenses plus non-interest expenses divided by interest income plus non-interest income. *Non-performing Loans* (*Non-perf. loans*) is the ratio between nonaccrual loans and lease financial receivables divided by total interest income. *Size* is the logarithm of total assets. *Type of entity* is a dummy variable that takes the value of 1 if both merging banks are classified as the same entity, 0 otherwise. *Experience* is a dummy variable that takes the value of 1 if the acquirer bank has previous merger experience, 0 otherwise. The regressions include year-fixed effects and State fixed effect and robust standard errors. Standard errors are reported in parentheses. *p<0.1, **p<0.05, ***p<0.01. Coverage: 1994 to 2013.

Analysis using the traditional OLS approach

The final robustness test is focused on comparing the results obtained from the previous analysis using a traditional GLM approach with regressions using standard OLS. Table 2.12, on page 39, shows outputs for our model (1) with similar results to those presented in Table 2.7. In this way, we confirm that complementarities in *loan composition* enhance post-merger performance while complementarities in their *loan market composition* have a negative effect on merger outputs. For the similarities variables, we find that similarities in liquidity ratio can achieve positive outputs for all the time-year windows, while dissimilarities in efficiency ratio are positively related to the change in performance only for the short- and medium-term windows. Lastly, differences between partner banks in their strategies to control for doubtful loans are positive enhancing for merger performance for all the time windows.

Table 2.12. The impact of similarities and complementarities on M&A performance: OLS regression

	Two-year window		Three-year window		Four-year window	
	ΔROE	**ΔROA**	**ΔROE**	**ΔROA**	**ΔROE**	**ΔROA**
Loan composition	-0.014	-0.0012	-0.024*	-0.0024**	-0.021*	-0.0020*
	(0.009)	(0.001)	(0.011)	(0.001)	(0.009)	(0.001)
Loan market composition	-0.000030	-0.0000019	-0.00032*	-0.000028*	-0.00040*	-0.000034
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Efficiency	0.15***	0.016***	0.099*	0.014**	0.017	0.0013
	(0.036)	(0.003)	(0.042)	(0.005)	(0.057)	(0.005)
Liquidity	-0.023***	-0.0017***	-0.015	-0.0030***	-0.0076	-0.0030**
	(0.006)	(0.000)	(0.009)	(0.001)	(0.009)	(0.001)
Non-performing loans	1.00	0.068*	3.37***	0.17***	3.14***	0.16***
	(0.878)	(0.033)	(0.412)	(0.036)	(0.374)	(0.040)
Relative Size	-0.018*	-0.0019*	-0.017	-0.0012	-0.042***	-0.0035***
	(0.009)	(0.001)	(0.011)	(0.001)	(0.011)	(0.001)
Type of entity	0.026*	0.0013	-0.00084	-0.00026	0.0023	-0.00022
	(0.011)	(0.001)	(0.012)	(0.001)	(0.012)	(0.001)
Experience	0.000056	-0.00040	0.0055	-0.00022	-0.0082	-0.00066
	(0.008)	(0.000)	(0.010)	(0.001)	(0.009)	(0.001)
Constant	-0.023	-0.00025	-0.0052	0.00073	0.020	0.0035
	(0.028)	(0.002)	(0.023)	(0.002)	(0.023)	(0.002)
Years FE	Yes	Yes	Yes	Yes	Yes	Yes
Target State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276	276	189	189	144	144

Note: ΔROE and ΔROA are respectively the change of ROE and ROA at the time window t (two-, three- or four-years). We calculate them as the average of the post-merger performance ratios from acquirer minus the average of the performance ratios from partner banks in the pre-merger phase. Loan composition measures the strategic complementarity in loan portfolios while Loan market composition measures the differences in the loan market composition between the acquiring bank and target bank. Liquidity is the ratio between liquid assets to total deposits and federal funds purchased and securities sold. Efficiency is the ratio of interest expenses plus non-interest expenses divided by interest income plus non-interest income. Non-performing Loans is the ratio between nonaccrual loans and lease financial receivables divided by total interest income. We use the Euclidean distance to measure the similarity between acquirer and target in terms of Liquidity, Efficiency, and Non-performing Loans. Relative Size is calculated as the amount of the target's total assets divided by the acquirer's total assets. Type of entity is a dummy variable that takes the value of 1 if both merging banks are classified as the same entity, 0 otherwise. Experience is a dummy variable that takes the value of 1 if the acquiring bank has previous merger experience, 0 otherwise. The regressions include year-fixed effects, State fixed effect and robust standard errors. Standard errors are reported in parentheses. *p<0.1, **p<0.05, ***p<0.01.

2.5 Summary and conclusions

This study examines how strategic fit impacts M&A's post-performance for banks that decide to engage a merger deal. We expose the importance of strategic fit to generate positive mergers outputs. Differently from previous studies (Ramaswamy, 1997; Altunbaş and Marqués-Ibañez, 2008; Kim and Finkelstein, 2009) we show how and to what extent both sources of strategic fit - complementarities and similarities – affect the lending strategy of the merger deal. In particular, we analyse how strategic fit in the loan portfolio, liquidity and non-performing loans impact on achieving positive post-merger outputs.

This chapter provides important new findings and policy implications. The overall results show that complementarities in the loan portfolio have a double effect. In one way, differences in the loan portfolio composition between merging banks result in better post-merger performance. In the other way, greater differences in the aggregate loan markets between conjoining banks erode post-merger performance. Our first finding supports the advantages of product diversification strategies comparing with product specialization strategies while our second finding indicates that the benefits of geographically focused strategies outweigh the benefits of geographic diversification strategies.

In respect to similarities, using our entire samples, we find that a sameness in their liquidity levels improves performance, whereas only dissimilarities in their efficiency achieve positive post-merger performance. Furthermore, non-performing loan ratios boost performance for all the time period samples. However, when we select only intra-mergers from our sample, similarities in liquidity levels between partner banks contribute to generating positive merger outputs only in the short term. Robustness checks support the evidence that complementarities and similarities between merging banks in their loan composition enhance performance in the three samples we use.

These findings confirm that is possible for partner banks to achieve positive post-merger performance. In this way, our results suggest that regulators should consider similarities and complementarities in key aspects between partner banks before a merger deal is approved. Furthermore, it is advisable for financial authorities to look at the geographic and product strategies of the acquirer banks to ensure that synergies created from similarities and complementarities between merging banks are achievable. Policy makers should analyse which combination of similarities and/or complementarities can help partner banks to achieve positive merger outputs not only in the short-term but to hold these benefits for the medium- and long-term time. This is also important because complementarities, which initially enhance performance, can reverse their effects in the longer term. Thus, regulators will be able to avoid premature bailouts of mergers recently authorized which can affect economies of local markets. Additionally, financial authorities should be aware that the strategic fit in liquidity levels between partner banks and its effects on merger performance might be different between intra-mergers and inter-mergers.

Further research might investigate how other sources of strategic fit between partner banks can achieve post-merger performance distinct from the loan portfolio composition or liquidity levels. An additional extension of our study might explore how complementarities and/or similarities in technology resources together with complementarities and/or similarities in specific banking products or services can enhance performance.

Chapter 3: Did the Dodd-Frank Act. 2010 enhance the risk exposure of complex bank holding companies in the US?

Did the Dodd-Frank Act. 2010 enhance the risk exposure of complex bank holding companies in the US?

Abstract

We examine the impact of the 2010 Dodd-Frank Act. on the risk exposure of US Bank Holding Companies. In particular, we compare the stability and engagement in the shadow banking activities of complex institutions that were subject to tight supervision and restrictions under the Dodd-Frank Act., to those of non-complex institutions. By employing difference-in-difference estimators, we find that the Dodd-Frank Act. enhances the stability of those complex banks classified as either credit-extending institutions or defined as complex by supervisory-judgment, while it did not impact on other types of institutions. Our findings for shadow-banking activities are mixed. Again, complex institutions with credit-extending activities are the only entities to have reduced their income derived from activities with their non-bank affiliates. Overall, we find evidence that large complex institutions decrease their debt exposure with non-bank affiliates after the regulatory change. However, at the aggregated level, consolidated bank holding companies increased engagement in non-traditional financial activities with their non-bank affiliates.

JEL classification: G21, G32, G28, N21

Keywords: Banks, financial risk, government policy, regulation, bank holding companies.

3. Did the Dodd-Frank Act. 2010 enhance the risk exposure of complex bank holding companies in the US?

3.1 Introduction

The organisational complexity of bank holding companies (BHCs)[13] in the U.S. has increased dramatically over the last twenty years. So far, there is no generally accepted measure of complexity for financial institutions. Cetorelli and Goldberg (2014) show different ways to observe the complexity of the financial entities in three different aspects. Firstly, banks can become more complex when they engage in more and different financial activities especially through their subsidiaries. Secondly, the organizational structure inside the BHCs can create a complex institution that, most of the time, involves banks with non-bank institutions that have different regulatory frameworks. This complicates the job of banking authorities to fully understand and to properly track the risk that complex institutions are exposed to. Thirdly, financial institutions can also increase their complexity when they expand their activities beyond their home market. In this case, greater differences between home regulations and foreign regulatory framework as well as the technologies that facilitates the moving of financial resources, can again create a very complicated network of activities which is difficult for governments to evaluate across the world (Cetorelli *et al.*, 2012)

The deregulation process over the past decades has contributed to the changes to the business model of US banks and intensified increases in the size and complexity of banks. Before the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 (Riegle-Neal Act.), banks were geographically clustered in specific locations and limited in their business activities. Starting with the Riegle-Neal Act., banks were allowed to expand their branching network outside their home state and to enter into non-traditional banking sectors by acquiring non-bank subsidiaries (Olson, 2012; Cetorelli *et al.*, 2014). Later, the Gramm Leach Bliley Financial Modernization Act. of 1999 (Gramm-Leach-Bliley Act.) intensified the increased bank complexity by reducing the remaining barriers between investment banking and commercial banking. This enabled BHCs to offer specialised investment services and products to their commercial bank's customers through one of their non-bank affiliate holdings (Copeland, 2012).

These changes in the law allowed BHCs to increase their number of branches and subsidiaries as well as to enter into new non-traditional banking activities to achieve economies of scales and/or scope (Stiroh and Rumble, 2006; Anderson and Joeveer, 2012). This partly explains the wave of merger activity over the last two decades, where the number of BHCs declined from 5,860 in 1991 to 4,660 by the end of 2011 (Avraham *et al.*, 2012). This consolidation process created not only

[13] We use the terms bank as an independent commercial bank, or BHC as a bank holding company, or FHC as a financial holding company that controls one or more commercial banks.

larger financial entities, but also more complex institutions which experienced negative repercussions during the 2008-10 financial downturn (Cetorelli *et al.*, 2012; DeYoung and Torna, 2013). This was partially driven by banks engaging in riskier non-banking activities and "shadow banking", with their non-bank subsidiaries. Shadow banking activities refer to a wide range of types of securitization and non-traditional funding sources, such as asset-backed commercial paper (ABCP), asset-backed securities (ABS), collateralized debt obligations (CDOs) and repurchase agreements (repos). These activities are performed by specialised shadow bank intermediaries, which are typically linked to each other through an intermediation chain to fund long-term illiquid assets through short-term liabilities. However, this is a fragile system that can lead to a run on liquidity as occurred during the subprime crisis of 2007 revealed (Pozsar *et al.*, 2010).

In October 2008, the U.S. government launched the Troubled Asset Relief Program (TARP) in order to enhance banking stability and soundness. As a consequence of this injection of extraordinary state aid into the banking system, in July 2010, the government enacted the Dodd–Frank Wall Street Reform and Consumer Protection Act. (Dodd-Frank Act.) with the scope to tackle the risky activities and complexity of banks by fixing limits on their non-traditional banking activities (Avraham *et al.*, 2012). A first question that arises from this compelling evidence is whether, and to what extent, the Dodd-Frank Act. affected the stability of complex BHCs. A second question is to what extent this law reduced BHCs 'shadow banking with their non-bank subsidiaries. To date the researcher could not find an answer to these questions in the previous literature. This chapter aims to cover this gap and address these issues.

This chapter contributes to the existing literature in several ways. This is the first study that analyses how, and to what extent, complex BHCs have increased their performance volatility and stability as a consequence of the Dodd-Frank Act. Secondly, it takes a closer look at the flows between the BHC with the non-banking institutions by examining the balances due to non-bank subsidiaries to the total liabilities ratio, non-equity investments that entities hold in their non-bank partners, and the total of non-bank income. This enables us to observe how banks have reshaped their activities when they have increased their non-bank activities with their non-bank affiliates. Next, we analyse how this impact affects the different categories of complex institutions.

Our results show that the re-regulatory change improve stability for complex institutions, while, at the same time, it reduces their balances held with their non-bank partners. This means that the Dodd-Frank Act. 2010 achieved enhancement of the stability of banks as well as reducing part of their shadow banking activities with their non-bank subsidiaries. However, this impact cannot be applied equally to the different categories of complex institutions. Only complex banks classified as credit-extending-activities enhance their risk of defaulting and cutting down their income derived from non-bank subsidiaries. Furthermore, institutions with supervisory judgement classification achieve improve bank stability and reduce investments to their non-bank affiliates.

The only institutions that show an increase in their investments in their non-banks subsidiaries are the complex entities with management-factors. Lastly, we did not find evidence that complex entities classified as non-bank-financial factors, with high-risk-activities as well as multiple-factors, improve their risk to default or reduce their shadow banking activities after the regulatory change.

Finally, we perform several checks for robustness. For example, we rerun the main model excluding the credit-extending complex category and the US States, where 25% of the total number of observations is concentrated (California, Illinois, New York and Texas). We address potential selection-bias issues by focusing solely on large institutions. We attempt to rule out the possibility that alternative forces may drive our results by using placebo experiments. In particular, we examine whether banks had started to change their behaviour before the introduction of the Dodd-Frank Act. We also check the sensitivity of our results by identifying the BHCs that had received a capital injection (TARP liquidity programme) from the government during the period of analysis. Our results are robust to all these checks. Finally, we examine the changes in the flows between the BHCs with the non-banking institutions for the consolidated balance sheet. This allow us to infer whether BHCs increased their flows with non-banking institutions outside the group as a consequence of more restrictive requirements at the group level.

This chapter is organised as follows: Section 2 provides an overview of shadow banking activities. Section 3 shows the re-regulation framework for the U.S. financial sector, while Section 4 shows a review of the related literature. Section 5 provides the methodology and data used to conduct this study, Section 6 presents our findings and, finally, Section 7 present the conclusions of the research.

3.2. Shadow banking activities in complex institutions

A general definition of the shadow banking activities has been given by Adrian and Ashcraft (2012), who define it as a network of specialised financial entities that channel funds from savers to investors using specialised financial instruments that involve not only securitization, but also a wide range of funding techniques. These specialised financial entities are also called "shadow banks" because they perform similarly to the traditional banks, but without the umbrella of financial support by the government in the case of a downturn, and with a different regulatory framework (Grung-Moe, 2014).

These non-bank entities do not take deposits in the traditional way and offer a range of sophisticated financial products to satisfy different investor profiles from the financial market (Pozsar *et al.*, 2010). According to Adrian and Ashcraft (2012), some of the specialized financial instruments that can be performed through shadow banking activities are the following: asset-backed commercial paper (ABCP), structured investment vehicles (SIVs), a repurchase agreement (repo), asset-backed securities (ABS), as well as their special variations, such as collateralized debt obligation (CDO), collateralized mortgage obligation (CMO) and collateralized loan obligations (CLOs).

In this way, shadow banking can convert risky loans into short-term instruments that are supposedly free of risk (Cetorelli *et al.*, 2012). However, there are several risks associated with the shadow banking activities. As pointed out by Adrian (2015), most of the shadow banking activities do not have any explicit liquidity support in the case of a downturn, but they can benefit indirectly from government backstops through the credit lines of commercial banks, which can distort the pricing of shadow banking activities. Adrian (2015) also point out that many shadow financial activities do not need to fulfil capital requirements. This fact contributes to making these activities even riskier. Furthermore, agency problems can arise between all the participants in shadow banking activities, such as the originators of the loans, lenders, investors, invested funds, assets managers, and credit rating agencies, which can give a false impression of the price of this activity. For example, the over-reliance on ratings from credit rating agencies, that created a subprime mortgage bonds bubble, led to the financial crisis in 2007 (Pozsar *et al.*, 2010).

Therefore, non-banking activities have modified the traditional model, by which banks are the deposit-funded institution, keeping their loans until maturity, and have evolved into a more complex model, with a wholesale-funded entity and securitization of their loans that involve different shadow banking entities (Strahan, 2010; Cetorelli *et al.*, 2012).

The phenomenon of shadow banking can be dated to the de-regulation process in the 1990s. Since the 1990s, banks started to move into non-traditional banking sectors by acquiring a variety of non-bank subsidiaries, such as broker-dealers, insurance brokers, investment companies, assets manager entities, and insurance underwriters among others (Cetorelli *et al.*, 2012). With the enactment of the Gramm-Leach-Bliley Act in 1999 (Gramm-Leach-Bliley Act.), BHCs were able to become Financial Holding Companies (FHC) in order to control banks and non-banks entities under the same institution, even though they had different supervisory regulators (Avraham *et al.*, 2012). Moreover, with the support of the traditional banks, non-bank institutions considerably increased their financial activities, which also helped to increase banks' size on their consolidated balance sheets (Bord and Santos, 2012).

A wide range of literature focus on how the growth of the shadow banking activities contributed to the 2007 financial crisis (DeYoung and Torna, 2013; Peni *et al.*, 2013; Jacobides, 2015). Pozsar *et al.* (2010) explain how the fragile shadow banking system led to a run on liquidity in the mortgage subprime market, creating a bubble that detonated in late 2007. Compared to previous crises, this caught the attention of governments, because of their impact on the entire global financial system, and they adopted extreme measures to recover financial and economic stability (Laeven and Valencia, 2012).

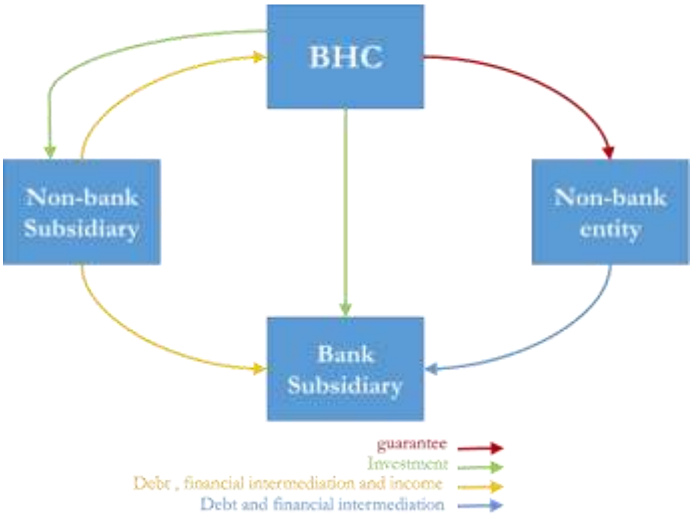
Another strand of the literature explains how shadow banking activities increased after the 2007 financial crisis to satisfy the risk appetite of a growing financial market (Pozsar *et al.*, 2010). Gorton *et al.* (2010) argue that mutual funds, as well as securitization and repurchase agreements, increased thanks to the shelter that the government provided with the TARP liquidity program. Moreover, technological innovation and advanced credit scoring systems have contributed to the growth of the global financial intermediation by banks (Cetorelli and Peristiani, 2012) and they have become harder to track by regulators (Lippe *et al.*, 2015). What is more, due to the non-traditional liquidity program from the Central Bank in 2008 to avoid a systemic crisis, it is difficult to measure the real impact of the shadow banking system (Pozsar *et al.*, 2010). Thus, established policies to control these activities represent a major challenge for central banks to prevent a systemic meltdown of the financial markets (Grung-Moe, 2014), especially because most of the non-bank activities involve subsidiaries under different regulatory frameworks (Afonso *et al.*, 2014).

The basic shadow banking activities that BHCs usually engage with their non-bank subsidiaries are that the BHCs invests in the non-bank affiliate through loans, advances, notes, bonds, debentures and other receivables due from their subsidiaries. Meanwhile, the holding company receives from the non-bank subsidiary loans, financial intermediation and income, such as dividends, interest management and services fees. Related to the financial intermediation, the BHC generate loans which are packaged into sophisticated financial instruments, such as asset-backed securities (ABS) or collateralized debt obligation (CDO), to be sold in the financial market with the help of the non-bank entities. Adrian and Ashcraft (2012) shows that the type, and number, of non-bank entities involved in the financial intermediation might depend on the quality of the loans generated by the bank. Lower quality of assets, such as subprime mortgages, might require being re-packaged again into another type of financial instrument to achieve the quality needed to be acquired by another non-bank entity.

Figure 2.1, below, shows a basic flow of how BHCs engage in non-banking activities with their non-bank affiliates within the same group and with non-bank entities outside the holding group.

Figure 3.1. Financial activities between BHCs and their subsidiaries from the same holding

0.1Figure 3.1. Financial activities between BHCs and their subsidiaries from the same holding



Note: Figure 3.1 shows part of the financial activities between BHCs and their subsidiaries from the same holding. The holding company continuously makes non-equity investments in both subsidiaries; this can be loans, advances, notes, bonds, debentures and other receivables due from their subsidiaries. BHCs receive from the non-bank subsidiary loans, financial intermediation and income such as dividends, interest management, services fees as well as the equity in undistributed income (losses). After the Dodd-Frank Act. had been enacted, BHCs were forced to reduce their non-banking activities with their non-bank subsidiaries. Therefore, they continue doing part of their non-financial activities with non-bank entities outside the holding company in which the subsidiary bank conducts financial intermediation, and BHCs can support them as a guarantor for these activities.

3.3 Re-regulation changes in the U.S. financial sector

The US government enacted the Dodd-Frank Wall Street Reform and Consumer Protection Act on July 21, 2010 in order to tackle the growing complexity of banking institutions, which was considered to be one of the main drivers of the 2007 financial crisis. One of its main objectives was to reorganise and simplify the banks' business models and to put limits on their non-banking activities (Lippe *et al.*, 2015). As reported in Section 112 (a)(1)(A) STAT. 1395, the Dodd-Frank Act. aimed:

> "to identify risks to the financial stability of the United States that could arise from the material financial distress or failure, or ongoing activities, of large, interconnected bank holding companies or non-bank financial companies, or that could arise outside the financial services marketplace;"

However, much of the concern of policy makers was related to the reduction of investment and borrowing activities intra-groups. Therefore, the measure attempted to introduce some limits to these shadow banking activities by forcing banks to report intra-group activities. In particular, BHCs with assets of $50 billion or more are required to produce a report with the following information:

> "(4) the extent to which the activities and operations of the company and any subsidiary thereof, could, under adverse circumstances, have the potential to disrupt financial markets or affect the overall financial stability of the United States".[14]

Despite these re-regulatory changes, scholars have argued that the complexity problem of financial entities is not completely solved (Strahan, 2013) and that the increasing complexity of global commerce and legal frameworks has not been fully addressed (Lippe *et al.*, 2015). Therefore, a complete regulatory reform is needed (Gorton *et al.*, 2010; Cetorelli and Goldberg, 2014). Furthermore, the impact of this regulatory framework on the volume of transactions between subsidiaries of BHCs is still not clear.

3.4 Literature on complexity of financial institutions

Little attention has been paid to the problem of the complexity of institutions, despite its importance for the stability of the financial system. Few studies have focused their analysis on how to measure the complexity of financial institutions. Cetorelli and Goldberg (2014) provide measures of the business and geographic complexity of the entities for domestic and foreign banking organisations from the US that have had a worldwide presence. They find that size is not necessary related to all their measures of complexity. Avraham *et al.* (2012) describe how the number of subsidiaries of the fifty top Tier US BHCs are related to their industry and geographic concentration, both inside and external to the US.

Furthermore, a few papers have examined the main factors that enable financial entities to trigger their complexity. Cetorelli *et al.* (2014) argue that complexity is seen as part of the evolution of the structure of banks. They investigate the changes in the family network, using a sample of one thousand and thirteen banks and thrifts from the US from the years 1988 to 2012. They argue that banks reduce their "centric" activities through expanding geographically with new subsidiaries, in most cases, with non-bank entities. Furthermore, most of these new subsidiaries reshaped the activity range of the banks, in that complexity was not exclusive to the largest financial entities in the sector. Similarly, from an international perspective, Carmassi and Herring (2015) shows how the current legislation encourages banks to adopt complex structures in relation to their different subsidiaries located in other countries. Using a sample of 29 institutions, considered to be global systemically important banks (G-SIBs), they claim that regulations which help to maintain some independence between subsidiaries and their headquarters will contribute to maintaining the stability of the entities if their head office fails.

The existing literature also examines the problems of size and the systemic risk posed by financial institutions. These studies analyse how "too big to fail" TBTF institutions continue to grow, although policy makers try to set boundaries on their activities which might affect all the industrial

[14] Dodd-Frank Wall Street Reform and Consumer Protection Act. § 116(a)(1)–(4) STAT. 1406.

sectors that are related to them in the case of a downturn (Strahan, 2013). Furthermore, this literature emphasises that the largest TBTF institutions have more interrelations with more companies from other sectors. Thus, these entities are the priority for governments to be included in a bailout to overcome any crisis (Kaufman, 2015). Nevertheless, the literature does not fully investigate how the variety of business structures within a holding creates more risky entities when there is a regulatory change. Additionally, most of these studies only consider the largest complex entities and do not compare to their largest non-complex counterparts, which might also have a significant influence on their markets.

This chapter contributes to the existing literature in several ways. In this study, we assess how the stability of the complex BHCs in the US are affected by the regulatory change of 2010. Prior literature that analyses the effectiveness of the Dodd-Frank Act. 2010 on bank stability do not compare these effects between complex and non-complex entities. Furthermore, we analyse the effectiveness of this law to control for the non-banking activities that the complex BHCs in the US decide to engage with their non-bank subsidiaries. We study how banks have reshaped their non-banking activities with their non-bank subsidiaries after the Dodd-Frank Act. was enacted in 2010 by comparing data between the large BHCs and their consolidated counterparts. Furthermore, we analyse how this regulatory change affects the different types of complex institutions. Again, previous research in the complexity of financial institutions focus their analysis only in the largest and complex BHCs and do not compare between the different categories of complex institutions.

3.5 Methodology

3.5.1 The complexity and shadow banking activities of BHCs

In order to have a better understanding of the relationship between regulatory changes and the complexity of banks, in this study, we analyse how the Dodd-Frank Act. affects the stability of complex banks and the financial activities with their non-banking subsidiaries. In this study, we use the BHCs complexity indicator of the FED to identify the complex and non-complex entities. We select a time window sample to capture the pre- and post-period times using a difference-in-difference estimation to compare the evolution of the risk to default and non-banking activities of the two groups.

To measure the complexity of BHCs we refer to code RSSD9057 from the Consolidation Report of Condition and Income (Call Reports) of the entities. In the mid-1990s, the Federal Reserve (FED) established an indicator to classify the complexity of BHCs into seven different categories: credit-extending-activities, non-bank-financial-factors, high-risk-activities, public-debt, management-factors, multiple-factors and supervisory-judgment. The first classification, credit-extending-activities is for entities that increase their credit lending activities either with their parent

BHCs or non-bank subsidiaries or engage debt outstanding to the general public. The second classification is complex became of Non-bank-financial-factors it is the nature and scale of non-bank activities that determine wheter the BHC is complex in this way. High-risk-activities is for entities that engage, directly or through their subsidiaries, in considerably high-risk non-banking activities such as securities broker or dealer activities, insurance underwriting, among others. The public –debt category is when the entity issues significant debt to the general public in which unsophisticated investors may be at risk of loss. The Management-factors classification is when entities show complex management practices such as inter-company transactions or centralised risk management practices. The multiple-factors category is when entities have the presence of two or more the mentioned complex categories. Lastly, the supervisory judgement is when non-complex institutions are designated as complex organizations for supervisory purposes.[15]

Panels A and B in Table 3.1, in the next page, show the composition of large and consolidated BHCs by their complexity category, as well as the average of total assets, non-equity investments and income derived from non-bank subsidiaries for the years 2007 to 2013. Note that although the number of non-complex institutions is considerably greater than the number of complex banks, the latter has a higher average of total assets and financial activities with their non-bank affiliates. Furthermore, we observe that the most representative complex banks are classified as credit-extending-activities, not only in number, but also in terms of the average of total assets and non-bank-activities, followed by the multiple-factors and management-factors categories. It is important to mention that large BHCs with multiple-factors indicator show an average loss of their non-bank income during this time window, which may be due to the financial crisis of 2008.

In this study, we use Call Reports data from US domestic BHCs to capture part of the shadow banking activities that banks engaged in with their non-bank affiliates from the same holding. We consider the non-equity investments on non-bank subsidiaries, which are the sum of advances, notes, bonds, debentures and other receivables due from these entities. Furthermore, we take into account balances due to non-bank subsidiaries. In this way, we can observe the degree of funding that banks received from their non-banks partners, which are considered to be riskier than traditional liability funding. The main reason for this is that non-bank affiliates do not have any support shelter from their regulatory authorities, compared to the bailout programs launched by the banking authorities in order to overcome a financial crisis. (Pozsar *et al.*, 2010). Moreover, we consider the income derived from non-bank affiliates, which allow us to see the benefits that banks received due to intermediation activities, interest management, service fees and dividends from their shadow banking partners, which can also be used in regulatory arbitrage.[16]

[15] Appendix 3.A displays details of the different classifications of complexity.

[16] Note, data for non-equity investments and non-bank income for the consolidated BHCs is not available so we only consider balances due to non-bank subsidiaries in our analysis of this type of entities.

Table 3.1 Composition of the BHCs

Panel A. Composition of the large BHCs by complexity category from dataset 2007-2013

Complexity category	BHCs	Observations	Total assets*	Non-bank Balances*	Non-bank investment*	Non-bank income*
Non-complex	1,811	31,958	1,269,986	117,688	268,100	14,394
Credit-extending-activities	73	1,555	43,595,179	2,841,056	4,825,401	203,926
Non-bank-financial-factors	24	363	673,069	24,887	6,856	14,233
High-risk-activities	25	353	531,211	31,922	14,530	3,946
Management-factors	64	1,031	1,539,068	127,163	23,264	5,288
Multiple-factors	39	539	5,792,705	274,086	90,675	-42,850
Supervisory-judgment	27	270	542,172	19,005	841	425

Panel B. Composition of the consolidated BHCs by complexity category from dataset 2007-2013

Complexity category	BHCs	Observations	Total assets*	Non-bank Balances*
Non-complex	1,398	25,822	4,464,074	398,352
Credit-extending-activities	63	1,270	243,447,465	6,001,661
Non-bank-financial-factors	22	347	1,995,663	0
High-risk-activities	21	320	4,387,017	5,851
Management-factors	61	1,013	9,129,030	301
Multiple-factors	25	409	28,022,502	175,233
Supervisory-judgment	19	182	6,831,940	0

Panel C. Number of large BHCs by complexity category from sample

Complexity category	BHCs	Observations	Total assets*	Non-bank Balances*	Non-bank investment*	Non-bank income*
Non-complex	938	6,566	1,499,391	103,014	383,195	19,572
Credit-extending-activities	50	350	51,858,921	3,948,853	5,596,823	276,058
Non-bank-financial-factors	8	56	334,729	30,374	3,703	23,096
High-risk-activities	11	77	415,362	21,405	849	63
Management-factors	34	238	1,597,499	170,996	6,112	4,323
Multiple-factors	20	140	6,512,532	377,715	100,447	-72,421
Supervisory-judgment	6	42	557,189	9,046	1,220	24

Panel D. Number of consolidated BHCs by complexity category from sample

Complexity category	BHCs	Observations	Total assets*	Non-bank Balances*
Non-complex	774	5,418	5,194,364	941,640
Credit-extending-activities	39	273	274,160,559	8,469,208
Non-bank-financial-factors	8	56	1,451,930	0
High-risk-activities	10	70	4,057,144	0
Management-factors	34	238	9,506,427	1
Multiple-factors	16	112	30,640,577	158,473
Supervisory-judgment	3	21	10,405,918	0

Note: Panel A depicts the composition of the large BHCs according to their complexity indicator code that appears in the item RSSD9057 from the Call Reports for years 2007 to 2013. Total assets is taken from item BHCP2170. Non-bank balances due to non-bank subsidiaries is taken from item BHCP3606. Non-bank investments include the sum of loans, advances, bonds and debentures investments (item BHCP0537) and other receivables (item BHCP0538). While non-bank income is the sum of operating income (item BHCP1279) and equity income (losses) derived from non-bank subsidiaries (item BHCP3147), it does not include equity investments in order to observe the growth of the investments from banks to their non-bank affiliates during the time span. Panel B show the composition of the consolidated BHCs during the same period of time. For this latter, total assets is taken from item BHCK2170 and balances due to non-bank subsidiaries is taken from item BHCK5045. Note that non-bank investments and non-bank income are not available for consolidated entities. Panel C and D present the composition of the sample for large BHCs and their consolidated counterparts. Data obtained from Call Reports, reporting forms FR Y-9LP and FR Y-9C. *All values are average in thousands of dollars.

3.5.2 Data description

The data for this project is obtained through the Federal Reserve Bank of Chicago website. It contains the Call Reports from the small, large and consolidated holding companies, such as BHCs, saving and loan holding companies and saving holding companies. We selected quarterly data from the large BHCs (reporting forms FR Y-9LP) from which it is possible to obtain the data on income and non-equity investments derived from non-bank activities with their non-bank subsidiaries. Our sample window covers the period 2009Q4 to 2011Q2. This time span is chosen to capture the short-term effects of the Dodd-Frank on stability and the non-bank activities of the banks. During this period the number of financial entities in the data set is 5,560.

Criteria for selecting our sample is as follows: we drop entities that do not appear for all the quarters of the sample and, at the same time, we delete the saving and loan holding companies and other domestic entities which are different from the large BHCs or FHC.[17] We also remove the non-domestic institutions. Next, we only consider holdings located in the U.S. territories, such as Puerto Rico and Hawaii. Furthermore, we choose the entities which maintain their complexity or non-complexity indicators during the time span selected.

Our final sample is a balanced dataset which contains 129 complex institutions, 938 non-complex entities and a total of 7,469 observations.[18] Regarding the composition of our sample, the 50 complex institutions classified as credit-extending-activities represent 38% of the complex banks from our sample, followed by 34 with management-factors. Panel C in Table 3.1, above, displays details of the composition of our sample by complexity category.

3.5.3 Model

We use the difference-in-difference estimations to compare the evolution of the risk between two groups: a treated group that integrates complex BHCs and a control group with non-complex BHCs, which are considered unaffected by the change in regulation. This enables us to analyse the effectiveness of the Dodd-Frank Act. the complexity of the BHCs. Our first analysis fixed effects dummies to control for unobserved heterogeneity at State and bank level. Furthermore, we cluster heteroscedasticity-adjusted standard errors at the bank level in order to avoid serial correlation between banks.

Firstly, we analyse the effects of the regulatory changes on risk for the complex BHCs using the following model:

$$\Delta\, ln(\mathcal{Y}_{it}) = \alpha + \beta_1\, Complex_i + \beta_2\, Complex_i * Post_i + \beta_3 X_{i,t-1} + \delta + \varepsilon_{it} \tag{1}$$

Where:

$\Delta\, ln(\mathcal{Y}_{it})$	=	Growth rate of the dependent variable for the BHC i in state at time t.
$Complex_i$	=	Dummy variable equal to 1 for the complex BHCs, 0 otherwise.
$Post$	=	Dummy variable equal to 1 for the quarters following the change in regulation, 0 otherwise.
$X_{i,t-1}$	=	Depicts the vector for the control variables lagged.
δ	=	Fixed-effects dummy variables.
ε_{it}	=	Error term.

[17] We consider the FHC part of the sample due a bank affiliate of a BHC or FHC as a separately chartered institution which can be controlled through partial or complete ownership by another BHC or FHC.

[18] For details about sample selection, see Panel A in Appendix 3.B.

Using the growth of the dependent variable in our analysis eliminates unobserved variables that are individual-specific and constant over time, which is not relevant to our analysis. Our main explanatory variable of interest is the coefficient β_2 from the interaction term $Complex_i * Post_i$ which represents the impact of the change in regulation for the periods following its implementation. The analysis of this coefficient allow us to see how complex BHCs responded to the new requirements of the Dodd-Frank Act. Additionally, we use lagged values for the control variables in order to avoid correlation with omitted variables. Our second test is to focus our analysis on how the different categories of complexity impact bank stability. To conduct this analysis, we modify our original equation 1) and we decompose our main explanatory variable into six different variables, which represent the interaction between each type of complexity and the change in regulation. This means that we generate interaction variables for each of the following complexity categories: credit-extending-activities, non-bank-financial-factors, high-risk-activities, management-factors, multiple-factors and supervisory-judgment. Note that we do not include a variable for public debt complexity as none of the entities from our sample has this indicator. Thus, our modified equation is as follow:

$$\triangle\, ln(Y_{it}) = \alpha + \beta_1 Complex + \beta_2 \sum_{j=1}^{j=6} Complex\ indicator_i * Post_i + \beta_3 X_{i,t-1} + \delta \quad (2)$$

where $Complex\ indicator$ is the dummy variable equal to 1 for each type of the complexity indicators for the BHC i, and 0 otherwise. The coefficient β_2 captures the difference-in-difference effect of the re-regulatory change on the dependent variable for each type of complexity category.

In addition, we are interested in the impact of the Dodd-Frank Act. on complex entities that continued receiving the support of the government's liquidity program, TARP. To conduct this part of our research we use the difference-in-difference-in-differences technique (DIDID), by which we estimate the following regression specification:

$$\begin{aligned}\triangle\, \ln(Y_{it}) = {} & \alpha + \beta_1 Complex + \beta_2\, Complex_i * + \beta_3 Complex * Post_i + \beta_4 Tarp + \\ & \beta_3 Complex * Post_i * Tarp + \delta + \varepsilon_{it}\end{aligned} \quad (3)$$

in which the added variable $Tarp$ is a dummy variable that takes the value 1 if the entity received support from this program, 0 otherwise. For this equation our variable coefficient of interest is β_3 which represents the effects of the change in the law on the complex entities that still received support under the liquidity program.

3.5.4 Variable definitions

We use different measures to represent risk and non-banking activities as dependent variables to compare the effects of the Dodd-Frank Act. between them.

Regarding the risk measures that we include in this study, firstly, we include the Z-score which has been commonly used in the banking literature as a proxy of stability of banks (Stiroh and Rumble, 2006; Elyasiani and Zhang, 2015; Meslier *et al.*, 2016). The interpretation is that lower values of Z-score mean that banks increase their probabilities to default, while higher values of this measure mean that banks achieve to reduce it. following Lepetit and Strobel (2015) Z-score which is calculated as follows:

$$Z = \frac{\text{CAR} + \text{ROA}}{\sigma_{roa}} \tag{4}$$

where the Z-score is defined as the sum of the capital-to-asset ratio and the return on assets divided by the standard deviation of the return on assets.[19] We calculate the standard deviation over a four-quarter rolling time window. This enables us to avoid the changes in the Z-score being affected exclusively by variations in their capital levels and profitability. Following Danisewicz *et al.* (2015), we uses a log transformation of this measure to control for the skewed distribution.

As our second risk measure we use volatility of ROA, which is a component from the Z-score, this measure has been also used by previous researchers in order to depict return volatility (Laeven and Levine, 2009; Berger *et al.*, 2010a; Beck *et al.*, 2013). This variable is calculated as the negative of the natural logarithm of the standard deviation of ROA over a four-quarter rolling time window. We use this time window in order to capture the changes of volatility of the year prior the regulatory change. The negative sign is needed to be comparable with bank stability, in which higher levels of this variable means that banks achieve to reduce their return volatility. The formula for this dependent variable is the following:

$$Volatility\ ROA = -\ln(\sigma_{roa}) \tag{5}$$

We consider three different measures to represent the non-banking activities that BHCs engage in through their non-bank subsidiaries which are proxies of the activities that regulators look to control through the Dodd-Frank Act. 2010. Firstly, we calculate the ratio of balances due to non-bank subsidiaries to total liabilities. This ratio allows us to observe how the change in regulation has affected banks' holding of non-bank liabilities with their affiliates that are considered to be riskier than traditional funding, due to the absence of guarantee schemes (Pozsar *et al.*, 2010). The second measure of non-banking activities is based on the non-equity investments that entities hold in their non-bank partners. To calculate this variable we consider the sum of the loans, advances, notes, bonds, debentures and other receivables due from non-bank subsidiaries and associated non-bank companies. We take the log transformation in order to include it our equation. It is important to mention that to calculate this measure we do not consider the equity investments to

[19] See Appendix 3.C for details about the items taken from Call Reports to calculate all the variables exposed in this study.

fully observe the flow of investments that banks do in their non-bank affiliates. Furthermore, this dependent variable will allow us to analyse if the regulatory change affects banks to continue investing in their non-bank subsidiaries. Our last measure of non-banking activities is computed using the total of non-bank income that banks receive from their non-bank subsidiaries. To calculate this variable we consider the operating income and equity income. In this way, we take into account the sum of dividends, interest management, services fees, and other income, as well as the equity in undistributed income (losses) derived from non-bank subsidiaries. As with the previous dependent variable, this one also requires a log transformation. This dependent variable will enable us to observe if the regulatory change of 2010 reduces the income that banks receive from their non-bank subsidiaries.

We include different control variables to identify specific features from the BHCs that can affect their risk to default. Firstly, we select a variable to depict bank size, calculated as total assets (ln). Previous research has shown that larger institutions are less risky and implies a lower likelihood of bank insolvency (De Haan and Poghosyan, 2012). We analyse the ability of banks to meet their financial obligations through the total liabilities to total equity ratio. High levels of leverage means that banks have been aggressive in financing their growth with debt. However, uncontrolled debt levels can lead to a risk detriment. Thus, the relation with the dependent variable is expected to be negative (Saunders *et al.*, 1990). We also include a loan-loss-provisions to total assets ratio to represent the ex-ante measure for the level of expected losses. Previous research has shown that bank managers use their loan loss provisions as a tool to smooth their income during peak (low) times of loan demand (Shrieves and Dahl, 2003), which has an adverse effect on bank stability. Furthermore, we compute a control variable in order to analyse how the strategy to diversify funding resources affects their default risk. Following Berger *et al.* (2010b), we use HHI to calculate the degree of concentration on their liabilities.[20] To calculate this variable we consider the following items: total deposits, borrowing with a maturity of one year or less, securities sold under agreements to repurchase, other borrowed money with a remaining maturity of more than one year, subordinated notes and debentures, balances due to subsidiaries and related institutions and other liabilities. Moreover, we consider a variable for gross domestic product (GDP) to capture the growth in demand for credit in each state of the USA. Lastly, we include a dummy for the institutions that received support from TARP during the time window of our sample. This variable takes the value of 1 for every month that each bank received extraordinary liquidity from this program until they repaid, and 0 otherwise. Note that some entities continues reporting debt from this program until the last quarter of our time window.

[20] The Hirschman Herfindahl Index (HHI) measure is defined as the sum of all exposure fractions under a specific classification.

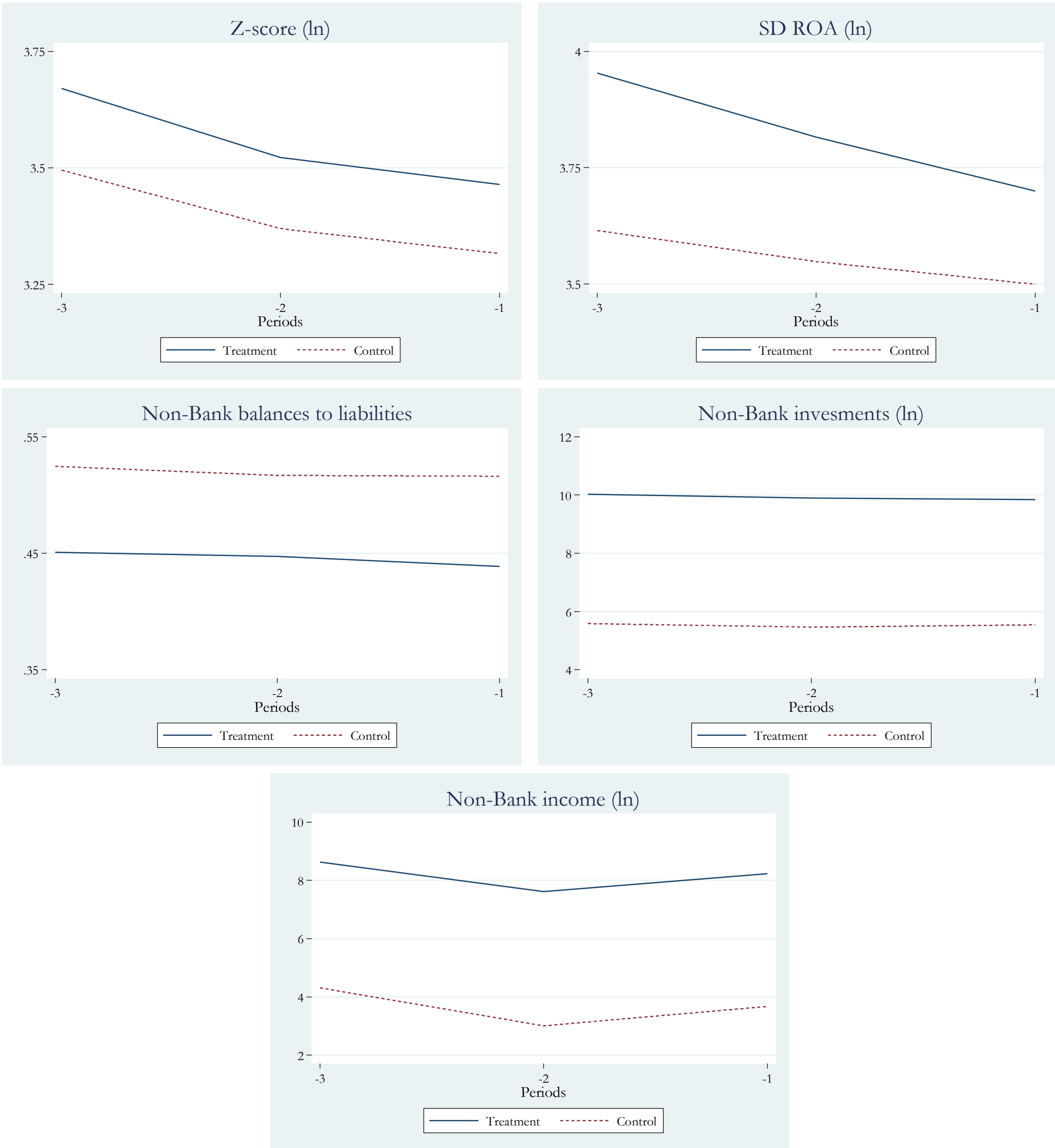
We are also concerned by the fact that some banks could have changed their risk attitude and shadow banking activities before the effective introduction of the Dodd-Frank Act. Therefore, we rerun our analysis by using the four-quarter period immediately preceding the Dodd-Frank Act. (Placebo experiment).

Parallel trends and summary statistics

In order to fulfil the validity of the difference-in-differences estimation, we conduct a parallel trend analysis for the dependent variables between the two groups for the period prior to the treatment. This means that, in the absence of the change in regulation, the treated group would have performed similarly to the control group. Figure 3.2, below, shows visual evidence that our data supports the assumption of parallel trends for our five dependent variables for the periods prior the regulatory change. The graphs in this figure represent the logarithm values of our two measures of risk (Z-score and volatility of ROA) and our three proxies of non-banking activities (non-bank balances to liabilities, non-bank investments and non-bank income). This shows that during the three periods prior the regulatory change the continuous lines that represent the treatment group from our sample, move parallel to the dotted lines which represent the control group. This gives evidence that complex entities do not behave differently from their non-complex counterparts and that complex BHCs do not anticipate any change in their risk levels or non-banking activities with their non-bank subsidiaries up to three-quarters before the law was enacted.

Additionally, to support the graphic illustration of the evolution of bank stability, we conduct t-tests to verify the assumption of parallel trends. We examine whether there are significant differences in the quarterly growth rate of each dependent variable between the treatment and control group during each pre-treatment quarter. The diagnostics in Table 3.2, in the next page, support the assumption of parallel trends: the null of equality of means cannot be rejected. It is important to mention that to satisfy this assumption it does not require equal levels between the two groups, simply that they are different (Lemmon and Roberts, 2010).

Figure 3.2. Parallel trends graphic illustration



Note: Figure 2.2 depicts the behaviour of the dependent variables during the periods preceding the regulatory change. The complex BHCs (the treatment group) are presented by a continuous line, whereas the non-complex large BHCs (the control group) are represented by a dotted line. Data source: Call Reports reporting forms FR Y-9LP. Coverage: 2009Q3 to 2011Q2.

Table 3.2.Treatment and control group in periods prior the Dodd-Frank Act. 2010

	Control	Treatment	Difference	t-Statistics	p-value
ΔZ-score(ln)	0.03	0.06	-0.04	-1.60	0.11
ΔVolatility of ROA	0.01	0.05	-0.03	-1.51	0.13
ΔNon-bank balances/liabilities	-0.00	-0.00	0.00	0.29	0.77
ΔNon-bank investments (ln)	0.01	-0.14	0.15	2.59	0.01
ΔNon-bank income (ln)	-0.04	0.03	-0.07	-1.32	0.19

***p<0.01, **p<0.05, *p<0.1

Descriptive statistics of the variables are displayed below in Table 3.3. Panel A shows the summary statistic, while Panel B reports the correlation matrix. Panel A indicates, that the average size of the BHCs from our sample, in terms of total assets, is 3,931,143,000 $US. While the mean value of our most important measure of risk, the Z-score, is 240, and the average value for the volatility of ROA is 7%. Regarding the non-bank balances to liabilities ratio, its mean is 51%, showing that entities from our sample have a higher concentration of their liabilities on balances held with their non-bank subsidiaries. The mean of the logarithm non-bank investments variable is 7.3. Lastly, the average mean of the variable that depicts non-bank income is 4.5. Finally, in Panel B it can be observed that there are no high correlations between the independent variables and hence no multicollinearity problems.

Table 3.3. Summary statistics and correlation matrix

Panel A. Summary statistics

	N	Mean	SD	Min	Max
Z-score	7440	240	3,909	-8.9	96,527
Z-score (ln)	7259	3.4	1.3	-5.6	11
Delta Z-score(ln)	7173	.031	.66	-6.8	6.5
Volatility of ROA	7461	.07	.36	0	16
Volatility of ROA (ln)	7441	3.6	1.2	-2.8	11
Delta Volatility of ROA	7425	.018	.59	-6.7	6.5
Nonbank balances/liabilities	6465	.51	.42	0	1
Delta Nonbank balances/liabilities	6376	-.0019	.063	-1	1
Nonbank investments (ln)	1035	7.3	4.9	0	19
Delta Nonbank investments	976	-.05	.83	-7.6	5.6
Nonbank income (ln)	3062	4.5	3.2	0	17
Delta Nonbank income	2859	-.026	1	-7	5.8
Complex*Dodd-Frank	7469	.052	.22	0	1
Total assets*	7469	3,931,143	29,566,390	-55,641	461,270,000
Bank size(LAG)	7459	12	1.8	0	20
Leverage ratio	7469	.49	4.7	-138	149
Leverage ratio(LAG)	7461	.5	4	-59	149
Loan loss provision ratio	7468	.00014	.0028	-.038	.17
Loan loss provision(LAG)	7460	.00017	.0024	-.038	.07
Diver liabilities	6465	.81	.22	.22	1.1
Diver liabilities(LAG)	6458	.81	.22	.22	1.1

Panel B. Correlation matrix

		1	2	3	4	5	6	7	8
1	Complex	1							
2	Complex*Dodd-Frank	0.6278	1						
3	Bank size(LAG)	0.4811	0.3033	1					
4	Leverage ratio(LAG)	-0.0034	-0.0036	-0.032	1				
5	Loan loss provision(LAG)	-0.0046	-0.0327	-0.0156	0.0015	1			
6	Diver liabilities(LAG)	-0.2482	-0.1569	-0.2529	-0.0004	-0.0305	1		
7	GDP	-0.0127	0.045	-0.0013	0.0286	-0.0266	-0.078	1	
8	TARP	-0.0294	-0.0471	0.0667	-0.0291	0.0007	0.0032	-0.0702	1

Note: Panel A presents summary statistics on all variables used throughout this chapter. Panel B shows the correlation matrix between the independent variables and our main measure of bank stability the △Z-score. *All values are in thousands of dollars.

3.6 Results

3.6.1 Main results

The difference-in-difference regressions results shown in Table 3.4, in the next page, present the effects of the Dodd-Frank Act. on risk for complex BHCs. Note, in this analysis we run our model 1) with only two explanatory variables: *Complex* and our main independent variable, the interaction term between complex and the change in regulation. Note the *Complex* variable is negative and significant for our two variables to depict stability and it is positive for the non-bank investments and non-bank income. The coefficients for the interaction variable are positive and meaningful for the Z-score and negative and significant for the non-bank balances regression in column 3. This shows that a one standard deviation increase in the main interaction variable between the complex and Dodd-Frank is associated with a 1.76% (0.0801*0.22) increase in the growth of Z-score and a 3.63% (-0.165*0.22) decrease in the growth of non-bank income. This means that considering the entire time window of our analysis, the complex BHCs from our sample show a decrease in their stability and an increase in their non-banking activities with their non-bank subsidiaries. However, for the quarters after the regulatory change, the complex BHCs improve their risk to default and to reduce their non-bank income from their non-bank affiliates.

These preliminary results support the idea that the implementation of the Dodd-Frank Act. enhances stability for the complex BHCs as well as banks reducing their income derived from their non-bank affiliates.

Table 3.4. Complexity of the BHCs and stability

	(1) ΔZ-score(ln)	(2) ΔVolatility ROA	(3) ΔNon-bank balances	(4) ΔNon-bank investments	(5) ΔNon-bank income
Complex	-0.89***	-0.069***	7.2e-12	1.28***	1.47***
	(0.041)	(0.017)	(5.5e-12)	(2.0e-11)	(0.011)
*Complex*Dodd-Frank*	0.080*	0.073	-0.0062	0.053	-0.16**
	(0.041)	(0.040)	(0.0065)	(0.096)	(0.064)
Constant	0.48***	-0.044***	0.00055***	-4.04***	0.76***
	(0.041)	(2.9e-13)	(7.1e-13)	(2.0e-11)	(1.5e-12)
Bank FE	Yes	Yes	Yes	Yes	Yes
State*quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	7173	7425	6376	976	2859
R-squared	0.091	0.086	0.13	0.19	0.071
Number of Banks	1054	1066	938	170	519

Note: This table presents the results of difference-in-difference regressions examining the effect of Dodd-Frank Act. for large complex BHCs on their stability in columns 1 and 2 and on their non-bank activities in columns 3 to 5. We estimate $\Delta\ ln(y_{it}) = \alpha + \beta_1 Complex + \beta_2\ Complex_i * Post_i + \delta + \varepsilon_{it}$ where $\Delta\ ln(y_{it})$ denotes the dependent variable of bank i at time t. In column 1 the dependent variable that represent bank's stability is the Δ(Z-score(ln)) and for column 2 is the volatility of ROA $(-\ln(\sigma_{roa}))$. The proxy for non-bank income in columns 3 to 5 are Δ(balances held with non-bank subsidiaries to total liabilities ratio), Δ(non-bank investments from non-bank subsidiaries(ln)) and Δ(non-bank income derived from non-bank subsidiaries(ln)). The main explanatory variable is the interaction between the Dodd-Frank and the complex dummy variables. The $Post_i$ is a dummy variable equal to 1 for all the quarters following this law was enacted, and 0 otherwise; $Complex_i$ is a dummy variable equal to 1 for all the complex BHCs, and 0 otherwise. The coefficient β_2 represents the effect of the re-regulatory change on the complex institutions. The regressions include state-fixed effects and bank fixed effect and standard errors are clustered on bank level. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports reporting forms FR Y-9LP. Coverage: 2009Q4 to 2011Q2.

Our second analysis is shown in Table 3.5, in the next page, in which we include the control variables for all the equations. The *Complex* variable continues being negative and significant in relation to both measures of stability. However, in this case, this variable is negative and significant only for the non-bank income in which prior analysis this relation is shown positive. In this case, our main explanatory variable is positive and significant for the first two columns. Compare this with the previous results, the magnitude of this effect increases up to 2.86% (0.13*0.22) at 13% for the Z-score and 2.09% (.095*0.22) for ROA volatility. Meanwhile, the main coefficient for the non-bank income variable continues to be negative. Regarding the control variables, we find that bank size affects negatively on bank stability and positively on non-bank income. The financial leverage is positive for the risk of default and for non-bank income. The loan loss provisions is only negative in the case of non-bank income. The diversification in liabilities variable is negative for non-bank balances. These results support the assumption that, in general terms, the re-regulatory change enhances stability for complex institutions and reduces their balances held with their non-bank partners. However, the growth of bank size in terms of assets contributes to deteriorating their risk of default, but it increases the income derived from non-bank activities. Furthermore, entities that maintain their financial leverage levels can improve their stability but, at the same time, enhance their non-bank income. Moreover, institutions with higher levels of loan loss provisions reduce their shadow banking income. Banks with low variety in their funding strategies manage to reduce their income derived from non-bank subsidiaries. Not surprisingly, GDP impacts negatively stability and volatility of banks as well as their non-bank income. Lastly, entities that received liquidity support through the TARP liquidity program during the time span of our analysis show a positive impact on their balances due to non-bank affiliates.

Table 3.5. Regressions with control variables

	(1) ΔZ-score(ln)	(2) ΔVolatility ROA	(3) ΔNon-bank balances	(4) ΔNon-bank investments	(5) ΔNon-bank income
Complex	-0.61***	-0.26***	-0.0079	-1.06	-2.93**
	(0.135)	(0.075)	(0.008)	(1.087)	(1.028)
*Complex*Dodd-Frank*	0.13**	0.095*	-0.0041	0.044	-0.18*
	(0.043)	(0.042)	(0.006)	(0.113)	(0.072)
Bank size(LAG)	-0.67***	-0.34***	0.0082	-0.14	0.52*
	(0.192)	(0.095)	(0.008)	(0.358)	(0.224)
Leverage ratio(LAG)	0.25*	0.0035*	0.00018	-0.0011	0.025*
	(0.110)	(0.002)	(0.000)	(0.003)	(0.010)
Loan loss provision(LAG)	1.64	-2.29	-0.59	1.88	-37.4**
	(3.493)	(3.212)	(0.566)	(3.737)	(12.617)
Diver liabilities(LAG)	-0.074	-0.11	-0.16***	0.52	0.087
	(0.126)	(0.115)	(0.032)	(0.593)	(0.322)
GDP	-1.57**	-1.88***	-0.045	-0.98	-3.97***
	(0.500)	(0.431)	(0.055)	(0.869)	(0.395)
TARP	0.14	0.13	0.027*	-0.16	-0.21
	(0.113)	(0.104)	(0.013)	(0.232)	(0.211)
Constant	8.31***	4.19***	0.062	-0.14	-4.61
	(2.202)	(1.126)	(0.095)	(5.893)	(2.572)
Bank FE	Yes	Yes	Yes	Yes	Yes
State*quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	6204	6446	6374	938	2785
R-squared	0.11	0.099	0.16	0.20	0.089
Number of Banks	940	952	938	164	509

Note: This table presents the results of difference-in-difference regressions examining the effect of Dodd-Frank Act. for large complex BHCs on their stability in columns 1 and 2 and on their non-bank activities in columns 3 to 5. We estimate $\Delta\, ln(y_{it}) = \alpha + \beta_1 Complex + \beta_2\, Complex_i * Post_i + \beta_3 X_{i,t-1} + \delta + \varepsilon_{it}$ where $\Delta\, ln(y_{it})$ denotes the dependent variable of bank i at time t. In column 1 the dependent variable that represents bank's stability is the Δ(Z-score(ln)) and for column 2 is the volatility of ROA $(-\ln(\sigma_{roa}))$. The proxies for non-bank activities in columns 3 to 5 are Δ(balances held with non-bank subsidiaries to total liabilities ratio), Δ(non-bank investments from non-bank subsidiaries(ln)) and Δ(non-bank income derived from non-bank subsidiaries(ln)). The vector of lagged control variables $X_{i,t-1}$ include bank size (total assets (ln)), leverage ratio (total liabilities to total equity), loan loss provision ratio (loan loss provision to total assets) and diversification of liabilities calculated as the HHI of their liabilities, GDP and the dummy variable TARP that takes value 1 if the bank is still receiving support from TARP program, 0 otherwise. The main explanatory variable is the interaction between the Dodd-Frank and the complex dummy variables. The Dodd-Frank is a dummy variable equal to 1 for all the quarters following this law was enacted, and 0 otherwise; Complex is a dummy variable equal to 1 for all the complex BHCs, and 0 otherwise. The coefficient β_2 represents the effect of the re-regulatory change on the complex institutions. The regressions include state-fixed effects and bank fixed effect and standard errors are clustered on bank level. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports reporting forms FR Y-9LP. Coverage: 2009Q4 to 2011Q2.

Next we focus our analysis on the impact of the Dodd-Frank Act. on all the categories of complexity. Outputs in Table 3.6, in page 65, shows evidence that the Dodd-Frank Act. 2010 enhances stability only for the complex BHCs classified as credit-extending activities and by supervisory-judgment during the time window of our sample. Furthermore, the entities classified as supervisory-judgment manage to decrease their investments with their non-bank partners, while complex institutions with management-factors classification show an increase. Furthermore, we find significant evidence that the complex entities with credit-extending-activities are the only ones to cut down their income derived from non-bank subsidiaries after the change in the law. There is no evidence that the complex entities that are classified as non-bank-financial factors, high-risk-activities as well as multiple-factors, improve their risk to default or reduce their shadow banking activities after the regulatory change. These results show evidence that the regulatory change does not achieve control for the risk of all the categories of complex institutions. Complex entities, classified as supervisory judgement benefit from the regulatory change due to these type of entities, have special supervision that might enable banking authorities to have more control on their stability and investments derived from activities whit their non-bank affiliates. Furthermore, it shows that this law achieves an impact on the majority of complex institutions from our sample, which might engage a considerable amount of the non-banking activities of the US banking sector. However, complex entities that mainly conduct non-banking activities or higher levels of risky shadow banking activities do not have any effect after the law was enacted, this might be because the regulators are unable to fully understand all the activities of these type of complex institutions. Note that the control variables remain similar to those in the previous analysis.

Table 3.6. Regressions with disaggregated complex classification

	(1) ΔZ-score(ln)	(2) ΔVolatility ROA	(3) ΔNon-bank balances	(4) ΔNon-bank investments	(5) ΔNon-bank income
*Credit extending activities*Dodd-Frank*	0.16*	0.14*	-0.0074	-0.048	-0.21*
	(0.065)	(0.067)	(0.011)	(0.16)	(0.086)
*Nonbank financial factors*Dodd-Frank*	-0.26	-0.24	0.050	-0.14	0.17
	(0.32)	(0.30)	(0.051)	(0.14)	(0.35)
*High risk activities*Dodd-Frank*	0.17	0.14	-0.016	0.76	-0.30
	(0.090)	(0.093)	(0.030)	(0.41)	(0.28)
*Management factors*Dodd-Frank*	0.12	0.054	-0.0010	0.23*	-0.17
	(0.083)	(0.083)	(0.0084)	(0.11)	(0.14)
*Multiple factors*Dodd-Frank*	0.089	0.088	-0.014	-0.088	-0.24
	(0.095)	(0.090)	(0.012)	(0.23)	(0.24)
*Supervisory judgment*Dodd-Frank*	0.32*	0.28*	0.00071	-0.27***	0.052
	(0.14)	(0.12)	(0.0057)	(0.0072)	(0.11)
Bank size(LAG)	-0.68***	-0.35***	0.0086	-0.18	0.53*
	(0.19)	(0.096)	(0.0078)	(0.32)	(0.22)
Leverage ratio(LAG)	0.25*	0.0035*	0.00018	-0.0011	0.025*
	(0.11)	(0.0018)	(0.00023)	(0.0028)	(0.0099)
Loan loss provision(LAG)	1.73	-2.16	-0.62	0.85	-37.7**
	(3.47)	(3.21)	(0.56)	(3.69)	(12.5)
Diver liabilities(LAG)	-0.083	-0.11	-0.16***	0.53	0.10
	(0.13)	(0.12)	(0.032)	(0.59)	(0.32)
GDP	-1.57**	-1.89***	-0.045	-1.08	-3.97***
	(0.50)	(0.43)	(0.054)	(0.89)	(0.40)
TARP	0.14	0.13	0.027*	-0.19	-0.22
	(0.11)	(0.10)	(0.013)	(0.24)	(0.22)
Constant	8.48***	4.29***	0.056	-0.74	-7.72*
	(2.23)	(1.14)	(0.094)	(4.36)	(3.58)
Bank FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	6204	6446	6374	938	2785
R-squared	0.11	0.100	0.16	0.20	0.089
Number of Banks	940	952	938	164	509

Note: This table presents the results of difference-in-difference regressions examining the effect of Dodd-Frank Act. for large complex BHCs on their stability in columns 1 and 2 and on their non-bank activities in columns 3 to 5. We estimate $\Delta\, ln(Y_{it}) = \alpha + \beta_1 Complex + \beta_2 \sum_{j=1}^{j=6} Complex\ indicator_i * Post_i + \beta_3 X_{i,t-1} + \delta + \varepsilon_{it}$ where $\Delta\, ln(Y_{it})$ denotes the dependent variable of bank i at time t. In column 1 the dependent variable that represents bank's stability is the Δ(Z-score(ln)) and for column 2 is the volatility of ROA $(-\ln(\sigma_{roa}))$. The proxies for non-bank activities in columns 3 to 5 are Δ(balances held with non-bank subsidiaries to total liabilities ratio), Δ(non-bank investments from non-bank subsidiaries(ln)) and Δ(non-bank income derived from non-bank subsidiaries(ln)). The vector of lagged control variables $X_{i,t-1}$ include bank size (total assets (ln)), leverage ratio (total liabilities to total equity), LLP ratio (loan loss provision to total assets) and diversification of liabilities calculated as the HHI of their liabilities, GDP and the dummy variable TARP that takes value 1 if the bank is still receiving support from TARP program, 0 otherwise. $Complex$ is a dummy variable equal to 1 for all the complex BHCs, and 0 otherwise. The $Complex\ indicator_i$ is a dummy variable that takes value 1 for one of the six complexity indicators of $bank_i$ and 0 otherwise. The $Post_i$ is a dummy variable equal to 1 for all the quarters following this law was enacted, and 0 otherwise. The main explanatory variable is the interaction between the $Post_i$ and the $Complex\ indicator_i$ dummy variables. The coefficient β_2 represents the effect of the re-regulatory change on the risk to default for the variety of complex institutions. The regressions include state-fixed effects and bank fixed effect and standard errors are clustered on bank level. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports reporting forms FR Y-9LP. Coverage: 2009Q4 to 2011Q2.

3.6.2 Robustness checks

Removing the concentration of complex entities in our sample

Our first robustness check is focused on evaluating whether there is any influenced derived from the concentration in our sample of complex entities classified as credit-extending-activities. Table 3.7, in the next page, shows these outputs for all the equations. In this way, we verify that complex institutions with supervisory-judgment indicator improve their stability after the re-regulatory change. Meanwhile, management-factors do not show an increase in their non-bank investments, and there is still no evidence of any effect on the complex institutions with non-bank financial-factors, with high-risk-activities and multiple-factors indicators. It is important to mention that the supervisory-judgment classification is given to entities for supervisory purposes; in this manner, the regulator classifies banks as complex institutions when they do not appear to be complex in order to have more control over them through the reporting and supervisory activities. Regarding GDP it shows the same results as in the previous analysis, which can be interpreted as the slow growth of the economy in the US after the financial crisis of 2007 affects stability of the BHCs during the time span of our analysis. While entities that are still receiving TARP support during this period of time achieve to reduce only their non-bank investments but there is no evidence that banks that are still receive support from this liquidity program, achieve a reduction in their risk of default.

Table 3.7. Regressions removing the concentration of entities in our sample

	(1) ΔZ-score(ln)	(2) ΔVolatility ROA	(3) ΔNon-bank balances	(4) ΔNon-bank investments	(5) ΔNon-bank income
*Nonbank financial factors*Dodd-Frank*	-0.27	-0.25	0.050	-0.12	0.16
	(0.32)	(0.30)	(0.051)	(0.13)	(0.35)
*High risk activities*Dodd-Frank*	0.18	0.13	-0.016	0.76	-0.29
	(0.090)	(0.093)	(0.030)	(0.41)	(0.28)
*Management factors*Dodd-Frank*	0.12	0.048	-0.0017	0.15	-0.17
	(0.083)	(0.083)	(0.0085)	(0.11)	(0.15)
*Multiple factors*Dodd-Frank*	0.082	0.080	-0.015	-0.13	-0.25
	(0.097)	(0.091)	(0.012)	(0.22)	(0.23)
*Supervisory judgment*Dodd-Frank*	0.32*	0.28*	0.00070	-0.27***	0.054
	(0.14)	(0.12)	(0.0058)	(0.0077)	(0.11)
Bank size(LAG)	-0.74***	-0.36***	0.0075	-0.25	0.51*
	(0.20)	(0.099)	(0.0078)	(0.34)	(0.23)
Leverage ratio(LAG)	0.22	0.0034	0.00018	0.0013	0.026*
	(0.11)	(0.0017)	(0.00023)	(0.0025)	(0.0099)
Loan loss provision(LAG)	2.26	-2.50	-0.73	3.68	-38.4**
	(4.39)	(4.31)	(0.76)	(4.77)	(12.6)
Diver liabilities(LAG)	-0.11	-0.13	-0.16***	0.82	0.028
	(0.13)	(0.12)	(0.032)	(0.63)	(0.34)
GDP	-1.29*	-1.62***	-0.032	-0.94	-4.03***
	(0.50)	(0.43)	(0.055)	(1.00)	(0.40)
TARP	0.070	0.077	0.018	-0.59*	-0.33
	(0.14)	(0.13)	(0.012)	(0.28)	(0.37)
Bank FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	5865	6105	6034	737	2567
R-squared	0.11	0.099	0.17	0.21	0.091
Number of Banks	891	903	889	132	471

Note: This table presents the results of difference-in-difference regressions examining the effect of Dodd-Frank Act. for large complex BHCs on their stability in columns 1 and 2 and on their non-bank activities in columns 3 to 5 without the credit extension complex category. We estimate $\Delta\ ln(Y_{it}) = \alpha + \beta_1 Complex + \beta_2 \sum_{j=1}^{j=5} Complex\ indicator_i * Post_i + \beta_3 X_{i,t-1} + \delta + \varepsilon_{it}$ where $\Delta\ ln(Y_{it})$ denotes the dependent variable of bank i at time t. In column 1 the dependent variable that represents bank's stability is the Δ(Z-score(ln)) and for column 2 is the volatility of ROA ($-\ln(\sigma_{roa})$). The proxies for non-bank activities in columns 3 to 5 are Δ(balances held with non-bank subsidiaries to total liabilities ratio), Δ(non-bank investments from non-bank subsidiaries(ln)) and Δ(non-bank income derived from non-bank subsidiaries(ln)). The vector of lagged control variables $X_{i,t-1}$ include bank size (total assets (ln)), leverage ratio (total liabilities to total equity), LLP ratio (loan loss provision to total assets) and diversification of liabilities calculated as the HHI of their liabilities, GDP and the dummy variable TARP that takes value 1 if the bank is still receiving support from TARP program, 0 otherwise. $Complex$ is a dummy variable equal to 1 for all the complex BHCs, and 0 otherwise. The $Complex\ indicator_i$ is a dummy variable that takes value 1 for one of the five complexity indicators of bank i without including the credit extension category, and 0 otherwise. The $Post_i$ is a dummy variable equal to 1 for all the quarters following this law was enacted, and 0 otherwise. The main explanatory variable is the interaction between the $Post_i$ and the $Complex\ indicator_i$ dummy variables. The coefficient β_2 represents the effect of the re-regulatory change on the risk to default for the variety of complex institutions. The regressions include state-fixed effects and bank fixed effect and standard errors are clustered on bank level. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports reporting forms FR Y-9LP. Coverage: 2009Q4 to 2011Q2.

Removing the State concentration from our sample

As a second robustness check, we remove banks located in four US States that concentrate 25% of the total observations to observe whether our results are influenced by this concentration. These US States are California, Illinois, New York, and Texas. Table 3.8, in the next page, depicts this result, in which it can be observed that these are similar to those presented in Table 3.6, in page 65. Only the credit-extending-activities category is no longer significant for the non-bank income equation. We confirm that even with the concentration of one-quarter of the total entities of the sample being from four US States, the complex institutions classified as credit-extending-activities improved their risk of default. However, entities classified as supervisory-judgement do not show any effect on their stability, which might be concentrated in the States removed to obtain this sub-sample. Furthermore, the entities with management –factors category is no longer significant for the non-bank investments, again, this might be because most of these type of complex institutions might have their headquarters located in the States of California, Illinois, New York or Texas.

Regarding the control variables, bank size shows similar results to those presented in the previous analysis, which confirms that the largest banks show a decrease of their stability but an increase in their non-bank income. In this case, the leverage ratio is not significant to any of the stability measures nor for the non-bank income, as shown in the previous analysis in Table 3.6. This can be because banks not located in the four States removed to obtain this subsample, might have less opportunities to obtain non-banking traditional funding that can enable them to enhance their stability as well as to generate more income derived from the activities that these banks engage with their non-bank affiliates. Lastly, the diversification of liabilities continues being negative and significant for non-bank balances. We confirm that banks which increase their funding options can reduce their debt with their non-bank subsidiaries. However, we do not find evidence that entities with more diversification in their liabilities can enable them to reduce their risk to default or to decrease their investments and income with their non-bank affiliates.

Lastly, the diversification of liabilities continues being negative and significant only for non-bank balances. We confirm that banks which increase their funding options can reduce their debt with their non-bank subsidiaries. However, we do not find evidence that entities with more diversification in their liabilities enables them to reduce their risk of default or to decrease their investments and income with their non-bank affiliates.

Table 3.8. Regressions removing the State concentration from our sample

	(1) ΔZ-score(ln)	(2) ΔVolatility ROA	(3) ΔNon-bank balances	(4) ΔNon-bank investments	(5) ΔNon-bank income
*Credit extending activities*Dodd-Frank*	0.17*	0.15	-0.0044	-0.010	-0.26*
	(0.084)	(0.088)	(0.015)	(0.22)	(0.10)
*Nonbank financial factors*Dodd-Frank*	-0.27	-0.25	0.050	-0.18	0.15
	(0.32)	(0.30)	(0.051)	(0.18)	(0.36)
*High risk activities*Dodd-Frank*	0.12	0.081	-0.030	0.71	-0.36
	(0.060)	(0.060)	(0.043)	(0.60)	(0.41)
*Management factors*Dodd-Frank*	0.12	0.048	-0.00085	0.24	-0.17
	(0.086)	(0.086)	(0.0087)	(0.13)	(0.15)
*Multiple factors*Dodd-Frank*	0.0089	0.0025	-0.0022	-0.15	-0.13
	(0.12)	(0.12)	(0.0071)	(0.23)	(0.21)
*Supervisory judgment*Dodd-Frank*	0.21	0.21	0.0059	-0.26***	0.059
	(0.12)	(0.11)	(0.0046)	(0.0066)	(0.11)
Bank size(LAG)	-0.81**	-0.41***	0.011	-0.17	0.59*
	(0.26)	(0.12)	(0.0074)	(0.36)	(0.23)
Leverage ratio(LAG)	0.20	0.0037	0.00020	-0.0020	0.016
	(0.20)	(0.0024)	(0.00033)	(0.0030)	(0.11)
Loan loss provision(LAG)	2.47	-2.83	-0.039	-0.34	-37.2**
	(3.92)	(2.85)	(0.28)	(3.79)	(12.4)
Diver liabilities(LAG)	-0.13	-0.17	-0.17***	0.037	-0.15
	(0.14)	(0.13)	(0.038)	(0.52)	(0.37)
GDP	-1.23	-1.57**	-0.046	-1.12	-3.83***
	(0.64)	(0.55)	(0.078)	(1.19)	(0.49)
TARP	0.092	0.087	0.023	-0.14	-0.28
	(0.15)	(0.13)	(0.012)	(0.34)	(0.26)
Constant	9.99***	5.01***	0.045	2.88	-8.57*
	(3.00)	(1.38)	(0.096)	(6.20)	(3.68)
Bank FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	4571	4756	4708	658	2024
R-squared	0.11	0.10	0.16	0.21	0.075
Number of Banks	693	703	694	116	373

Note: This table presents the results of difference-in-difference regressions examining the effect of Dodd-Frank Act. for large complex BHCs without entities located in California, Illinois, New York, and Texas, on their stability in columns 1 and 2 and on their non-bank activities in columns 3 to 5. We estimate $\Delta\ ln(Y_{it}) = \alpha + \beta_1 Complex + \beta_2 \sum_{j=1}^{j=6} Complex\ indicator_i * Post_i + \beta_3 X_{i,t-1} + \delta + \varepsilon_{it}$ where $\Delta\ ln(Y_{it})$ denotes the dependent variable of bank i at time t. In column 1 the dependent variable that represents bank's stability is the Δ(Z-score(ln)) and for column 2 is the volatility of ROA ($-\ln(\sigma_{roa})$). The proxies for non-bank activities in columns 3 to 5 are Δ(balances held with non-bank subsidiaries to total liabilities ratio), Δ(non-bank investments from non-bank subsidiaries(ln)) and Δ(non-bank income derived from non-bank subsidiaries(ln)). The vector of lagged control variables $X_{i,t-1}$ include bank size (total assets (ln)), leverage ratio (total liabilities to total equity), LLP ratio (loan loss provision to total assets) and diversification of liabilities calculated as the HHI of their liabilities, GDP and the dummy variable TARP that takes value 1 if the bank is still receiving support from TARP program, 0 otherwise. $Complex$ is a dummy variable equal to 1 for all the complex BHCs, and 0 otherwise. The $Complex\ indicator_i$ is a dummy variable that takes value 1 for one of the six complexity indicators of bank i, and 0 otherwise. The $Post_i$ is a dummy variable equal to 1 for all the quarters following this law was enacted, and 0 otherwise. The main explanatory variable is the interaction between the $Post_i$ and the $Complex\ indicator_i$ dummy variables. The coefficient β_2 represents the effect of the re-regulatory change on the risk to default for the variety of complex institutions. The regressions include state-fixed effects and bank fixed effect and standard errors are clustered on bank level. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports reporting forms FR Y-9LP. Coverage: 2009Q4 to 2011Q2.

Regressions analysing entities with support from the TARP liquidity program

For our next analysis, we applied our model 3), in which we use the Difference-in-Difference-in-Differences (DIDID) to analyse the effect Dodd-Frank Act. on the risk of default and non-bank activities of the complex BHCs that are still receiving support from the TARP liquidity program after this law was enacted. The results, in Table 3.9, below, shows that the coefficient for the main interaction variable (Complex*Dodd-Frank*TARP) is not significant. This means that the regulatory change does not show any effect on the stability of the complex entities as well as on their non-banking activities. This can be explained due to the fact that the majority of the largest and complex banks had already repaid all the money that they had received from this program when the law was enacted. Furthermore, this liquidity program gave extra support to shadow banking activities before this law was established, which do not allow us to see their real effect on their risk to default and their non-banking activities (Pozsar *et al.*, 2010). Regarding the control variables, these show similar to those presented in the previous analysis.

Table 3.9. Regressions analysing entities with support from the TARP liquidity program

	(1) ΔZ-score (ln)	(2) ΔVolatility ROA	(3) ΔNon-bank balances	(4) ΔNonbank investments	(5) ΔNonbank income
Complex	-0.58***	-0.23**	-0.0087	-0.88	-2.94**
	(0.13)	(0.073)	(0.0084)	(1.09)	(1.03)
*Complex*Dodd-Frank*	0.096*	0.064	-0.0023	0.13	-0.16*
	(0.041)	(0.040)	(0.0066)	(0.12)	(0.075)
*Complex*Dodd-Frank*TARP*	0.31	0.33	-0.019	-0.59	-0.17
	(0.20)	(0.21)	(0.017)	(0.35)	(0.25)
Bank size(LAG)	-0.67***	-0.34***	0.0083	-0.11	0.52*
	(0.19)	(0.095)	(0.0078)	(0.35)	(0.22)
Leverage ratio(LAG)	0.25*	0.0035*	0.00018	-0.00086	0.025*
	(0.11)	(0.0018)	(0.00023)	(0.0026)	(0.0099)
Loan loss provision(LAG)	2.32	-1.72	-0.62	0.22	-37.3**
	(3.39)	(3.22)	(0.56)	(5.17)	(12.7)
Diver liabilities(LAG)	-0.078	-0.11	-0.16***	0.58	0.086
	(0.13)	(0.12)	(0.032)	(0.59)	(0.32)
GDP	-1.57**	-1.89***	-0.045	-0.89	-3.97***
	(0.50)	(0.43)	(0.055)	(0.87)	(0.40)
TARP	0.11	0.10	0.029*	-0.033	-0.18
	(0.11)	(0.11)	(0.013)	(0.23)	(0.20)
Constant	8.36***	4.22***	0.060	-0.73	-4.50
	(2.20)	(1.13)	(0.095)	(5.84)	(2.58)
Bank FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	6204	6446	6374	938	2785
R-squared	0.11	0.100	0.16	0.20	0.089
Number of Banks	940	952	938	164	509

Note: This table presents the results of the difference-in-difference-in-differences (DIDID) regressions to examine the effects of the Dodd-Frank Act. for large complex BHCs that continue receiving support from the TARP liquidity program when this law was enacted. We estimate $\Delta \ln(\mathcal{Y}_{it}) = \alpha + \beta_1 Complex + \beta_2\, Complex_i * + \beta_3 Complex * Post_i + \beta_4 TARP + \beta_3 Complex * Post_i * TARP + \delta + \varepsilon_{it}$ where $\Delta\, ln(\mathcal{Y}_{it})$ denotes the dependent variable of bank i at time t. In column 1 the dependent variable that represents bank's stability is the Δ(Z-score(ln)) and for column 2 is the volatility of ROA ($-\ln(\sigma_{roa})$). The proxies for non-bank activities in columns 3 to 5 are Δ(balances held with non-bank subsidiaries to total liabilities ratio), Δ(non-bank investments from non-bank subsidiaries(ln)) and Δ(non-bank income derived from non-bank subsidiaries(ln)). The vector of lagged control variables $X_{i,t-1}$ include bank size (total assets (ln)), leverage ratio (total liabilities to total equity), LLP ratio (loan loss provision to total assets) and diversification of liabilities calculated as the HHI of their liabilities, GDP and the dummy variable TARP that takes value 1 if the bank is still receiving support from the TARP liquidity program. $Complex$ is a dummy variable equal to 1 for all the complex BHCs, and 0 otherwise. The $Post_i$ is a dummy variable equal to 1 for all the quarters following this law was enacted, and 0 otherwise. The main explanatory variable is the interaction between the $Post_i$ and the $Complex\ indicator_i$ dummy variables. The coefficient β_3 represents the DIDID effect of the re-regulatory change on the risk to default for the complex institutions with TARP support. The regressions include state-fixed effects and bank fixed effect and standard errors are clustered on bank level. *p<0.1, **p<0.05, ***p<0.01. Data source: Callx Reports reporting forms FR Y-9LP. Coverage: 2009Q1 to 2010Q2.

Analysing for consolidated BHCs

Next, we are interested to know whether our main results can be applied to the consolidated BHCs. The importance of this part of our analysis is because some of the rules imposed through the enactment of the Dodd-Frank Act. apply to the consolidated BHCs. Thus, it is important to compare the effectiveness of this regulatory change between larger and consolidated BHCs in order to observe differences between both groups. To conduct this part of our analysis, we select data from the consolidated financial statements for holding companies reports (FR Y-9C), which is available from our main data source. For this sample, there is a total of 884 entities, of which 110 are complex institutions and 774 are non-complex ones.[21] Panel D in Table 3.10, in the next

[21] See panel B in Appendix 3.B for details of the sample selection

page, depicts the number of entities for this sample according to their complexity category. In this case, the complex entities with the credit-extending-activities category are the only ones to increase their average of total assets compared to our previous sample. It is important to mention that consolidated financial information is it is not available for the non-bank investments and non-bank income derived from non-banking subsidiaries. Thus, we only use two dependent variables, for stability and the non-bank balances from non-bank partners. Then, we rerun model 1) and the results are presented in Table 3.10, below. It can be seen that the results are quite similar to those shown in Table 3.5, above, with similar magnitudes of the change in Z-score, but they are negative and significant for the volatility of ROA. We can interpret this as meaning that, despite the regulatory change enhancing the stability of banks, their non-bank subsidiaries continued engaging in non-banking activities inside or outside the financial group, which that might increase their volatility, affecting their risk to default. Furthermore, we find no effect on balances due to non-bank partners. Lastly, we find that results for the control variables are similar to those shown in Table 3.6.

Table 3.10. Basic regressions and regressions with control variables for consolidated BHCs

	(1) ΔZ-score(ln)	(2) ΔVolatility ROA	(3) ΔNon-bank balances	(4) ΔZ-score(ln)	(5) ΔVolatility ROA	(6) ΔNon-bank balances
Complex	0.64***	-0.35***	0.000022	3.71*	-2.53**	-0.00032
	(0.019)	(0.040)	(0.000020)	(1.65)	(0.84)	(0.00034)
*Complex*Dodd-Frank*	0.078	0.069	-0.000050	0.13*	0.10*	0.000031
	(0.044)	(0.043)	(0.000047)	(0.050)	(0.046)	(0.000097)
Bank size(LAG)				-0.39	-0.40**	-0.0026
				(0.21)	(0.14)	(0.0029)
Leverage ratio(LAG)				8.43**	3.93**	-0.000040
				(2.67)	(1.40)	(0.0017)
Loan loss provision(LAG)				9.88***	-1.77*	0.0026
				(2.16)	(0.90)	(0.0017)
Diver liabilities(LAG)				0.16	0.18	0.00032
				(0.31)	(0.28)	(0.00040)
GDP				-0.93	-1.83***	-0.0049
				(0.50)	(0.42)	(0.0052)
TARP				0.094	0.11	-0.00018
				(0.10)	(0.100)	(0.00029)
Constant	0.068**	-0.050***	0.000029	-5.39**	5.86*	0.041
	(0.025)	(1.1e-12)	(0.000027)	(1.87)	(2.67)	(0.045)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
State*quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5987	6177	5787	5941	6130	5783
R-squared	0.084	0.074	0.0075	0.11	0.091	0.0076
Number of Banks	877	884	863	877	884	863

Note: This table presents the results of difference-in-difference regressions examining the effect of Dodd-Frank Act. for complex consolidated BHCs. For columns 1 to 3 we estimate $\Delta\, ln(y_{it}) = \alpha + \beta_1 Complex + \beta_2\, Complex_i * Post_i + \delta + \varepsilon_{it}$ and for columns 5 to 6 we estimate $\Delta\, ln(y_{it}) = \alpha + \beta_1 Complex + \beta_2\, Complex_i * Post_i + \beta_3 X_{i,t-1} + \delta + \varepsilon_{it}$ where $\Delta\, ln(y_{it})$ denotes the dependent variable of bank i at time t. In column 1 the dependent variable that represents bank's stability is the Δ(Z-score(ln)) and for column 2 is the volatility of ROA ($-\ln(\sigma_{roa})$). The proxy for non-bank activities is Δ(balances held with non-bank subsidiaries to total liabilities ratio). $X_{i,t-1}$ represents the vector for the control variables. The main explanatory variable is the interaction between the Dodd-Frank and the complex dummy variables. The $Post_i$ is a dummy variable equal to 1 for all the quarters following this law was enacted, and 0 otherwise; $Complex_i$ is a dummy variable equal to 1 for all the complex BHCs, and 0 otherwise. The coefficient β_2 represents the effect of the re-regulatory change on the complex institutions. The regressions include state-fixed effects and bank fixed effect and standard errors are clustered on bank level. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports reporting forms FR Y-9C. Coverage: 2009Q4 to 2011Q2.

The next test uses model 3), the results of which are displayed in Table 3.11, in the next page. Following the previous analysis, in columns 1 to 3 we run this model including all the complexity categories. Columns 4 to 6 are the regressions without the credit-extending-category and in columns 7 to 9 we remove the four US States that concentrate 25% of the total observations. The outputs show that entities with credit-extending-activities are still significant. However, the coefficients for the rest of the categories are not significant. This gives evidence that the Dodd-Frank Act. does achieve to improve the risk levels of all the categories of consolidated and complex BHCs. In this case, the non-bank balances variable is not significant to any of the regressions showing that there is no effect of this regulatory change to control the debt that consolidated BHCs engage with their non-bank subsidiaries. This might be because at the consolidated level it is not possible to observe any effect of the regulatory change in the short-time of our analysis. Regarding the control variable, we find that bank size is negative and significant only in terms of volatility of ROA, meaning that the largest and consolidated BHCs achieve to improve their risk levels after the law was passed. For the leverage ratio, we find similar results to those presented in previous analysis in which entities that show higher levels of leverage improve their rsk to default after the law was enacted. A similar picture can be observed for loan loss provisions. Lastly, there is no evidence that the diversification of liabilities is significant.

Table 3.11. Regressions with disaggregated complexity categories

	(1) ΔZ-score (ln)	(2) ΔVolatility ROA	(3) ΔNon-bank balances	(4) ΔZ-score (ln)	(5) ΔVolatility ROA	(6) ΔNon-bank balances	(7) ΔZ-score (ln)	(8) ΔVolatility ROA	(9) ΔNon-bank balances
*Credit extending activities*Dodd-Frank*	0.2*	0.2*	0.00010				0.3*	0.2*	0.00005
	(0.08)	(0.08)	(0.0001)				(0.1)	(0.1)	(0.00006)
*Nonbank financial factors*Dodd-Frank*	-0.07	-0.09	0.00002	-0.08	-0.10	0.000008	-0.08	-0.1	0.000003
	(0.3)	(0.2)	(0.00010)	(0.3)	(0.2)	(0.0001)	(0.3)	(0.3)	(0.000005)
*High risk activities*Dodd-Frank*	0.2	0.1	0.0003	0.2	0.1	0.0003	0.10	0.09	-0.000002
	(0.10)	(0.07)	(0.0003)	(0.10)	(0.07)	(0.0003)	(0.08)	(0.06)	(0.000003)
*Management factors*Dodd-Frank*	0.1	0.06	0.00003	0.1	0.05	0.00002	0.1	0.05	-0.000001
	(0.09)	(0.08)	(0.00006)	(0.09)	(0.08)	(0.00006)	(0.09)	(0.08)	(0.000001)
*Multiple factors*Dodd-Frank*	0.03	0.02	-0.0003	0.03	0.006	-0.0003	-0.04	-0.05	-0.0001
	(0.1)	(0.1)	(0.0003)	(0.1)	(0.1)	(0.0003)	(0.1)	(0.1)	(0.0001)
*Supervisory judgment *Dodd-Frank*	0.3	0.3	-0.00009	0.3	0.3	-0.0001	0.3	0.3	0.000004
	(0.2)	(0.2)	(0.0003)	(0.2)	(0.2)	(0.0003)	(0.2)	(0.2)	(0.000005)
Bank size(LAG)	-0.4	-0.4**	-0.003	-0.4	-0.4**	-0.003	-0.3	-0.3	0.00003
	(0.2)	(0.1)	(0.003)	(0.2)	(0.1)	(0.003)	(0.2)	(0.2)	(0.00003)
Leverage ratio(LAG)	8.4**	3.9**	-0.00002	8.8**	4.1**	-0.0004	8.9*	4.7*	0.0002
	(2.7)	(1.4)	(0.002)	(2.9)	(1.5)	(0.002)	(3.5)	(2.0)	(0.0001)
Loan loss provision(LAG)	9.9***	-1.7	0.003	10.4***	-1.7	0.002	12.3***	-1.4	0.0002
	(2.2)	(0.9)	(0.002)	(2.3)	(0.9)	(0.002)	(2.9)	(1.0)	(0.0002)
Diver) liabilities(LAG)	0.2	0.2	0.0003	0.2	0.3	0.0003	0.3	0.4	0.000003
	(0.3)	(0.3)	(0.0004)	(0.3)	(0.3)	(0.0004)	(0.3)	(0.3)	(0.00005)
GDP	-0.9	-1.8***	-0.005	-0.7	-1.6***	-0.005	-0.7	-1.8**	0.00003
	(0.5)	(0.4)	(0.005)	(0.5)	(0.4)	(0.005)	(0.7)	(0.6)	(0.00004)
TARP	0.1	0.1	-0.0002	0.03	0.02	-0.0003	0.06	0.07	-0.000004
	(0.1)	(0.1)	(0.0003)	(0.1)	(0.1)	(0.0004)	(0.1)	(0.1)	(0.000006)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5941	6130	5783	5671	5858	5532	4447	4594	4312
R-squared	0.1	0.09	0.008	0.1	0.09	0.008	0.1	0.09	0.1
Number of Banks	877	884	863	838	845	825	658	664	646

Note: This table presents the results of difference-in-difference regressions examining the effect of Dodd-Frank Act. for complex consolidated BHCs on their stability in columns 1 and 2 and on their non-bank activities in columns 3 to 5. We estimate $\Delta\ ln(Y_{it}) = \alpha + \beta_1 Complex + \beta_2 \sum_{j=1}^{j=6} Complex\ indicator_i * Post_i + \beta_3 X_{i,t-1} + \delta + \varepsilon_{it}$ where $\Delta\ ln(Y_{it})$ denotes the dependent variable of bank i at time t. In column 1 the dependent variable that represents bank's stability is the Δ(Z-score(ln)) and for column 2 is the volatility of ROA ($-\ln(\sigma_{roa})$). The only proxy for non-bank activities in columns 3 is Δ(balances held with non-bank subsidiaries to total liabilities ratio. The vector of lagged control variables $X_{i,t-1}$ include bank size (total assets (ln)), leverage ratio (total liabilities to total equity), LLP ratio (loan loss provision to total assets) and diversification of liabilities calculated as the HHI of their liabilities, GDP and the dummy variable TARP that takes value 1 if the bank is still receiving support from TARP program, 0 otherwise. $Complex$ is a dummy variable equal to 1 for all the complex BHCs, and 0 for the non-complex BHCs. The $Complex\ indicator_i$ is a dummy variable that takes the value 1 for each of the six complexity indicators of bank i, and 0 otherwise. The $Post_i$ is a dummy variable equal to 1 for all the quarters following this law was enacted, and 0 otherwise. The main explanatory variable is the interaction between the $Post_i$ and the $Complex\ indicator_i$ dummy variables. The coefficient β_2 represents the effect of the re-regulatory change on the risk to default for the variety of complex institutions. The regressions include state-fixed effects and bank fixed effect and standard errors are clustered on bank level. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports reporting forms FR Y-9C. Coverage: 2009Q4 to 2011Q2.

Then, our next analysis regards the DIDID regressions for the effects on stability and non-bank balances for the complex entities that received support from TARP liquidity program when the Dodd-Frank Act. was enacted. These outputs, shown in Table 3.12, below, are quite similar to those shown in Table 3.10, above, for the large BHCs. This supports the idea that the extraordinary liquidity support from the government makes it impossible us to observe the real effect on the risk to default for the financial entities.

Table 3.12. DIDID regressions using TARP for consolidated BHCs

	(1) ΔZ-score (ln)	(2) ΔVolatility ROA	(3) ΔNon-bank balances
Complex	3.70*	-2.53**	-0.00031
	(1.64)	(0.83)	(0.00034)
*Complex*Dodd-Frank*	0.089	0.064	0.0000094
	(0.048)	(0.043)	(0.00010)
*Complex*Dodd-Frank*TARP*	0.34	0.36	0.00020
	(0.20)	(0.21)	(0.00018)
Bank size(LAG)	-0.39	-0.40**	-0.0026
	(0.21)	(0.14)	(0.0029)
Leverage ratio(LAG)	8.49**	4.00**	-0.0000061
	(2.68)	(1.41)	(0.0017)
Loan loss provision(LAG)	9.91***	-1.74	0.0026
	(2.16)	(0.90)	(0.0017)
Diver liabilities(LAG)	0.17	0.20	0.00033
	(0.31)	(0.28)	(0.00040)
GDP	-0.93	-1.83***	-0.0049
	(0.50)	(0.42)	(0.0052)
TARP	0.064	0.081	-0.00019
	(0.11)	(0.10)	(0.00028)
Constant	-5.48**	5.82*	0.041
	(1.87)	(2.67)	(0.045)
Bank FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	5941	6130	5783
R-squared	0.12	0.092	0.0076
Number of Banks	877	884	863

Note: This table presents the results of the difference-in-difference-in-differences (DIDID) regressions to examine the effects of the Dodd-Frank Act. for complex consolidated BHCs that continue receiving support from the TARP when this law was enacted. We estimate $\Delta \ln(Y_{it}) = \alpha + \beta_1 Complex + \beta_2\ Complex_i * + \beta_3 Complex * Post_i + \beta_4 Tarp + \beta_3 Complex * Post_i * Tarp + \delta + \varepsilon_{it}$ where $\Delta\ ln(Y_{it})$ denotes the dependent variable of bank i at time t. In column 1 the dependent variable that represents bank's stability is the Δ(Z-score(ln)) and for column 2 is the volatility of ROA ($-\ln(\sigma_{roa})$). The only proxy that represents non-banking activities in column 3 is Δ(balances held with non-bank subsidiaries to total liabilities ratio).The vector of lagged control variables $X_{i,t-1}$ include bank size (total assets (ln)), leverage ratio (total liabilities to total equity), LLP ratio (loan loss provision to total assets) and diversification of liabilities calculated as the HHI of their liabilities, GDP and the dummy variable TARP that takes value 1 if the bank is still receiving support from TARP program. $Complex$ is a dummy variable equal to 1 for all the complex BHCs, and 0 otherwise. The $Post_i$ is a dummy variable equal to 1 for all the quarters following this law was enacted, and 0 otherwise. The main explanatory variable is the interaction between the $Post_i$ and the $Complex\ indicator_i$ dummy variables. The coefficient β_3 represents the DIDID effect of the re-regulatory change on the risk to default for the complex institutions with TARP support. The regressions include state-fixed effects and bank fixed effect and standard errors are clustered on bank level. *p<0.1, **p<0.05, ***p<0.01. Data source: Call, Reports reporting forms FR Y-9C. Coverage: 2009Q1 to 2010Q2.

Using a random complex category for the non-treatment sub-sample

Finally, for our last robustness check, we randomly allocate a complexity category only to all the non-complex banks from our sample, thereby creating another fictional treatment and control groups. The aim of this analysis is to check whether the regulatory change only affects the real complex institutions from our original sample. In this way, we expect to obtain not significant values for our key variables compared to those obtained in the previous analysis. Table 3.13, below, shows the outputs for this test. We find that almost none of the coefficients for the different interactions variables and types of complexity are significant compared to those displayed in Table 3.6, above. As expected, only the control variables for bank size and GDP maintain their significance in this analysis; this is because these issues affected any financial institution whether they are a complex entity, or not. Thus, we fail to find significant values for the interaction variable for this simulated sample, and we confirm that there are no alternative forces that influence our main results.

Table 3.13. Placebo test regressions

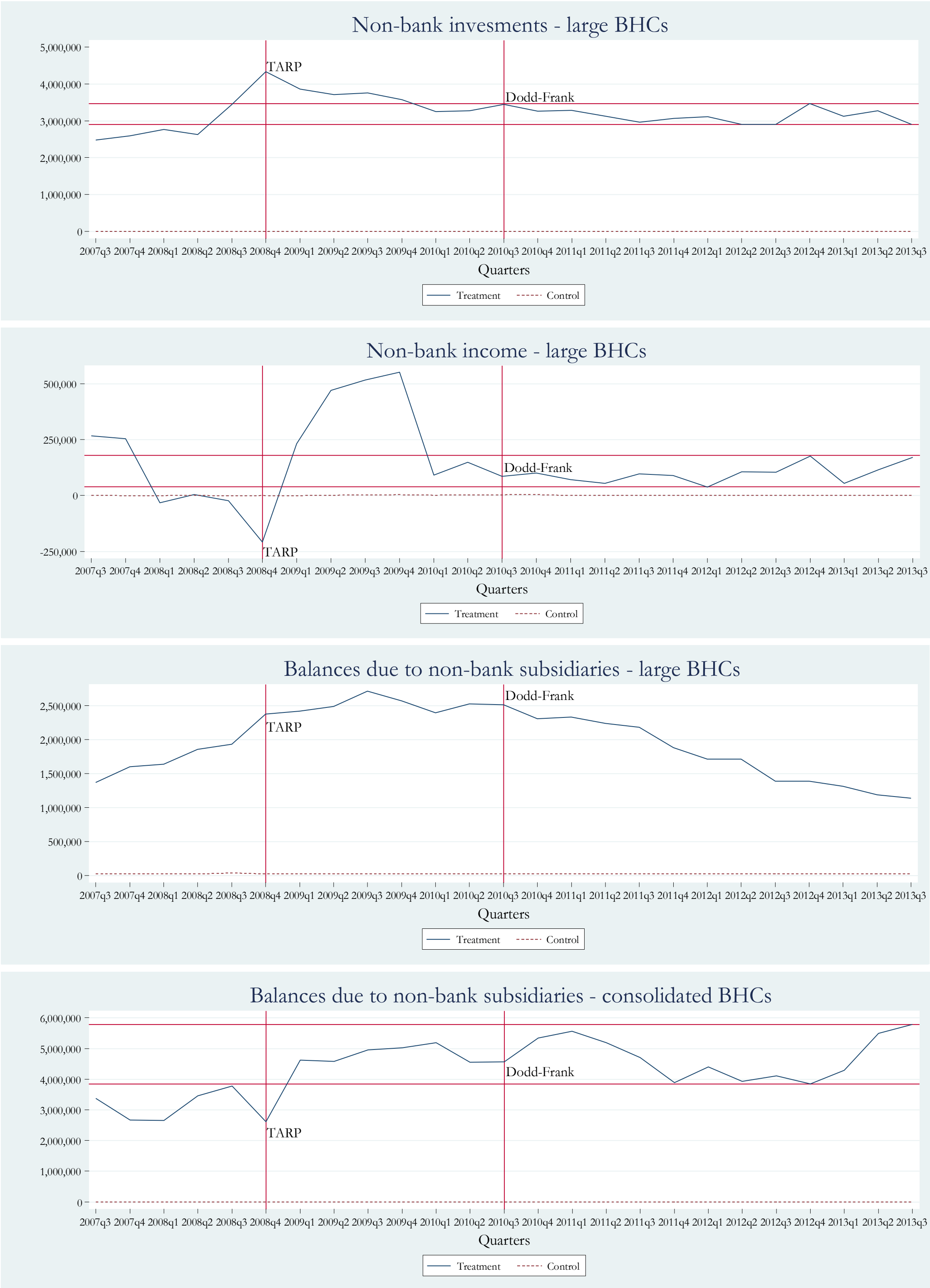
	(1) ΔZ-score(ln)	(2) ΔVolatility ROA	(3) ΔNon-bank balances	(4) ΔNon-bank investments	(5) ΔNon-bank income
*Credit extending activities*Dodd-Frank*	0.045	0.044	-0.0024	-0.10	-0.11
	(0.054)	(0.051)	(0.0044)	(0.10)	(0.087)
*Nonbank financial factors*Dodd-Frank*	0.069	0.052	0.00067	0.073	-0.12
	(0.047)	(0.043)	(0.0041)	(0.11)	(0.075)
*High risk activities*Dodd-Frank*	0.0076	0.056	-0.00070	-0.050	-0.17**
	(0.051)	(0.056)	(0.0057)	(0.098)	(0.061)
*Management factors*Dodd-Frank*	0.021	0.0071	0.0038	-0.22	-0.076
	(0.050)	(0.045)	(0.0021)	(0.24)	(0.047)
*Multiple factors*Dodd-Frank*	-0.050	-0.074*	0.0030	-0.12	-0.14
	(0.037)	(0.036)	(0.0055)	(0.20)	(0.073)
*Supervisory judgment*Dodd-Frank*	0.085	0.071	-0.0016	-0.11	-0.059
	(0.047)	(0.045)	(0.0040)	(0.092)	(0.067)
Bank size(LAG)	-0.97***	-0.45***	0.015*	-0.41	0.62**
	(0.22)	(0.098)	(0.0075)	(0.38)	(0.23)
Leverage ratio(LAG)	0.24	0.0023	-0.000039	-0.000060	0.021*
	(0.13)	(0.0021)	(0.000068)	(0.0021)	(0.0082)
Loan loss provision(LAG)	4.90	0.83	-1.02	-16.0	-52.7*
	(4.57)	(4.53)	(0.84)	(16.2)	(21.5)
Diver liabilities(LAG)	-0.20	-0.20	-0.17***	0.62	-0.13
	(0.13)	(0.11)	(0.034)	(0.76)	(0.35)
GDP	2.74***	2.14***	0.0081	-1.52	-3.83***
	(0.33)	(0.25)	(0.031)	(1.13)	(0.42)
TARP	0.093	0.12	0.0096	-0.30	-0.092
	(0.17)	(0.14)	(0.012)	(0.20)	(0.21)
Constant	10.7***	4.98***	0.0059	4.62	-6.14*
	(2.43)	(1.08)	(0.085)	(4.25)	(2.76)
Bank FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	5363	5580	5515	544	2281
R-squared	0.15	0.14	0.18	0.24	0.088
Number of Banks	815	826	813	101	417

Note: This table presents results of the placebo test regressions. We allocate a complexity category randomly to all the banks classified as non-complex from our original sample and then re-estimate the regression using model 2. Complex entities are not considered in this analysis in order to capture alternative forces that might influence our main results. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports reporting forms FR Y-9LP. Coverage: 2009Q1 to 2010Q2.

Aggregated analysis of shadow banking activities for the whole sample

Figure 3.3, in the page 76, presents a graphic representation of the total amount of non- banking activities that complex and non-complex BHCs engaged in with their non-bank partners. Note that non-bank investments show a rapid increase before the TARP liquidity programme and reach a peak when this program was launched in the last quarter of 2008, followed by a steady fluctuation and showing a slight increase two years after the Dodd-Frank Act. was enacted. Related to non-bank income, there is a remarkable recovery when the liquidity program was set up and a sharp drop two quarters before the law, followed by a constant fluctuation. Balances due to non-bank affiliates for the large BHCs show a steady decrease after the re-regulatory change while, for consolidated BHCs, it can be seen to have increased following the change in the law. This issue provides evidence that, despite the Dodd-Frank Act. setting limits on the activities between banks and their non-bank affiliates, at the aggregated level banks continue to increase their non-traditional financial activities with their non-bank affiliates three years after the law was enacted. Regarding non-bank investments, a reduction during the four quarters after the re-regulation is observed and, while non-bank income decreased for the period after the re-regulatory change, it shows a recovery in the long term. From the graphic representation, it can be observed how the liquidity program affects the non-banking activities that banks engage with their non-bank subsidiaries in that the law manage to continue to control this aspects, but its effects appear to have diminished after two years. This supports the idea that regulators succeeded in limiting financial institutions, but it only has temporary effect, and that new modifications should be undertaken to control their non-financial activities (Lippe *et al.*, 2015).

Figure 3.3. Financial activities with non-bank subsidiaries



Note: Figure 3.3 represents the behaviour of the dependent variables between the treatment and control groups during a six-year window (twelve periods-quarter before and twelve periods-quarter after the regulatory change). The complex BHCs (the treatment group) are presented by a continuous line, whereas the non-complex BHCs (the control group) are represented by a dotted line. The vertical line in the period -7 represents the quarter in which the TARP liquidity program was released while the vertical line in period 0 represents the quarter in which the Dodd-Frank was enacted. The institutions considered in this time span are fulfilled the following criteria: appear all the periods, domestic entities, not located in US territories and maintain the same complexity indicator during the time span. Data source: Call Reports reporting forms FR Y-9LP for the large BHCs and FR Y-9C for the consolidated BHCs. Coverage: 2007Q3 to 20103Q3.

3.7 Summary and conclusion

Since the 1994 Riegle–Neal Act., and later with the Gramm Leach Bliley Financial Modernization Act. in 1999, banks have started to grow and to expand into non-bank sectors. This has led to an increase in the organisational complexity of bank holding companies over the last twenty years. Nowadays, complex institutions are entities that exert their control over many subsidiaries and across multiple parts of the financial sector. However, they also rely on non-bank subsidiaries to provide specialised services (Cetorelli *et al.*, 2014). In other words, these institutions engage in a shadow banking system. Both the size and the complexity of the shadow banking system have made these institutions very difficult to monitor from a regulator's perspective. This is of great concern for policy makers, as the failure of these institutions can lead to system-wide problems. While bank soundness has always been on the agenda of policy makers, this has become even more crucial after the high number of bailouts and failures during the 2008-2009 financial crisis. As complex institutions played a crucial role in generating and spreading the financial crisis, the US government enacted the Dodd-Frank Wall Street Reform and Consumer Protection Act. on July 21, 2010, to better regulate these entities. Specifically, the scope of such a regulatory change was to tackle the complexity of financial institutions and to establish limits on banks' non-banking activities in response to the financial downturn of 2008.

Grounded in these considerations, this chapter raises a simple but powerful research question: how effective was this regulatory change in reducing the risk exposure of US Bank Holding Companies? This is the first study, to the best of our knowledge, to examine the impact of the 2010 Dodd-Frank Act. on the stability and shadow banking activities of complex US Bank Holding Companies. To conduct this research we gather a sample of 129 complex, and 978 non-complex, BHCs, covering the period between 2009Q4 to 2011Q2. We use difference-in-difference estimators to compare the stability and engagement in shadow-banking activities by complex institutions that were subject the Dodd-Frank Act. with the activities of non-complex institutions.

We find that the Dodd-Frank Act. has had a positive impact on the stability of complex and large BHCs, but this cannot be said for all categories of complex entities. Only entities that are considered complex due to their credit-extending activities and complex entities classified by supervisory-judgment improve their stability. Shifting our attention to the shadow banking system, our research provides mixed results. This evidence is again controversial for policy makers, as the Dodd-Frank Act. appears to have only reduced the non-banking activities for a specific type of complex institution. In detail, we find that entities classified as management-factors increase the investment in non-bank activities, while the result is the opposite in the case of complex institutions classified by supervisory-judgment. Furthermore, complex entities with credit-extending-activities classification are the only ones to reduce their income derived from activities with their non-bank affiliates. In addition, we are not able to present evidence of any effect of the regulatory change on balances due to non-bank subsidiaries. Finally, we do not find evidence that the change in the law has affected multiple-factors, non-bank-financial-factors and high-risk-activities in complex institutions. A possible explanation is that the extraordinary liquidity program TARP, set up by the government to help banks to overcome the financial crisis of 2008, does not allow us to observe the effectiveness of this law on the complex banks, because it gave extra support to entities that conducted non-traditional bank activities through their non-bank partners. Overall, complex institutions decrease their debt exposure with their non-bank affiliates after the re-regulatory change. In contrast, by focusing on the non-banking activities at the aggregate level, our findings suggest an opposite trend. The findings show that consolidated BHCs increase their balances due to non-bank affiliates after the regulatory change, indicating that Dodd-Frank Act. manage to set boundaries on the financial activities between banks and their non-bank subsidiaries. However, at the consolidated level, banks continue to engage in financial activities with their non-bank affiliates. Lastly, our findings show that the Dodd-Frank Act. succeeded in limiting BHCs to reducing their non-banking investments and non-banking income with their non-bank affiliates, but only temporarily because its effects appear to be diminished in the two years following the enactment of the law. This indicates a further proliferation of non-banking activities, potentially with non-bank-institutions under the control of other BHCs through the intermediation of commercial banks.

This chapter provides two important policy implications. Firstly, the 2010 Dodd-Frank Act. has only partially increased the stability of US Bank Holding Companies. Some types of complex institutions appear to be continuing to engage in shadow banking activities. Secondly, by taking into consideration the nature of complexity, policy makers can better monitor and assess the risk taking of BHCs, and consequently intervene to limit their investment in risky activities. Only, two types of complex institutions (credit-extending-activities and by supervisory-judgment) appear to have responded positively to regulatory intervention.

Chapter 4: The impact of complexity in US bank holding companies on corporate governance

The impact of complexity in US bank holding companies on corporate governance

Abstract

This chapter analyses the influence of the complexity of BHC's on their board composition according to the busyness degree of board members. Financial entities require the expertise of independent board directors from other boards to understand the growing complexity of financial activities of banks. In the same way, the knowledge of executive directors is needed to control the increasing complex structure inside the holding. By employing a fractional response model, we find that the complexity of banks has an adverse impact on the proportion of board members without any other directorship, while it remains positive for directors that sit on other boards. Furthermore, we find that complex BHCs are reducing their proportion of independent directors with three or more directorships and replacing them with outsiders that hold fewer than three. Regarding insider directors, in general terms, we find that complex entities require more executive members that hold up to two directorships. However, the largest complex entities from our sample, across the whole time span of our analysis, show higher proportions of executive directors with three or more directorships. We conclude that complexity increases the need for independent directors with expertise and knowledge from other boards. Nevertheless, complex BHCs require independent directors with fewer commitments to outside boards in order to achieve more precise advisory and/or supervisory knowledge to control their complex activities.

JEL classification: G21, G34, G39, L22

Keywords: Bank governance, busy directors, multiple directorships, board composition, holding company, complexity.

4. The impact of complexity in US bank holding companies on corporate governance.

4.1 Introduction

Over the last two decades, the complexity of US Bank Holding Companies (BHC) has increased dramatically. Deregulation has contributed to changes in the business model of US banks and intensified the increase in size and complexity of banks. Before the Riegle-Neal Interstate Banking and Branching Efficiency Act. of 1994 (Riegle-Neal Act.), banks were geographically clustered in specific locations and restricted in their business activities. But after the Riegle-Neal Act, banks were allowed to expand their branching networks outside their home state and enter into non-traditional banking sectors by acquiring non-bank subsidiaries (Olson, 2012; Cetorelli *et al.*, 2014). The increase in the complexity of banks may have led to an increase in board size and resulted in significant changes in their board composition. As pointed out by Boone *et al.* (2007), the scope and complexity of a firm's operations tend to have an impact on the board's composition. Consistent with this view, previous papers (Ronald *et al.*, 2000; Borokhovich *et al.*, 2004; Coles *et al.*, 2008) suggest that larger institutions are more likely to appoint higher numbers of outside and independent directors to better control for agency problems and monitor their more diversified operations.

Independent or non-executive directors on bank boards play a fundamental role in providing monitoring services, as well as valuable advisory services to banks' non-financial counterparts (John *et al.*, 2016). Furthermore, a higher number of outsiders can reduce the influence of executive directors on decisions making that might affect bank risk-taking, and so agency problems between managers and shareholders decrease (Nguyen *et al.*, 2016). Moreover, non-executives can help to reduce conflicts and opacity issues among the CEO and executive board members, especially when relevant information is not effectively disclosed, which is common in a complex organization (Bushman *et al.*, 2004). In fact, they usually possess plenty of recognized experience and expertise, acquired by being involved in different industrial sectors that help reinforce their understanding of complex financial activities that banks nowadays decide to engage in (Adams and Mehran, 2012). Furthermore, non-executive board members can help to ensure compliance with regulatory requirements in reporting relevant risky activities (Bushman *et al.*, 2004), especially when they are also members of the audit or compensation committees (John *et al.*, 2010; Sun and Liu, 2014). From an economic perspective, the increase in the proportion of outsiders on the board, can improve bank performance (De Andres and Vallelado, 2008) as well as banks' lending practices (Sumner and Webb, 2005). On a negative note, non-executive board members tend to be "busy directors" as they serve on more corporate boards (John *et al.*, 2016). This can negatively affect their monitoring activities. As the busyness degree increases, the monitoring of outsiders becomes less efficient due to "free-riding" problems and low attendance at board meetings (Jiraporn *et al.*, 2009; Adams *et al.*, 2010). This phenomenon can be associated with lower performance levels of banks (Fich and Shivdasani, 2006). On the other hand, a few papers show that the degree of corporate directors' 'busyness' can exert a positive influence on firms' market performance (Di Pietra *et al.*, 2008). The reason is that busy directors can better signal the success and initiatives in entities' business activities to capital markets because they tend to be well connected, with reputable corporate, social and political links (Di Pietra *et al.*, 2008; Goldman *et al.*, 2009). Given the contrasting view in the existing literature, our first research question attempts to examine how complex banks appoint non-executive directors to the board. A further empirical question, concerns the appointment of independent directors according to their busyness degree. As our final contribution, we examine how the proportion of executive directors and their number of directorships is related to the complexity structure of the BHCs.

In this chapter, we identify important contributions to the existing financial literature. This is the first study that shows how and to what extend board composition is affected by the complexity of the financial activities of banks. Prior literature only analyse the relationship between board composition and either performance, or risk of the entities (Belkhir, 2009; Berger *et al.*, 2014). We investigate how the busyness degree of independent and executive directors depends on the complexity and organizational structure of the banks. While prior literature consider either outsiders (Adams and Mehran, 2012) or insiders (Elyasiani and Zhang, 2015), we analyse the effects of complexity of banks for both types of board members. Moreover, we use a larger sample of BHCs for a longer period, compared to prior studies which just consider the largest entities for shorter time spans (Adams and Mehran, 2003; Adams, 2012a). Furthermore, we use more classifications of the busyness of the board of directors according to with their commitments to other outside boards in order to analyse how these classifications are more related to complexity categories of the BHCs from the US, comparing with prior literature that does not consider the complexity category of the banks in their samples. Moreover, we study how the board members according with their busyness degree with other boards are related to the number of corporate governance concerns, in which again, there is no evidence of previous research that study the relation between busyness degree of the board directors and governance concerns in the US banking sector. We find that complex entities increase their requirements of independent board members. However, these institutions require greater comitment from outsiders, which hold no more than two directorships. Regarding insider directors, in general terms, we find that complex institutions also require that executive board members do not hold more than two directorships. Nevertheless, the largest BHCs that appear during the whole time span of our analysis, exhibit higher proportions of insiders that hold three or more directorships. This can be explained by larger institutions requiring their executive directors to serve on more affiliated boards, in order to control their complex structure.

This chapter is organised as follows: In the next section, we review the related literature. In section 3, we describe the methodology we use to conduct this study and explain our robustness checks. In section 4, we present results. Finally, in section 5 we conclude.

4.2 Literature review

4.2.1 Complexity of banks

While the extent literature captures the problems of size (too-big-to-fail) and the systemic risk posed by financial institutions (Strahan, 2013; Jacobides, 2015; Kaufman, 2015), the complexity of institutions is less analysed despite its importance for the stability of the financial sector (Cetorelli and Goldberg, 2014).

Studies that focus on the analysis of the complexity of banks, try to explain how financial institutions have become more complex in different aspects. Firstly, these studies explain how banks increase their complexity when they decide to expand their financial business activities (Cetorelli and Goldberg, 2014). After regulatory changes, banks were allowed to engage in non-financial activities and new sophisticated financial products, increasing their portfolio to achieve economies of scale or economies of scope. However, managers from the head office cannot effectively supervise this range of products, which have different maturity and are targeted at various sectors. This increases the cost to monitor and control all their products, thus increasing their risk (Cetorelli and Peristiani, 2012). Secondly, studies also explain how banks become more complex when they increase their number of subsidiaries. When US banks were allowed to become a Financial Holding Company (FHC), they started to acquire or set up new non-bank financial institutions, in order to enter into non-traditional financial activities (Cetorelli *et al.*, 2012). However, the interaction between banks and these subsidiaries has become more complex due to all the subsidiaries having different regulations and in which the banking authorities are unable to effectively supervise these activities (Lippe *et al.*, 2015). Thirdly, studies suggest that banks who expand geographically to enter into new markets, create more complex structures between head offices and subsidiaries that sometimes involve regulatory frameworks from different countries that are more difficult to monitor by regulators (Cetorelli and Goldberg, 2014; Cetorelli *et al.*, 2014). Mostly they focus their analysis on SIFIs (Systemically Important Financial Institutions) due to their relevance for financial stability of the market (Carmassi and Herring, 2015; Lumsdaine *et al.*, 2015) but they do not consider large financial institutions which have a relevant impact on their regional markets.

Regarding measures from the regulator, the Federal Reserve (FED) established an indicator that classifies the complexity of BHCs into seven categories: credit-extending-activities, non-bank-financial-activities, high-risk activities, public-debt, management-factors, multiple-factors and supervisory-judgement. This complexity indicator is shown as code RSSD9057 from the

Consolidation Report of Condition and Income (Call Reports). The credit-extending-activities category is assigned to banks that engage in financial activities in order to expand their credit operations either with their parent bank holding or its non-bank affiliates or hold debt outstanding to the general public. The majority of the US BHCs have this classification. The non-financial-factors category is for banks that show a substantial degree of non-bank activities. The higher-risk-activities is for banks that engage high-risk non-banking activities such as securities or broker/dealer activities, insurance underwriting, merchant banking among others, in which banks perform these activities directly or through its affiliates. Public debt is when entities hold significant debt to the general public in which unsophisticated shareholders from those types of entities might be at risk of loss in case of bankruptcy. Management-factors classification is when the organizational structure of the entities increase their complexity such as inter-company transactions or centralized policies and procedures. Multiple-factors is when entities present more than one of the previous categories. Finally, supervisory-judgment is an institution that does not have any of the previous categories, although the regulator classifies them as complex for supervisory purposes.[22]

4.2.2 Board composition in the banking sector

The literature on corporate governance in the US banking sector emphasise the differences between banks and non-financial entities in their board composition (Adams and Mehran, 2003; Mehran and Mollineaux, 2012). The proportion of outsiders is one of the most consistent differences found by scholars (John *et al.*, 2016). It has been claimed that the percentage of independent directors sitting on US bank boards is between seventy and eighty-five percent (Adams and Mehran, 2003; Belkhir, 2009) while for the non-financial sector it is between sixty to seventy percent (Bhagat and Black, 2002; Adams and Mehran, 2012).

One reason to have more outsiders on bank boards is their requirement for higher levels of advice due to the sophisticated financial activities in which complex banks decide to engage in (Andres *et al.*, 2012). In this way, researchers point out that the recognisable knowledge and expertise of independent directors from other industrial sectors can help to understand the financial activities of the institutions, in which this valuable knowledge cannot be obtained from insider directors. (Mehran and Mollineaux, 2012). Furthermore, independent directors are more sensible about the needs and problems of other industrial sectors, and their advice for the diversification of products and financial services might be required by banks (Hoskisson *et al.*, 2002) .

Another reason highlighted by researchers is that independent board directors provide monitoring services (John *et al.*, 2016). A higher number of outsiders can decrease agency problems between managers and shareholders reducing the influence of executive directors on the decision making

[22] See Appendix 3.A for details about the different classifications of complexity.

that might affect bank risk-taking (Nguyen *et al.*, 2016). Furthermore, it has been found that non-executive members of the board can relieve conflicts and opacity problems between the CEO and executive board members when relevant information is not disclosed promptly (Bushman *et al.*, 2004). Moreover, independent board members through their monitoring service can relieve agency problems between manager and shareholders, especially when outsiders are also members of the audit or compensation committees (Sun and Liu, 2014; John *et al.*, 2016). Moreover, a higher proportion of independent directors can also alleviate compliance with regulatory requirements in reporting relevant risky activities on time that might affect the financial sector in their regions (Barakat and Hussainey, 2013).

The enhancing performance benefits of having independent board members has been studied in the financial literature for the US banking sector. De Andres and Vallelado (2008) claim that an appropriate number of outsiders can improve banks performance. Belkhir (2009) find a positive relation between larger boards with more independent directors and two performance measures: Tobin's Q and ROA. Additionally, it has been found that outsiders on the board can improve lending practices of banks (Sumner and Webb, 2005).

Since the presence of independent board members is important in order to understand the complexity of banks, we develop our first hypothesis as follows:

> **H1.** Complex BHCs require higher proportions of independent board directors.

Regarding busyness of board members, it has been found that directors that serve on other corporate boards might have adverse effects on their monitoring and advising activities. Jiraporn *et al.* (2009) claim that busy directors have higher levels of absents on board meetings. This can also lead to "free-riding" problems between their outside board members (Adams *et al.*, 2010). According to Fich and Shivdasani (2006), this phenomenon can be associated with a deteriation in bank performance. In a positive way, Di Pietra *et al.* (2008) argue that the degree of busyness for board directors can exert a positive influence on the market performance of the institutions. An explanation for this is that the networking of the busy director with reputable corporations and their social and political links can give better advisory support related to capital markets (Di Pietra *et al.*, 2008; Goldman *et al.*, 2009). Thus, when we consider that complexity might require higher levels of advice and knowledge from other industries and that independent directors are the most suitable source, we formulate our following hypothesis:

> **H2.** Complex BHCs require higher proportions of independent board directors sitting on other boards.

Related to the busyness degree of the executive board members, prior literature points out the importance for larger financial institutions to maintain insiders sitting on other boards of affiliated companies. Adams and Mehran (2012) find that bank board size increases by adding executive directors that hold other directorships inside the same holding. They argue that insider directors are more suitable to deal with the growing organisational complexity. Furthermore, Armstrong *et al.* (2016) claim that to maintain a suitable number of executives on the bank board will help control the current performance of the entity and to solve asymmetry information that outsiders cannot fully understand. Thus, our following hypothesis is formulated as follows:

> **H3**. Complex BHCs require higher proportions of insider board directors sitting on other boards.

4.3 Methodology

4.3.1 Data description

The corporate governance data for this project is obtained through the institutional shareholder services (ISS) database which contains data on various characteristics of the individual board directors from a universe of Standard and Poor's 1500 companies. From this dataset, we select information related to board affiliation (independent, executive and linked) and number of directorships (outside boards). Furthermore, we obtain financial data from Call Reports related to consolidated bank holding companies (reporting forms FRY-9C).[23] Our sample covers the period from 1998 to 2015. We select this time span because it covers the post-branching regulation period in which the complexity of banks was considerably affected as well as regulatory changes that impact corporate governance of banks such as the Sarbanes-Oxley Act. 2002 and Dodd-Frank Act. 2010. Our final sample is an unbalanced panel dataset which consists of 138 BHCs selected by hand with 1,300 observations.[24]

As a preliminary analysis of the data contained in our sample, we display in Table 4.1, below, the yearly board composition by the total number of independent and insider directors, as well as by their business degree category[25] of the complex and non-complex BHCs. It can be observed that the average board size for complex and non-complex entities shows a steady decrease, in which both type of entities show similar average board size during the time span of our analysis, 13.60 members for complex and 12.86 members for the non-complex counterparts. Again, for the mean number of independent directors, we do not observe a relevant difference between these types of entities. A similar picture can be seen for the mean number of insiders, in which complex and non-

[23] Although Call Reports are published quarterly, we collapse this financial information by taking an average of the quarters to arrive at a yearly figure, in order to align with the corporate governance data of the banks which is annual data.
[24] We do not consider BHCs that appear in only one year because the main assumption of a panel data is to have banks that are observed for at least a two-year period. Appendix 4.A displays the complete list with the names of the BHCs for our sample.
[25] In this study we classify outsider and insider board members according to the following busyness degree classification: very-busy directors hold three or more outside directorships; busy directors that hold more than one outside directorship; not-busy directors that do not have any outside directorship and not-too-busy directors who hold up to two outside directorships (Ferris *et al.*, 2003; Elyasiani and Zhang, 2015).

complex entities depict an average of 3.36 and 3.38, respectively. However, the main difference between complex and non-complex institutions can be seen in the average number of independent directors that hold three or more outside directorships. In this case, complex entities show average of 4.69 directors while non-complex institutions have only 1.69 directors. Another relevant difference is that non-complex banks show a higher number of board members without any outside directorship, not only for independent but also for insider directors.

Table 4.1. Board composition of the BHCs for the sample from 1998 to 2015B

	Board composition			Independent directors				Insider directors			
Year	Board size	Indep.	Insider	Very-busy	Busy	Not-busy	Not-too-busy	Very-busy	Busy	Not-busy	Not-too-busy
Complex BHCs											
1998	16.21	10.81	5.40	1.79	5.76	5.05	3.98	0.33	2.19	3.21	1.86
1999	15.89	11.00	4.89	1.58	5.43	5.57	3.85	0.40	1.79	3.09	1.40
2000	15.16	10.42	4.74	1.28	4.81	5.61	3.53	0.32	1.75	2.98	1.44
2001	15.19	10.51	4.68	1.18	4.61	5.89	3.44	0.23	1.60	3.09	1.37
2002	14.17	9.74	4.43	1.09	4.40	5.34	3.30	0.30	1.64	2.79	1.34
2003	13.60	9.47	4.13	1.09	4.13	5.35	3.04	0.27	1.44	2.69	1.16
2004	13.16	9.59	3.57	1.06	4.49	5.10	3.43	0.24	1.29	2.27	1.06
2005	13.55	10.04	3.51	0.89	4.68	5.36	3.79	0.32	1.43	2.09	1.11
2006	13.32	9.53	3.79	0.77	4.53	5.00	3.77	0.19	1.32	2.47	1.13
2007	13.35	10.33	3.02	0.80	4.57	5.76	3.76	0.13	0.93	2.09	0.80
2008	13.29	10.29	3.00	0.86	4.60	5.69	3.74	0.10	0.98	2.02	0.88
2009	13.02	10.05	2.97	0.77	4.60	5.45	3.83	0.08	0.95	2.03	0.88
2010	12.75	10.20	2.55	0.57	4.78	5.43	4.20	0.08	0.77	1.77	0.70
2011	12.44	10.18	2.26	0.62	4.62	5.56	4.00	0.08	0.69	1.56	0.62
2012	12.45	10.42	2.03	0.63	4.76	5.66	4.13	0.03	0.68	1.34	0.66
2013	12.46	10.46	2.00	0.65	4.59	5.86	3.95	0.05	0.81	1.19	0.76
2014	12.24	10.47	1.76	0.50	4.44	6.03	3.94	0.03	0.74	1.03	0.71
2015	12.56	10.84	1.72	0.63	4.59	6.25	3.97	0.00	0.72	1.00	0.72
Average:	13.60	10.24	3.36	0.93	4.69	5.55	3.76	0.18	1.21	2.15	1.03
Non-complex BHCs											
1998	16.74	11.95	4.79	0.42	3.21	8.74	2.79	0.05	1.11	3.68	1.05
1999	16.83	11.96	4.88	0.46	2.46	9.50	2.00	0.04	0.92	3.96	0.88
2000	15.79	11.25	4.54	0.08	1.63	9.63	1.54	0.08	0.58	3.96	0.50
2001	14.77	10.86	3.91	0.18	1.27	9.59	1.09	0.05	0.23	3.68	0.18
2002	12.82	8.65	4.18	0.06	1.00	7.65	0.94	0.06	0.29	3.88	0.24
2003	12.35	9.29	3.06	0.06	1.47	7.82	1.41	0.06	0.12	2.94	0.06
2004	13.67	9.67	4.00	0.11	1.56	8.11	1.44	0.00	0.44	3.56	0.44
2005	12.48	8.62	3.86	0.14	1.48	7.14	1.33	0.00	0.43	3.43	0.43
2006	11.95	8.71	3.24	0.05	1.14	7.57	1.10	0.00	0.29	2.95	0.29
2007	11.59	8.78	2.81	0.15	1.63	7.15	1.48	0.00	0.37	2.44	0.37
2008	11.72	8.81	2.91	0.09	1.63	7.19	1.53	0.00	0.50	2.41	0.50
2009	11.90	8.61	3.29	0.19	1.90	6.71	1.71	0.03	0.52	2.77	0.48
2010	11.84	8.91	2.94	0.06	1.88	7.03	1.81	0.03	0.56	2.38	0.53
2011	11.44	8.69	2.75	0.09	1.69	7.00	1.59	0.06	0.44	2.31	0.38
2012	11.65	8.97	2.68	0.12	1.38	7.59	1.26	0.06	0.38	2.29	0.32
2013	11.49	8.89	2.59	0.08	1.43	7.46	1.35	0.03	0.32	2.27	0.30
2014	11.38	9.20	2.17	0.10	1.88	7.32	1.77	0.03	0.25	1.92	0.22
2015	11.25	9.07	2.14	0.17	1.83	7.25	1.65	0.05	0.28	1.90	0.22
Average:	12.86	9.49	3.38	0.15	1.69	7.80	1.55	0.03	0.45	2.93	0.41
Differences:	0.74	0.75	-0.02	0.79	3.00	-2.25	2.21	0.14	0.76	-0.78	0.62

Note: Table 1 depicts yearly average board composition of the complex and non-complex US BHCs from the sample according to the type of director and their busyness degree. The type of director is taken from the classification column available in the Institutional Shareholder Services (ISS) database. For the insider directors, we consider executives and linked board directors together. Very-busy directors are board members that hold three or more outside directorships, busy directors hold one or more outside directorships, not-busy directors do not have any outside directorship and not-too-busy directors hold only one or two outside directorships Coverage: 1998 to 2015.

Following a preliminary analysis of our dataset, Table 4.2, in the page 91, presents the average number of outside directorships, audit committee members, compensation committee members as well as interlocking members[26] yearly between complex and non-complex entities. We observe that complex entities have more directors that hold outside directorships comparing with the non-complex institutions, with an average of 2.42 and 1.16 board members, respectively. Regarding board members that are part of the audit or compensation committees, both types of entities show similar average numbers, which might suggest that complex and non-complex banks require the same number of board members to fulfil regulatory requirements related to the composition their committees (Armstrong *et al.*, 2016). Note that the average number of interlocking board members was reduced to zero not only for complex institutions, but also for the non-complex entities. A possible explanation for this is that the regulatory changes from the Dodd-Frank Act. 2010, forced financial institutions to reduce the number of insiders as part of their compensation committees and replace them with external compensation advisors (Conyon, 2015). The aim is to put limits on how banks determine salary, bonus, stock and remuneration for their top managers and to avoid conflict when interlocking directors are part of these committees.

Additionally, in Figure 4.1, in the page 92, we include graphic representation of the behaviour of the proportions of board members in terms of proportions between complex and non-complex institutions from our sample. We observe that the proportion of independent directors for complex entities increases continuously especially after the Sarbanes-Oxley Act. was enacted in 2002, reaching 86% at the end of 2015. Meanwhile, there is a constant fluctuation for their non-complex counterparts, showing 81% in the last year of the sample. This is linked with a dramatic reduction in the proportion of insiders for both types of institutions. In which complex entities fall by more than half, from 0.34% in 1998 to 0.14% in 2015. Similarly, non-complex entities reduce their percentage of insiders sitting on their boards from 0.30% to 0.19% during the same period. Regarding the proportion of board members according to their busyness degree, there is a steady decline in the percentage of very-busy directors for the complex institutions, while it is remains stable for the non-complex banks. Meanwhile, there are steady fluctuations for the proportions of busy, not-busy and not-too-busy directors for both type of institutions. However, it is noticeable that non-complex banks require higher proportions of board directors without any other directorship comparing with their complex counterparts. Analysing these proportions but now focusing only on independent directors, we observe a gradually declining proportion of very-busy independent directors for complex entities, comparing with the non-complex entities in which this proportion is more stable. Note that this reduction for complex institutions is linked with the slight increases in the proportions of the other types of independent directors that hold

[26] We consider interlocking directors as board members that also serve on another affiliate board within the same holding.

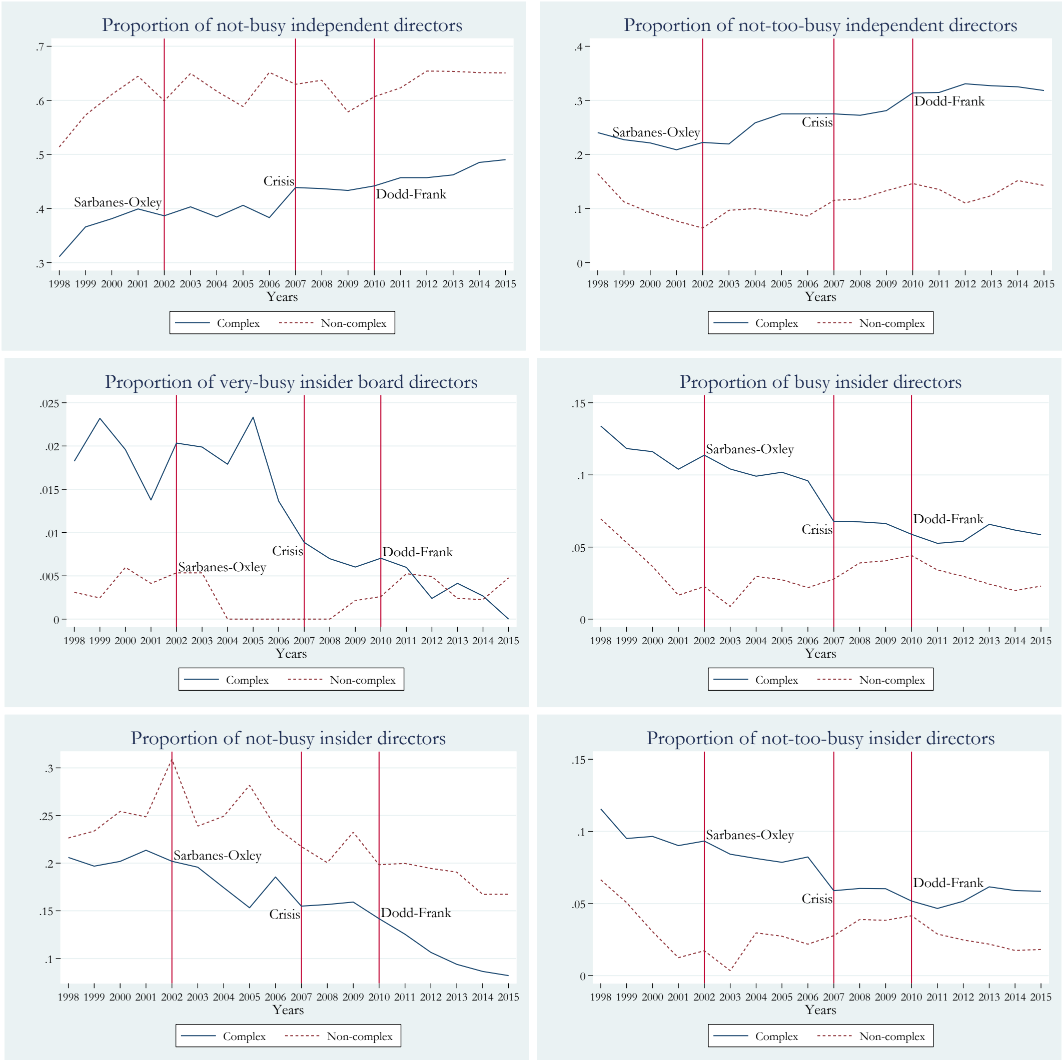
less or any other directorships. This shows that complex entities require outsiders with less commitments to other boards. For the percentage of insider directors, it can be observed that this proportion is declining for complex institutions in all their busyness categories and a dramatic decline can be seen in the proportion of very-busy insiders. However, a slight recovery can be seen in the percentages of busy and not-too-busy insiders, after the Dodd-Frank Act. This is evidence that complex entities require higher proportions of insiders that hold no more than two directorships.

Table 4.2. Outside directorships and board committee members from 1998 to 2015

Year	Outside directorships	Audit committee members	Compensation committee members	Interlocking members
Complex BHCs				
1998	3.21	4.69	4.48	0.69
1999	2.87	4.79	4.55	0.55
2000	2.56	4.77	4.40	0.44
2001	2.46	4.63	4.56	0.33
2002	2.53	4.64	4.42	0.38
2003	2.47	4.44	4.33	0.22
2004	2.61	4.27	3.86	0.14
2005	2.57	3.43	2.87	0.11
2006	2.40	3.19	2.83	0.06
2007	2.43	4.30	4.28	0
2008	2.38	4.45	4.33	0.05
2009	2.42	4.53	4.55	0.10
2010	2.25	4.45	4.47	0.08
2011	2.10	4.44	4.64	0
2012	2.18	4.55	4.47	0
2013	2.16	4.30	4.30	0
2014	1.91	4.38	4.44	0
2015	2.03	4.28	4.41	0
Average:	2.42	4.36	4.23	0.17
Non-complex BHCs				
1998	1.74	4.68	4.37	0
1999	1.63	4.71	4.83	0.13
2000	1.13	4.33	4.63	0.08
2001	1.05	4.32	4.32	0.09
2002	1.00	3.76	3.94	0.06
2003	1.12	4.29	3.59	0.00
2004	0.89	4.11	3.67	0.00
2005	1.00	3.00	2.90	0.10
2006	0.90	2.90	3.19	0
2007	1.15	3.96	4.15	0
2008	1.06	4.13	4.00	0
2009	1.29	4.26	4.23	0
2010	1.19	4.41	4.16	0.06
2011	1.13	4.78	4.25	0
2012	1.15	4.53	4.15	0
2013	1.03	4.46	4.19	0
2014	1.23	4.20	4.18	0
2015	1.20	4.47	4.38	0
Average:	1.16	4.19	4.06	0.03
Differences:	1.26	0.17	0.17	0.14

Note: Table 2 depicts the average number of outside directorships, average number of board members of the audit committee, board members of the compensation committee and interlocking board members by year for the complex and non-complex BHCs from our sample. Data source: Institutional Shareholder Services (ISS) database. Coverage: 1998 to 2015.

Figure 4.1. Behaviour of the proportion of board directors according to their busyness degree



Note: Figure 4.1 depicts the average yearly percentage for the independent and insider board members and the yearly average percentage according to their busyness degree between complex and non-complex BHCs from our sample. Complex institutions are represented by a continuous line, whereas the non-complex entities are represented by a dashed line. Independent directors are board members that are not related to the administration of the bank whereas insider directors are the executives and linked directors with the administration of the institution. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. The horizontal lines represent the year in which occur the two main regulatory changes that might affect board composition in the banking sector, the Sarbanes-Oxley Act. 2002 and the Dodd-Frank Act. 2010 as well as the financial crisis of 2007. Data source: Institutional Shareholder Services (ISS) database. Coverage: 1998 to 2015.

Next, in Table 4.3 Panel A, below, we present the composition of our sample according to their complexity category. Our final sample contains 78 non-complex and 101 complex BHCs during the time span of our analysis. We observe that a higher number of complex entities have credit-extending-activities classification with 74 followed by the management-factors category with nine. Both type of complex entities also concentrate the higher average amount in terms of total assets from the sample. With respect to board size, the credit-extending-activities and multiple-factors classifications show the largest board size with an average of fourteen board members but the latter category has more independent directors sitting on their board with eleven. Meanwhile, the non-complex institutions show an average of twelve board members and nine outsiders. The average number of insiders from the sample is three. Again, the credit-extending-activities shows the highest average with four members while the high-risk-activities and management-factors categories exhibit the lowest average with two members. This overview shows us that board size is different depending on the complexity classification of the entities as well as their requirements of independent directors. Entities classified as credit-extending-activities might require higher levels of advice from their executive board members which might better understand the internal organisational complexity comparing with their independent counterparts. Moreover, entities with multiple-factors classification have on average one more outsider sitting on their board. This might be interpreted as that this type of complex bank has more advisory and/or monitoring requirements from their independent board members in order to control for the variety of financial activities that they decide to engage in.

Table 4.3. Composition of the BHCs by complexity category

Panel A. Complete sample

Complexity category	BHCs	Observations	Total assets*	Board size	Outsiders	Insiders
Non-complex	78	490	27,648,131	13	9	3
Credit-extending-activities	74	671	201,017,079	14	10	4
Nonbank-financial-factors	2	12	7,280,194	12	9	3
High-risk-activities	5	31	12,443,400	11	9	2
Public-Debt	2	3	36,946,242	10	7	3
Management-factors	9	54	49,138,917	11	8	2
Multiple-factors	6	32	11,730,550	14	11	3
Supervisory-judgment	3	7	23,340,169	10	7	3

Panel B. BHCs that maintain their same complexity indicator

Complexity category	BHCs	Observations	Total assets*	Board size	Outsiders	Insiders
Non-complex	45	328	30,723,252	12	9	3
Credit-extending-activities	52	503	210,791,039	15	11	4
High-risk-activities	1	6	5,792,583	10	7	2
Management-factors	2	15	154,912,536	9	8	2
Multiple-factors	1	12	12,719,634	13	12	1

Panel C. Sample with balanced dataset and entities that maintain their complexity indicator

Complexity category	BHCs	Observations	Total assets*	Board size	Outsiders	Insiders
Non-complex	1	18	57,596,261	20	14	6
Credit-extending-activities	14	252	344,479,332	14	11	3

Note: Table 4.3 depicts the composition of the BHCs from the sample according to their complexity indicator code that appears in the item RSSD9057 from the Call Reports. Total assets is taken from item BHCP2170 from Call Reports (reporting form FR Y-9LP), board size, the number of outsiders and number of insider board members is taken from Institutional Shareholder Services (ISS) database. Coverage: 1998 to 2015. Note that for panels A and B some entities might show different complexity categories during the time span of our sample. *All values are average in thousands of dollars. **Average number of board members.

4.3.2 Endogeneity test

Before applying our main model, we conduct an endogeneity test to investigate if the composition of the board has an effect on the complexity of banks. To conduct this test we apply the following logit regression:

$$\triangle\, Complex_{it} = \alpha + \beta_1 + \beta_2 \triangle\, Directors_{it} + \beta_3 \triangle\, X_{i,t} + \delta + \varepsilon_{it} \tag{1}$$

Where:

$\triangle\, Complex_{it}$	=	Dummy variable that takes the value of 1 if the BHC i at year t changes from non-complex to any other complex indicator according to the code RSSD9057 from Call Reports, 0 otherwise.
$\triangle\, Directors_{it}$	=	Dummy variable that takes the value of 1 if the BHC changes in the number of board members, 0 otherwise.
$\triangle\, X_{i,t}$	=	Percentage change of the control variables.
δ	=	Year fixed-effects dummy variable.
ε_{it}	=	Error term.

We apply the Logit for binary response by maximum likelihood approach for this endogeneity test. As control variables we include *bank size* which is calculated as the log of total assets as well as return on assets (*ROA*) which is calculated as the net income divided by total assets.

The aim of this test is to investigate if any change in board composition affects banks to become complex. If the coefficient β_2 for the change in the number of board members is significant for the change in complexity, we might confirm the presence of endogeneity within our model. It is important to mention that during the time span of our study twenty four institutions change their complexity indicator from non-complex to complex.

The regressions include year fixed effects dummies so as to control for unobserved heterogeneity at year level. Specifically, we are looking to control for regulatory changes and crisis during the time span of our sample, such as the Sarbanes-Oxley Act. 2002, Dodd-Frank Act. 2010 and the financial crisis of late 2007. Additionally, we cluster heteroscedasticity-adjusted standard errors at the bank level in order to avoid serial correlation between banks.

In this study, we consider independent directors as board members that do not have any ties with the management of the bank. Whereas, insiders are the executives as well as the affiliated outsider and linked directors, such as former CEO, family related and retired executives (Hermalin and Weisbach, 1998).

Following previous studies (Ferris *et al.*, 2003; Fich, 2005; Elyasiani and Zhang, 2015), we divide the directors into four categories depending on their degree of involvement with outside board activities. In particular, we classify them as follows:

i) not-busy directors if they are not engaged in another outside directorship, prior studies find no difference in the effectiveness of the monitoring and/or advisory role between non-busy directors and directors with higher commitments from other outside boards (Ferris *et al.*, 2003);

ii) busy directors if they appear in one or more directorships different from the financial entity, the aim of this category is to denote how the variation in the degree of the less-busy directors is being affected by the complex institutions.

iii) very-busy directors if they hold three or more outside directorships, which are the board members that exceed the limit of the number of directorships recommended by the National Association of Corporate Directors is considered to be too distracted to properly fulfil their duties in the board of the institution (Fich and Shivdasani, 2006). It is important to mention that this is the most common classification used in the banking literature to depict the busyness degree of board directors (Fich, 2005; Elyasiani and Zhang, 2015).

iv) not-too-busy directors if they hold up to two outside directorships, this classification is within the recommendation by the Council of Institutional Investors. This organization is less lenient about the number of outside boards that board members hold because they argue that board directors require more time in order to give more effective advisory and/or monitoring service to the institution (Ferris *et al.*, 2003).

Comparing with previous literature, in this study, we decide to include all the possible categories of busyness that a board member can have and not only focus on directors that hold three of more outside directorships as well as to analyse outsider and insider board members. It is important to mention that we obtain the number of outside directorships through the ISS dataset which displays this data for each board director for the sample.

To conduct this part of our study we run six different variations of our model to depict the change in the number of independent, insiders, very-busy, busy, not-busy and not-too-busy respectively.

4.3.3 Model

To study the effects of bank complexity on busyness of board directors from BHCs, we estimate our following model:

$$Y_{it} = \alpha + \beta_1 + \beta_2\, Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it} \tag{2}$$

Where:

Y_{it} = Proportion of independent, insider, very-busy, busy, not-busy and not-so-busy board directors of the BHC i at time t.

$Complex_{it}$ = Complexity indicator of the BHC i at time t according to the code RSSD9057 from call reports.[27]

$X_{i,t}$ = Vector for the control variables.

δ = Year fixed-effects dummy variable.

ε_{it} = Error term.

[27] For our study we consider the two non-complex categories together with the other seven categories of complexity that are displayed in this code.

Following Papke and Wooldridge (1996) we apply a fractional response probit technique as our dependent variable is a proportion with values that rank between 0 and 1.

Similar to our endogeneity test, the regressions include year fixed effects dummies so as to control for unobserved heterogeneity at year level and we cluster heteroscedasticity-adjusted standard errors at the bank level.

Then, we include four relevant corporate governance variables for our model: Firstly, *board size*, which is calculated as the logarithm of the number of directors sitting on the board. Prior literature find that financial entities have larger boards comparing with commercial entities due to their requirements of directors with experience from other boards (Mehran and Mollineaux, 2012).

Secondly, the logarithm number of board members in the audit committee. We expect this variable to be positively related to the proportion of independent directors due to their valuable monitoring service needed by banks (Armstrong *et al.*, 2016).

Thirdly, we include the logarithm number of board members on the compensation committee. This variable is also expected to be positively related to the proportion of outsiders on the board due to the importance to maintain independence in decision taking for executive compensation for bank managers (Conyon, 2015).

Lastly, we include a dummy variable that takes the value of 1 if the BHC has interlocking directors that are sitting on another affiliated board, 0 otherwise. In this case, we expect that the insider board members might be positively related to this dummy variable as banks might require board members with knowledge from their subsidiary boards (Cetorelli and Goldberg, 2014).

We also include a control variable *bank size* which is calculated as the log of total assets. In this vein, previous studies (Boone *et al.*, 2007; Coles *et al.*, 2008) argue that largest entities with more complex operations tend to have larger boards.

We consider a measure of performance which is the return on assets (*ROA*), calculated as net income divided by total assets. We also include a variable to depict the one-period delayed value of *ROA*, to capture the delayed response of performance on the composition of the banks board (Coles *et al.*, 2008).

Lastly, we include the natural logarithm of the number of bank subsidiaries for each BHCs. This data is obtained from the Summary of Deposits (SOD)[28] which displays the number of banks subsidiaries that appear inside the same parent BHCs from our sample for every year during the time span of our study. The aim to include this variable is to capture how the degree of busyness board directors has been affected by the number of bank subsidiaries. Previous literature points

[28] This data is available through the following link from the (Federal Deposit Insurance Corporation) FDIC: https://www5.fdic.gov/sod/sodMarketBank.asp?barItem=2. Last access 4 September 2016.

out that board members that often have subsidiary directorships are more suitable to help for the growing complexity of banks (Adams and Mehran, 2012). In this way, it is expected that executive directors that hold other directorships might have a higher relationship with this variable due to they are more likely to occupy board positions from affiliates inside the BHCs (Elyasiani and Zhang, 2015).

As an additional analysis, we investigate the link between board compositions of the complex US BHCs and corporate social responsibility, and study to what extent the composition of the bank board affects complex entities to control for their corporate governance concerns. To this aim, we obtain data from MSCI ESG KLD STATS, which is an annual data set of positive and negative environmental, social, and governance performance indicators applied to a representative universe of traded and publicly entities from the US and non-US countries. From this source, we collect data related to the number of corporate governance concerns for 79 complex BHCs, with 630 observations from our original sample, and covering the time span of our main analysis. This data shows showed the number of negative social performance indicators that entities have in different aspects of corporate social responsibility, such as environmental, social, governance structures, controversial investments, among others. In this way, we consider that banks which manage to reduce their number of concerns show a positive corporate governance performance by their boards. The main objective of this part of our study is to analyse how the proportion of board directors, according to their degree of busyness and their attendance of the board meetings, influence the control of the corporate concerns of the institution. Thus, the equation to conduct this test is the following:

$$Concerns_{it} = \alpha + \beta_1 + \beta_2 Y_{it} + \beta_3 Y_{it} * \theta_{it} + \beta_4 \theta_{it} + \beta_5 X_{i,t} + \delta + \varepsilon_{it} \tag{3}$$

Where:

$Concerns_{it}$ = Number of corporate governance concerns of the BHC i at time t.

Y_{it} = Proportion of independent, insider, very-busy, busy, not-busy and not-so-busy board directors of the BHC i at time t.

θ_{it} = Proportion of board directors (independent and/or insider) with low attendance of the BHC i at time t.

$Y_{it} * \theta_{it}$ = Interaction variable of the BHC i at time t.

$X_{i,t}$ = Vector for the control variables.

δ = Year fixed-effects dummy variable.

ε_{it} = Error term.

The variable θ_{it} represents the proportion of board members that attended less than 75% of the board meetings. It is important to mention that this data is obtained from the ISS dataset, which is the main corporate governance data source for this study. Furthermore, we include the interaction variable $\Upsilon_{it} * \theta_{it}$ in order to observe how board members that show low attendance affect the number of concerns. We include the same vector of control variables as model (2). Furthermore, we apply the ordered logit approach because our dependent variable, $Concerns_{it}$, has more than two categories and the values of each category have a meaningful sequential order (from low to high). Moreover, we include year, state and bank fixed effects dummies so as to control for unobserved heterogeneity at year, state and bank level and we apply robust standard errors.

Table 4.4, below, depicts summary statistics and a correlation matrix of the independent variables.

Table 4.4 Summary statistics and correlation matrix

Panel A. Summary statistics

	N	Mean	SD	Min	Max
% Independent directors	1300	.75	.13	.22	1
% Insiders directors	1300	.25	.13	0	.78
% Very-busy directors	1300	.056	.1	0	.76
% Busy directors	1300	.32	.28	0	1
% Not-busy directors	1300	.68	.28	0	1
% Not-too-busy directors	1300	.27	.22	0	.94
% Very-busy independent	1300	.047	.09	0	.65
% Busy independent	1300	.26	.24	0	.87
% Not-busy independent	1300	.49	.23	0	1
% Not-too-busy independent	1300	.21	.19	0	.83
% Very-busy insiders	1300	.0092	.029	0	.19
% Busy insiders	1300	.067	.089	0	.5
% Not-busy insiders	1300	.18	.13	0	.73
% Not-too-busy insiders	1300	.058	.08	0	.5
Number of corporate governance concerns	977	.47	.66	0	3
Board size	1300	13	3.7	6	32
Board size (log)	1300	2.5	.27	1.8	3.5
Num. audit members	1300	4.3	1.4	0	15
Num. audit members(log)	1297	1.4	.32	0	2.7
Num. compensation members	1300	4.2	1.5	0	11
Num. compensation members(log)	1294	1.4	.34	0	2.4
Bank size*	1300	117,081,732	346,228,278	161,631	2,524,018,250
Bank size (log)	1300	17	1.6	12	22
ROA	1300	.0069	.01	-.14	.12
ROA (t-1)	1216	.0072	.01	-.14	.12
Number of subsidiaries	1266	3.4	5.2	1	48
Number of subsidiaries (log)	1266	.7	.89	0	3.9
Interlocking board members	1300	.088	.28	0	1

Panel B. Correlation matrix

		1	2	3	4	5	6	7	8
1	Board size (log)	1							
2	Bank size (log)	0.2981	1						
3	ROA	0.0347	-0.0242	1					
4	ROA (t-1)	0.0209	-0.0371	0.8233	1				
5	Members audit committee (log)	0.3481	0.173	-0.0703	-0.0786	1			
6	Members compensation committee (log)	0.269	0.1205	-0.0679	-0.0817	0.5614	1		
7	Number of subsidiaries (log)	0.3554	0.3184	0.075	0.0891	0.1672	0.1283	1	
8	Interlocking board members	0.1496	0.1369	0.0092	0.0139	0.0482	0.0212	0.2314	1

*Thousands of dollars.

We run our model for each classification of board directors that we define previously as by type of director: independent and insiders, as well as by their busyness degree: very-busy, busy, not busy and not-too-busy directors. The aim is to observe how complexity influences the total proportion of each classification of directors. Then we re-run our model using the same busyness degree classification but now separated between independent and insider directors. This will enable us to answer our hypothesis previously established.

4.4 Results

4.4.1 Main results and endogeneity test

Our fist analysis is focused on the endogeneity test in which we run our model (1). Table 4.5, below, depicts outputs for the change in the complexity indicator and the change in board composition. Note that the first two columns consider the change in the total number of outsiders and insider directors while the last four columns take into account changes in the number of very-busy, busy, not-busy and not-too-busy board members, respectively. This table shows that none of the coefficients for the change in the number of any type of board directors are significant. As expected, the *change in bank size* is positive and meaningful for almost all of this set of regressions. Thus, we conclude that the change in the complexity of the BHCs in not related to the change in the busyness of board directors.

Table 4.5. Endogeneity test using change in the number of directors

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Change in number of insider directors	0.60					
	(0.52)					
Change in number of independent directors		-1.09				
		(1.30)				
Change in number of very-busy directors			-1.00			
			(0.73)			
Change in number of not-busy directors				-0.39		
				(0.76)		
Change in number of busy directors					-0.71	
					(1.03)	
Change in number of not-too-busy directors						-0.53
						(0.86)
Change in bank size	29.9	39.7	124.4**	42.4	56.6*	66.4**
	(25.9)	(21.8)	(42.0)	(22.9)	(25.3)	(25.7)
Change in ROA	-0.0089	-0.0060	2.07	-0.011	-0.0031	-0.0037
	(0.012)	(0.0091)	(1.76)	(0.016)	(0.0050)	(0.0055)
Constant	-4.41***	-4.45***	-21.6***	-3.76***	-4.97***	-4.24***
	(1.10)	(1.13)	(1.64)	(0.78)	(1.30)	(1.03)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	945	949	109	886	540	486
Number of Banks	137	137	38	137	108	108

Note: This table presents the results of Logit regressions results in which we conducted an endogeneity test to investigate if the change in the number of board member according to their type of director and busyness degree affect banks to become complex. We estimate the following model: $\Delta\ Complex_{it} = \alpha + \beta_1 + \beta_2\ \Delta\ Directors_{it} + \beta_3\ \Delta\ X_{i,t} + \delta + \varepsilon_{it}$. Where $\Delta\ Complex_{it}$ is a binary variable that takes the value of 1 if the BHC i at the year t change its non-complex indicator to any other complex classification according to the code RSSD9057 from Call Reports, 0 otherwise. The $Directors_{it}$ is also a binary variable that takes the value of 1 for Model 1, if the bank change in the number of insider director, 0 otherwise; for model 2, the bank change in the number of independent directors, 0 otherwise; for model 3, the bank change in the number of very-busy directors, 0 otherwise ; for Model 4, if the bank change in the number of not-busy directors, 0 otherwise; for Model 5, if the bank change in the number or busy directors, 0 otherwise and for Model 6, if the bank change in the number of not-too busy directors, 0 otherwise. Independent directors are board members that are not related to the administration of the bank whereas insider directors are the executives and linked directors with the administration of the institution. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $\Delta\ X_{i,t}$ is the vector of the change for the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets and ROA is the net income divided by total assets. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports. Coverage: 1998 to 2015.

Now, we investigate the effects of complexity on the composition of bank boards in which we apply our model (2). Panel A from Table 4.6, in the page 103, shows results of this analysis. As a first glance, we do not find any evidence that the complexity of banks affects the total proportion of independent as well as the total proportion of insider directors sitting on the board. However, when we look through the different categories of board directors according to their busyness degree, we find that all of them are being affected by the complexity of the entities. The proportions of very-busy, not-busy and not-too-busy directors show a positive relation with complex entities while the not-busy directors is negative. Due to the difficulty to interpret outputs of the probit regression, we include in panel B from the same table, the marginal effects results to observe more clearly the magnitude of these impacts. In this way, we find that for complex institutions the proportion of very-busy, not-busy and not-too-busy board members increase in 3.8%, 7.6% and 7.4%, respectively. Whereas the percentage of not-busy directors decrease in the same magnitude as the busy directors showing a drop of 7.6%. These preliminary findings are in line with previous literature, which argue that financial institutions require more outsiders on their boards because of their valuable contributions to knowledge from other industrial sectors as well as independence from the management team to reduce agency problems with stockholders (Conyon, 2015; Armstrong *et al.*, 2016)

Regarding the control variables, we find that *board size* is only negatively related to the proportion of very-busy independent directors. Again, the marginal effects outputs show that the largest bank boards reduce their proportion of outsiders with three or more directorships by 5.1%. This means that banks with largest boards might need more director without any other commitments from other boards.

Not surprisingly, *bank size* results are significant for all regressions, in which it is been found negative for the total proportion of insiders and for the proportion of not-busy directors whereas it is positive for the other categories. This means that the largest entities require higher proportions of independent directors as well as a lower percentage of board members without any other outside directorships.

Next, the performance measure (ROA) is negatively related to the total proportion of outsiders while being positive for insiders. For the busyness degree of the board members, it shows positive for the very-busy and busy directors and negative for the not-busy directors. Meanwhile, the delayed performance measure (ROA_{t-1}) is negative for the total proportion of independent directors but positive for the proportion of total insiders. This is in line with prior literature which find that the presence of outsiders on boards can enhance performance of the entity for the current period, but it might have negative effects for the short-term period (Coles *et al.*, 2008).

Related to the number of board members in the audit committee, it is positive for the total proportion of outsiders and is negative for the total proportion of insiders. We confirm previous studies in which they find that banks include more independent board members as part of their audit committee to maintain independence between the financial reporting of the entities and bank managers (Armstrong *et al.*, 2016).

For the number of board members in the compensation committee, this negatively affects the busy and not-too-busy directors and positively the not-busy directors. This can be interpreted as banks prefer to maintain in their compensation committees board members without any other directorships, which might provide a better understanding about internal policies and procedures. We do not find any effect of the numbers of compensation committee members on the total proportion of independent directors neither in the total proportion of insider directors.

Then, we do not find evidence that the number of subsidiaries from the BHCs have any impact on the percentage of aggregated categories of board members.

Lastly, we find that the dummy variable to depict bank boards that have interlocking board members from their affiliates, is negative for the total proportion of ousiders and board members without any outside directorships, and is positive for the total proportion of insiders, very-busy and busy directors. This finding is in line with prior studies which find a positive relation between affiliate board members and busyness degree of the board directors (Fich and Shivdasani, 2006). This also supports the idea that banks benefits from having higher numbers of insider directors that are also sitting on other affiliate boards (Elyasiani and Zhang, 2015).

Table 4.6. The effects of complexity on categories of board directors

Panel A. Fractional response regressions

	% Independent directors	% Insiders directors	% Very-busy directors	% Busy directors	% Not-busy directors	% Not-too-busy directors
Complex BHC	0.024	-0.024	0.38**	0.26*	-0.26*	0.25*
	(0.055)	(0.055)	(0.14)	(0.11)	(0.11)	(0.10)
Board size (log)	-0.11	0.11	-0.51**	-0.13	0.13	0.033
	(0.10)	(0.10)	(0.16)	(0.19)	(0.19)	(0.17)
Bank size (log)	0.042*	-0.042*	0.27***	0.36***	-0.36***	0.26***
	(0.017)	(0.017)	(0.030)	(0.032)	(0.032)	(0.031)
ROA	-2.78*	2.78*	8.62	4.49*	-4.49*	2.35
	(1.37)	(1.37)	(4.55)	(2.20)	(2.20)	(1.60)
ROA (t-1)	-3.67**	3.67**	-2.92	-1.42	1.42	-0.66
	(1.12)	(1.12)	(3.48)	(2.06)	(2.06)	(1.86)
Num. audit members(log)	0.23***	-0.23***	0.076	0.13	-0.13	0.12
	(0.064)	(0.064)	(0.13)	(0.11)	(0.11)	(0.10)
Num. compensation members(log)	-0.010	0.010	0.079	-0.23*	0.23*	-0.28**
	(0.069)	(0.069)	(0.14)	(0.11)	(0.11)	(0.11)
Number of subsidiaries (log)	-0.030	0.030	-0.039	0.062	-0.062	0.057
	(0.032)	(0.032)	(0.043)	(0.045)	(0.045)	(0.045)
Interlocking board members	-0.15*	0.15*	0.31**	0.32**	-0.32**	0.15
	(0.061)	(0.061)	(0.12)	(0.12)	(0.12)	(0.098)
Constant	-0.14	0.14	-5.20***	-6.19***	6.19***	-5.09***
	(0.32)	(0.32)	(0.62)	(0.63)	(0.63)	(0.57)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.02	0.02	0.15	0.18	0.18	0.11
Observations	1,184	1,184	1,184	1,184	1,184	1,184
Number of Banks	138	138	138	138	138	138
Wald test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Panel B. Marginal effects results

	% Independent directors	% Insiders directors	% Very-busy directors	% Busy directors	% Not-busy directors	% Not-too-busy directors
Complex BHC	0.0074	-0.0074	0.038*	0.076*	-0.076*	0.074*
	(0.017)	(0.017)	(0.015)	(0.032)	(0.032)	(0.030)
Board size (log)	-0.035	0.035	-0.051**	-0.039	0.039	0.0098
	(0.032)	(0.032)	(0.017)	(0.055)	(0.055)	(0.051)
Bank size (log)	0.013*	-0.013*	0.027***	0.11***	-0.11***	0.076***
	(0.0052)	(0.0052)	(0.0030)	(0.0078)	(0.0078)	(0.0084)
ROA	-0.85*	0.85*	0.87	1.33*	-1.33*	0.69
	(0.42)	(0.42)	(0.45)	(0.65)	(0.65)	(0.47)
ROA (t-1)	-1.13**	1.13**	-0.30	-0.42	0.42	-0.19
	(0.34)	(0.34)	(0.36)	(0.61)	(0.61)	(0.55)
Num. audit members(log)	0.070***	-0.070***	0.0077	0.039	-0.039	0.035
	(0.020)	(0.020)	(0.013)	(0.032)	(0.032)	(0.030)
Num. compensation members(log)	-0.0032	0.0032	0.0080	-0.069*	0.069*	-0.081**
	(0.021)	(0.021)	(0.014)	(0.034)	(0.034)	(0.031)
Number of subsidiaries (log)	-0.0091	0.0091	-0.0039	0.018	-0.018	0.017
	(0.0097)	(0.0097)	(0.0044)	(0.013)	(0.013)	(0.013)
Interlocking board members	-0.047*	0.047*	0.032*	0.095**	-0.095**	0.044
	(0.019)	(0.019)	(0.012)	(0.037)	(0.037)	(0.029)

Note: This table presents the results of fractional response probit regressions, examining the effects of complexity of BHCs on their board composition for the total proportion of independent and insider directors and according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2\, Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of independent, insiders, very-busy, busy, not busy and not-too-busy board members of the BHC i at the year t. Independent directors are board members that are not related to the administration of the bank whereas insider directors are the executives and linked directors with the administration of the institution. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $Complex_{it}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $X_{i,t}$ is the vector of the following control variables: Board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

Next, we investigate how complexity impacts the different categories of independent directors according to their degree of busyness. Table 4.7, in the page 106, shows outputs for the regressions using our model (2). We observe that complexity affects the very-busy, busy and not-too-busy independent directors in a positive way. However, it can be seen that this impact is different among these types of outsiders. Outsiders that hold up to two directorships depict a higher impact of 5.6% comparing with outsiders that have three or more directorships showing 3.6%. This indicates that even that complex entities still need the expertise and knowledge from very-busy board members sitting on three or more outside directorships, complex entities increase more their requirements of outsiders with less commitments from other boards.

Regarding *board size* we find that is only negative and highly significant for the very-busy independent directors. This shows that larger board reduce their needs of outsiders sitting in three or more other boards, supporting our previous idea that banks require more committed board members.

Then, we find that *Banks size* is highly significant for all the regressions showing similar effects to those in Table 4.6, in the page 103. We confirm that the largest entities require more independent directors that hold other directorships sitting on their boards, this might be because the experience from other industries is needed to understand their complex financial activities that they decide to engage in (Bushman *et al.*, 2004).

Finally, we find that the proportion of independent directors without any outside directorship has a negative relation with bank performance, and it is also negative for entities that have interlocking directors sitting on their boards. This means that banks might not obtain benefits from this type of outsiders to generate income. Furthermore, when the organisational structure of the banks requires more directors from other affiliated boards, complex banks reduce their proportion of independent directors without any other directorships.

We conduct the same analysis but focus on the proportion of insider directors. Table 4.8, in the page 107 depicts these outputs. We find that complex banks increase their proportion of busy-directors and not-too-busy insiders up to 3.1% and 2.8%, respectively. We do not find evidence that complex institutions affect their proportion of very-busy and not-busy insiders during the time span of our analysis. Related to *board size*, we do not find evidence of an effect on the proportion of any of the categories of insider directors. Meanwhile, *bank size* shows higher levels of significance with the same effects shown in previous tables. We confirm that largest entities require more insiders holding more than one directorships as well as reducing their need for insiders without any other directorship.

Regarding to the number of insiders in the audit committee, we find it negative and highly significant only for the proportion of not-busy directors. Again, this is in line with prior literature which argue that entities reduce their insider representation in their audit committees due to regulatory changes aimed at protecting shareholders from relevant financial information that is not readily disclosed by executives that can affect their wealth (Armstrong *et al.*, 2016).

Then, the number of insiders on the compensation committee is negative on the proportions of busy and not-too-busy directors. This might be the result of the regulatory enforcement focused to reduce the presence of insiders in the compensation committee in order to control for excesses in the compensation packages awarded to bank executives, especially during the recent financial crisis of 2007 to 2008 (Conyon, 2015).

Lastly, we find that the number of subsidiaries and boards with interlocking board directors are positive for the busy and not-too-busy board members. This shows that banks require higher proportions of insiders that hold up to two outside directorships when the number of subsidiaries inside the holding is greater, this type of insider are especially require to control for the growing complex structure between the banks and their affiliates (Cetorelli *et al.*, 2014).

Table 4.7. The effects of complexity on categories of independent board directors

Panel A. Fractional response regressions

	% Very-busy independent	% Busy independent	% Not-busy independent	% Not-too-busy independent
Complex BHC	0.41**	0.23*	-0.095	0.21*
	(0.14)	(0.11)	(0.070)	(0.10)
Board size (log)	-0.59***	-0.12	0.064	0.057
	(0.17)	(0.18)	(0.12)	(0.17)
Bank size (log)	0.28***	0.33***	-0.27***	0.25***
	(0.029)	(0.028)	(0.020)	(0.028)
ROA	8.37	3.43	-4.95***	1.25
	(5.08)	(1.90)	(1.46)	(1.86)
ROA (t-1)	-1.95	-2.31	-1.23	-1.98
	(3.61)	(2.14)	(1.80)	(2.07)
Num. audit members(log)	0.10	0.14	0.083	0.13
	(0.13)	(0.11)	(0.082)	(0.11)
Num. compensation members(log)	0.16	-0.13	0.037	-0.18
	(0.14)	(0.11)	(0.081)	(0.10)
Number of subsidiaries (log)	-0.050	-0.0027	-0.036	-0.00099
	(0.045)	(0.042)	(0.032)	(0.041)
Interlocking board members	0.23*	0.067	-0.21*	-0.050
	(0.12)	(0.12)	(0.096)	(0.10)
Constant	-5.31***	-5.94***	4.02***	-5.21***
	(0.61)	(0.58)	(0.42)	(0.55)
Year FE	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.15	0.14	0.09	0.10
Observations	1,184	1,184	1,184	1,184
Number of Banks	138	138	138	138
Wald test	0.0000	0.0000	0.0000	0.0000
Panel B. Marginal effects results				
Complex BHC	0.036**	0.066*	-0.034	0.056*
	(0.014)	(0.030)	(0.025)	(0.027)
Board size (log)	-0.052**	-0.034	0.023	0.015
	(0.016)	(0.050)	(0.043)	(0.045)
Bank size (log)	0.024***	0.091***	-0.095***	0.066***
	(0.0026)	(0.0068)	(0.0064)	(0.0070)
ROA	0.74	0.96	-1.77***	0.33
	(0.44)	(0.53)	(0.52)	(0.49)
ROA (t-1)	-0.17	-0.65	-0.44	-0.53
	(0.32)	(0.60)	(0.64)	(0.55)
Num. audit members(log)	0.0090	0.040	0.030	0.035
	(0.012)	(0.030)	(0.029)	(0.028)
Num. compensation members(log)	0.014	-0.036	0.013	-0.049
	(0.012)	(0.031)	(0.029)	(0.028)
Number of subsidiaries (log)	-0.0044	-0.00076	-0.013	-0.00026
	(0.0039)	(0.012)	(0.011)	(0.011)
Interlocking board members	0.020	0.019	-0.075*	-0.013
	(0.010)	(0.033)	(0.035)	(0.027)

Note: This table presents the results of fractional response probit regressions, examining the effects of complexity of BHCs on the proportion of independent board members and according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2\ Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of very-busy, busy, not busy and not-too-busy independent board members of the BHC i at the year t. Independent directors are board members that are not linked to the administration of the bank. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $Complex_{it}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

Table 4.8. The effects of complexity on categories of insider board directors

Panel A. Fractional response regressions

	% Very-busy insiders	% Busy insiders	% Not-busy insiders	% Not-too-busy insiders
Complex BHC	0.18	0.26*	-0.084	0.26*
	(0.23)	(0.11)	(0.067)	(0.11)
Board size (log)	-0.030	-0.018	0.16	-0.020
	(0.24)	(0.21)	(0.099)	(0.20)
Bank size (log)	0.13***	0.10***	-0.12***	0.088***
	(0.034)	(0.025)	(0.025)	(0.026)
ROA	6.43	3.62	1.72	3.02
	(4.71)	(2.88)	(1.82)	(3.23)
ROA (t-1)	-6.62	1.69	3.51**	2.51
	(4.62)	(2.40)	(1.26)	(2.58)
Num. audit members(log)	-0.023	0.012	-0.28***	0.020
	(0.16)	(0.11)	(0.078)	(0.11)
Num. compensation members(log)	-0.22	-0.34**	0.14	-0.33**
	(0.16)	(0.11)	(0.082)	(0.12)
Number of subsidiaries (log)	0.0011	0.12*	-0.044	0.13*
	(0.071)	(0.050)	(0.037)	(0.054)
Interlocking board members	0.40**	0.44***	-0.16	0.38***
	(0.14)	(0.081)	(0.092)	(0.076)
Constant	-4.33***	-3.09***	1.06*	-2.91***
	(0.79)	(0.51)	(0.46)	(0.51)
Year FE	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.10	0.08	0.03	0.07
Observations	1,184	1,184	1,184	1,184
Number of Banks	138	138	138	138
Wald test	0.0000	0.0000	0.0000	0.0000
Panel B. Marginal effects results				
Complex BHC	0.0043	0.031*	-0.021	0.028*
	(0.0055)	(0.013)	(0.017)	(0.012)
Board size (log)	-0.00072	-0.0022	0.041	-0.0022
	(0.0057)	(0.025)	(0.025)	(0.022)
Bank size (log)	0.0031***	0.012***	-0.030***	0.0095***
	(0.00083)	(0.0030)	(0.0061)	(0.0028)
ROA	0.15	0.43	0.43	0.33
	(0.11)	(0.35)	(0.46)	(0.35)
ROA (t-1)	-0.16	0.20	0.88**	0.27
	(0.11)	(0.29)	(0.31)	(0.27)
Num. audit members(log)	-0.00054	0.0014	-0.069***	0.0021
	(0.0037)	(0.013)	(0.020)	(0.012)
Num. compensation members(log)	-0.0053	-0.040**	0.034	-0.036*
	(0.0040)	(0.014)	(0.021)	(0.014)
Number of subsidiaries (log)	0.000025	0.014*	-0.011	0.014*
	(0.0017)	(0.0061)	(0.0093)	(0.0061)
Interlocking board members	0.0095*	0.053***	-0.040	0.041***
	(0.0037)	(0.0095)	(0.023)	(0.0081)

Note: This table presents the results of fractional response probit regressions, examining the effects of complexity of BHCs on the proportion of insider board members according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2\ Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of very-busy, busy, not busy and not-too-busy insider board members of the BHC i at the year t. Independent directors are board members that are not related with the administration of the bank. We consider as insiders the executives and linked directors from the bank. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $Complex_{it}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

It is important to mention that we conduct additional analysis to those previously mentioned. However, they are not included here because results are not significant comparing with those obtained using our model (2). We include state fixed effects in our regressions in order to capture heterogeneity among the different states from our sample. However, we decide to include year fixed effects to capture regulatory changes and financial crisis in which we obtain better results.

Furthermore, we conduct additional robustness tests in which we applied the difference-in-differences approach to evaluate if our results are driven by regulatory changes such as the Sarbanes-Oxley Act. 2002 and Dodd-Frank Act. 2010, however, they are not significant. Thus, we decide to include year fixed effects in our main model in order to capture changes in regulation.

4.4.2 Robustness checks

Analysis using GLM

As a first robustness we apply our model (2) using the Generalized Linear Model (GLM) which is considered an alternative to estimate our regressions using the binomial family and logit link as the values of our dependent variable are bounded by 0 and 1, or in other words is a proportion (Papke and Wooldridge, 1996). Table 4.9, in the page 110, shows results for these outputs for the total categories of board directors. We find similar results to those displayed in table 4.5, above. However, we observe that standard errors are a little bit higher comparing with those using the fractional response technique. In this case, the marginal effects show that complexity positively affects the proportion of very-busy, busy and not-too-busy directors at the level of 5%, 8.2% and 8.2%, respectively. And again, complexity impacts negatively and up to 8.2% the proportion of not-busy directors. In this way, we confirm that complex entities affect positive board members that hold another directorship, and it is negative for the board members that are not sitting on other boards. We find similar results for the proportions of the different categories of independent and insider board members.[29]

Entities that maintain constant complexity

For our second robustness check, we re-run our model (2) but this time, we remove from our sample entities that do not maintain the same complexity indicator during the time span of our analysis. The aim of this analysis is to observe if banks that hold the same complexity maintain the same composition of board members. Panel B in Table 4.3, above, displays the composition of this sub-sample by complexity indicator. This sub-sample consists of 101 BHCs with 864 observations. We observe that 45 are non-complex entities, while for the complex entities we find 52 for credit-extending-activities, 1 for high-risk-activities, 2 for management-factors and 1 for multiple-factors. Table 4.10, in the page 111, shows outputs for these set of regressions. We observe that results are similar to those shown in Table 4.6, above, but with some differences. We find that for the complex banks, the proportion of busy and not-too-busy directors increase to 9.4% and 12%, respectively. Note that for busy and not-too-busy board members, their coefficients increase considerably comparing with our previous. It is important to mention that for this case we do not find evidence that complex entities have an effect on the proportion of very-busy board members. Furthermore, we find that our measure of performance (*ROA*) is

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[29] Appendix 4.B and 4.C display outputs for these regressions.

negative and significant for the proportion of total outsiders while it is positive and also significant for the percentage of total insiders. Moreover, we find that only the number of board members in the audit committee continues being significant, showing positive for the proportion of outsiders and negative for the percentage of insiders. The number of board directors in the compensation committee is no longer significant comparing with previous analysis. Thus, for the entities that maintain their same complexity category during the time span of our analysis, we find evidence that the impact of complexity is higher on the compositions of their boards.

Table 4.9. GLM regressions for the total categories of board directors

Panel A. GLM results

	% Independent directors	% Insiders directors	% Very-busy directors	% Busy directors	% Not-busy directors	% Not-too-busy directors
Complex BHC	0.033	-0.033	0.98**	0.47*	-0.47*	0.47**
	(0.095)	(0.095)	(0.32)	(0.19)	(0.19)	(0.18)
Board size (log)	-0.18	0.18	-0.96**	-0.23	0.23	0.048
	(0.18)	(0.18)	(0.32)	(0.32)	(0.32)	(0.30)
Bank size (log)	0.073*	-0.073*	0.54***	0.60***	-0.60***	0.43***
	(0.029)	(0.029)	(0.064)	(0.057)	(0.057)	(0.054)
ROA	-4.49	4.49	18.0*	8.00*	-8.00*	4.17
	(2.33)	(2.33)	(9.08)	(3.64)	(3.64)	(2.62)
ROA (t-1)	-6.19**	6.19**	-5.68	-2.82	2.82	-1.25
	(1.93)	(1.93)	(7.17)	(3.42)	(3.42)	(3.06)
Num. audit members(log)	0.38***	-0.38***	0.16	0.22	-0.22	0.21
	(0.11)	(0.11)	(0.24)	(0.17)	(0.17)	(0.17)
Num. compensation members(log)	-0.019	0.019	0.20	-0.40*	0.40*	-0.45*
	(0.12)	(0.12)	(0.29)	(0.20)	(0.20)	(0.18)
Number of subsidiaries (log)	-0.050	0.050	-0.10	0.11	-0.11	0.095
	(0.054)	(0.054)	(0.087)	(0.074)	(0.074)	(0.076)
Interlocking board members	-0.26*	0.26*	0.56*	0.52*	-0.52*	0.24
	(0.10)	(0.10)	(0.23)	(0.21)	(0.21)	(0.16)
Constant	-0.32	0.32	-10.4***	-10.4***	10.4***	-8.46***
	(0.54)	(0.54)	(1.26)	(1.11)	(1.11)	(0.98)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,184	1,184	1,184	1,184	1,184	1,184
Number of Banks	136	136	136	136	136	136
Pregibon t-test	-1.15	1.15	12.16	1.01	-1.01	0.67

Panel B. Marginal effects results

	% Independent directors	% Insiders directors	% Very-busy directors	% Busy directors	% Not-busy directors	% Not-too-busy directors
Complex BHC	0.0060	-0.0060	0.050**	0.082*	-0.082*	0.082**
	(0.017)	(0.017)	(0.019)	(0.033)	(0.033)	(0.030)
Board size (log)	-0.033	0.033	-0.049**	-0.040	0.040	0.0083
	(0.032)	(0.032)	(0.017)	(0.055)	(0.055)	(0.052)
Bank size (log)	0.013*	-0.013*	0.027***	0.11***	-0.11***	0.074***
	(0.0052)	(0.0052)	(0.0030)	(0.0079)	(0.0079)	(0.0084)
ROA	-0.81	0.81	0.91*	1.39*	-1.39*	0.72
	(0.42)	(0.42)	(0.45)	(0.63)	(0.63)	(0.45)
ROA (t-1)	-1.12**	1.12**	-0.29	-0.49	0.49	-0.22
	(0.35)	(0.35)	(0.37)	(0.60)	(0.60)	(0.53)
Num. audit members(log)	0.069***	-0.069***	0.0080	0.038	-0.038	0.036
	(0.019)	(0.019)	(0.013)	(0.030)	(0.030)	(0.029)
Num. compensation members(log)	-0.0035	0.0035	0.010	-0.069*	0.069*	-0.079*
	(0.021)	(0.021)	(0.015)	(0.034)	(0.034)	(0.032)
Number of subsidiaries (log)	-0.0089	0.0089	-0.0053	0.018	-0.018	0.017
	(0.0097)	(0.0097)	(0.0044)	(0.013)	(0.013)	(0.013)
Interlocking board members	-0.046*	0.046*	0.028*	0.090*	-0.090*	0.042
	(0.018)	(0.018)	(0.012)	(0.036)	(0.036)	(0.029)

Note: This table presents the results of GLM regressions using the binomial family and logit link, examining the effects of complexity of BHCs on their board composition for the total proportion of independent and insider directors and according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2 \; Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of independent, insiders, very-busy, busy, not busy and not-too-busy board members of the BHC i at the year t. Independent directors are board members that are not related to the administration of the bank whereas insider directors are the executives and linked directors with the administration of the institution. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $Complex_{it}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

Table 4.10. Regressions with only BHCs that maintain a constant complexity indicator

Panel A. Fractional response regressions

	% Independent directors	**% Insiders directors**	**% Very-busy directors**	**% Busy directors**	**% Not-busy directors**	**% Not-too-busy directors**
Complex BHC	0.078	-0.078	0.26	0.30*	-0.30*	0.37**
	(0.091)	(0.091)	(0.18)	(0.15)	(0.15)	(0.13)
Board size (log)	-0.14	0.14	-0.45*	-0.13	0.13	0.010
	(0.093)	(0.093)	(0.19)	(0.23)	(0.23)	(0.20)
Bank size (log)	0.043*	-0.043*	0.26***	0.32***	-0.32***	0.21***
	(0.021)	(0.021)	(0.039)	(0.035)	(0.035)	(0.034)
ROA	-4.00**	4.00**	9.92	3.59	-3.59	1.13
	(1.33)	(1.33)	(5.58)	(2.36)	(2.36)	(1.62)
ROA (t-1)	-2.56	2.56	-4.19	-1.42	1.42	-0.57
	(1.47)	(1.47)	(4.38)	(2.06)	(2.06)	(1.75)
Num. audit members(log)	0.22*	-0.22*	0.086	0.15	-0.15	0.14
	(0.087)	(0.087)	(0.15)	(0.11)	(0.11)	(0.11)
Num. compensation members(log)	-0.082	0.082	0.093	-0.11	0.11	-0.16
	(0.095)	(0.095)	(0.16)	(0.13)	(0.13)	(0.12)
Number of subsidiaries (log)	0.013	-0.013	0.027	0.11*	-0.11*	0.084
	(0.034)	(0.034)	(0.047)	(0.050)	(0.050)	(0.047)
Interlocking board members	-0.19**	0.19**	0.27*	0.22	-0.22	0.055
	(0.071)	(0.071)	(0.13)	(0.14)	(0.14)	(0.10)
Constant	-0.020	0.020	-5.21***	-5.77***	5.77***	-4.55***
	(0.42)	(0.42)	(0.76)	(0.76)	(0.76)	(0.66)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.02	0.02	0.14	0.18	0.18	0.11
Observations	786	786	786	786	786	786
Number of Banks	101	101	101	101	101	101
Wald test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Panel B. Marginal effects results						
Complex BHC	0.024	-0.024	0.031	0.094*	-0.094*	0.12**
	(0.027)	(0.027)	(0.024)	(0.044)	(0.044)	(0.041)
Board size (log)	-0.043	0.043	-0.055*	-0.042	0.042	0.0032
	(0.028)	(0.028)	(0.024)	(0.073)	(0.073)	(0.062)
Bank size (log)	0.013*	-0.013*	0.032***	0.099***	-0.099***	0.067***
	(0.0065)	(0.0065)	(0.0042)	(0.0094)	(0.0094)	(0.0100)
ROA	-1.21**	1.21**	1.21	1.12	-1.12	0.36
	(0.40)	(0.40)	(0.66)	(0.74)	(0.74)	(0.51)
ROA (t-1)	-0.77	0.77	-0.51	-0.44	0.44	-0.18
	(0.44)	(0.44)	(0.54)	(0.65)	(0.65)	(0.55)
Num. audit members(log)	0.066*	-0.066*	0.010	0.046	-0.046	0.044
	(0.026)	(0.026)	(0.018)	(0.036)	(0.036)	(0.036)
Num. compensation members(log)	-0.025	0.025	0.011	-0.036	0.036	-0.051
	(0.029)	(0.029)	(0.020)	(0.040)	(0.040)	(0.037)
Number of subsidiaries (log)	0.0038	-0.0038	0.0033	0.036*	-0.036*	0.026
	(0.010)	(0.010)	(0.0057)	(0.016)	(0.016)	(0.015)
Interlocking board members	-0.057**	0.057**	0.032*	0.070	-0.070	0.017
	(0.021)	(0.021)	(0.016)	(0.043)	(0.043)	(0.033)

Note: This table presents the results of fractional response probit regressions for the BHCs that maintain their complexity indicator during the time span of our analysis, examining the effects of complexity of BHCs on their board composition for the total proportion of independent and insider directors and according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2\ Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of independent, insiders, very-busy, busy, not busy and not-too-busy board members of the BHC i at the year t. Independent directors are board members that are not related to the administration of the bank whereas insider directors are the executives and linked directors with the administration of the institution. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $Complex_{it}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

Then, we run our model (2) focusing on the categories of independent directors for entities that do not change their complexity indicator during the time span of our study. Table 4.11, in the next page, displays results of these regressions. We find that the impact of complex banks on their proportions of busy and not-too-busy independent directors increases considerably comparing with those displayed in Table 4.7, in this case, complex entities increase by up to 8.9% the proportion of these types of director. Again, we do not find evidence that an increase in the complexity of institutions affects the proportions of very-busy board directors.

Next, we continue with our analysis but now focus on insider directors. Table 4.12, in the page 114, presents outputs for this analysis. In this case, complex entities increase by 4.2% their proportions of not-too-busy insider directors. This is a modest difference comparing with those results presented in Table 4.8. This means that requirements of complex banks related to the proportion of not-too-busy insider directors do not increase in the same magnitude as their needs of independent board members. This might be because the internal complexity of the financial entities, in which insiders are more necessary because of their knowledge of internal politics and procedures (Bushman *et al.*, 2004), is not growing as fast as their financial activities (Cetorelli *et al.*, 2014). In this way, independent directors can give valuable advice about changes in other industries in which financial entities may be offering very sophisticated financial products. Thus, banks might constantly look to increase their proportion of directors sitting on other boards in order to gain insights from other industries (Coles *et al.*, 2008).

Table 4.11. Regressions with only BHCs that maintain a constant complexity indicator – independent directors

Panel A. Fractional response regressions

	% Very-busy independent	% Busy independent	% Not-busy independent	% Not-too-busy independent
Complex BHC	0.35	0.29*	-0.098	0.31*
	(0.19)	(0.15)	(0.11)	(0.14)
Board size (log)	-0.59**	-0.18	0.089	0.0011
	(0.19)	(0.21)	(0.15)	(0.19)
Bank size (log)	0.27***	0.29***	-0.24***	0.21***
	(0.038)	(0.032)	(0.025)	(0.033)
ROA	9.74	2.22	-5.09**	-0.46
	(5.61)	(1.92)	(1.61)	(2.09)
ROA (t-1)	-3.27	-1.33	-1.04	-0.60
	(4.33)	(1.92)	(1.93)	(1.76)
Num. audit members(log)	0.088	0.13	0.079	0.12
	(0.14)	(0.12)	(0.10)	(0.13)
Num. compensation members(log)	0.15	-0.011	-0.098	-0.062
	(0.15)	(0.13)	(0.10)	(0.12)
Number of subsidiaries (log)	-0.0046	0.051	-0.045	0.041
	(0.051)	(0.049)	(0.041)	(0.048)
Interlocking board members	0.18	-0.040	-0.14	-0.16
	(0.12)	(0.13)	(0.10)	(0.10)
Constant	-5.08***	-5.38***	3.70***	-4.63***
	(0.72)	(0.69)	(0.53)	(0.63)
Year FE	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.14	0.14	0.10	0.09
Observations	786	786	786	786
Number of Banks	101	101	101	101
Wald test	0.0000	0.0000	0.0000	0.0000
Panel B. Marginal effects results				
Complex BHC	0.039	0.089*	-0.035	0.089*
	(0.023)	(0.044)	(0.038)	(0.040)
Board size (log)	-0.064**	-0.055	0.031	0.00031
	(0.022)	(0.065)	(0.054)	(0.055)
Bank size (log)	0.029***	0.088***	-0.085***	0.059***
	(0.0036)	(0.0086)	(0.0083)	(0.0090)
ROA	1.06	0.68	-1.81**	-0.13
	(0.60)	(0.59)	(0.57)	(0.60)
ROA (t-1)	-0.36	-0.41	-0.37	-0.17
	(0.48)	(0.59)	(0.68)	(0.51)
Num. audit members(log)	0.0096	0.039	0.028	0.036
	(0.016)	(0.037)	(0.037)	(0.037)
Num. compensation members(log)	0.016	-0.0034	-0.035	-0.018
	(0.017)	(0.038)	(0.036)	(0.034)
Number of subsidiaries (log)	-0.00050	0.016	-0.016	0.012
	(0.0055)	(0.015)	(0.015)	(0.014)
Interlocking board members	0.020	-0.012	-0.049	-0.046
	(0.014)	(0.039)	(0.037)	(0.030)

Note: This table presents the results of fractional response probit regressions for the BHCs that maintain their complexity indicator during the time span of our analysis, examining the effects of complexity of BHCs on the proportion of independent board members and according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2\ Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of very-busy, busy, not busy and not-too-busy independent board members of the BHC i at the year t. Independent directors are board members that are not linked to the administration of the bank. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $Complex_{it}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

Table 4.12. Regressions with only BHCs that maintain a constant complexity indicator – insider directors

Panel A. Fractional response regressions

	% Very-busy insiders	% Busy insiders	% Not-busy insiders	% Not-too-busy insiders
Complex BHC	-0.20	0.28	-0.15	0.36*
	(0.25)	(0.15)	(0.11)	(0.15)
Board size (log)	0.26	0.13	0.15	0.085
	(0.24)	(0.18)	(0.13)	(0.18)
Bank size (log)	0.13**	0.075**	-0.11***	0.055*
	(0.044)	(0.023)	(0.032)	(0.025)
ROA	7.64	4.44	2.84	3.95
	(8.21)	(3.27)	(2.42)	(3.44)
ROA (t-1)	-14.5*	-1.09	3.61	-0.56
	(5.87)	(2.30)	(1.89)	(2.46)
Num. audit members(log)	0.091	0.081	-0.32**	0.078
	(0.18)	(0.12)	(0.10)	(0.13)
Num. compensation members(log)	-0.18	-0.31*	0.24	-0.31*
	(0.20)	(0.13)	(0.12)	(0.15)
Number of subsidiaries (log)	0.14	0.13*	-0.12*	0.11*
	(0.072)	(0.052)	(0.048)	(0.057)
Interlocking board members	0.40*	0.46***	-0.12	0.41***
	(0.16)	(0.088)	(0.11)	(0.085)
Constant	-5.29***	-3.22***	1.01	-2.84***
	(0.91)	(0.59)	(0.61)	(0.63)
Year FE	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.12	0.07	0.05	0.06
Observations	786	786	786	786
Number of Banks	101	101	101	101
Wald test	0.0000	0.0000	0.0000	0.0000
Panel B. Marginal effects results				
Complex BHC	-0.0051	0.037	-0.034	0.042*
	(0.0063)	(0.019)	(0.026)	(0.018)
Board size (log)	0.0065	0.017	0.035	0.0100
	(0.0064)	(0.024)	(0.031)	(0.021)
Bank size (log)	0.0034**	0.0098**	-0.026***	0.0065*
	(0.0012)	(0.0030)	(0.0077)	(0.0029)
ROA	0.19	0.58	0.66	0.47
	(0.21)	(0.43)	(0.57)	(0.41)
ROA (t-1)	-0.37*	-0.14	0.84	-0.066
	(0.15)	(0.30)	(0.44)	(0.29)
Num. audit members(log)	0.0023	0.011	-0.076**	0.0092
	(0.0047)	(0.016)	(0.025)	(0.015)
Num. compensation members(log)	-0.0045	-0.041*	0.055	-0.037
	(0.0052)	(0.018)	(0.029)	(0.019)
Number of subsidiaries (log)	0.0035*	0.017*	-0.027*	0.013
	(0.0017)	(0.0068)	(0.011)	(0.0068)
Interlocking board members	0.010*	0.060***	-0.028	0.048***
	(0.0043)	(0.012)	(0.025)	(0.010)

Note: This table presents the results of fractional response probit regressions for the BHCs that maintain their complexity indicator during the time span of our analysis, examining the effects of complexity of BHCs on the proportion of insider board members according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2\ Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of very-busy, busy, not busy and not-too-busy insider board members of the BHC i at the year t. Independent directors are board members that are not related with the administration of the bank. We consider as insiders the executives and linked directors from the bank. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $Complex_{it}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

Balanced dataset with entities that maintain their complexity category

For our third robustness check, we focus our analysis on the banks that appear during all years within the time period of our analysis and maintain a constant complexity indicator. For this analysis, we have 15 BHCs with 270 observations that meet this criterion. Panel C in Table 4.3, above, displays the composition of this sample by their complexity type. We observe that only one entity is a non-complex institution while for the complex entities, all have the credit-extending-activities category, and table 4.13, in the next page, shows these outputs. These results shows that the effects of complex BHCs on the proportion of board members according to their busyness degree are similar to those displayed in Table 4.6, but with higher coefficients. In this way, complex entities show an impact of 12%, 26%, -26% and 25% for the very-busy, busy, not-busy and not-too-busy directors, respectively. We confirm that complex BHCs have a positive higher impact on the total proportion of board members with two or fewer directorships and a negative impact on the percentage of board directors without any other directorship.

The same analysis is applied to the categories of independent directors in which table 4.14, in the page 117, shows the outputs. We find that the effects of complex entities on the proportions of independent directors is consistent with prior findings. Again the coefficients presented in these set of regression are higher comparing with those in Table 4.7, and a higher significant level for the proportion of busy, not-busy and not-too-busy independent directors. This means that for the largest banks from our sample that survive during for all of our time span and while maintaining their same complexity indicator, their requirements of independent directors that hold up to two directorships increase more than their needs of outsiders sitting on three or more outside boards. This supports our previous finding that banks still maintain higher proportions of outsiders sitting on their boards. Nevertheless, it seems that financial entities need independent directors more commitment and without too many distractions from other boards, in order to fulfil their advisory requirements on their complex activities.

Now, we focus our analysis on the proportions of the different categories of insider board members. Table 4.15, in the page 118, displays results for this analysis. In this case, we find that the proportion of very-busy, busy and not-busy insiders are now significant with a 16%, 6.3% and -7.4%. The proportion of insider directors that hold up to two outside directorships is no longer significant comparing with outputs displayed in Table 4.8. Thus, we can conclude that for this subsample, complex entities that maintain their complexity indicator and survive during the whole time span of our analysis, require higher proportions of executive board members that hold three or more directorships and reduce their needs for insider directors without any other directorship. Executive board members might be needed to control for their subsidiaries or affiliates.

Table 4.13. The effects of complexity on categories of board directors with balanced dataset and a constant complexity indicator

Panel A. Fractional response regressions

	% Independent directors	% Insiders directors	% Very-busy directors	% Busy directors	% Not-busy directors	% Not-too-busy directors
Complex BHC	0.20	-0.20	0.58***	0.76***	-0.76***	0.65***
	(0.11)	(0.11)	(0.18)	(0.11)	(0.11)	(0.12)
Board size (log)	0.34	-0.34	-0.045	-0.33	0.33	-0.28
	(0.20)	(0.20)	(0.23)	(0.18)	(0.18)	(0.17)
Bank size (log)	0.081	-0.081	0.18**	0.26**	-0.26**	0.13
	(0.064)	(0.064)	(0.059)	(0.085)	(0.085)	(0.073)
ROA	-3.16	3.16	-7.04	-3.95	3.95	1.91
	(4.57)	(4.57)	(7.62)	(4.82)	(4.82)	(2.61)
ROA (t-1)	3.19	-3.19	-6.51	-4.02	4.02	0.98
	(5.49)	(5.49)	(6.98)	(3.96)	(3.96)	(3.37)
Num. audit members(log)	0.021	-0.021	-0.027	0.36**	-0.36**	0.36**
	(0.16)	(0.16)	(0.22)	(0.11)	(0.11)	(0.11)
Num. compensation members(log)	-0.037	0.037	0.20	0.11	-0.11	-0.052
	(0.21)	(0.21)	(0.23)	(0.18)	(0.18)	(0.17)
Number of subsidiaries (log)	-0.037	0.037	0.044	0.12**	-0.12**	0.069
	(0.045)	(0.045)	(0.076)	(0.038)	(0.038)	(0.049)
Interlocking board members	-0.19*	0.19*	0.18	0.12	-0.12	-0.020
	(0.091)	(0.091)	(0.29)	(0.17)	(0.17)	(0.13)
Constant	-1.88	1.88	-4.74***	-4.92***	4.92***	-2.98**
	(1.11)	(1.11)	(1.14)	(1.20)	(1.20)	(0.94)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.03	0.03	0.07	0.09	0.09	0.03
Observations	262	262	262	262	262	262
Number of Banks	15	15	15	15	15	15
Wald test	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Panel B. Marginal effects results						
Complex BHC	0.055	-0.055	0.12*	0.26***	-0.26***	0.25***
	(0.028)	(0.028)	(0.047)	(0.038)	(0.038)	(0.048)
Board size (log)	0.094	-0.094	-0.0091	-0.11	0.11	-0.11
	(0.054)	(0.054)	(0.047)	(0.060)	(0.060)	(0.065)
Bank size (log)	0.022	-0.022	0.037***	0.091**	-0.091**	0.051
	(0.018)	(0.018)	(0.0099)	(0.028)	(0.028)	(0.027)
ROA	-0.87	0.87	-1.43	-1.36	1.36	0.73
	(1.28)	(1.28)	(1.59)	(1.65)	(1.65)	(1.00)
ROA (t-1)	0.88	-0.88	-1.32	-1.39	1.39	0.38
	(1.48)	(1.48)	(1.44)	(1.36)	(1.36)	(1.30)
Num. audit members(log)	0.0057	-0.0057	-0.0056	0.12***	-0.12***	0.14**
	(0.044)	(0.044)	(0.045)	(0.038)	(0.038)	(0.042)
Num. compensation members(log)	-0.010	0.010	0.041	0.037	-0.037	-0.020
	(0.059)	(0.059)	(0.047)	(0.064)	(0.064)	(0.064)
Number of subsidiaries (log)	-0.010	0.010	0.0089	0.041**	-0.041**	0.027
	(0.012)	(0.012)	(0.015)	(0.013)	(0.013)	(0.019)
Interlocking board members	-0.052*	0.052*	0.036	0.040	-0.040	-0.0075
	(0.025)	(0.025)	(0.061)	(0.060)	(0.060)	(0.050)

Note: This table presents the results of fractional response probit regressions for the BHCs that maintain their complexity indicator and which also appear during all the time span of our analysis, examining the effects of complexity of BHCs on their board composition for the total proportion of independent and insider directors and according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2\ Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of independent, insiders, very-busy, busy, not busy and not-too-busy board members of the BHC i at the year t. Independent directors are board members that are not related to the administration of the bank whereas insider directors are the executives and linked directors with the administration of the institution. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $Complex_{it}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

Table 4.14. The effects of complexity on categories of independent directors with balanced dataset and a constant complexity indicator

Panel A. Fractional response regressions

	% Very-busy independent	% Busy independent	% Not-busy independent	% Not-too-busy independent
Complex BHC	0.41*	0.69***	-0.44***	0.65***
	(0.17)	(0.13)	(0.079)	(0.14)
Board size (log)	-0.25	-0.050	0.39*	0.088
	(0.23)	(0.19)	(0.16)	(0.21)
Bank size (log)	0.18**	0.23**	-0.21***	0.14
	(0.057)	(0.077)	(0.036)	(0.071)
ROA	-7.38	1.29	-3.02	5.83
	(7.44)	(4.18)	(5.18)	(3.47)
ROA (t-1)	-7.00	2.81	-0.40	6.98
	(6.38)	(3.31)	(4.47)	(4.08)
Num. audit members(log)	-0.035	0.17	-0.20	0.22**
	(0.21)	(0.10)	(0.13)	(0.070)
Num. compensation members(log)	0.30	0.22	-0.32**	0.060
	(0.21)	(0.18)	(0.11)	(0.17)
Number of subsidiaries (log)	0.021	0.0063	-0.052	-0.010
	(0.067)	(0.049)	(0.045)	(0.054)
Interlocking board members	0.13	-0.18	0.019	-0.28*
	(0.25)	(0.16)	(0.14)	(0.12)
Constant	-4.20***	-5.22***	3.16***	-4.25***
	(1.05)	(1.17)	(0.68)	(0.98)
Year FE	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.06	0.06	0.06	0.04
Observations	262	262	262	262
Number of Banks	15	15	15	15
Wald test	0.0000	0.0000	0.0000	0.0020
Panel B. Marginal effects results				
Complex BHC	0.075*	0.26***	-0.14***	0.24***
	(0.038)	(0.051)	(0.023)	(0.058)
Board size (log)	-0.046	-0.019	0.12*	0.033
	(0.043)	(0.072)	(0.050)	(0.078)
Bank size (log)	0.033***	0.086**	-0.067***	0.051*
	(0.0082)	(0.027)	(0.011)	(0.025)
ROA	-1.37	0.48	-0.96	2.16
	(1.41)	(1.57)	(1.63)	(1.27)
ROA (t-1)	-1.30	1.05	-0.13	2.59
	(1.21)	(1.25)	(1.41)	(1.54)
Num. audit members(log)	-0.0064	0.065	-0.065	0.081**
	(0.038)	(0.038)	(0.040)	(0.025)
Num. compensation members(log)	0.056	0.083	-0.10**	0.022
	(0.040)	(0.070)	(0.035)	(0.064)
Number of subsidiaries (log)	0.0040	0.0024	-0.016	-0.0037
	(0.013)	(0.018)	(0.014)	(0.020)
Interlocking board members	0.023	-0.067	0.0061	-0.11*
	(0.048)	(0.062)	(0.045)	(0.047)

Note: This table presents the results of fractional response probit regressions for the BHCs that maintain their complexity indicator and which also appear during all the time span of our analysis, examining the effects of complexity of BHCs on the proportion of independent board members and according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2\ Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of very-busy, busy, not busy and not-too-busy independent board members of the BHC i at the year t. Independent directors are board members that are not linked to the administration of the bank. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $\boldsymbol{Complex_{it}}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

Table 4.15. The effects of complexity on categories of insider directors with balanced dataset and a constant complexity indicator

Panel A. Fractional response regressions

	% Very-busy insiders	% Busy insiders	% Not-busy insiders	% Not-too-busy insiders
Complex BHC	3.81***	0.35**	-0.48***	0.17
	(0.32)	(0.12)	(0.13)	(0.14)
Board size (log)	0.58*	-0.46**	-0.0065	-0.75***
	(0.28)	(0.16)	(0.30)	(0.19)
Bank size (log)	0.12	0.023	-0.17	0.012
	(0.063)	(0.032)	(0.12)	(0.036)
ROA	9.82	-9.12*	15.7*	-8.81*
	(25.4)	(4.63)	(7.01)	(4.22)
ROA (t-1)	-0.66	-13.8**	9.52	-13.9***
	(23.2)	(4.41)	(8.72)	(3.91)
Num. audit members(log)	0.065	0.32*	-0.34	0.36*
	(0.24)	(0.13)	(0.19)	(0.16)
Num. compensation members(log)	-0.26	-0.30*	0.29	-0.24
	(0.29)	(0.14)	(0.22)	(0.17)
Number of subsidiaries (log)	0.074	0.18***	-0.17**	0.16**
	(0.099)	(0.052)	(0.064)	(0.064)
Interlocking board members	0.22	0.44***	-0.24	0.43***
	(0.23)	(0.068)	(0.14)	(0.11)
Constant	-9.44***	-0.79	2.49	0.11
	(1.24)	(0.55)	(1.88)	(0.71)
Year FE	Yes	Yes	Yes	Yes
Pseudo-R-squared	0.14	0.05	0.08	0.04
Observations	262	262	262	262
Number of Banks	15	15	15	15
Wald test	0.0000	0.0000	0.0000	0.0000

Panel B. Marginal effects results

	% Very-busy insiders	% Busy insiders	% Not-busy insiders	% Not-too-busy insiders
Complex BHC	0.16***	0.063**	-0.074***	0.027
	(0.045)	(0.024)	(0.014)	(0.023)
Board size (log)	0.024	-0.084**	-0.00099	-0.12***
	(0.015)	(0.029)	(0.046)	(0.034)
Bank size (log)	0.0051*	0.0043	-0.026	0.0019
	(0.0026)	(0.0058)	(0.019)	(0.0058)
ROA	0.41	-1.66*	2.40*	-1.41*
	(1.08)	(0.81)	(1.18)	(0.65)
ROA (t-1)	-0.028	-2.51***	1.46	-2.22***
	(0.97)	(0.73)	(1.39)	(0.56)
Num. audit members(log)	0.0027	0.057*	-0.052	0.057*
	(0.010)	(0.023)	(0.030)	(0.028)
Num. compensation members(log)	-0.011	-0.054*	0.044	-0.039
	(0.012)	(0.026)	(0.036)	(0.029)
Number of subsidiaries (log)	0.0031	0.032***	-0.027**	0.026**
	(0.0037)	(0.0089)	(0.0094)	(0.0100)
Interlocking board members	0.0094	0.079***	-0.036	0.068***
	(0.010)	(0.013)	(0.023)	(0.020)

Note: This table presents the results of fractional response probit regressions for the BHCs that maintain their complexity indicator and which also appear during all the time span of our analysis, examining the effects of complexity of BHCs on the proportion of insider board members according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2 \, Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of very-busy, busy, not busy and not-too-busy insider board members of the BHC i at the year t. Independent directors are board members that are not related with the administration of the bank. We consider as insiders the executives and linked directors from the bank. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $\boldsymbol{Complex_{it}}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $\boldsymbol{X_{i,t}}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

The effects of board composition on corporate governance responsibility

For our last analysis, we apply model (3) in order to find the link between the board composition and corporate governance responsibility. Table 4.16, in the page 120, shows the results of the regressions for the total proportions of independent and insider directors. Note that the coefficient of the total proportion of independent directors is positive to the number of concerns, while the total proportion of insider directors is negative. This first finding shows that a higher presence of independent directors on bank boards increases the number of concerns, whereas a higher percentage of insider directors can reduce their number. Furthermore, the interaction variable between the percentage of insider directors and their percentage of low attendance is negative and significant. This might be because executive board members attend more meetings and are more involved in solving more problems related to social objectives that can affect bank governance (John *et al.*, 2016). Moreover, we find that only the interaction variable between the total proportion of very-busy directors and low attendance is positive and significant. We can interpret this as meaning that the combination of board members with more commitments from outside boards can also show low attendance of board meetings, which means that banks increase their number of corporate governance concerns.

Then, we focus our analysis on independent directors. Table 4.17, in the page 121, shows the results of this analysis. Again, we find that the interaction variable between very-busy independent and low attendance is positive and significant. Furthermore, the proportions of busy independent directors are positive in relation to the number of concerns. This confirms the previous results showing that directors that hold three or more directorships might have less time to attend board meetings to be involved in discussing corporate governance concerns. This behaviour is especially observed in independent directors.

Lastly, we analyse for the proportion of insider directors, and Table 4.18, in the page 122, displays the results of this analysis. We find that the only significant coefficient from these results is the interaction between not-busy insider directors and their low attendance. We do not find evidence that the interactions between very-busy insiders and low attendance affect the number of concerns. Thus, we conclude that board members without any commitments from any outside board might attend board meetings more regularly, which might enable this type of director to be more involved in the decision making related to concerns about the corporate governance responsibility of the BHCs.

Table 4.16. The effects of board composition of complex BHCs on corporate governance concerns

	Model 1	Model 2	Model 3	Model 4
% Independent directors	2.88*			
	(1.39)			
*% Independent directors * % Low attendance independent*	61.9*			
	(30.4)			
% Low attendance independent	-48.3*			
	(22.4)			
% Insiders directors		-2.83*		
		(1.44)		
*% Insiders directors * % Low attendance insider*		-164.2*		
		(83.8)		
% Low attendance insider		39.5		
		(25.7)		
% Very-busy directors			0.31	
			(1.45)	
*% Very-busy directors * % Low attendance*			66.2**	
			(25.3)	
% Low attendance			-10.5*	2.57
			(4.28)	(8.19)
% Not-busy directors				-2.35
				(1.32)
*% Not-busy directors * % Low attendance*				-11.0
				(14.3)
% Busy directors				
*% Busy directors * % Low attendance*				
% Not-too-busy directors				
*% Not-too-busy directors * % Low attendance*				
Board size (log)	2.34*	2.38*	2.41*	2.54**
	(1.00)	(1.00)	(1.01)	(0.99)
Bank size (log)	0.66	0.61	0.57	0.48
	(0.65)	(0.64)	(0.68)	(0.65)
ROA	9.45	11.8	10.5	7.68
	(17.4)	(17.5)	(17.2)	(17.9)
ROA (t-1)	-37.1	-36.4	-41.4	-40.4
	(22.4)	(22.1)	(22.9)	(23.3)
Num. audit members(log)	-0.84	-0.80	-0.71	-0.79
	(0.52)	(0.53)	(0.52)	(0.53)
Num. compensation members(log)	-0.56	-0.62	-0.53	-0.60
	(0.58)	(0.60)	(0.60)	(0.59)
Number of subsidiaries (log)	0.58*	0.63*	0.62*	0.59*
	(0.25)	(0.25)	(0.25)	(0.25)
Interlocking board members	-1.45**	-1.36**	-1.58***	-1.68***
	(0.47)	(0.48)	(0.47)	(0.46)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	630	630	630	630

Note: This table presents the results of ordered logit regressions for a subsample of complex BHCs in order to investigate the effects of the proportion of total board members according to their busyness degree classification on the number of corporate governance concerns. We estimate the following model: $Concerns_{it} = \alpha + \beta_1 + \beta_2 Y_{it} + \beta_3 Y_{it} * \theta_{it} + \beta_4 \theta_{it} + \beta_5 X_{i,t} + \delta + \varepsilon_{it}$. Where $Concerns_{it}$ denotes the number of corporate governance concerns of the BHC i at time t. Y_{it} is the proportion of independent, insider, very-busy and not-busy directors of the BHC i at time t. θ_{it} is the proportion of board directors (independent and/or insider) with low attendance of the BHC i at time t. $Y_{it} * \theta_{it}$ is the interaction variable between the proportion of board director and low attendance of the BHC i at time t. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-, state- and bank-fixed effects and robust standard errors. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC, ISS and MSCI ESG KLD STATS dataset. Coverage: 1998 to 2015.

Table 4.17. The effects of board composition of complex BHCs on corporate governance concerns- only independent directors

	Model 1	Model 2
% Very-busy independent	0.72	
	(1.55)	
*% Very-busy independent * % Low attendance independent*	69.0*	
	(30.0)	
% Low attendance independent	-7.68	-4.23
	(5.19)	(8.36)
% Not-busy independent		-0.83
		(1.38)
*% Not-busy independent * % Low attendance independent*		7.53
		(20.4)
% Busy independent		
*% Busy independent * % Low attendance independent*		
% Not-too-busy independent		
*% Not-too-busy independent * % Low attendance independent*		
Board size (log)	2.36*	2.56*
	(1.01)	(1.01)
Bank size (log)	0.54	0.43
	(0.66)	(0.64)
ROA	9.67	7.88
	(17.3)	(17.9)
ROA (t-1)	-40.9	-39.4
	(22.9)	(23.1)
Num. audit members(log)	-0.69	-0.65
	(0.52)	(0.52)
Num. compensation members(log)	-0.50	-0.51
	(0.59)	(0.58)
Number of subsidiaries (log)	0.59*	0.57*
	(0.26)	(0.25)
Interlocking board members	-1.60***	-1.57***
	(0.48)	(0.47)
Year FE	Yes	Yes
State FE	Yes	Yes
Bank FE	Yes	Yes
Observations	630	630

Note: This table presents the results of ordered logit regressions for a subsample of complex BHCs in order to investigate the effects of the proportion of independent board directors according to their busyness degree classification on the number of corporate governance concerns. We estimate the following model: $Concerns_{it} = \alpha + \beta_1 + \beta_2 Y_{it} + \beta_3 Y_{it} * \theta_{it} + \beta_4 \theta_{it} + \beta_5 X_{i,t} + \delta + \varepsilon_{it}$. Where $Concerns_{it}$ denotes the number of corporate governance concerns of the BHC i at time t. Y_{it} is the proportion very-busy and not-busy independent directors of the BHC i at time t. θ_{it} is the proportion of independent board directors with low attendance of the BHC i at time t. $Y_{it} * \theta_{it}$ is the interaction variable between the proportion of board director and low attendance of the BHC i at time t. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-, state- and bank-fixed effects and robust standard errors. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC, ISS and MSCI ESG KLD STATS dataset. Coverage: 1998 to 2015.

Table 4.18. The effects of board composition of complex BHCs on corporate governance concerns- only executive directors

	Model 1	Model 2
% Very-busy insiders	-0.47	
	(4.36)	
*% Very-busy insiders * % Low attendance insider*	-108.0	
	(167.4)	
% Low attendance insider	-8.93	16.7
	(8.20)	(14.0)
% Not-busy insiders		-2.56
		(1.54)
*% Not-busy insiders * % Low attendance insider*		-210.8*
		(94.0)
% Busy insiders		
*% Busy insiders * % Low attendance insider*		
% Not-too-busy insiders		
*% Not-too-busy insiders * % Low attendance insider*		
Board size (log)	2.47*	2.45*
	(1.02)	(1.01)
Bank size (log)	0.46	0.65
	(0.67)	(0.66)
ROA	10.6	14.2
	(17.2)	(17.5)
ROA (t-1)	-38.8	-39.1
	(22.4)	(22.5)
Num. audit members(log)	-0.60	-0.79
	(0.52)	(0.53)
Num. compensation members(log)	-0.55	-0.66
	(0.59)	(0.61)
Number of subsidiaries (log)	0.59*	0.61*
	(0.25)	(0.25)
Interlocking board members	-1.53**	-1.65***
	(0.47)	(0.48)
Year FE	Yes	Yes
State FE	Yes	Yes
Bank FE	Yes	Yes
Observations	630	630

Note: This table presents the results of ordered logit regressions for a subsample of complex BHCs in order to investigate the effects of the proportion of insider board directors according to their busyness degree classification on the number of corporate governance concerns. We estimate the following model: $Concerns_{it} = \alpha + \beta_1 + \beta_2 Y_{it} + \beta_3 Y_{it} * \theta_{it} + \beta_4 \theta_{it} + \beta_5 X_{i,t} + \delta + \varepsilon_{it}$. Where $Concerns_{it}$ denotes the number of corporate governance concerns of the BHC i at time t. Y_{it} is the proportion very-busy and not-busy insider directors of the BHC i at time t. θ_{it} is the proportion of insider board directors with low attendance of the BHC i at time t. $Y_{it} * \theta_{it}$ is the interaction variable between the proportion of board director and low attendance of the BHC i at time t. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-, state- and bank-fixed effects and robust standard errors. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC, ISS and MSCI ESG KLD STATS dataset. Coverage: 1998 to 2015.

4.5 Summary and conclusions

The complexity of banks has dramatically increased in the last two decades, and the de-regulation process from the 1990's has contributed to the modification of the traditional business model for US banks. Financial institutions were enabled to expand their branching network, as well to enter into non-traditional financial activities, which has impacted their board composition to control these changes. During this period of constant growth in the complexity of banks, previous studies have investigated the role of independent and/or insider board directors in order to control for risk and/or performance in the entities (John *et al.*, 2016). However, these studies do not differentiate between complex and non-complex institutions. This growth in the complexity of banks has led to an increase in board size and a reconfiguration of board composition, in which the requirements of complex entities on independent directors are continually higher compared to those placed on executive board members. Bank requirements for advisory and/or monitoring knowledge from outsiders is needed to untangle the complexity of the variety of financial activities that they decide to engage in (Adams and Mehran, 2012). Nevertheless, independent directors can also be considered to be busy, as they maintain other directorships which can affect their effectiveness as bank board members (Jiraporn *et al.*, 2009).

We address this gap in the literature by showing how the involvement of independent directors differs between complex and non-complex entities. We find that, during the time span of our study, complex BHCs continued to require higher proportions of independent directors sitting on their boards. However, when we disaggregate outsiders according to their commitments with other boards, the percentage of independent directors that hold three of more outside directorships does not increase at the same level as the proportion of outsiders that hold fewer directorships. This means that banks still require the knowledge and expertise from other boards, and that banks are replacing their very-busy directors with outsiders who have fewer commitments or distractions with other boards.

Regarding the proportion of insiders, in general terms, we find that banks require higher proportions of board members who are also sitting on other boards. This might be happening because complex institutions require executives to be seated on affiliated boards. This is because insiders might have plenty of knowledge about the organisational structure inside the BHC, which makes them more suitable to occupy interlocking positions in order to help control the complexity inside the financial institution. We also find that the BHCs from our sample, which appear during the whole time span of our analysis and which maintain their complexity indicator, increase their proportion of insiders sitting on three of more outside boards. This might be because larger institutions have a higher number of subsidiaries, whereby insiders might be required to sit on affiliated boards in order to help entities to control their increasingly complex structure.

Our last analysis reveals that independent directors that hold three or more outside directorships might have less time to attend to board meetings, which also might affect banks' ability to control their number of corporate governance concerns. However, this can be balanced with the presence of more executive directors without any other directorship, as this type of directors can help to reduce the variety of the corporate governance responsibilities concerns of the BHCs.

This chapter provides three main policy implications. Firstly, banking authorities should consider the individual complexity of banks when considering laws to regulate the appointment of board members. Regulations that force financial institutions to maintain greater proportions of independent directors sitting on bank boards should consider the effectiveness of board members that are too busy attending outside boards. Our findings show that complex institutions require more committed independent directors to sit on their boards, in order to receive a proper advisory and/or monitoring service from them. Lastly, policy makers should consider that a reduction in the proportion of executive directors in a complex institution might affect the monitoring of banks, as insiders that hold other directorships have plenty of knowledge about the complexity of the bank holding company, whereas insiders without any other directorships might help banks to reduce their number of corporate governance responsibilities concerns.

Chapter 5: Conclusions

5. Conclusions

5.1 Introduction

This final chapter provides the overall concluding remarks for each of the preceding chapters. In particular, this conclusion not only highlights the individual contributions of each chapter to the existing literature, but also the limitations of this research. Finally, this chapter emphasises the public policy implications of the thesis and puts forward avenues for possible future research.

5.2 Chapter 2: How important is strategic fit for post-M&A performance in the US banking sector?

Chapter 2 analyses the importance of strategic fit for post-merger performance, which is a starting point for a bank to become a complex institution. While previous studies explain merger success through the strategies of geographic expansion or product diversification, this chapter points out that the existing banking literature does not provide a complete understanding of how strategic fit between merging banks can enhance post-merger performance, specifically how the main sources of strategic fit, similarities and complementarities, can be properly combined to achieve merger success. In this way, chapter 2 expands the analysis of how strategic fit can enhance merger outputs through understanding similarities and complementarities.

This chapter uses a cross-sectional sample of mergers from the US banking sector with three different time-year windows to depict the short-, medium- and long-terms effects. This sample is derived from a uniquely selected dataset over the years 1994 to 2013, which include mergers where acquirer banks are of all sizes (large, medium and small banks). Furthermore, this chapter applies a strict sample selection of mergers to fully isolate the effects of strategic fit from previous or subsequence mergers. Additionally, it presents a unique mapping of the accounting codes from Call Reports, aimed to build the loan portfolios as well as financial ratios between target and acquirer institutions which can be compared to the twenty years considered in the time framework of this analysis. The estimation procedure, using a Generalized Linear Model (GLM), presents strong evidence of how complementarities and similarities can be combined in areas such as loan portfolio, doubtful loans, as well as cost efficiency and liquidity levels, in order to achieve positive post-merger performance. Firstly, it is shown that higher differences in loan portfolio composition between partner banks are positively related to post-merger performance for all the time-year windows. Meanwhile, higher differences in the loan market portfolio between merging banks are negatively related to post-mergers performance, but only for the three- and four-year windows. These findings suggest that mergers, where partner banks have different profiles in their portfolio strategies and also take place within the same State, increase the probabilities of merger success, especially for the medium and long terms windows. Then, it is revealed that dissimilarities in efficiency levels between partner banks can improve performance, but only for the short- and medium-term windows. This result can be interpreted as, that conjoining banks can enjoy benefits from differences in their cost control strategies for the two and three years after the merger deal. However, the advantages of these dissimilarities might not be observed four years after the deal due to partner banks having to fully integrate their cost structures in the longer-term. Furthermore, it is found that only similarities in liquidity levels can achieve positive performance, whereas only dissimilarities in their strategies, to control for doubtful loans, enhance post-merger performance for all the time windows. A vast array of robustness checks confirm the core results of the effects of combining complementarities and similarities in a merger deal. These robustness checks include the re-estimation of the main model using only intra-state mergers, excluding from the sample mergers from Texas and Illinois, which account for almost twenty percent of the sample, excluding mergers where the acquirer is a large bank using separated ratios from partner banks, and applying the traditional OLS approach as an alternative model.

5.3 Chapter 3: Did the Dodd-Frank Act. 2010 enhance the risk exposure of complex bank holding companies in the US?

Chapter 3 is focused on analysing the effectiveness of the Dodd-Frank Act. 2010 to control risk levels and non-banking financial activities of the different categories of complex BHCs in the US. To this end, this chapter applies difference-in-difference estimators to compare risk and non-banking activities between two groups: a treated group of complex BHCs and a control group with non-complex BHCs.

The study draws upon a balanced panel dataset, with more than 6,000 bank-year observations for 1,067 US BHCs for the period 2009Q4 to 2011Q2 to capture the short-term period of this regulatory change. The regression results show that the Dodd-Frank Act. 2010 enhances risk levels for complex and large BHCs. However, this cannot be applied to all the eight categories of complex institutions. Only entities with credit-extending-activities and by supervisory-judgment classifications manage to enhance stability after this law was enacted. Regarding the effectiveness of this law to control for shadow banking activities that BHCs engage in with their non-bank subsidiaries, this chapter presents mixed results. Expressed more precisely, entities classified as management-factors increase investment in non-bank activities, while the result is the opposite in the case of complex institutions classified by supervisory-judgment. Furthermore, complex entities with credit-extending-activities classification are the only ones to reduce their income derived from activities with their non-bank affiliates. There is no evidence that the change in the law has affected complex institutions classified as multiple-factors, non-bank-financial-factors and high-risk-activities. Finally, the results show no evidence that the regulatory change has an effect on balances due to their non-bank subsidiaries for all the categories of complex BHCs. Several robustness checks are presented in this chapter: Core results are corroborated by removing entities with the credit-extending-activities category, which represent 38% of the complex institutions from the sample. Then, banks located in four US States that concentrate 25% of the total observations are removed. Moreover, the main model is re-evaluated using a sample of consolidated BHCs to observe whether regulatory change affects differently the consolidated complex BHCs. Additionally, another placebo test is presented where a sub-sample of non-complex BHCs are given a randomly complex category, in order to check whether the law only affects the real complex institutions from the original sample. Lastly, a graphic representation of the behaviour of the non-bank activities shows an increasing trend in banks engaging with their non-bank affiliates for the large and consolidates BHCs. In this last analysis, it is found that consolidated BHCs continued increasing their balances due to non-bank subsidiaries three years after the law was enacted, while the large BHCs show a steady decline. This chapter concludes that banking regulators have successfully limited the non-banking activities of BHCs, but this effect is only temporary.

5.4 Chapter 4: The impact of complexity in US bank holding companies on corporate governance.

Chapter 4 takes a corporate governance perspective and examines the influence of the complexity of BHCs on their board composition according to the degree of busyness of board members. This chapter exposes how complex entities modify the composition of their boards with independent and executive board members that sit on other outside boards in order to receive proper advisory and/or monitoring knowledge from them.

Using a sample of 138 consolidated BHCs from the US for years 1998 to 2015 and applying a fractional response model, this chapter shows that even complex entities are replacing their independent directors that hold three of more outside directorships with independent directors that hold up to two outside directorships. This means that complex banks still require the knowledge and expertise from other boards. However, they are replacing their very-busy directors, due to the need for outsiders who have fewer commitments or distractions with other boards. A similar picture is shown for the proportion of insiders, in which complex entities require higher proportions of executive board members to be sitting on other boards. This might happen because complex entities require insider board directors that might be seated on affiliated boards. In this way, complex banks need higher proportions of these types of directors because of their rich knowledge about the organisational structure inside the BHC, which makes them more suitable to occupy interlocking positions in order to help control the complexity inside the financial institution. Robustness checks corroborate the core results using a GLM model, which shows similar results to those generated by the fractional response model. Furthermore, the main model is run using a subsample of complex entities that maintain a constant complexity indicator during the time span of this analysis, again showing similar results. An additional robustness check is conducted using a balanced dataset of 15 largest BHCs that maintain their complexity indicator, and find that they increase their proportion of insiders sitting on three of more outside boards. This might be because larger institutions have a higher number of subsidiaries in which insiders might be required to sit on affiliated boards to help entities to control their increasingly complex structure.

5.5 Summary and Public Policy Implications.

This thesis offers several important contributions to the banking literature. To this end, several different econometric approaches (GLM, difference-in-difference, fractional response model and OLS) and a variety of samples from the US banking sector (M&As, large and consolidated BHCs) are employed for the purpose of this thesis.

Chapter 2 point out that the existing banking literature do not provides a complete understanding about how strategic fit between merging banks can enhance post-merger performance, specifically how the main sources of strategic fit, similarities and complementarities, can be properly combined to achieve merger success. Throughout this chapter, robust empirical evidence finds that complementarities in the loan portfolio composition between partner banks can enhance merger performance, while complementarities in their loan market composition erode it. Furthermore, dissimilar cost efficiency strategies between conjoining entities have a positive relation with merger performance but only for the short- and medium-terms. Moreover, only similarities in liquidity levels, as well as only differences in their strategies to manage doubtful loans between partner banks, have an enhancing effect on post-merger performance.

Comparing these results with the existing literature, no prior research encompasses both the analysis of similarities and complementarities in the same study, as well as comparing them across three different time-year windows to observe their evolution through time. Furthermore, the composition of the sample, with a variety of banks from various sizes and forty-four States, provides representative results for all the US States. As a last contribution, this chapter presents a unique cross-sectional sample of mergers that avoid overlaps with prior or subsequent mergers to fully isolate the effects of strategic fit on post-mergers performance.

These results give rise to an important public policy consideration: bank managers and regulators should consider strategic fit to increase the probability of merger success. The results indicate that a proper combination of complementarities and similarities between partner banks should be analysed by banking authorities before approval of the merger deal to achieve positive post-merger performance that can be held not only for the short-term, but also for the medium- and long-terms.

In chapter 3, it is shown that the Dodd-Frank Act. 2010 has partially achieved stability of risk levels in complex BHCs. However, this is attributable to only two of the eight categories of complex institution (credit-extending-activities and supervision-judgement). Regarding shadow banking activities, this chapter presents mixed results, depending on the complexity category of complex banks, in which again two categories appear to reduce their non-bank activities with their non-bank affiliates (credit-extending-activities and by supervision-judgement), while others increase it (management-factors) or show no effect derived from this re-regulatory change (multiple-factors, non-bank-financial-factors and high-risk-activities). This chapter contributes to the banking literature in several ways. Firstly, it is shown how complex BHCs increase their stability following this regulatory change. Secondly, this chapter analyses the effectiveness of this law to control the non-banking activities that BHCs engage in with their non-bank subsidiaries. Lastly, it analyses how this impact affects the different categories of complex institutions.

Thus, chapter 3, provides two important policy implications: firstly, The Dodd-Frank Act 2010 has only partially increased the stability of complex BHCs in the US, and some types of complex entities appear to continue to engage in shadow banking activities with their non-bank subsidiaries. Secondly, policymakers should consider the nature of the complexity to have a better monitoring of the risk levels of the BHCs, as well as to set more accurate limits on their non-banking activities and to impact all the categories of complex entities.

Chapter 4 shows evidence that complex BHCs reduce their proportion of busy directors that hold three or more directorships, and increase their proportions of not-too-busy directors that hold up to two directorships. A similar picture is found in the proportion of insider directors that hold other directorships. However, the largest entities that appear during all the years of the time span of this analysis show higher proportions of executive directors sitting on three or more outside boards. This chapter provides important contributions to the existing financial literature. Firstly, it demonstrates how the complexity of the BHCs influences the composition of their board of directors. Secondly, this chapter analyses how the degree of busyness of board members depends on the complexity and organisational structure of the banks. Lastly, the analysis in this chapter considers independent and executive directors and uses a sample that not only includes the largest and consolidated BHCs, but also medium size entities, and for a large time span of 18 years.

This chapter provides three main policy implications. Firstly, banking authorities should consider the individual complexity of banks when considering imposing laws to regulate the appointment of board members. Secondly, legislation that forces financial institutions to maintain greater proportions of independent directors sitting on bank boards should consider the effectiveness of board members that are too busy attending outside boards. Findings presented in this chapter show that complex institutions require more committed independent directors sitting on their boards, in order to receive a proper advisory and/or monitoring service from them. Lastly, policymakers should also consider how a considerable reduction in the proportion of executive directors might affect the monitoring of banks, in which insiders have plenty of knowledge about the complexity of the bank holding company.

5.6 Limitations.

While this thesis presents very solid results and quite a range of policy implications for banking authorities and different regulators from the US banking sector, a number of limitations for preceding chapters are mentioned here in this section.

The starting year of 1994 for the analysis of chapter 2 was chosen because the accounting data from Call Reports changed radically when compared to the data available before this year. Thus, it is difficult to calculate variables and a loan portfolio that can be compared through time when including mergers before 1994.

In chapter 2, the classification of the loan portfolio for six different types of loans (commercial, residential, agricultural, other real estate, consumer and other minor loans and leases) to calculate for complementarities is unique.[30] Nevertheless, this classification is similar to those from other studies (Kim and Finkelstein, 2009).

Furthermore, regressions used in chapter 2 include year fixed effects dummies so as to control for unobserved heterogeneity at the year level, such as regulatory changes. Thus, this study does not split any analysis before or after the Gramm-Leach-Bliley Act 1999 or the Dodd-Frank Act 2010. However, a deeper analysis is needed to compare whether mergers that took place after this regulatory changes have different behaviours in their complementarities and similarities.

Regarding Chapter 3, the analysis focuses on the effectiveness in the short-term of the Dodd-Frank Act when this law was initially announced in July of 2010. Thus, this chapter does not cover amendments or delayed applications of this law for other aspects of non-financial activities.

Moreover, chapter 3 only considers three different aspects related non-banking activities that BHCs engage in with their non-bank subsidiaries, because in most cases the accounting data for other types of non-bank activities is not available in the Call Reports for quarters preceding the quarter in which the Dodd-Frank Act 2010 was enacted.

Chapter 4 applies a fractional response model and compares results when using the GLM approach. These two methods are considered to be the most appropriate to use when the dependent variable is a percentage (Papke and Wooldridge, 2008). However, there are other alternative techniques, such as logit transformation and zero-inflated beta models, which are not covered in this chapter.

Moreover, chapter 4 only analyses the relationship between the complexity of the entities and the composition of their boards. However, this chapter does not study how this

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[30] See Appendix 2B for the accounting codes that are built to create the loan portfolio between partner banks.

relationship affects compensation of board members, due to the fact that this information is not available in the corporate governance dataset obtained from the Institutional Shareholder Services (ISS).

Lastly, this thesis uses data only from the banking sector from the US; the replication of similar research in samples from other countries might have different results due to differences in regulatory frameworks, as well as the availability of data.

5.7 Avenues for future research.

Any investigation tends to give rise to additional questions. Therefore, this section exposes valuable avenues for future research.

Firstly, future work is advisable to investigate in more detail how complementarities and similarities can be applied to other relevant aspects, such as technology resources (e.g. automatic traded machines (ATMs) networks), or in specific banking products or services that could be relevant for merger deals in the banking sector.

Secondly, while this thesis presents an analysis of the effects of strategic fit on performance during a time span of twenty years, future research could compare subsamples of mergers from this time framework to observe in detail whether complementarities and similarities are due to regulatory changes or financial crisis.

Thirdly, the investigation of the effectiveness of amendments or delayed applications of the Dodd-Frank Act 2010, aimed to regulate non-banking activities of the complex financial entities, is beyond the scope of this thesis. Future studies could analyse whether this law continues controlling the types of activities that complex entities decide to engage in with their non-bank affiliates.

Fourthly, while this thesis offers robust evidence of the effects of complexity on the board composition, it does not aim to explore how risk or performance of the complex entities is affected. Future research could model the link between the different proportions of board directors according to their degree of busyness and changes in risk and/or performance of the complex financial institutions.

Appendices

Appendix 1.A. Mergers code definition

1 = Charter discontinued (merger or purchase and assumption)

Non-survivor transfers its assets to one or more survivors. Non-survivor ceases to exist as a head office. One charter has been discontinued, or will be discontinued in the near future. Non-survivor has not failed; government assistance is not involved.

5 = Split

Non-survivor transfers between 40 and 94 percent of its assets to one or more newly formed survivors. Non-survivor and survivor continue to exist. Non-survivor has not failed; government assistance is not involved.

7 = Sale of assets

Non-survivor transfers between 40 and 94 percent of its assets to one or more existing survivors. Non-survivor and survivor continue to exist. Non-survivor has not failed; government assistance is not involved.

9 = Charter retained (Merger or Purchase and Assumption)

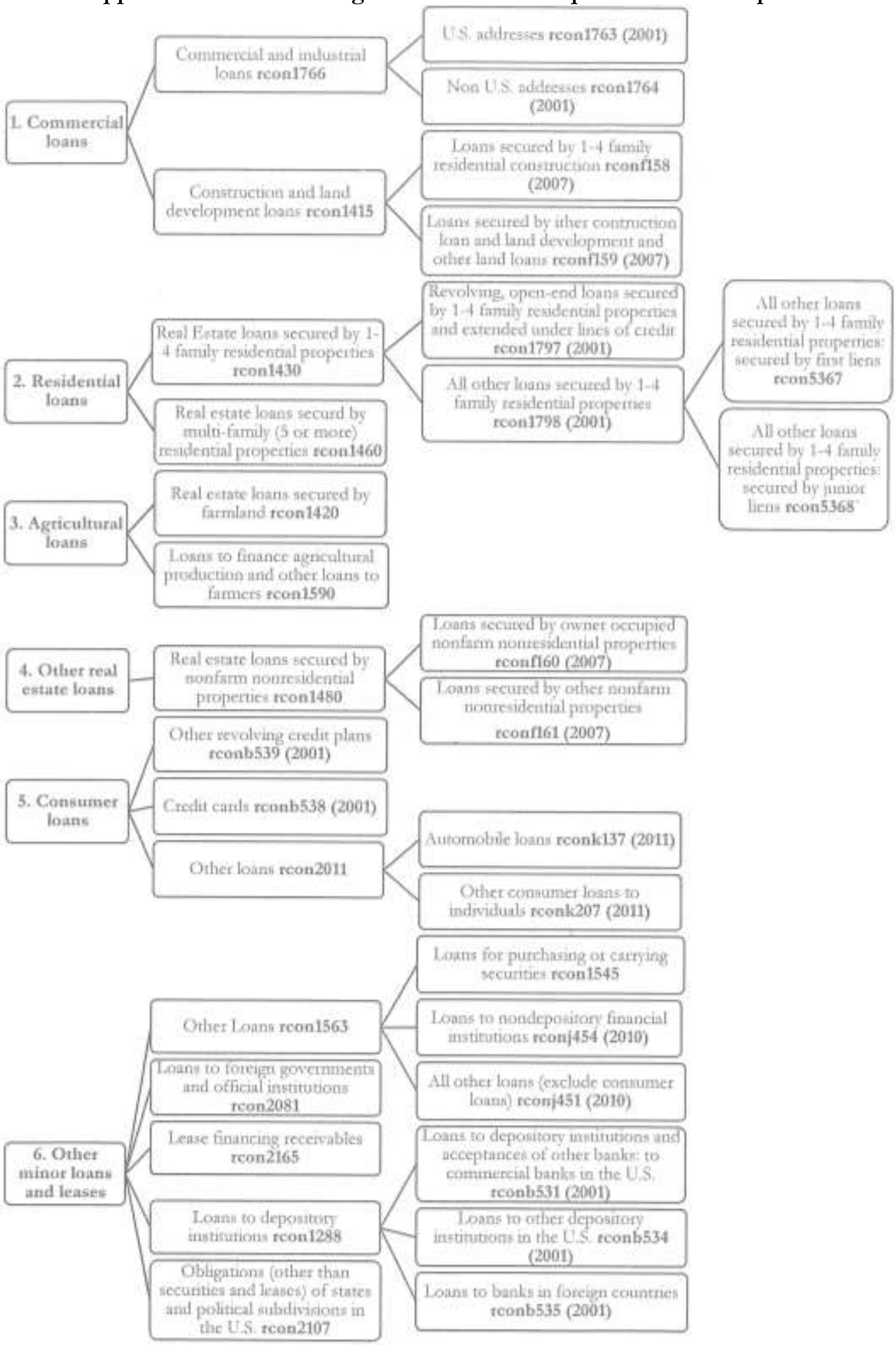
Non-survivor transfers 95 percent or more of its assets to one or more survivors. The charter that had been associated with non-survivor continues to exist and a new ID_RSSD is assigned to it. Non-survivor has not failed; government assistance is not involved.

50 = Failure: Government Assistance Provided

Non-survivor fails and ceases to exist. Disposition was arranged by the FDIC, RTC, NCUA, or other regulatory agency. Assets may be distributed to other entities as well as the regulatory agency.

Source: https://www.chicagofed.org /publications/financial-institution-reports/merger-data. Last access August 11th 2016.

Appendix 2.A. Accounting codes from Call Reports for the loan portfolio



Note: Appendix 2.A shows the mapping and changes on Call Reports of the accounting codes which are considered for the loan portfolio of the banks, covering the entire time framework of our dataset from 1994 to 2013.

Appendix 2.B. Definition of variables

Variable name	Definition	Call Reports items (reporting form FFIEC 031)
⊿ROA	Calculated as the average of the post-merger ROA ratio, minus the sum of the average of the ROA ratios for the merging banks in the pre-merger phase, the ROA is calculated as follows: net income divided by total assets.	RIAD4340/RCFD2170
⊿ROE	Calculated as the average of the post-merger ROE ratio, minus the sum of the average of the ROE ratios for the merging banks in the pre-merger phase, the ROE is calculated as follows: net income divided by total equity	RIAD4340/RCFD3210
Loan composition	This is the calculation of the distance between loan portfolio of the bidder banks and the target banks; it includes the average data of the loan composition in the pre-merger phase. The distance measure used is the Pearson product moment correlation coefficient (r). We consider the following classification of loans: commercial loans, residential loans, agricultural loans, other real estate loans, consumer loans, and other minor loans and leases.	Commercial loans: Sum(RCON1766, RCON1415); Residential loans: Sum(RCON1430, RCON1460); Agricultural loans: Sum(RCON1420, RCON1590); Other real estate loans: RCON1480; Consumer loans: Sum(RCONB539, RCONB538, RCON2011; Other minor loans and leases: Sum(RCON1563, RCON2081, RCON2165, RCON1288, RCON2107)
Loan market composition	Calculated as the distance between the loan markets from partner banks by using the Mahalanobis distance. It includes the average data of the loans market from the pre-merger period. We consider the same classification of loans used in previous variable but in this case at the aggregated state level	Commercial loans: Sum(RCON1766, RCON1415); Residential loans: Sum(RCON1430, RCON1460); Agricultural loans: Sum(RCON1420, RCON1590); Other real estate loans: RCON1480; Consumer loans: Sum(RCONB539, RCONB538, RCON2011; Other minor loans and leases: Sum(RCON1563, RCON2081, RCON2165, RCON1288, RCON2107)
Liquidity ratio	Calculated as the sum of cash, securities purchased and federal funds sold divided by the sum of deposits, securities and federal funds purchased.	(Sum (RCFD0081, RCFD0071, RCFD1754, RCFD1773, RCFD1350))/(Sum(RCON2200, RCFD2800))
Non-performing loans	Calculated as the ratio between non-accrual loans and lease financial receivables divided by total interest income.	RCFD1403/RIAD4107
Efficiency	Calculated as the ratio between the sum of total interest expenses plus total non-interest expenses divided by the sum of total interest income plus total non-interest income.	(RIAD4073+RIAD4093)/ (RIAD4107+(RIAD4079)
Relative Size	Calculated as a target's total assets to acquirer's total assets.	RCFD2170(target)/ RCFC2170 (acquirer)
Type of entity	A dummy variable that takes the value of 1 if merging banks match the same type of institutions according to the entity type code classification display in code RSSD9331, 0 otherwise	RSSD9331
Experience	A dummy variable that takes the value of 1 if acquirer bank has been involved in a previous merger deal, 0 otherwise.	N/A

Appendix 2.C. T-test: The mean differences between acquiring and target banks

Panel A. Two-year window

Variables	Acquirer	Target	Difference	t-Statistics	p-value
Capital	0.10	0.11	-0.01	-1.58	0.12
Efficiency	0.76	0.85	-0.09	-8.75	0.00
Liquidity	0.40	0.49	-0.09	-2.20	0.03
Non-performing loans	0.00	0.01	-0.00	-2.75	0.01
Size	5.21	4.67	0.54	22.17	0.00

Panel B. Three-year window

Variables	Acquirer	Target	Difference	t-Statistics	p-value
Capital	0.11	0.11	-0.01	-1.33	0.19
Efficiency	0.76	0.84	-0.08	-7.05	0.00
Liquidity	0.40	0.48	-0.09	-1.97	0.05
Non-performing loans	0.00	0.01	-0.00	-3.11	0.00
Size	5.14	4.65	0.49	16.98	0.00

Panel C. Four-year window

Variables	Acquirer	Target	Difference	t-Statistics	p-value
Capital	0.11	0.11	-0.01	-0.81	0.42
Efficiency	0.76	0.84	-0.08	-7.22	0.00
Liquidity	0.40	0.47	-0.07	-1.59	0.11
Non-performing loans	0.00	0.01	-0.00	-3.40	0.00
Size	5.12	4.63	0.50	15.66	0.00

Note: ***p<0.01, **p<0.05, *p<0.1

Appendix 3.A. Description of the BHC's complexity indicator code (RSSD9057)

1	Complex institutions with material credit-extending activities either of the parent bank holding company or its nonbank subsidiaries or debt outstanding to the general public.
2	Non-complex BHCs
3	Complex: Nonbank Financial Factors. Nature and scale of nonbank activities warrant designation as complex for supervisory purposes.
4	Complex: High Risk Activities. Company engages, either directly or through its subsidiaries, in significant non-banking activity having an inherently high risk profile. Examples include securities broker/dealer activities, insurance underwriting, and merchant banking; other activities may also trigger this designation if identified by the supervisory Reserve Bank as high-
5	Complex: Public Debt. Company issues significant debt to the general public such that unsophisticated investors may be at risk of loss.
6	Complex: Management Factors. Management practices such as the nature of inter-company transactions or centralized risk management policies and procedures warrant designation as complex for supervisory purposes.
7	Complex: Multiple Factors. Company meets two or more criteria for the complex designation, more than one of which are material in the judgment of the supervisory Reserve Bank. While the intensity of the supervisory approach may not differ from other complex companies, this designation alerts examiners to the presence of more than one factor.
8	Complex: Supervisory Judgment. Company does not appear to be complex, however, at the discretion of the supervisory Reserve Bank, it is designated a complex organization for supervisory purposes.
9	Non-complex: Supervisory Judgment appear to be complex, however at the discretion of the supervisory Reserve Bank, it is designated a non-complex organization for supervisory purposes.

Source: MDRM data dictionary search from the Federal Reserve Board website:
http://www.federalreserve.gov/apps/mdrm/data-dictionary

Appendix 3.B. Sample selection

Panel A. Sample selection for main regressions – large BHCs

	BHCs	Observations
Total number of entities	5,560	25,070
1 Drop banks that do not appear all the periods and non-large BHCs	-4,458	-17,356
2 Delete non-domestic entities	-1	-7
3 No BHCs located in US territories	-16	-112
4 Remove BHCs that do not maintain the same complexity indicator	-18	-126
Total	1,067	7,469

Panel B. Sample selection for main regression - consolidated BHCs

	BHCs	Observations
Total number of entities	5,560	25,070
1 Drop banks that do not appear all the periods and non-consolidated BHCs	-4,648	-18,686
2 Delete non-domestic entities	-1	-7
3 No BHCs located in US territories	-12	-84
4 Remove BHCs that do not maintain the same complexity indicator	-15	-105
Total	884	6,188

Appendix 3.C. Definition of the variables

Variable name	Definition	Mapping to Call Reports line items	
		Large BHCs (reporting forms FR Y-9LP)	**Consolidated BHCs (reporting forms FR Y-9C)**
Z-score	The sum of CAR and ROA divided by standard deviation of ROA; this last one is calculated over a four-quarter rolling time window.	$\frac{(\frac{BHCP4340}{BHCP3210}+(\frac{BHCP4340}{BHCP2170}}{\sigma_{roa}}$	$\frac{(\frac{BHCK4340}{BHCK3210}+(\frac{BHCK4340}{BHCK2170})}{\sigma_{roa}}$
Volatility of ROA	The negative of the natural logarithm of the standard deviation of ROA over a four-quarter rolling time window.	$-\ln(\sigma_{roa})$	$-\ln(\sigma_{roa})$
Non-bank balances to total liabilities	Balances held with non-bank subsidiaries to total liabilities (LIAB). This latter is the sum of deposits, securities sold under agreement to repurchase, borrowings with a remaining maturity of more than 1 year, other borrowed money with a remaining maturity of more than 1 year, subordinated notes and debentures, other liabilities, and balances due to subsidiaries and related institutions.	BHCP3606/ Sum (BHCP2200, BHCP0279, BHCP2309, BHCP2332, BHCP0368, BHCP4062, BHCP2930, BHCP3605, BHCP3606, BHCP3607)	BHCK5045/BHCK2948
Non-bank investments	Natural logarithm of the sum of non-equity investments and other receivables due from non-bank subsidiaries).	ln(BHCP0537+BHCP0538)	N/A
Non-bank income	Natural logarithm of the sum of operating income and equity income (losses) derived from non-bank subsidiaries.	ln(BHCP1279+BHCP3147)	N/A
Bank size	Natural logarithm of total assets).	ln(BHCP2170)	ln(BHCK2170)
Leverage financial ratio	Total liabilities divided by total equity capital.	(Sum (BHCP2200, BHCP0279, BHCP2309, BHCP2332, BHCP0368, BHCP4062, BHCP2930, BHCP3605, BHCP3606, BHCP3607))/BHCP3210	BHDM6631+BHDM6636+ BHFN6631+BHFN6636+ BHDMB993+BHCKB995+ BHCK3548+BHCK3190+ BHCK4062+BHCKC699+ BHCK2750)/ BHCK3300
Loan loss provision ratio	Loan loss provision divided by total assets.	BHCP4230/BHCP2170	BHCK4230/BHCK2170
Liabilities diversification	The HHI of their following liabilities: deposits, securities sold under agreement to repurchase, borrowings with a remaining maturity of more than 1 year, other borrowed money with a remaining maturity of more than 1 year, subordinated notes and debentures, other liabilities and balances due to subsidiaries and related institutions.	((BHCP2200/LIAB)^2)+ ((BHCP0279/LIAB)^2)+ (((BHCP2309+BHCP2332) /LIAB)^2)+ ((BHCP0368/LIAB)^2)+ ((BHCP4062/LIAB)^2)+ ((BHCP2930/LIAB)^2)+ (((BHCP3605+BHCP3606 +BHCP3607)/LIAB)^2)	((BHDM6631/BHCK2948)^2)+ ((BHDM6636/BHCK2948)^2)+ ((BHFN6631/BHCK2948)^2)+ ((BHFN6636/BHCK2948)^2)+ ((BHDMB993/BHCK2948)^2)+ ((BHCKB995/BHCK2948)^2)+ ((BHCK3548/BHCK2948)^2)+ ((BHCK3190/BHCK2948)^2)+ ((BHCK4062/BHCK2948)^2)+ ((BHCKC699/BHCK2948)^2)+ ((BHCK2750/BHCK2948)^2)

Data source: Call Reports reporting forms FR Y-9LP and FR Y-9C.

Appendix 4.A. List of the BHCs from sample

1st Source
Amsouth Bancorporation
Associated Banc-Corp
Banc One
Bancorpsouth, Inc.
Bancwest
Bank of America Corporation
Bank of Hawaii Corporation
Bank of The Ozarks, Inc.
Bankboston
Banknorth Group Inc
Banner Corporation
Bay View Capital
BB&T Corporation
BBCN Bancorp, Inc.
Boston Private Financial Holdings, Inc.
Brookline Bancorp, Inc.
Capital One Financial Corporation
Cardinal Financial Corporation
Cascade Bancorp
Cathay General Bancorp
CCB Financial
Central Pacific Financial Corp.
Centura Banks
Charter One Financial
Chittenden Corp.
Citigroup Inc.
City National Corporation
Comerica Incorporated
Commerce Bancorp, Inc.
Commerce Bancshares, Inc.
Community Bank System, Inc.
Community First Bankshares
Compass Bancshares, Inc.
Corus Bankshares, Inc.
Countrywide Financial Corp.
Cullen/Frost Bankers, Inc.
CVB Financial Corp.
East West Bancorp, Inc.
Fifth Third Bancorp
First Bancorp.
First Commonwealth Financial Corp.
First Financial Bancorp.
First Financial Bankshares, Inc.
First Horizon National Corporation
First Midwest Bancorp, Inc.
First Niagara Financial Group, Inc.
First Security (Utah)
First Virginia Banks
Firstar
Firstmerit Corporation
Fleetboston Financial
Franklin Resources, Inc.
Fulton Financial Corporation
GBC Bancorp
Glacier Bancorp, Inc.
Greater Bay Bancorp
Greenpoint Financial
Hancock Holding Company
Hanmi Financial Corporation
Hudson United Bancorp
Huntington Bancshares Inc.
Imperial Bancorp
Independent Bank Corp.
Independent Bank Corp. (Michigan)
International Bancshares Corp.
Investors Financial Services Corp.
Irwin Financial Corp.
Keycorp
Keystone Financial
M&T Bank Corporation
Marshall & Ilsley Corp.
Marshall & Ilsley Corporation
MB Financial, Inc.
MBNA Corp
Mellon Financial Corp.
Mercantile Bankshares Corp.
Morgan (J.P.) Chase & Co
Morgan (J.P.)
National City Corp.
National Commerce Financial
NBT Bancorp Inc.
New York Community Bancorp, Inc.
North Fork Bancorporation, Inc.
Northern Trust Corporation
Old Kent Financial
Old National Bancorp
Pacwest Bancorp
Park National
Popular
Privatebancorp, Inc.
Prosperity Bancshares, Inc.
Provident Bankshares Corp.
Provident Financial Group
Regions Financial Corporation
Republic Bancorp, Inc.
Riggs National Corp
Southtrust
Southwest Bancorporation Of Texas
State Street Corporation
Sterling Bancorp (New York)
Sterling Bancshares, Inc.
Sterling Financial Corp.
Summit Bancorp
Suntrust Banks, Inc.
Susquehanna Bancshares, Inc.
SVB Financial Group
Synovus Financial Corp.
BHC Name
TCF Financial Corporation
Texas Capital Bancshares, Inc.
The Bank Of New York Mellon Corp.
The Charles Schwab Corporation
The Colonial Bancgroup, Inc.
The Goldman Sachs Group, Inc.
The PNC Financial Services Group, Inc.
The South Financial Group Inc.
Trustco Bank Corp New York
Trustmark Corporation
U.S. Bancorp
U.S. Trust
UCBH Holdings, Inc.
UMB Financial Corporation
Umpqua Holdings Corporation
BHC Name
Union Planters
Unionbancal
United Bankshares/West Virginia
United Community Banks, Inc.
Valley National Bancorp
Wachovia
Wachovia Corp.
Washington Federal, Inc.
Webster Financial Corporation
Wells Fargo & Company
Westamerica Bancorporation
Whitney Holding Corporation
Wilshire Bancorp, Inc.
Wintrust Financial Corporation
Zions Bancorporation

Appendix 4.B. GLM regressions for the total categories of independent board directors

Panel A. GLM results

	% Very-busy independent	% Busy independent	% Not-busy independent	% Not-too-busy independent
Complex BHC	1.09**	0.46*	-0.15	0.42*
	(0.34)	(0.20)	(0.11)	(0.19)
Board size (log)	-1.16***	-0.22	0.10	0.094
	(0.34)	(0.31)	(0.20)	(0.30)
Bank size (log)	0.56***	0.54***	-0.44***	0.41***
	(0.064)	(0.050)	(0.035)	(0.049)
ROA	17.6	6.00	-8.10***	2.18
	(10.3)	(3.22)	(2.34)	(3.21)
ROA (t-1)	-3.82	-4.15	-1.88	-3.32
	(7.54)	(3.68)	(2.89)	(3.53)
Num. audit members(log)	0.22	0.25	0.15	0.24
	(0.25)	(0.17)	(0.13)	(0.18)
Num. compensation members(log)	0.37	-0.21	0.059	-0.29
	(0.28)	(0.19)	(0.13)	(0.19)
Number of subsidiaries (log)	-0.13	-0.0094	-0.059	-0.0083
	(0.096)	(0.071)	(0.051)	(0.071)
Interlocking board members	0.43	0.10	-0.35*	-0.093
	(0.23)	(0.20)	(0.16)	(0.18)
Constant	-10.8***	-9.97***	6.63***	-8.80***
	(1.27)	(1.02)	(0.71)	(0.97)
Year FE	Yes	Yes	Yes	Yes
Observations	1,184	1,184	1,184	1,184
Number of Banks	136	136	136	136
Pregibon t-test	11.74	2.88	2.00	2.74

Panel B. Marginal effects results

	% Very-busy independent	% Busy independent	% Not-busy independent	% Not-too-busy independent
Complex BHC	0.048**	0.075*	-0.032	0.064*
	(0.017)	(0.031)	(0.025)	(0.028)
Board size (log)	-0.050**	-0.035	0.022	0.014
	(0.016)	(0.050)	(0.043)	(0.046)
Bank size (log)	0.024***	0.089***	-0.096***	0.063***
	(0.0026)	(0.0068)	(0.0066)	(0.0070)
ROA	0.77	0.98	-1.77***	0.33
	(0.44)	(0.52)	(0.51)	(0.49)
ROA (t-1)	-0.17	-0.68	-0.41	-0.51
	(0.33)	(0.60)	(0.63)	(0.54)
Num. audit members(log)	0.0097	0.040	0.032	0.037
	(0.011)	(0.029)	(0.029)	(0.028)
Num. compensation members(log)	0.016	-0.034	0.013	-0.045
	(0.012)	(0.032)	(0.029)	(0.028)
Number of subsidiaries (log)	-0.0059	-0.0015	-0.013	-0.0013
	(0.0041)	(0.012)	(0.011)	(0.011)
Interlocking board members	0.019	0.017	-0.076*	-0.014
	(0.010)	(0.033)	(0.035)	(0.028)

Note: This table presents the results of GLM regressions using the binomial family and logit link, examining the effects of complexity of BHCs on their board composition for the proportion of independent board directors according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2\ Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of independent, insiders, very-busy, busy, not busy and not-too-busy board members of the BHC i at the year t. Independent directors are board members that are not related to the administration of the bank whereas insider directors are the executives and linked directors with the administration of the institution. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $Complex_{it}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

Appendix 4.C. GLM regressions for the total categories of insider board directors

Panel A. GLM results

	% Very-busy insiders	% Busy insiders	% Not-busy insiders	% Not-too-busy insiders
Complex BHC	0.60	0.61*	-0.12	0.62*
	(0.64)	(0.24)	(0.12)	(0.25)
Board size (log)	-0.043	-0.066	0.30	-0.080
	(0.61)	(0.42)	(0.17)	(0.43)
Bank size (log)	0.33***	0.20***	-0.22***	0.17**
	(0.092)	(0.048)	(0.047)	(0.052)
ROA	16.7	6.99	2.93	5.91
	(12.6)	(6.40)	(3.13)	(7.51)
ROA (t-1)	-15.7	3.98	5.83**	5.61
	(12.3)	(5.41)	(2.19)	(6.07)
Num. audit members(log)	-0.060	0.030	-0.49***	0.046
	(0.39)	(0.21)	(0.14)	(0.21)
Num. compensation members(log)	-0.57	-0.64**	0.24	-0.64*
	(0.41)	(0.23)	(0.14)	(0.25)
Number of subsidiaries (log)	-0.0016	0.24*	-0.078	0.28*
	(0.18)	(0.099)	(0.066)	(0.11)
Interlocking board members	0.92**	0.81***	-0.27	0.73***
	(0.34)	(0.15)	(0.17)	(0.15)
Constant	-9.85***	-5.72***	2.10*	-5.41***
	(2.03)	(1.04)	(0.85)	(1.07)
Year FE	Yes	Yes	Yes	Yes
Observations	1,184	1,184	1,184	1,184
Number of Banks	136	136	136	136
Pregibon t-test	8.49	8.36	1.60	6.74
Panel B. Marginal effects results				
Complex BHC	0.0056	0.037*	-0.017	0.032*
	(0.0063)	(0.015)	(0.017)	(0.013)
Board size (log)	-0.00041	-0.0039	0.042	-0.0042
	(0.0057)	(0.025)	(0.025)	(0.022)
Bank size (log)	0.0031***	0.012***	-0.031***	0.0088**
	(0.00086)	(0.0029)	(0.0063)	(0.0027)
ROA	0.16	0.42	0.41	0.31
	(0.12)	(0.38)	(0.44)	(0.39)
ROA (t-1)	-0.15	0.24	0.82**	0.29
	(0.12)	(0.32)	(0.30)	(0.31)
Num. audit members(log)	-0.00056	0.0018	-0.069***	0.0024
	(0.0036)	(0.012)	(0.019)	(0.011)
Num. compensation members(log)	-0.0053	-0.038**	0.034	-0.033*
	(0.0041)	(0.014)	(0.021)	(0.014)
Number of subsidiaries (log)	-0.000015	0.015*	-0.011	0.014*
	(0.0017)	(0.0060)	(0.0092)	(0.0060)
Interlocking board members	0.0086*	0.049***	-0.039	0.038***
	(0.0036)	(0.0088)	(0.024)	(0.0075)

Note: This table presents the results of GLM regressions using the binomial family and logit link, examining the effects of complexity of BHCs on their board composition for the proportion of insider board directors according to their busyness degree classification. We estimate the following model: $Y_{it} = \alpha + \beta_1 + \beta_2\ Complex_{it} + \beta_3 X_{i,t} + \delta + \varepsilon_{it}$. Where Y_{it} denotes the proportion of independent, insiders, very-busy, busy, not busy and not-too-busy board members of the BHC i at the year t. Independent directors are board members that are not related to the administration of the bank whereas insider directors are the executives and linked directors with the administration of the institution. The very-busy directors are board members that hold three or more outside directorships, busy directors hold more than one outside directorship, not-busy directors do not have any outside directorship and the not-too-busy directors hold up to two outside directorships. $Complex_{it}$ is a dummy variable that takes the value of 1 if the BHC is a complex institutions according to its complexity indicator displayed in the code RSSD9057 from Call Reports, 0 otherwise. $X_{i,t}$ is the vector of the following control variables: board size(log) is calculated as the log of the number of board members; bank size is the log of total assets; ROA is the net income divided by total assets and ROA(t-1) is the one year delayed value of ROA; The log value of the number of board member that are also part of the audit committee; The log value of the number of board member that are also part of the compensation committee and the log value of the number bank subsidiaries that the BHC display according to the Summary of Deposits (SOD) database in that year; Interlocking board members is a dummy variable that takes the value of 1 if the board has interlocking affiliates board members, 0 otherwise. The regressions include year-fixed effects and standard errors are clustered robust at bank level. Standard errors in parentheses. *p<0.1, **p<0.05, ***p<0.01. Data source: Call Reports and SOD database from the FDIC. Coverage: 1998 to 2015.

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