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 multidimensional complexity measure that captures banks' diversification and diversity, controlling for size and other 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. Both findings provide explanations why banks want to be complex. The evidence challenges the view that higher bank complexity is per se bad and is consistent with theoretical models showing 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 take the perspective of both banks and regulators, investigating how bank complexity affects performance and systemic risk. The measure of bank complexity we use is analogous to Hausmann et al. (2011), who examine 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 banking activities they perform in analogy to the number of products as in Hausmann et al. (2011). Following the International Monetary Fund et al. (2009), we consider three categories of key banking activities: domestic banking, cross-border banking, and derivative activities. The wider the range of activities within these three categories (diversification[1]), and the more rare these activities in the banking system (diversity), the more complex is a bank. Hence, we measure the complexity of banks and not the complexity of bank products.

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[1] We capture diversification of bank activities in the complexity measure, following the proposal of the International Monetary Fund et al. (2009). There is a large body 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 do not summarize here.

At the bank level, we find that more complex banks exhibit a significantly higher profitability, a significantly lower default risk, and a significantly higher market share. The intuition behind this result 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, generate monopoly power (Tufano, 1989). Hence, choosing unique activities increases profitability and market share, by lowering the competitive pressure on banks. Moreover, lower competition positively affects the charter value of banks, reducing their incentives to take excessive risk (Keeley, 1990; Allen and Gale, 2004).[2]

At the systemic level, our results challenge the conventional wisdom that bank complexity creates systemic risk. We document no statistically significant link between complexity and ΔCoVaR (Adrian and Brunnermeier, 2008), but an inversely U-shaped relation between complexity and marginal expected shortfall (MES) (Acharya et al., 2010). One interpretation of the latter result is that the conventional wisdom, which highlights the welfare costs of a greater bank interconnectedness and more complicated bankruptcy procedures, only holds up to a certain level of complexity. There are theoretical arguments suggesting complexity, that is performing unique and rare activities, decreases systemic risk by increasing bank diversity. In particular, Wagner (2010, 2011) argues that diversification reduces idiosyncratic risk but creates systemic risk, as it implies that banks hold the same portfolios. Such behavior of banks increases the risk of joint asset liquidation, which depresses asset prices and jeopardizes financial stability. Hence, some degree of diversity among banks' portfolios is optimal. Complex banks are those banks that are able to differentiate from each other.

We base our analysis on data from both consolidated and parent-only financial statements of U.S. bank holding companies (BHCs[3]; Y-9C and Y-9LP/SP) during the period 1986-2013. We exclude foreign

[2] These results are consistent with evidence provided by Moenninghoff, Ongena and Wieandt (2015), showing that the official designation of Global Systemically Important Banks (G-SIBs) leads to positive aggregate absolute and relative abnormal returns, and thereby increased value, for G-SIBs.

[3] We employ banks and BHCs interchangeably in this paper.

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.

To mitigate the potential endogeneity concern between bank complexity and performance, we exploit the introduction of the Gramm-Leach-Bliley (GLB) Act of 1999 as a source of exogenous variation. The GLB 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 more the banks that were already active in non-commercial banking prior to the GLB Act. The rationale is that these banks benefit the most from expanding further into non-commercial banking activities and increase their complexity. Empirically, we identify these banks as the BHCs with Section 20 subsidiaries as of 1999, which we obtain from Cornett, Ors and Tehranian (2002). 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.

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, 2011) shows the existence of a trade-off between diversification and diversity, using a framework with endogenous costs of liquidating assets. 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 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. This uncertainty has a similar effect as the diversity component of our measure, that is they both increase complexity. Note that, while in Caballero and Simsek (2013) the network of cross exposures would not matter without asymmetric information, complexity does not necessarily coincide with the opaqueness of banks (e.g., Morgan, 2002; Flannery, Kwan and Nimalendran, 2004). Outsiders might be unable to assess a bank's value even if they are informed about all its activities. If the latter are strongly interconnected and/or their value depends on subjective criteria, the bank is fully transparent, but also too complex to depict at the same time.

Second, we contribute to the scarce but growing empirical literature on bank complexity. The few studies in this area focus on unidimensional measures of organizational complexity, suggesting that an intricate network of subsidiaries impairs an effective oversight and potential resolution in case of financial distress. For instance, Cetorelli and Goldberg (2014) provide a discussion of measures of organizational and business complexity. Carmassi and Herring (2015) show that the organizational complexity of 29 globally systemically important banks (G-SIBs; hereof eight U.S. banks) has increased in pre-crisis times, and slightly decreased in the aftermath of the crisis, and the large mergers and acquisitions are the main drivers of this effect. Lumsdaine et al. (2015) document a decrease in organizational complexity of 29 G-SIBs during 2011 and 2013, which might have occurred in response to regulatory requirements. We note that organizational complexity is an important aspect of banks' overall complexity but it is not special for banks, as evidenced by the large literature on non-financial conglomerates (e.g., Lang and Stulz, 1994; Berger and Ofek, 1995). We therefore measure bank complexity in a way that captures the specialness of banking. Our complexity measure is multidimensional and directly related to the diversification and diversity of domestic, cross border and off balance sheet banking activities performed by banks. The underlying intuition is that more specific banking activities require more expertise than standard activities. Our measure indirectly captures banks' organizational structure due to mergers and acquisitions, organic growth, innovation in banking activities, and geographic coverage.

2. Bank complexity

2.1. Measuring bank complexity

The literature does not provide a general definition of bank complexity, as pointed out by Cetorelli and Goldberg (2014). Different studies in this area use different measures of complexity. We first motivate and describe how we measure bank complexity, and then we show how our multidimensional measure relates to bank size and alternative measures used in other studies.

To measure bank complexity we consider the number of activities performed by a bank (diversification) and their ubiquity (diversity). 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[4].

To calculate the measure of complexity, we follow three steps, along the lines of Hausmann et al. (2011). 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 (N) 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.

Second, we 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:

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

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

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[5], 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.

Third, we aggregate the three bank-specific complexity measures, corresponding to the three categories of activities we consider in this study. This step 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 $Complexity^{Bank}_{i,t}$ as the factor with the greatest explanatory power of the three $Complexity_{i,c,t}$ measures.[6]

The measure of complexity we use in this study captures 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 activities is high). In contrast, bank B scores low on diversification, but high on diversity (since the ubiquity of the bank's activities is low). This means bank A is more complex in terms of diversification, but B is more complex it terms of

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[5] 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.

[6] We perform the factor analysis on a year-by-year basis to avoid a 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.

diversity. Eventually, the interaction of diversification and diversity determines the overall level of bank complexity.

2.2. Alternative measures of bank complexity and bank size

Our measure *directly* captures bank complexity because it is closely tied to the domestic, cross border and derivative activities carried out by banks (International Monetary Fund et al., 2009). Moreover, through its diversification and diversity components, our measure *indirectly* captures bank complexity due to organizational structure, interconnectedness and financial innovation. We therefore expect a small but positive correlation with alternative measures of complexity.

Subsequently, we compare our multidimensional measure, which we label $Complexity^{Bank}$ for convenience, with alternative approaches to measuring bank complexity. We consider the number of banks' subsidiaries ($Complexity^{Org}$; Goldberg and Cetorelli, 2014; Carmassi and Herring, 2015; Lumsdaine et al., 2015), the number of different U.S. counties in which a bank is active ($Complexity^{Geo}$), and a simplified version of the complexity indicator for G-SIBs suggested by the Basel Committee on Banking Supervision (2013, pp. 9; $Complexity^{BCBS}$)[7]. Table 1 reports the pairwise correlations for our sample of yearly U.S. bank data from 1998 to 2013 because data on the number of bank subsidiaries is only available from 1998. The correlations with $Complexity^{BCBS}$ can only be computed for the period from 2010 to 2013 because the inputs for this indicator are only available for this period.

(Insert Table 1 here)

As expected, Table 1 shows that our measure $Complexity^{Bank}$ is moderately positively related to other measures, indicating that it captures some additional aspects of complexity that are not captured by the other measures.

[7] We calculate the sum of OTC derivative notional value, trading book value and structured financial product value over total assets to arrive at this measure. We cannot consider level 3 assets as suggested by Basel Committee Banking Supervision (2013) due to limitations on data availability.

Finally, we show how bank complexity relates to bank size. Figure 1 shows the scatterplot of bank complexity against banks' total assets, using yearly U.S. bank data from 1986 to 2013.

(Insert Figure 1 here)

Overall, there is a significantly positive correlation between bank complexity and bank size (0.3755) [8], but it is neither perfect nor is the relationship strictly monotonic. The link is negative for relatively small banks and it is positive for medium-sized and 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. A weak positive relationship between bank complexity and bank size is also confirmed by the TOP 30 ranking of banks shown in Appendix 2. The five most complex banks are among the ten largest, but some of the most complex banks are ranked relatively low in terms of total assets. In all subsequent analyses, we will use financial ratios of banks and explicitly control of bank size in any analysis.

3. Data

We gather annual accounting data from both consolidated and parent-only financial statements of U.S. bank holding companies (BHCs) (Y-9C and Y-9LP/SP) during the period 1986. 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. In total, we have 4,386 BHCs with 38,632 bank-year observations. Table 2 shows the main variables and reports summary statistics.

(Insert Table 2 here)

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[8] Interestingly, the correlations between bank size and $Complexity^{Org}$ (0.5621) and $Complexity^{Geo}$ (0.6751) are much higher, leaving a smaller fraction of complexity left unexplained.

We observe that the domestic activity index ranges from 0.41 to 1.00, 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 1.00. 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. Our baseline estimation strategy exploits the panel structure of the dataset, which allows us to include bank and year fixed effects. Moreover, we 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 3 reports the results.

(Insert Table 3 here)

The coefficient of $\mathit{Complexity}^{Bank}$ is positive and statistically significant at the 5%-level for all three performance measures. The effect is also significant 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).

The results in Table 3 indicate that complexity is beneficial for banks on average, but they do not show which aspect of bank complexity, i.e., the domestic, the cross border, or the derivative activity index, contributes more to performance. Table 4 shows the corresponding results.

(Insert Table 4 here)

The results indicate that the domestic activity index mainly drives the link between overall complexity and profitability. It implies the wider and the more bank-specific the range of domestic on- and off- balance sheet activities, the greater profitability. This result 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.

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 non-commercial banking before the GLB act. These banks most likely desired to expand their scale and scope of non-commercial 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 BHCs with Section 20 subsidiaries before the year 1999. Banks with Section 20 subsidiaries were already active in non-commercial 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 and Non-Section 20 BHCs to the enactment of the GLB Act. Figure 2 shows the evolution of the median bank complexity over time, distinguishing by whether the BHCs have established section 20 subsidiaries before 1999. 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) after 1999, 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). Overall, 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.[9]

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 indicate that *Section 20 BHCs* improve their performance more than Non-Section 20 BHCs in the post-GLB period, a result which is consistent with the results in the previous section. We include time and bank

[9] 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 Non-section 20 BHCs and their motivation to expand into wider aspects of banking activities exist even before they set up their first section 20 subsidiaries.

fixed effects and the same control variables as in Table 2 and 3 in the regression model. Table 5 reports the results.

(Insert Table 5 here)

In Panel A of Table 5 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 5, 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.[10] Consistent with the results from Panel A, we find that, relative to smaller banks, complexity increased for the Top 2% banks and that large banks improve their performance more than their smaller counterparts in the post-GLB period.

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

4.3. Bank complexity and systemic risk

In the analysis 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 from taxpayers. Indeed, Laeven, Ratnovski and Tong (2015) show that "*large banks tend to have lower capital, less-stable funding, more market-*

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

based activities, and be more organizationally complex than small banks." They also show that large banks create more systemic risk, but they are not individually riskier, when they engage more in market-based activities or are more organizationally complex. To assess whether our previous bank level findings also hold at the system level, we 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).[11] 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 6 reports the results for overall bank complexity and its components, respectively.

(Insert Table 6 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 6 shows the domestic (cross border) activity

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

component of complexity have a significant effect on MES (ΔCoVaR). 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. By engaging in sophisticated and unique banking activities, a very complex bank differentiates itself from average banks and is hence able to substantially reduce the risk of "fire sale" the same assets during financial shocks. These results are consistent with the study of Elsinger, Lehar and Summer (2006), who find that correlation in banks' asset portfolios dominates contagion as the main source of systemic risk. The implication is that banks with less correlated businesses are likely to reduce their sensitivity to systemic risk. Hence, our results on systemic risk provide a further explanation, next to the effect on performance, why banks have incentives to become complex.

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 7 reports the regression results of the impact of bank diversification on performance.

(Insert Table 7 here)

We confirm the results from Table 3 and 4 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 augment the regression models from Table 3 and Table 6 by adding one of the alternative measures of complexity at the time, respectively. As shown in Table 1, there is a moderately positive correlation between these measures. We can include two complexity measures at the same time to the regression model, but not all of these measures simultaneously. These additional checks by and large confirm our previous results. $Complexity^{Bank}$ has a significant effect on bank performance and banks' sensitivity to systemic shocks.

Third, we study the robustness of the main results on systemic risk as shown in Table 6, controlling for bank diversification. For each outcome variable (ΔCoVaR and MES), we report four regression results. Table 8 presents the results.

(Insert Table 8 here)

The results from Table 8 are consistent with those reported in Table 6. 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.

Fourth, the recent financial crisis raises the question of how bank complexity responds during times of crisis 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 9 reports the regression results.

(Insert Table 9 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 multidimensional 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. 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 (MES). 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. Both findings provide explanations why banks have incentives to be complex. 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[12]

Domestic Activities
Core domestic deposit • Demand deposits • Savings deposits • Time deposits below limit • Time deposits above limit[13] Other borrowing • Federal Funds purchased • Commercial paper • Subordinated notes and debentures • Other unclassified borrowings Loans • Real estate loans • Commercial loans • Individual loans • Agriculture loans • Loans held for sale • Other loans • Lease financing receivable Other bank investments • Held for maturity security • Available for sale security • Interest-bearing bank balances • Federal funds sold Fiduciary activities[14] • Fiduciary activities Bank commitments • Letters of credit • Recourse exposure • Loan commitments Non-bank financial activities[15] • Investment banking activities • Venture capital activities • Insurance activities

[12] 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.

[13] 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.

[14] We use fee income from fiduciary activities to represent the total volume of fiduciary activity. In case when this activity has volumes larger than total assets, we restrict the normalized ratios to be 1 to avoid biases caused by these extreme values.

[15] We use total income from investment banks, venture capital and insurance activities to represent the volume of these activities. In case when these activities have volumes larger than total assets, we restrict the normalized ratios to be 1 to avoid biases caused by these extreme values.

Cross Border Activities
• Total deposits in foreign offices • 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	Bank Complexity rank	Size rank	Bank Complexity	Total assets (bn $)	Bank name	Bank Complexity rank	Size rank	Bank 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. Correlation of bank complexity measures

This table reports the pairwise correlations of the measure of bank complexity used in this study (*Complexity*^{Bank}) and alternative measures. The alternative measures are *Complexity*^{Org} (organizational complexity measured by the logarithm of total number of bank and non-bank subsidiaries), *Complexity*^{Geo} (geographic complexity measured by the number of U.S. counties in which a bank is active) and *Complexity*^{BCBS} (OTC derivatives, trading book and available for sale instruments, and structured financial products) as alternative measures. The sample period is 1998-2013, except for *Complexity*^{BCBS}, which we can calculate only for the period 2010-2013. All the correlation coefficients are significant at least 5%-level.

	Complexity^{Bank}	*Complexity*^{Org}	*Complexity*^{Geo}	*Complexity*^{BCBS}
Complexity^{Bank}	1.0000			
Complexity^{Org}	0.3805	1.0000		
Complexity^{Geo}	0.0689	0.2497	1.0000	
Complexity^{BCBS}	0.2804	0.4489	0.0080	1.0000

Table 2. 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*
$\Delta CoVar$	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^{Bank}	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 3. 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 2.

	ROA	*Log Z-score*	*Market Share*
$Complexity^{Bank}_{t-1}$	*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 4. 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 2.

	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 5. 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 2.

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

	Full sample				Matched sample			
	Complexity^{Bank}	*ROA*	*Log Z-score*	*Market share*	*Complexity^{Bank}*	*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 5 (continued)

Panel B: Top 2% banks versus other banks

	Complexity^{Bank}	*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 6. Bank 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 $\Delta CoVaR$ 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. Variable definitions are given in Table 2.

	$\Delta CoVar$				*MES*			
	Domestic activity index	*Cross border activity index*	*Derivative activity index*	$Complexity^{Bank}$	*Domestic activity index*	*Cross border activity index*	*Derivative activity index*	$Complexity^{Bank}$
$Complexity^{Bank}_{t-1}$	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)
$(Complexity^{Bank})^2_{t-1}$	-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 7. 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 2.

	ROA	*Log Z-score*	*Market Share*
Diversification$_{t-1}$	0.020	0.052	0.612
	(0.104)	(1.203)	(1.638)
Complexity$^{Bank}_{t-1}$	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 8. 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. Variable definitions are given in Table 2.

	ΔCoVaR				*MES*			
	Domestic activity index	*Cross border activity index*	*Derivative activity index*	*$Complexity^{Bank}$*	*Domestic activity index*	*Cross border activity index*	*Derivative activity index*	*$Complexity^{Bank}$*
$Diversification_{t-1}$	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)
$Complexity^{Bank}_{t-1}$	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)
$(Complexity^{Bank2})_{t-1}$	-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 9. 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^{Bank}*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 2.

	ROA	*Log Z-score*	*Market share*
$Complexity^{Bank}_{t-1}$	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)
*$Complexity^{Bank}_{t-1}$ * 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).

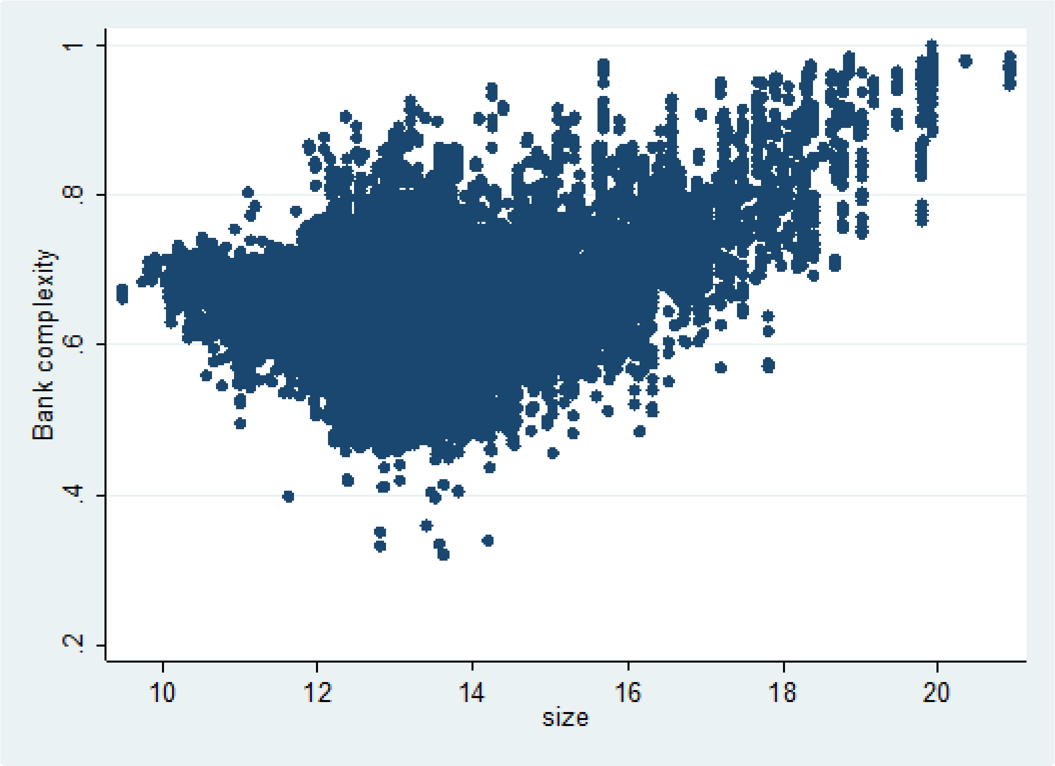

Figure 2. Bank complexity by section 20 versus non-section 20 BHCs

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.