Why banks want to be complex*

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Abstract

We investigate whether and how bank complexity affects performance and systemic risk. We base the analysis on a complexity measure that captures diversification and diversity, controlling for size and other bank characteristics. We find that more complex banks exhibit a higher profitability, lower risk, and higher market share. Moreover, we show an inversely U-shaped relation between bank complexity and banks' sensitivity to systemic shocks. The evidence challenges the view that higher bank complexity is per se bad and is consistent with theoretical models that show that diversity in the banking system is critical for financial stability.

Key words: Banks, performance, diversification, diversity, financial stability, systemic risk

JEL classification: G20, G21

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1. Introduction

The quasi collapse of the global financial system during the crisis of 2007-2009 has triggered an extensive debate about the role of large complex banks. The debate initially focused on bank size, revisiting the "too big to fail hypothesis", but it quickly shifted to broader topics such as systemic importance and complexity of banks. On the one hand, banks are now seen as "too complex to fail", as pointed out by the joint report of the International Monetary Fund et al. (2009). Researchers and policy makers argue that the main danger is that financial institutions and markets are becoming "too big to understand" or "too complex to depict", and therefore need to shrink and be simplified (Hu, 2012). On the other hand, bankers argue that caps on bank size are inefficient because both size and complexity help banks diversify risks and innovate to create additional profit opportunities. Some studies suggest that there are significant economies of scale even for the largest banks (e.g., Hughes and Mester, 2013).

In this paper, we investigate whether and how bank complexity affects performance and systemic risk. Our measure of bank complexity is defined in analogy to Hausmann et al. (2011), who use international trade data to measure the complexity of a country's economy. They argue that the higher the number of products a country exports and the lower the number of other countries exporting the same products, the greater the country's economic complexity. We apply the same logic to banks, using the number of activities they perform in analogy to the number of products used by Hausmann et al. (2011). The approach relates bank complexity to two fundamental concepts analyzed by Wagner (2011): diversification and diversity. Moreover, the concept of diversity resonates with Caballero and Simsek (2013), who argue that complexity increases when banks need to assess their exposure to banks farther away in the network in order to determine their own financial health. The diversity of bank activities increases complexity as does distance in Caballero and Simsek (2013).

To measure bank complexity we proceed as follows. In the first step, we consider the extent of three categories of key banking activities following the International Monetary Fund et al. (2009): domestic banking, cross-border banking, and derivative activities. This approach reflects diversification of banks.[1] The more a bank is active in each of the three categories of activities, the more complex it is. In a second step, we consider how ubiquitous these activities are in the financial system and use this information as weights for these activities. Banks are more complex when they engage more in activities that are more sophisticated and innovative, making them different from the average bank in the financial system. This approach reflects diversity of banks. For clarification, we do not measure complexity of bank products; our study is about complexity of banks. We explicitly consider that bank size and complexity are related but not the same (e.g., Bonner, 2004).

We conduct two sets of empirical tests. In the first, we take the bank's perspective, investigating the link between complexity and performance at the individual bank level. We focus on bank profitability, risk and market share. We hypothesize that more complex banks have higher profitability, higher market share and lower risk than other banks. The reason is that more complex banks are the ones engaging in a large number of sophisticated and innovative activities. Since they cannot be easily and immediately replicated, these activities allow banks to differentiate from their competitors. Such strategy is supposed to create value (e.g. Barney (1986); Hoberg and Phillips (2014); Foucault and Frésard (2015)) and, at least in the short term,

[1] We capture diversification of bank activities in the complexity measure, following the proposal of the International Monetary Fund et al. (2009). There is large strand of literature in corporate finance and banking on the effects of different forms of diversification on firm value, risk and performance (e.g., Lang and Stulz, 1994; Berger and Ofek, 1995; Stiroh, 2004; Stiroh, 2006), which we are not going to summarize here.

generate monopoly power (Tufano (1989)). Hence, choosing unique activities increases profitability and market share, by lowering the competitive pressure on banks. Moreover, this positively affects the charter value of banks, reducing their incentives to take excessive risk (Keeley, 1990; Allen and Gale, 2004).

In the second set of tests, we take the financial regulator's perspective, investigating how bank complexity relates to systemic risk, as measured by CoVaR (Adrian and Brunnermeier 2008) and marginal expected shortfall (MES) (Acharya et al. 2010). The conventional wisdom is that bank complexity increases systemic risk, independently of size. The reason is that a complex bank, i.e., a bank engaging in a wide range of sophisticated and innovative activities, is presumably more interconnected and difficult to resolve than a bank with a limited scope performing traditional activities. However, there are theoretical arguments suggesting complexity might decrease systemic risk. In particular, Wagner (2010) argues that diversification reduces idiosyncratic risk but creates systemic risk, as it implies that banks hold the same portfolios. This increases the risk of joint asset liquidation, which depresses asset prices and jeopardizes bank stability. Hence, some degree of diversity among banks' portfolios is optimal. Empirically, this implies complexity potentially decreases systemic risk, because performing unique and rare activities is a way for banks to differentiate from each other. Given these arguments have opposite predictions; we investigate the link between complexity and systemic risk allowing for non-monotonic effects.

We base our analysis on data from consolidated financial statements of U.S. bank holding companies (BHCs) during the period 1986-2013. We exclude foreign banks and focus on BHCs at their highest hierarchical level since we assume the strategic business decisions are made at the parent level rather than the subsidiary level. This leaves us with 4,386 BHCs, and a sample of

38,632 bank-year observations. The panel structure of the dataset allows us to lag our variable of interest (Complexity), add time and bank fixed effects, as well as time-varying bank controls, including size. Hence, our results capture the effect of complexity, net of size.

Since bank complexity and performance might be endogenously determined, we employ another empirical strategy to mitigate endogeneity concerns. This relies on a major structural break in the U.S. banking system, i.e. the Gramm-Leach-Bliley Act of 1999 (Financial Services Modernization Act). This act repealed the Glass-Steagall Act of 1933, and allowed banks to set up holding companies to carry out commercial banking, investment banking, and to some extent near- and non-bank activities. Our identification strategy relies on the hypothesis that the GLB Act affected banks that were already active in investment banking prior to the GLB Act more than other banks. The rationale is that these banks benefit the most from expanding further into investment banking activities and increase their complexity. Empirically, we use information on Section 20 subsidiaries of BHCs from Cornett, Ors and Tehranian (2002) to identify these banks. We also check the robustness of the results splitting banks based on their size, assuming the very large ones were the most affected by the GLB Act. This is consistent with Geyfman and Yeager (2009), who document that stock returns of large banks reacted more strongly to the announcement of the GLB act than those of small banks.

We obtain the following main results. First, we find that more complex banks exhibit a significantly higher profitability, a significantly lower default risk, and a significantly higher market share. Using the enactment of the Gramm-Leach-Bliley Act confirms these results. We document a positive impact of this law on complexity and performance, which is more pronounced for banks with a Section 20 subsidiary and for very large banks. Overall, these results are in line with our hypothesis, as they suggest that individual banks exhibit a better performance when they are more complex. Note that we control for bank size in all analyses.

Second, we do not find a monotonic positive relationship between complexity and systemic risk, as suggested by conventional wisdom. We fail to find a statistically significant link between complexity and ΔCoVaR. However, we do find an inversely U-shaped relation between complexity and MES. Interestingly, banks with intermediate complexity ("average banks") are those contributing the most to systemic risk, whereas the low and high complexity banks exhibit a lower impact. A candidate explanation for this result is the diversification-diversity trade-off in Wagner (2010). The reason is diversity, which is the strategy reducing systemic risk according to Wagner (2010), can be achieved either by engaging in unique activities or focusing on some of these activities. These two options correspond to high and low values of complexity, respectively. By contrast, a bank with intermediate complexity is presumably operating a large number of activities, but quite common. This resonates with the concept of full diversification, which is what leads to systemic risk in Wagner (2010).[2]

Our study contributes to the literature in the following ways. First, we provide evidence that is consistent with recent theoretical work on financial stability. Wagner (2010) shows the existence of a trade-off between diversification and diversity, using a framework with endogenous costs of liquidating assets. The intuition is that diversification reduces idiosyncratic risk, which reduces the probability of having to liquidate assets, while diversity lowers the exposure to systemic risk, as fewer investors liquidate the same portfolio at the same time. Our measure of bank complexity combines both features: the diversification of activities at the bank level and the diversity of activities at the financial system level. Furthermore, Caballero and

[2] In further analyses we compare the impact of bank complexity on performance and systemic risk, controlling for bank diversification. It turns out that diversity is a crucial component for the positive complexity-performance link. Several additional analyses and robustness tests confirm our results.

Simsek (2013) conceptualize complexity as banks' uncertainty about the cross exposures in a financial system. Banks know their own exposures but there is uncertainty about exposures of banks that are more distant to them in the network. Complexity is a passive factor during normal times, but it becomes an active factor during crises as it can trigger domino effects of bankruptcies. Complexity matters in their model indirectly through the uncertainty it generates and through the responses of banks to this uncertainty. Diversity in our measure of bank complexity has similar effects as the uncertainty about cross exposures of distant banks in the system in their theoretical model: both increase complexity.

Second, empirical work on bank complexity is scarce. Cetorelli, McAndrews and Traia (2014) consider the organizational structure of banks, i.e., the number and type of subsidiaries acquired through mergers and acquisitions. They document an increase in complexity over time, with bank holding companies expanding the type of their subsidiaries and becoming less bank-centric. For comparison, we measure bank complexity in a more general way, capturing changes in banks' organizational structure due to mergers and acquisitions but also organic growth in banking activities. The complexity measure we use reflects the diversity of bank activities, following the intuition that specific activities require more expertise than standard activities.

Third, our study indirectly relates to research on bank opaqueness. This literature is based on the argument that bank loans are subject to asymmetric information, which is supposed to make banks themselves informationally opaque (Campbell and Kracaw, 1980; Morgan, 2002; Flannery, Kwan and Nimalendran, 2004). We note that bank complexity and opaqueness are related, but do not coincide. For example, investors might be unable to assess a bank's value in spite of being informed on its activities. If these are strongly interconnected, or their value depends on subjective criteria, the bank is transparent, but also too complex to depict.

The rest of this paper is organized as follows. In Section 2 we motivate and explain how we measure bank complexity. In Section 3 we describe the data. In Section 4 we present the empirical results on the link between bank complexity and performance, and bank complexity and systemic risk. In Section 4 we summarize findings from further empirical checks and robustness tests. We conclude in Section 5.

2. Measuring bank complexity

The finance literature does not provide a general definition of bank complexity. Our approach is to use a measure of complexity originally defined for economies. We follow Hausmann et al. (2011), who consider an economy as complex if it "*can weave vast quantities of relevant knowledge together, across large networks of people, to generate a diverse mix of knowledge-intensive products*" (Hausmann et al. 2011, pp. 18). They develop an index based on the *number of products* a country exports and their *ubiquity*, that is the number of other countries exporting the same products. The idea is that the economy of a country being the only producer of many products is complex, because it requires a vast amount of knowledge.

We follow the same logic as Hausmann et al. (2011), using the activities a bank carries out and their ubiquity as the equivalent of the products produced by a country. We define an activity as any of the items of the FR_Y-9C Consolidated Financial Statements of Bank Holding Companies (BHCs) listed in Appendix 1. In line with the International Monetary Fund et al. (2009, p. 13), we divide activities in three broad categories, i.e. domestic, cross border, and derivatives. Moreover, we refine the set of activities to obtain 26 domestic, 7 cross border, and 14 derivative ones[3].

[3] See Appendix 1 for a breakdown and description of the activities.

To calculate the measure of complexity, we follow three steps. First, we define the ubiquity of an activity *a* in year *t* as:

$$Ubiquity_{a,t} = \frac{\sum_{i=1}^{N} I_{i,a,t}}{N_t} \tag{1}$$

The term $I_{i,a,t}$ is an indicator function that takes the value one if bank i operates the activity a in year t. This means ubiquity is the number of banks operating activity a in year t, as a fraction of the total number of banks in year t. Ubiquity is an activity-specific attribute, obtained using information on the whole banking system.

The second step is to calculate a bank-specific complexity measure, which reflects the ubiquity of the activities each individual bank operates. We group the activities in the three broad categories described above, i.e. domestic, cross border, and derivatives, and calculate the following bank-specific complexity measure for each category:

$$Complexity_{i,c,t} = \sum_{a \in c} \frac{Activity_{i,a,t}}{Assets_{i,t}} \left(1 - Ubiquity_{a,t}\right) \tag{2}$$

For each bank *i*, category *c*, and year *t*, complexity is the volume of activity *a* in category *c,* scaled by the total assets of the bank[4], and weighted by the complementary of activity *a*'s ubiquity. This means complexity increases with the number of activities a bank operates in each category *c*, and decreases with the ubiquity of these activities.

[4] Some of the activities have volumes larger than total assets. For example, a bank's fiduciary accounts may exceed its own total assets. In these cases, we restrict the normalized ratios to be 1 to avoid biases caused by these extreme values.

The third step is to aggregate the three bank-specific complexity measures, corresponding to the three categories of activities we consider in this study. This requires the definition of weights for the three categories. Instead of using equal weights, or using the total volume of the activities in each category, which would bias the measure in favor of derivative activities given their huge size, our approach is to "let the data speak". We use factor analysis, and define $Complexity_{i,t}$ as the factor with the greatest explanatory power of the three $Complexity_{i,c,t}$ measures.[5]

The concept of complexity we use in this study is related to two key dimensions of banks that are widely used in the literature (Wagner 2010, 2011). The first is diversification, as complexity increases with the number of different activities a bank operates. The second is diversity, in the sense that the lower the number of other banks operating certain activities, the more complex (and diverse) a bank engaged in those activities. Diversification and diversity interact with each other and jointly determine the level of bank complexity. For example, let us consider bank A and B from a large financial system. Bank A offers a wide range of products that are very common in the financial system, while B offers a smaller range of products that are uncommon and require sophisticated knowledge. Hence, bank A scores high on diversification, but low on diversity (since the ubiquity of the bank's products is high). In contrast, bank B scores low on diversification, but high on diversity (since the ubiquity of the bank's products is low). This means bank A is more complex in terms of diversification, but B is more complex it terms of diversity. Eventually, the interaction of diversification and diversity determines the overall level of bank complexity.

[5] We perform the factor analysis on a year-by-year basis to avoid possible look-ahead bias. We standardize the three bank-complexity measures before prior to the estimation. It turns out the first factor captures roughly 60% of the variation in the three bank-specific complexity measures. Since the distribution of this first factor is not normal, we take its natural logarithm and transform it into an index that is scaled between zero and one.

The concepts of diversification and diversity relate to other views of complexity in the literature. One view connects complexity to corporate governance, suggesting that an intricate network of subsidiaries impairs an effective oversight at the banking group level (e.g. Cetorelli et al. 2014; Lumsdaine et al. 2015). The concept of diversification is related to this view, because a bank engaged in a wide range of activities is likely to have a network of subsidiaries. Another view links complexity to the interconnectedness of banks (e.g. Caballero and Simsek 2013) that might trigger a domino effect once a bankruptcy occurs. Diversification is related to interconnectedness, in the sense that a bank exposed to many risk factors is more likely to be exposed to contagion. Finally, a widespread view connects complexity to financial innovation, which makes banks hard to value for outside investors. This relates to the concept of diversity, as the activities operated by very few banks are likely innovative.

Finally, we point out that size is not a sufficient statistic for complexity. Figure 1 shows a scatterplot of bank complexity against total assets, using yearly bank data from 1986 to 2013.

(Insert Figure 1 here)

The relation between bank complexity and bank size is not monotonic. The link is negative for relatively small banks and it is positive for large banks. In particular, the relation is positive for banks with total assets above $50 billion, for which the Dodd-Frank Act mandates enhanced prudential regulation standards. Overall, size and complexity are positively, but not perfectly, correlated. This observation can also be made on the basis of Appendix 2. The five most complex banks are among the ten largest, but some of the banks with high complexity are ranked much lower in terms of total assets.

3. Data

We obtain annual accounting data from FR_Y-9C Consolidated Financial Statements of Bank Holding Companies (BHCs)[6] in the United States from 1986 to 2013. We exclude banks with majority foreign ownership and consider the BHCs at their highest hierarchy position since we assume the strategic business decisions are made at the parent level rather than the subsidiary level. We have in total 4,386 BHCs with 38,632 bank-year observations. Table 1 shows the main variables and reports summary statistics.

(Insert Table 1 here)

We observe that the domestic activity index ranges from 0.41 to 1, with equal mean and median being at 0.80. It indicates a normal distribution of banks undertaking diversified activities. The majority of the banks do not undertake either cross border activity or derivative activity since the median values for both are zero and the mean values are relatively small, being 0.05 and 0.09, respectively. Using factor analysis, we derive the first factor which explains the variations of these three indices as our complexity measure, which ranges from 0.32 to 1. The mean and median of bank complexity are very close, indicating that the distribution of complexity is, unlike bank size, rather symmetric.

4. Empirical results

4.1 Bank complexity and performance

We start with a panel data analysis of the link between bank complexity and performance, as measured by profitability (ROA), risk (bank Z-score), and market share. We address the potential endogeneity by exploiting the panel structure of our dataset, which allows us to include bank and

[6] We use banks and BHCs interchangeably in this paper.

year fixed effects. Moreover, we only use lags of the independent variables, mitigating potential concerns about reverse causality. We further include a set of time-varying control variables to isolate the effect of bank complexity from other variables that might affect bank performance. We control for bank size (logarithm of total assets), leverage, liquidity, income diversification (non-interest rate income as a fraction of total operating income), and efficiency (cost to income ratio). It is crucial to include total assets as control variable in our analysis because we want to identify effects of bank complexity that go beyond bank size. Table 2 reports the results.

(Insert Table 2 here)

The coefficient of complexity is positive and statistically significant at the 5%-level for all three performance measures. The effect is also large in economic terms. If a bank increased its complexity level from the minimum to the average value, its profitability and market share would rise roughly by 15% and 64%, relative to the sample mean. Moreover, bank risk would decrease by 17%. The effect of size is statistically significant at the one percent level for ROA and market share. Whereas it is reasonable that large banks have more market share, the finding also implies that larger banks are less profitable. The results suggest that complexity, rather than size, makes it possible for banks to become more profitable and less risky.

These findings are consistent with the argument that complexity, which increases with the diversity of a bank's activities, is a strategy to differentiate from competitors and create value (e.g., Barney (1986); Hoberg and Phillips (2014); Foucault and Frésard (2015)). In other words, a complex bank, that is a bank engaging in a wide range of diverse activities, is less exposed to competition. Hence, our evidence of a negative link between complexity and risk is consistent with theories suggesting fiercer competition among banks increases their risk of default, by reducing their charter value (Keeley, 1990; Allen and Gale, 2004).

As explained before, complexity is based on a factor analysis of the three bank activity indices, namely the domestic, the cross border, and the derivative activity index. Hence, the previous results indicate that complexity is beneficial for banks on average, but they do not show which aspect of bank complexity contributes more to performance. Table 3 shows the results.

(Insert Table 3 here)

Results indicate the domestic activity index mainly drives the link between overall complexity and profitability. Considering the variables definitions, this implies the wider and the more bank-specific the range of domestic on- and off- balance sheet activities, the greater profitability. This still holds after including all the three components of complexity in the same regression. Furthermore, the domestic activity index is the component of complexity that reduces bank risk. Hence, not only does the scope and specificity of domestic activities increase profitability, but also correspond to the reduction of default risk. A bank's market share is affected more by cross border activities rather than derivative activities. Furthermore, it is not related to the bank domestic activity index.

By and large, the analysis shows that more complex banks exhibit a higher profitability, lower risk and higher market share, after controlling for size. Complexity in terms of domestic activities is the main driver of profitability and risk, while market share mainly depends on the scope and specificity of cross border activities. Complexity in terms of derivative activities does not affect bank performance.

4.2 Analysis of changes in bank complexity

We now investigate the link between changes in bank complexity and changes in performance, using the Gramm-Leach-Bliley Act of 1999 (GLB) as a source of exogenous variation. The GLB

Act repealed the Glass-Steagall (GS) Act of 1933, which required banks to engage only in activities closely related to commercial banking. Under the new rules, banks could establish financial holding companies, combining commercial banking, investment banking, and certain other activities. Hence, the GLB Act did not only make it possible for banks to grow, but also to become more complex.

Since the GLB Act applied to all U.S. banks, our empirical analysis also requires variation at the bank level. We hypothesize the restrictions of the GS Act were more binding for banks that were already active to some extent in investment banking before the GLB act. These banks most likely desired to expand their scale and scope of investment banking but could not. This reasoning implies that the enactment of the GLB Act should have induced these banks to engage more in new activities than other banks. Empirically, we identify these banks using information on Section 20 subsidiaries of BHCs before the year 1999. Banks with Section 20 subsidiaries were already active in investment banking but both scale and scope was limited, because of a 25% revenue cap. Hence, our empirical strategy relies on the different sensitivity of Section 20 BHCs and other BHCs to the enactment of the GLB Act. Figure 2 shows the evolution of the median bank complexity over time, distinguishing by whether the BHs have established section 20 subsidiaries before 1999. By following Cornett, ORS and Tehranian (2002), we set an indicator variable *Section 20 BHCs* to one for those BHCs that have already Section 20 subsidiaries in place before 1999, and Non-Section 20 BHCs to zero otherwise. Following the introduction of the GLB Act, complexity increases significantly for Section 20 banks on impact, but gradually reverts in the 2000s to its pre-1999 level. One explanation is that Section 20 BHCs initially expanded the range of their activities and became more different (increasing the complexity measure), but so did Non-Section 20 BHCs in the following years (decreasing the complexity measure again because the Section 20 BHCs lost their diversity on their un-ubiquitous activities). Hence, the pattern of Section 20 BHCs reflects the increase in the ubiquity of their activities in the 2000s, which makes them less diverse and therefore less complex according to our definition. Most important, Figure 2 provides evidence in support of our hypothesis that the GLB Act affected Section 20 BHCs more than Non-Section 20 BHCs.

(Insert Figure 2 here)

In the first model, we compare the treatment group (section 20 BHCs) with all other BHCs using the full sample. In the second model, we match the Section 20 BHCs with a group of other banks from same year and size decile using bank-specific variables to avoid possible biases from time and bank size effects. The bank-specific matching variables are bank size, equity ratio, liquidity ratio, non-interest income to total assets ratio and cost-to-income ratio. These restrictions help to reduce an omitted variable bias, an approach similar to blocking in a randomized experiment. We then look for each Section 20 subsidiary BHCs for another BHC with the closest (lowest absolute value) difference in the probability estimate. The procedure is carried out without replacement.[7]

We examine the effect of the GLB Act on bank complexity and afterwards the effect of the GLB Act on the performance of Section 20 BHCs versus other banks in the post-GLB years. Our main variable of interest is the interaction term of the variables *Section 20 BHCs* and *PostGLB,* which is an indicator variable of 1 if it is after year 1999, and 0 otherwi*se*. A positive coefficient on this variable would be consistent with the results in the previous section because an increase in bank complexity would correspond to an improvement in performance. We include time and

[7] Although the timing of a BHC to set up its first section 20 subsidiary varies among different BHCs, we use section 20 BHCs (treatment group) as bank fixed variable because we assume that these section 20 BHCs are different in nature from the other BHCs and their motivation to expand into wider aspects of banking activities exist even before they set up their first section 20 subsidiaries.

bank fixed effects and the same control variables as in Table 2 and 3 in the regression model. Table 4 reports the results.

(Insert Table 4 here)

In Panel A of Table 4 we find that the Section 20 BHCs, relative to non-section 20 BHCs, exhibit a significantly higher complexity, profitability and market share and significantly lower risk after the GLB Act of 1999.

In Panel B of Table 4, we use the variable *Top 2% banks* as indirect proxy for the banks whose complexity is most sensitive to the GLB act. We distinguish between very large banks and other banks, using the 98% size distribution threshold to define the most affected banks.[8] Consistent with the results from Panel A, we find that complexity increased for the Top 2% banks and that there is a consistently positive impact of the increase in bank complexity on bank performance.

The findings indicate that the GLB Act of 1999 led to an increase in complexity at Section 20 BHCs (Top 2% banks) and to a subsequent improvement of performance. The analysis confirms the results from the panel data analysis in the previous section.

4.3 Bank complexity and systemic risk

In the analyses above we document a positive effect of bank complexity on individual bank performance, which explains why banks want to be complex. However, these findings contradict the experience from the financial crisis of 2007-2009, which suggests that banks that were considered as "*too complex to fail*" took excessive risks because they enjoyed an implicit subsidy

[8] In robustness tests we consider various other bank size thresholds. The result is similar.

from taxpayers. To assess whether our bank level findings also hold at the system level, we now examine the link between bank complexity and systemic risk.

A key advantage of our analysis is that we can disentangle the effect of "*too big*" and "*too complex*" to fail. We examine the effects of complexity on two measures of systemic risk. The first measure is ΔCoVaR (Adrian and Brunnermeier 2008).[9] This measure indicates how much the maximum loss to the whole banking system (VaR) would change when an individual bank becomes financially distressed. The second measure is Marginal Expected Shortfall (MES) (Acharya et al. 2010). This measure indicates the expected capital shortfall of an individual bank in a crisis, defined as a systemic event where the whole banking system is undercapitalized. Finally, we note the analysis in this section is based on data from listed banks, because the computation of the systemic risk measures requires stock return data.

We regress the measures ΔCoVaR and MES, respectively, on bank complexity and its square, controlling for bank and year fixed effects as well as other bank level variables potentially related to systemic risk. These variables include bank size, bank risk (stock return volatility and leverage), stock return, and market to book ratio. The rationale for adding the squared term of bank complexity is to investigate potential non-linear effects on systemic risk. Table 5 reports the results for overall bank complexity and its components, respectively.

(Insert Table 5 here)

We obtain three results. First, overall complexity does not affect ΔCoVaR. Second, overall complexity has an inversely U-shaped effect on MES. Third, the inversely U-shaped effect is also found for the domestic activity index on ΔCoVaR. Moreover, Table 5 shows the domestic (cross border) activity component of complexity have a significant effect on MES (ΔCoVaR).

[9] We note that Adrian and Brunnermeier revised the definition of the ΔCoVaR measure. We use their most recent definition.

The coefficients have the same sign as total complexity, and are statistically significant at least at the 5%-level. This implies the domestic (cross border) activity component is the main driver of the effect of complexity on MES (ΔCoVaR).

Overall, the findings do not support the conventional wisdom that systemic risk increases with complexity. Our evidence suggests a non-monotonic relationship, with banks at an intermediate level of complexity contributing more to systemic risk. We rationalize this finding using the insights from Wagner (2010), who argues diversity of banks' portfolios mitigates the risk of joint asset liquidation. The intuition is the portfolios are diverse, that is different from the full diversification benchmark, either if banks engage in unique activities or specialize in some of the common activities. These two strategies correspond to high and low values of complexity, respectively. For example, low complexity banks tend to be small community banks, which are less sensitive to the stock market volatility, but rather to regional economic changes. By contrast, a bank with intermediate complexity is presumably operating a large number of activities, but quite common. Hence, the portfolio of these banks resembles the one with full diversification, resulting in a high systemic risk according to Wagner (2010).

5. Further empirical checks and robustness tests

We conduct further empirical checks and robustness tests to examine whether our main results are sensitive to the definition of complexity, sample periods, sub-samples, and bank size.

First, we study the differential effects of the two dimensions of bank complexity: diversification and diversity of banks. For this purpose, we compare the effect of complexity coming from diversification (i.e., ignoring diversity) with the overall complexity (coming from diversification and diversity). For this purpose, we create the variable *Diversification*, which is an HHI index of the sum of the squares of each bank activity as a share of total bank activities for each bank. Table 6 reports the regression results of the impact of bank diversification on performance.

(Insert Table 6 here)

We confirm the results from Table 2 and 3 when we add *Diversification* to the regression model. Diversification has no significant effect on bank performance, while complexity continues to have a positive effect on all three performance measures.

Second, we study the robustness of the main results on systemic risk as shown in Table 5, controlling for bank diversification. For each outcome variable (ΔCoVaR and MES), we report four regression results. Table 7 presents the results.

(Insert Table 7 here)

The results from Table 7 are consistent with those reported in Table 5. Overall complexity still exhibits the inversely U-shaped effect on MES, when we control for bank diversification. Also, there is no effect of complexity on ΔCoVaR. As before, we control for bank size, bank fixed effects and time fixed effects.

Third, the recent financial crisis raises the question of how bank complexity responds during crises and whether the impact of complexity on bank performance differs from the non-crisis times. We address this question by interacting our bank complexity measure and the indicator variable which equals one for the years between 2007 and 2009 and zero otherwise. Table 8 reports the regression results.

(Insert Table 8 here)

Whereas banks experienced deteriorating performance on profitability, stability and market share during the financial crisis of 2007-2009 (negative and significant coefficient for the crisis indicator variable), the positive impact of bank complexity on these bank performance measures is intensified during the same period, as indicated by the positive and significant coefficients of the interaction term between complexity and 2007-09 Financial crisis indicator in the regression models for Log Z-score and market share. These results suggest that bank's ability to diversify into rare and specific activities is one of the keys for banks to survive the distressed period. According to Wagner (2011), if all the banks diversify into the same activities, the benefits of diversification may be reduced. Hence, in order to gain more diversification benefits, banks may need to diversify more into more rare and specific activities, and hence become more complex. Another interpretation is that a complex bank tends to be more sophisticated, and a more sophisticated bank tends to have better ability to survive during a financial crisis.

6. Conclusion

We investigate the effects of bank complexity on performance and systemic risk. Using a comprehensive measure of bank complexity for U.S. bank holding companies from 1986 to 2013, we show that more complex banks exhibit higher profitability, lower risk, and greater market share. Our findings are consistent in panel data regressions and an analysis using the Gramm-Leach-Bliley Act of 1999 as stimulus for complexity and its performance impact. Our results explain why banks want to be complex. Furthermore, we investigate the effect of bank complexity on systemic risk, as measured by ΔCoVaR and MES. We find that banks with intermediate complexity are the most sensitive ones to systemic shocks. We fail to find that more complex banks exhibit a higher contribution to systemic risk, using the ΔCoVaR measure.

Our findings contribute to the ongoing debate on "too big" and "too complex to fail". We show bank level benefits of higher complexity, explaining banks' incentives to become complex. We also show that bank complexity affects systemic risk beyond bank size. However, this effect is non-monotonic, indicating that high complexity stemming from high diversity in activities lowers banks' sensitivity to systemic shocks. The evidence challenges the view that higher bank complexity is per se bad and is consistent with theoretical models showing that diversity in the financial system is critical for financial stability.

Appendix 1: Bank activities per category[10]

Domestic Activities
Core domestic deposit • Fully insured brokered deposits • Core deposits • Time deposits below limit • Time deposits above limit[11] Other borrowing • Federal Funds purchase • Federal home loan borrowed • Subordinated notes and debentures • Acceptance and other liabilities • Other unclassified borrowings Loans • Real estate loans • Commercial loans • Individual loans • Agriculture loans • Loans held for sale Other bank investments • Total securities • Interest-bearing bank balances • Federal funds sold • Trading account assets Fiduciary activities • Personal trust and agency balance • Corporate trust and agency balance • Investment management and investment advisory agency accounts • Foundation and endowment trust and agency balance • Other fiduciary balance Bank commitments • Letters of credit • Recourse exposure • Loan commitments
Cross Border Activities
• Total deposits in foreign offices

[10] We do not include standard balance sheet items that are held by each bank. These items may include, but not limited to, loan and lease allowance, premises and fixed assets, equity, etc.

[11] Time deposits at or below insurance limit equals total time deposits less than $100,000 prior to March 31, 2010, and total time deposits less than $100,000 + total time deposits of $100,000 through $250,000 from Schedule RC-E.

• Total foreign securities invested • Loans to foreign government and institutions • Loans to banks in foreign countries • Trading assets in foreign offices • Assets in foreign non-bank subsidiary • Other foreign loans
Derivative Activities
• Interest rate contracts • Foreign exchange contracts • Equity contracts • Commodity contracts • Futures and forwards • Written options • Purchased options • Swaps • Held-for-trading derivatives • Securitized assets • Credit derivatives bank as guarantor • Credit derivatives bank as beneficiary • Structured products • Over-the-counter (OTC) derivatives

Appendix 2: Ranking of banks by complexity (2013)

Bank name	Complexity rank	Size rank	Complexity	Total assets (bn $)	Bank name	Complexity rank	Size rank	Complexity	Total assets (bn $)
GOLDMAN SACHS GROUP	1	5	0.98	911.60	BANKGUAM HOLNDINGS	26	405	0.83	1.29
CITI GROUP	2	3	0.97	1880.38	MAINSOURCE FINANCIAL GROUP	27	208	0.83	2.86
JPMORGAN CHASE	3	1	0.97	2415.69	POPULAR	28	33	0.83	35.75
BANK OF AMERICA	4	2	0.96	2105.00	PNC FINANCIAL SERVICES GROUP	29	10	0.82	320.60
BANK OF NEW YORK MELLON	5	8	0.92	374.31	THIRD FEDERAL SAVINGS AND LOANS OF CLEVELAND, MHC	30	78	0.82	11.38
STATE STREET	6	12	0.92	243.03	ALLY FINANCIAL	31	16	0.82	151.17
GENERAL ELECTRIC CAPITAL	7	7	0.92	523.97	M&T BANK	32	23	0.81	85.16
NORTHERN TRUST	8	21	0.91	102.95	FLAGSTAR BANK HOLDING COMPANY	33	86	0.81	9.41
LOVE SAVINGS HOLDING COMPANY	9	611	0.90	0.86	FIFTH THIRD BANK	34	18	0.81	129.69
NATIONAL CONSUMER COOPERATIVE BANK	10	302	0.90	1.81	FIRST FINANCIAL	35	198	0.80	3.03
WELLS FARGO	11	4	0.90	1527.02	SVB FINANCIAL GROUP	36	38	0.80	26.42
DORAL FINANCIAL	12	94	0.89	8.49	U.S. BANCORP	37	9	0.80	364.02
CAROLINA FINANCIAL	13	596	0.88	0.88	LAURITZEN	38	299	0.80	1.83
AMERICAN INTERNATIONAL GROUP	14	6	0.87	541.33	PRESIDENTIAL HOLDING	39	921	0.79	0.55
CIT GROUP	15	28	0.87	47.14	OFG BANCORP	40	97	0.79	8.16
AMERI-NATIONAL	16	897	0.87	0.57	ARVEST BANK GROUP	41	66	0.79	14.11
FRANDSEN FINANCIAL	17	329	0.86	1.64	RAYMOND JAMES FINANCIAL	42	48	0.78	21.92
AMERICAN EXPRESS	18	15	0.86	153.39	FLORIDA CAPITAL GROUP	43	1033	0.78	0.41
SNBNY HOLDINGS	19	109	0.86	6.67	COMERICA	44	25	0.78	65.36
FIRST HORIZON NATIONAL	20	45	0.85	23.79	APPLE FINANCIAL HOLDINGS	45	76	0.78	11.65
JOHN DEERE CAPITAL	21	35	0.85	31.68	EXTRACO CORP	46	429	0.78	1.21
MIDLAND FINANCIAL	22	83	0.85	9.62	EAST WEST BANCORP	47	41	0.78	24.73
COMMONWEALTH BANKSHARES	23	644	0.84	0.82	LEADER BANCORP	48	791	0.78	0.66
BOK FINANCIAL	24	37	0.83	27.02	ESB FINANCIAL	49	291	0.77	1.91
SUNTRUST BANK	25	14	0.83	175.38	PRIVATE BANCORP	50	67	0.77	14.09

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Table 1: Variables and summary statistics

This table reports the definitions and summary statistics of the main variables. All the variables other than Log Total assets are winsorized at the 2nd and 98th percentiles of their distributions.

Variable	Definition	Mean	Median	Std. Dev.	Number of obs.
Dependent variables					
ROA%	Net income divided by total assets	*0.83*	*0.93*	*0.74*	*38632*
Log Z	Log value of Z-score, where Z-score is the average bank return on assets (net income divided by total assets) plus bank equity to assets ratio, scaled by the standard deviation of return on assets.	*3.81*	*3.87*	*0.98*	*38632*
Market share	Total assets divided by the total assets of the whole domestic banking system	*0.07*	*0.01*	*0.60*	*38632*
Δ*CoVar*	The change in the VaR of the system when the bank is at 99% percentile minus the VaR of the system when the bank is at the 50% percentile.	*2.9*	*2.86*	*3.38*	*8394*
MES	Marginal Expected Shortfall, which is a bank's expected equity loss per dollar in a year conditional on the banking sector experiencing one of its 5% lowest returns in that given year.	*1.54*	*1.27*	*1.89*	*8336*
Bank complexity					
Domestic activity Index	The sum of weighted average ratios against total assets which the bank engages in domestic banking activity, where the weight is one minus the ubiquity ratio, which is the ratio of the number of banks undertaking a particular activity in a particular year over the total number of the banks in the same year	*0.80*	*0.80*	*0.05*	*38632*
Cross border activity index	The sum of weighted average ratios against total assets which the bank engages in a cross border banking activity, where the weight is one minus the ubiquity ratio, which is the ratio of the number of banks undertaking a particular activity in a particular year over the total number of the banks in the same year	*0.05*	*0.00*	*0.17*	*38632*

Derivative activity Index	The sum of weighted average ratios against total assets which the bank engages in a derivative banking activity, where the weight is one minus the ubiquity ratio, which is the ratio of the number of banks undertaking a particular activity in a particular year over the total number of the banks in the same year	*0.09*	*0.00*	*0.21*	*38632*
Complexity	The first factor of factor analysis of the Domestic, Cross border and Derivative activity indices. It is our measure of bank complexity.	*0.64*	*0.63*	*0.06*	*38632*
Bank variables					
Section 20 BHCs	An indicator variable that is one if the BHC has established Section 20 subsidiaries before 1999, and 0 otherwise.	*0.0005*	*0.00*	*0.02*	*38632*
Diversification	Hirschmann-Herfindahl index of concentration of all the banking activities, which is the sum of the squares of the ratio of the volume of each activity divided by the volume of total activity of each bank each year. A bank is more diversified if this value is lower.	*0.76*	*0.75*	*0.03*	*38632*
Log Total assets	Log value of total assets in millions of US dollars	*13.21*	*12.92*	*1.35*	*38632*
Equity/Total assets%	Equity divided by total assets	*8.53*	*8.30*	*2.71*	*38632*
Liquid assets/Total assets%	The sum of cash and for sale securities divided by total assets	*0.11*	*0.00*	*0.14*	*38632*
Non-interest income/Total operating income%	Non-interest income divided by total operating income	*13.19*	*11.11*	*8.61*	*38632*
Cost to income%	Total operating cost divided by total income	*42.69*	*40.71*	*12.40*	*38632*
Stock return%	The buy-and-hold return on the BHC's stock over the calendar year	*13.07*	*14.11*	*34.11*	*8400*
Stock return volatility%	Annual standard deviation of stock return over the calendar year	*2.60*	*2.18*	*1.42*	*8396*
Market to Book ratio%	The ratio of market value to book value of equity	*1.52*	*1.44*	*0.67*	*8400*
Leverage%	Market value of total assets divided by market value of total equity	*10.38*	*8.10*	*7.60*	*8400*

Table 2: The effect of bank complexity on performance

This table presents regression results on the effect of bank complexity on *ROA*, natural *Log of Z-score*, and *Market Share*, All regressions are estimated with both time and bank fixed effects. The sample period is 1986-2013. T-statistics based on robust standard errors clustered by banks are shown in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. Variable definitions are given in Table 1.

	ROA	*Log Z-score*	*Market Share*
Complexity$_{t-1}$	*0.405****	*0.141****	*0.514**
	(2.849)	*(3.489)*	*(1.952)*
Log Total assets$_{t-1}$	*-0.213****	*-0.005*	*0.170****
	(-9.328)	*(-0.817)*	*(2.655)*
Equity/Total assets%$_{t-1}$	*0.033****	*0.071****	*0.007**
	(8.110)	*(54.661)*	*(1.693)*
Liquid assets/Total assets%$_{t-1}$	*0.179***	*0.026*	*-0.032*
	(2.228)	*(1.231)*	*(-0.663)*
Non-interest income/Total operating income%$_{t-1}$	*0.016****	*0.001*	*0.004***
	(9.539)	*(1.442)*	*(2.010)*
Cost to income%$_{t-1}$	*-0.021****	*0.000*	*0.001*
	(-18.192)	*(0.653)*	*(1.090)*
ROA%$_{t-1}$		*0.096****	*-0.000*
		(22.555)	*(-0.025)*
Constant	*4.053****	*2.487****	*-2.763***
	(11.415)	*(23.523)*	*(-2.455)*
Time fixed effects	*Yes*	*Yes*	*Yes*
Bank fixed effects	*Yes*	*Yes*	*Yes*
Number of observations	*33,767*	*33,673*	*33,767*
R^2	*0.262*	*0.482*	*0.054*

Table 3: The effect of the components of bank complexity on performance

This table presents regression results on the effect of bank complexity on *ROA*, natural *Log of Z-score*, and *Market Share*, All regressions are estimated with both time and bank fixed effects. The sample period is 1986-2013. T-statistics based on robust standard errors clustered by banks are shown in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. Variable definitions are given in Table 1.

	ROA				*Log Z-score*				*Market share*			
Domestic activity index$_{t-1}$	0.539***			0.536***	0.137***			0.136***	-0.124			-0.130
	(2.939)			(2.929)	(2.906)			(2.892)	(-1.365)			(-1.411)
Cross border activity index$_{t-1}$		0.076		0.070		0.017		0.015		0.067*		0.068*
		(1.166)		(1.084)		(1.026)		(0.936)		(1.779)		(1.807)
Derivative activity index$_{t-1}$			0.051	0.051			0.006	0.006			-0.017	-0.017
			(1.455)	(1.482)			(0.581)	(0.608)			(-0.758)	(-0.765)
Log Total assets$_{t-1}$	-0.207***	-0.210***	-0.211***	-0.212***	-0.003	-0.004	-0.004	-0.004	0.177***	0.175***	0.178***	0.176**
	(-9.106)	(-9.107)	(-9.154)	(-9.200)	(-0.501)	(-0.591)	(-0.560)	(-0.621)	(2.611)	(2.579)	(2.591)	(2.563)
Equity/Total assets%$_{t-1}$	0.033***	0.033***	0.033***	0.033***	0.071***	0.071***	0.071***	0.071***	0.007*	0.007*	0.007*	0.007*
	(8.269)	(8.135)	(8.156)	(8.232)	(54.807)	(54.545)	(54.593)	(54.776)	(1.691)	(1.677)	(1.694)	(1.674)
Liquid assets/Total assets%$_{t-1}$	0.002**	0.002**	0.002**	0.002**	0.000	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001
	(2.380)	(2.006)	(2.049)	(2.368)	(1.461)	(1.091)	(1.123)	(1.444)	(-1.251)	(-1.249)	(-1.197)	(-1.299)
Non-interest income/Total operating income%$_{t-1}$	0.016***	0.016***	0.016***	0.016***	0.001*	0.001*	0.001*	0.001	0.005**	0.005**	0.005**	0.005**
	(9.787)	(9.930)	(9.741)	(9.603)	(1.687)	(1.826)	(1.785)	(1.618)	(2.030)	(2.022)	(2.013)	(2.001)
Cost to income%$_{t-1}$	-0.021***	-0.021***	-0.021***	-0.021***	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(-18.161)	(-18.228)	(-18.197)	(-18.173)	(0.635)	(0.608)	(0.614)	(0.638)	(1.006)	(1.015)	(1.016)	(0.994)
ROA$_{t-1}$					0.096***	0.096***	0.096***	0.096***	-0.000	-0.000	-0.000	-0.000
					(22.538)	(22.529)	(22.516)	(22.540)	(-0.019)	(-0.059)	(-0.030)	(-0.037)
Constant	3.778***	4.251***	4.256***	3.844***	2.433***	2.552***	2.549***	2.444***	-2.434**	-2.508**	-2.547**	-2.413**
	(9.719)	(11.888)	(11.914)	(9.815)	(21.568)	(23.922)	(23.826)	(21.532)	(-2.526)	(-2.457)	(-2.470)	(-2.483)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	33,767	33,767	33,767	33,767	33,673	33,673	33,673	33,673	33,767	33,767	33,767	33,767
R^2	0.262	0.261	0.261	0.262	0.481	0.481	0.481	0.481	0.050	0.050	0.050	0.050

Table 4: Bank complexity and performance around the GLB Act

We consider the passage of Gramm–Leach–Bliley (GLB) Financial Modernization Act in 1999 as an exogenous shock to bank complexity to study the causal effects. This table presents regression results on the three dependent variables, ROA, natural log of Z-score, and market share for the full sample and the matched sample. In Panel A, we consider all BHCs that have Section 20 subsidiaries in place before 1999 as the treatment group (*Section 20 BHCs*) and other banks as control group. In the full sample analysis, we compare the treatment group with all other BHCs. In the matched sample analysis, we match these Section 20 BHCs based on bank-specific variables, and constrain the matching to the same year and same size decile. The matched sample serves as control group. In Panel B, we consider the largest two percent of banks as treatment group. The dummy variable *Top 2 % banks* equals one for BHCs larger than 98% of the size distribution, and zero otherwise. The dummy variable PostGLB is one after the year 1999, and zero otherwise. All regressions are estimated with both time and bank fixed effects. The sample period is 1986-2006. We exclude the time period after 2006 to avoid the negative impact on bank complexity during and after the 2007-09 financial crisis. T-statistics based on robust standard errors clustered by banks are shown in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. Variable definitions are given in Table 1.

Panel A: Section 20 BHCs versus non-Section 20 BHCs

	Full sample				Matched sample			
	Complexity	*ROA*	*Log Z-score*	*Market share*	*Complexity*	*ROA*	*Log Z-score*	*Market share*
*Section 20 BHCs*PostGLB*	0.078***	0.169**	0.127***	1.378**	0.049***	0.156	0.128**	1.185*
	(8.388)	(1.984)	(4.317)	(2.334)	(2.936)	(1.023)	(2.268)	(1.889)
Constant	0.623***	0.760***	3.056***	0.023**	0.773***	0.907***	2.756***	0.751**
	(406.067)	(32.392)	(310.768)	(1.979)	(92.433)	(15.153)	(98.910)	(2.514)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	31,893	31,893	31,499	31,893	511	511	511	511
R^2	0.132	0.066	0.176	0.144	0.531	0.270	0.442	0.243

Table 4 (continued)

Panel B: Top 2% banks versus other banks

	Complexity	*ROA*	*Log Z-score*	*Market share*
*Top 2% banks*PostGLB*	0.062***	0.143***	0.049***	0.846**
	(8.654)	(2.599)	(4.275)	(2.483)
Log Total assets$_{t-1}$		-0.196***	-0.004	0.123***
		(-7.367)	(-0.504)	(3.321)
Equity/Total assets%$_{t-1}$		0.016***	0.064***	0.005**
		(3.654)	(45.775)	(2.169)
Liquid assets/Total assets%$_{t-1}$		-0.002**	-0.000	-0.001
		(-2.150)	(-1.411)	(-0.940)
Non-interest income/ Total operating income%$_{t-1}$		0.008***	-0.001	0.003*
		(4.692)	(-1.346)	(1.710)
Cost to income%$_{t-1}$		-0.015***	0.001**	0.001
		(-11.853)	(2.473)	(1.159)
			0.081***	0.003
			(15.905)	(0.673)
Constant	0.624***	4.156***	2.689***	-1.704***
	(407.805)	(10.264)	(22.504)	(-3.124)
Time fixed effects	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes
Number of Observations	31,893	27,552	27,480	27,552
R^2	0.135	0.103	0.454	0.151

Table 5: The effect of bank complexity on systemic risk

This table presents regression results on the effect of bank complexity on systemic risk. We use two measures to proxy bank systemic risk. The first is $\Delta CoVaR$ from Adrian and Brunnermeier (2008), and the second is the marginal expected shortfall (*MES*) from Acharya et. al. (2010). Both systemic risk measures are transformed into their percentage forms to increase the magnitude of the estimated parameter coefficients. The table reports four regressions results with four different complexity measures for each systemic risk variables. All regressions are estimated with both time and bank fixed effects. The sample period is 1986-2013. T-statistics based on robust standard errors clustered by banks are shown in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	$\Delta CoVar$				*MES*			
	Domestic activity index	*Cross border activity index*	*Derivative activity index*	*Complexity*	*Domestic activity index*	*Cross border activity index*	*Derivative activity index*	*Complexity*
$Complexity_{t-1}$	17.832*	0.071	0.143	6.036	20.279*	0.436	1.281***	8.679**
	(1.883)	(0.122)	(0.355)	(1.386)	(1.830)	(0.799)	(3.810)	(2.359)
$Complexity^2_{t-1}$	-10.988*	-0.754	-0.302	-4.565	-12.224*	-0.759	-1.845***	-6.441**
	(-1.857)	(-0.737)	(-0.473)	(-1.374)	(-1.794)	(-0.930)	(-3.608)	(-2.413)
Annualized stock return$_{t-1}$	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(4.508)	(4.508)	(4.584)	(4.440)	(3.746)	(3.778)	(3.743)	(3.692)
Annualized stock return volatility$_{t-1}$	0.151***	0.154***	0.153***	0.153***	0.272***	0.276***	0.280***	0.276***
	(8.020)	(8.236)	(8.178)	(8.179)	(9.709)	(9.809)	(10.025)	(9.954)
$Leverage_{t-1}$	0.008**	0.007**	0.007**	0.008**	-0.024***	-0.025***	-0.026***	-0.025***
	(2.292)	(1.965)	(2.103)	(2.204)	(-5.067)	(-5.276)	(-5.510)	(-5.197)
Market to Book ratio$_{t-1}$	-0.017	-0.027	-0.026	-0.023	0.074	0.065	0.057	0.068
	(-0.298)	(-0.458)	(-0.443)	(-0.398)	(1.254)	(1.118)	(0.986)	(1.170)
Log Total assets$_{t-1}$	-0.110	-0.092	-0.108	-0.105	0.512***	0.514***	0.506***	0.517***
	(-1.561)	(-1.377)	(-1.520)	(-1.486)	(6.349)	(6.296)	(6.340)	(6.417)
Constant	-2.190	4.787***	4.973***	2.963*	-12.957***	-4.668***	-4.603***	-7.582***
	(-0.554)	(4.719)	(4.678)	(1.677)	(-2.819)	(-3.761)	(-3.792)	(-4.424)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	7,352	7,352	7,352	7,352	7,348	7,348	7,348	7,348
R^2	0.269	0.270	0.268	0.269	0.471	0.470	0.472	0.471

Table 6: Bank diversification, complexity and performance

This table presents regression results on the effect of bank complexity and diversification on *ROA*, natural *Log of Z-score*, and *Market Share*, All regressions are estimated with both time and bank fixed effects. The sample period is 1986-2013. T-statistics based on robust standard errors clustered by banks are shown in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. Variable definitions are given in Table 1.

	ROA	*Log Z-score*	*Market Share*
Diversification$_{t-1}$	0.020	0.052	0.612
	(0.104)	(1.203)	(1.638)
Complexity$_{t-1}$	0.410***	0.150***	0.611**
	(2.883)	(3.656)	(1.980)
Log Total assets$_{t-1}$	-0.213***	-0.006	0.166***
	(-9.293)	(-0.853)	(2.693)
Equity/Total assets%$_{t-1}$	0.033***	0.071***	0.007*
	(8.113)	(54.640)	(1.673)
Liquid assets/Total assets%$_{t-1}$	0.002**	0.000	-0.000
	(2.283)	(1.475)	(-0.712)
Non-interest income/Total operating income%$_{t-1}$	0.016***	0.001	0.004**
	(9.532)	(1.419)	(2.026)
Cost to income%$_{t-1}$	-0.021***	0.000	0.001
	(-18.214)	(0.696)	(1.274)
ROA%$_{t-1}$		0.096***	0.001
		(22.566)	(0.103)
Constant	4.041***	2.473***	-2.887**
	(11.355)	(23.380)	(-2.437)
Time fixed effects	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes
Number of observations	33,767	33,673	33,767
R^2	0.262	0.482	0.059

Table 7: Bank diversification, complexity and systemic risk

This table presents regression results on the effect of bank complexity on systemic risk. We use two measures to proxy bank systemic risk. The first is ΔCoVaR developed by Adrian and Brunnermeier (2008), and the second is the marginal expected shortfall (MES) developed by Acharya et. al. (2010). Both systemic risk measures are transformed into their percentage forms to increase the magnitude of the estimated coefficients. The table reports four regressions results with four different complexity measures for each systemic risk variables. . All regressions are estimated with both time and bank fixed effects. The sample period is 1986-2013. T-statistics based on robust standard errors clustered by banks are shown in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	ΔCoVaR				*MES*			
	Domestic activity index	*Cross border activity index*	*Derivative activity index*	*Complexity*	*Domestic activity index*	*Cross border activity index*	*Derivative activity index*	*Complexity*
Diversification$_{t-1}$	0.413	0.484	0.530	0.694	0.025	0.026	0.262	0.272
	(0.337)	(0.403)	(0.432)	(0.555)	(0.021)	(0.023)	(0.224)	(0.234)
Diversification$^2_{t-1}$	0.067	-0.411	-0.439	-0.408	0.479	-0.038	-0.180	0.023
	(0.046)	(-0.287)	(-0.301)	(-0.274)	(0.352)	(-0.029)	(-0.143)	(0.018)
Complexity$_{t-1}$	19.320**	0.067	0.153	6.705	21.747*	0.436	1.287***	9.118**
	(1.995)	(0.116)	(0.383)	(1.521)	(1.895)	(0.799)	(3.812)	(2.391)
Complexity$^2_{t-1}$	-11.826*	-0.744	-0.311	-5.009	-13.080*	-0.758	-1.850***	-6.738**
	(-1.960)	(-0.731)	(-0.487)	(-1.492)	(-1.857)	(-0.930)	(-3.608)	(-2.440)
Annualized stock return$_{t-1}$	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(4.497)	(4.518)	(4.593)	(4.427)	(3.735)	(3.780)	(3.745)	(3.681)
Annualized stock return volatility$_{t-1}$	0.150***	0.154***	0.153***	0.153***	0.272***	0.276***	0.280***	0.275***
	(8.019)	(8.243)	(8.184)	(8.171)	(9.678)	(9.795)	(10.008)	(9.923)
Leverage$_{t-1}$	0.008**	0.007**	0.008**	0.008**	-0.024***	-0.025***	-0.026***	-0.025***
	(2.346)	(1.996)	(2.128)	(2.273)	(-5.034)	(-5.267)	(-5.490)	(-5.157)
Market to Book ratio$_{t-1}$	-0.017	-0.028	-0.027	-0.024	0.074	0.065	0.056	0.068
	(-0.298)	(-0.473)	(-0.460)	(-0.404)	(1.265)	(1.117)	(0.979)	(1.171)
Log Total assets$_{t-1}$	-0.112	-0.093	-0.109	-0.108	0.510***	0.514***	0.505***	0.515***
	(-1.590)	(-1.392)	(-1.535)	(-1.518)	(6.340)	(6.301)	(6.341)	(6.409)
Constant	-2.883	4.727***	4.909***	2.644	-13.577***	-4.672***	-4.636***	-7.767***
	(-0.710)	(4.671)	(4.669)	(1.518)	(-2.843)	(-3.728)	(-3.790)	(-4.387)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	7,352	7,352	7,352	7,352	7,348	7,348	7,348	7,348
R^2	0.269	0.270	0.268	0.269	0.471	0.470	0.472	0.471

Table 8: The financial crisis, bank complexity and performance

This table presents regression results on the effect of the financial crisis on the relation between bank complexity and *ROA*, natural *Log of Z-score*, and *Market Share*. The variable *2007-2009 Financial Crisis* is an indicator variable which equals one for the years from 2007 to 2009, and zero otherwise. *Complexity*2007-09 Financial Crisis* is the interaction between these two variables. All regressions are estimated with both time and bank fixed effects. The sample period is 1986-2013. T-statistics based on robust standard errors clustered by banks are shown in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. Variable definitions can be found in Table 1.

	ROA	*Log Z-score*	*Market share*
Complexity$_{t-1}$	0.328**	0.081**	0.285*
	(2.396)	(2.139)	(1.681)
2007-09 Financial Crisis$_{t-1}$	-0.880***	-0.214***	-0.719
	(-4.813)	(-4.349)	(-1.630)
*Complexity$_{t-1}$ * 2007-09 Financial Crisis$_{t-1}$*	0.432	0.336***	1.261*
	(1.450)	(4.196)	(1.667)
Log Total assets$_{t-1}$	-0.213***	-0.006	0.170***
	(-9.343)	(-0.833)	(2.677)
Equity/Total assets%$_{t-1}$	0.033***	0.071***	0.006*
	(8.058)	(54.623)	(1.667)
Liquid assets/Total assets%$_{t-1}$	0.002**	0.000	-0.001
	(2.220)	(1.277)	(-0.965)
Non-interest income/Total operating income%$_{t-1}$	0.016***	0.001	0.004**
	(9.571)	(1.519)	(2.005)
Cost to income%$_{t-1}$	-0.021***	0.000	0.000
	(-18.228)	(0.579)	(0.940)
ROA$_{t-1}$		0.096***	0.000
		(22.688)	(0.068)
Constant	4.103***	2.529***	-2.592**
	(11.538)	(24.069)	(-2.522)
Time fixed effects	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes
Number of observations	33,767	33,673	33,767
R^2	0.262	0.483	0.064

Figure 1: Bank size and complexity

This figure displays a scatterplot of bank size (logarithm of total assets, in million USD) on the horizontal axis and bank complexity on the vertical axis, using yearly data from 1986 to 2013 (38,632 bank-year observations).

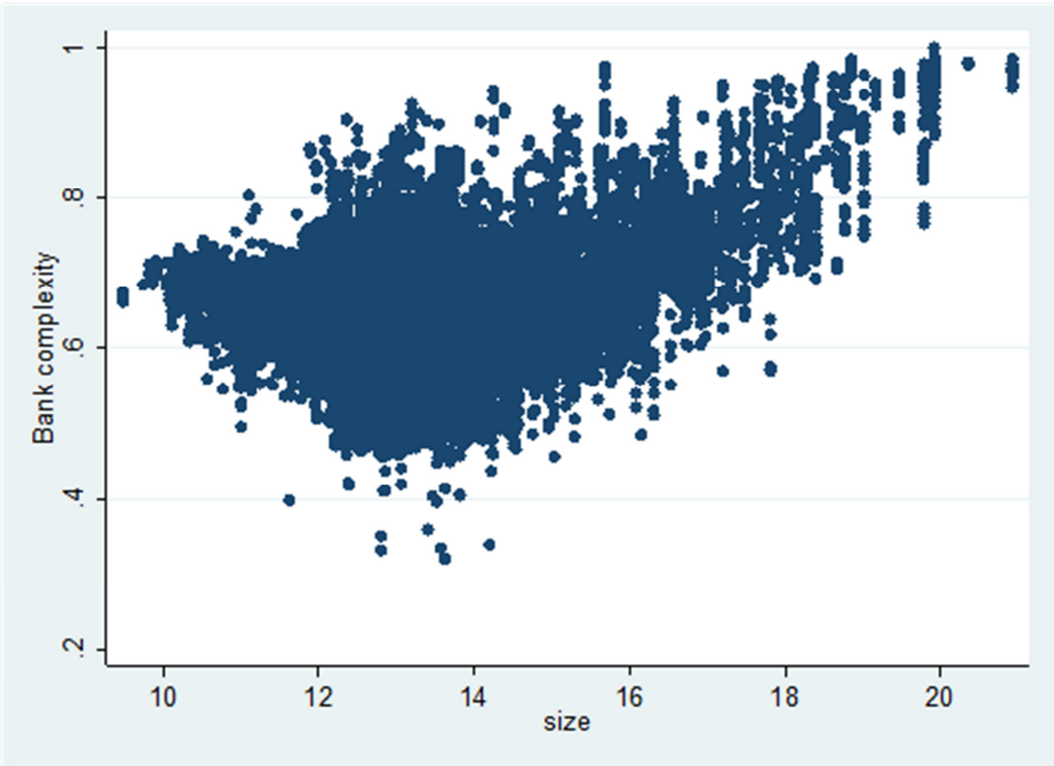

Figure 2: Bank complexity by section 20 versus non-section 20 BHCs

This figure shows the median of complexity of U.S. Section 20 BHCs and non-Section 20 BHCs over time. The category “section 20 BHCs” refers to BHCs that had already Section 20 subsidiaries in place before 1999 and “non-Section 20 BHCs” to BHCs that did not.