On the riskiness of bank: A two-sided story of activity strategies

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Abstract

Our results show that US banks with relatively high share of non-interest income become riskier with a moving toward non-interest-generating activities. The findings also find, although weakly, that banks with relatively low share of non-interest income enjoy the net gains from an increase of non-interest income activities. Interestingly, the data provides evidence to the bright side of diversification during the crises. Our main findings are robust with a battery of robustness tests. This study also yields an insight into why banks diversify under agency problems framework. Finally, the evidence has different implications for regulators, managers and investors.

JEL Classification Codes: G21, G28, G34, G38

Keyword: risk, diversification, non-interest income, banking, crises

1 Introduction

The banking industry is a particularly important sector in our economies, serves as a conduit through which disruptions in the smooth functioning could translate adverse fluctuations to the real economy. A sound banking system is a primary objective of regulators and policymakers. In response of the recent financial crisis, along with the adjustments of capital adequacy, liquidity requirements or the mandatory stress-testing of *SIFI (Systemically Important Financial Institutions)*, financial regulators are considering structural bank regulation measures, which aim to review and eventually limit the scope of activities that banks can operate (Gambacorta and Van Rixtel, 2013).

Historically, banks face strict restrictions on business lines, and suffer high competition pressures from non-banks entities on both sides of balance sheet, leading to return and risk problems (Saunders and Cornett, 2008, Chap 21) [1]. Since the 1970s, however, these restrictions are attenuated along with the wide deregulation of financial markets. Banks are increasingly allowed to expand to activities that were previously prohibited. They diversify their income stream into new activities, such as investment banking, venture capital, trading securities, and other activities that generate non-interest income, while they traditionally earn profit from lending activities in the form of interest income. Beyond deregulation, the technological progress as well as financial innovation contribute to spur banks to further diversify. The financial crisis of 2007-2009 come to unveal the dark side of the functional diversification, with the failures of large number of banks. Many commentators blamed the bank deregulation that allow banks to expand to highly volatile and complex non-bank activities such as investment banking, venture capital (DeYoung and Torna, 2013). Consequently, various initiatives such as *Vocker Rule* in US, *Vickers* in UK and *Liikanen* in EU propose *narrow banking* policies that aim to limit some of permissible activities of banks. This assumes that these activities contribute to higher riskiness in banks. In line with this view, banks should concentrate to their main and traditional activities.

Meanwhile, whether from the theoretical perspective or empirical studies, how diversification affects bank risk-taking still has been a contentious debate among financial economists. Under modern portfolio theory, it is generally believed that diversified banks can enjoy economies scope that boost performance and reduce risk. We call this channel as the

[1] The adoption of Banking Act of 1933 prohibits commercial banks (with deposits taking and loans making as main activities) to involve in non-bank activities such as underwriting, insurance, and distributions of stocks, bonds, etc. The Sections 16, 20, 21 and 32 which limit banks and securities firms to engage directly (Sections 16 and 21) and indirectly (Sections 20 and 32) in each others activities are commonly known as Glass-Steagall Act (Kroszner and Strahan, 2014). However, commercial banks still have the right to underwrite new issues of T-bills, notes, bonds and municipal general bonds; and engage in private placements of all types of bonds and equities, corporate.

Diversification-Stability Channel. Smith and Stulz (1985), Boyd, Chang, and Smith (1998), Buch, Koch, and Koetter (2012) among others provide evidence consistent with this view. However, if the diversified activity is inherently riskier than traditional banking business, and the these activities are highly correlated, the cost of diversification could totally outweigh the benefit, leading a higher risk for banks (Boyd and Runkle, 1993). Additionally, banks could use the federally-insured deposit to support risky investments (Litan, 1985). We call this channel as the *Diversification-Fragility Channel*. Demsetz and Strahan (1997), Stiroh (2004), Stiroh and Rumble (2006) among others support this hypothesis.

This study sheds light a straightforward question about how diversification affects bank risk-taking using data of US banks during 1986:Q1 and 2013:Q4 period. Since banking is an industry where there exist greater incentives of risk-taking and opportunistic behavior to compare with other industries due to the call-option nature of bank equity (Kanagaretnam, Lim, and Lobo, 2013), it offers an ideal context to study the relations between risk-taking and banks activities.

We measure banks diversification using an adjusted Herfindhall-Hrishman index (*HHI*), and *ZSCORE* as proxy of bank risk-taking behaviors. Our empirical analysis provides consistent evidence that banks benefit diversification gains; however, these gains are quickly outweighed by the increased share of riskier activities. By assessing the net effect of changes in non-interest income (*NON*) on *ZSCORE*, we find that for banks with relatively low reliance on *NON* (at 10^{th} percentile), a moving away from interest-generating activities translates into net gains for banks since the diversification gains dominate offsetting effects from a greater reliance on the more volatile activities. This evidence is consistent with *Diversification-Stability Channel*. However, the more banks rely on *NON*, the lower this net effect is. The net effect becomes negative at 50^{th} percentile of *NON* share, suggesting that banks become riskier with a greater reliance on non-interest-generating activities since the diversification gains are outweighed by offsetting effects related to a moving toward riskier activities. This finding lends support to *Diversification-Fragility Channel*.

To ensure robustness of our finding, we provide a battery of sensitivity tests. We first ad-dress potential endogeneity of the decision to diversify that is deliberate decisions of bank managers, by using the Heckman two-step model, an IV approach and the propensity score matching. Second, we re-estimate the analysis with alternative measures of diversification and risk. Our results remain unchanged.

Next, we investigate whether diversification affect differently banks risk during the financial crises. During banking crises, the net effects from a marginal increase of *NON* on *ZSCORE* is insignificant, whereas during market crises, the net effects is significantly positive, suggesting that diversified banks can lower their riskiness during market crises, lending support to the *Diversification-Stability Channel*.

Finally, our findings raise the question of why banks diversify. For this issue, we focus on the agency problems between managers and shareholders. The evidence suggest that the diversification benefits are more than offset by the costs associated with the moving toward *NON*, and this offset effects are more likely to be stronger under high agency problems circumstances.

Numerous studies address the similar question on the impacts of diversification on banks risk using US sample. Among these, the closest to our study is Stiroh and Rumble (2006). The findings in our main analysis confirm their findings. Our study, however goes beyond their study by considering a longer and more recent period, which provides a more granular and updated assessment on the impacts of diversification on banks risk. Earlier studies usually covered a shorter period, or a more focused and regulated banking environment (see e.g. Litan (1985), Boyd and Prescott (1986)), or a turbulence period (Stiroh and Rumble (2006)). Thus, the results of these studies could be biased by idiosyncratic events during the selected period, and may not reflect all aspects of the relationship between diversification and risk.

In related work, Laeven and Levine (2007) address the question on how markets value the diversification in banks using international data during 1998-2002, and suggest the diversification discount when diversified banks have a lower valuation than focused banks. Our findings could be viewed as complementary to their study, since our findings suggest that banks with greater reliance on non-interest-generating activities become riskier, leading to a potential discount in valuation.

Our study is also related to DeYoung and Torna (2013) who study whether the failures of US banks during the last financial crises are related to the shift toward nontraditional banking activities. The authors document that nontraditional income does not affect the probability of bank failure during the crises. In contrast, they suggest that higher concentration of stakeholder activities (i.e. investment banking, venture capital) reduces the probability of bank failure whereas higher concentration of fee-for-service activities (i.e. securities brokerage, insurance sales) help distressed banks avoid failure. Our results can be considered as complementary, because our results show that during banking crises, the net effects from increasing *NON* activities on *ZSCORE* are insignificant, whereas the net effects become significantly positive during the market crises, suggesting diversified banks are less risky.

This paper extents to the broader literature on diversification by investigating risk within an industry - that by their nature is designed to diversify thanks to their economies of scope of information provisions rather than across broad industries. The quite timely evidence in this paper have policy implications particularly relevant for the ongoing debate of the *ring-fencing* concept: a potential mandatory separation of commercial banking from certain investment banking activities. On the one hand, the evidence lends support both hypothesis *Diversification-Stability* and *Diversification-Fragility* during the normal time. The paper also documents (*partly*) the bright side of diversification during the crises consistent with *Diversification-Stability Channel*, on the other hand. Taken together, our results suggest there may be a combination of activities for an optimal model of banks. In addition, our study suggests that large banks do not benefit from a moving toward non-interest-generating activities, lending support to the calls for banks size and activities limitation. Furthermore, the paper also has implications for investors who are concern about banks performance, for bank borrowers and clients who are concern about banks soundness and their ability to provide stable services.

The paper is organized as follows. *Section 2* reviews briefly existing literature. *Section 3* describes the data, and variables, and a cursory look at banks risk and diversification. We present our econometric approach, and our baseline empirical results in *Section 4*. A battery of robustness tests is provided in *Section 5*. *Section 6* identify potential explanations for the decision of bank diversification. *Section 7* concludes the study.

2 Literature review

The moving toward some line of business that yield noninterest income (*NON*) stream (i.e. activities that earn fee rather interest) and its impact on bank risk was vigorously debated over the two past decades. Theoretically, there are conflicting predictions on whether the potential benefits from diversification of activities outweigh the costs. On the one hand, it is generally believed that the combine of different activities reduce the total risk of the diversified banks (e.g. Brewer, 1989). The conventional wisdom is that *NON* activities are considered as non-correlated, *or* at least weakly correlated, with interest-generating activities, resulting coinsurance effect, diversification gains and a more stable revenue stream (DeYoung and Roland, 2001), and a reduced bankruptcy risk (Saunders and Cornett, 2008). It is expected that as shifting away from traditional intermediation activities, banks earn less interest income and at the same time experience less interest and credit risk. Additionally, under assumption of absence of agency conflicts between banks and borrower, Diamond (1984) argues that diversified banks can en-hance the credibility in their loan making decisions and in their borrowers monitoring by over-coming information asymmetry between depositors and borrowers. Diversified banks can retrieve clients information during the loan decision-making process, and profitably re-use it for nonin-terest-generating activities such as securities underwriting or insurance (see e.g. Yasuda (2005), Bharath, Dahiya, Saunders, and Srinivasan (2007)). In turn, information from *NON* activities can facilitate and make loan making-decision more efficient, and improve credit risk management. Diamond (1984) also suggests that diversified banks have more stable credit supply under aggregate shocks, which may in turn lead to lower volatility of cash-flow from loan portfolio. Jensen (1986) suggests that financing projects with internal resources (from diversified units) allows to mitigate the manage-rial incentives, reducing as a result potential moral hazard problems. We call this channel as the *Diversification-Stability Channel*. The evidence of Litan (1985), Brewer (1989), Eisenbeis and Kwast (1991), Boyd et al. (1998) among others lend support to this channel. Recently, DeYoung and Torna (2013) suggest that banks with higher share of noninterest income experience lower probability of failure. Engle, Moshirian, Sahgal, and Zhang (2014) document no significant relationship between non-interest income and systemic risk in countries subject to high concentration in banking system.

On the other hand, research are concern about some nonbank activities may be riskier than traditional banking activities when viewed on a stand-alone basis (Saunders, 1994). Securities underwriting could be an example. In a firm commitment securities offering, the underwriters profit (i.e., the spread between the underwriters buy price and the public offer price) is capped whereas the downside risk could be much higher. The extent of the diversification gains depends on the co-movement of income stream generated from combined activities (Demirg-Kunt and Huizinga, 2010). If the sought-after activity is inherently riskier than banking business, and the these activities are highly correlated, the cost of diversification could outweigh the benefit, leading a higher risk for banks (Boyd, Graham, and Hewitt, 1993). A more diversified activities does not translate in risks reduction if there is a lack of expertise in the newly adopted business (Jimnez and Saurina, 2004). In addition, banks could use the federally-insured deposit to support risky investments, due to the risk-seeking behavior of managers/shareholders or the moral hazard associated to the fixed-rate deposit insurance (Litan, 1985). Literature documents that diversification raises the concern of intensified agency problems since functional diversification can increase banks size as well as banks opaqueness, leading to discretionary decisions to undertake value-decreasing investments (Berger and Ofek, 1995). We call this channel as the *Diversification-Fragility Channel*. Demsetz and Strahan (1997) examine the stock returns of banks from 1980-1993, indicate that better diversification does not translate into risk reductions. Similarly, DeYoung and Roland (2001) document a greater volatility of bank earnings with a moving toward fee-based activities for period of 1988-1995. Using both aggregate and bank-level data, Stiroh (2004), Stiroh and Rumble (2006) find diversification benefits from moving toward noninterest-generating activities, but these gains are outweighed by the increased exposure to noninterest activities. Geyfman and Yeager (2009), Demirg-Kunt and Huizinga (2010) also document similar evidence.

3 Data, variable, and descriptive statistics

3.1 Sample banks

The study uses the quarterly Call Reports (Report of Condition and Income) data from the Federal Reserve. We drop all non-commercial banks, remove any bank-quarters observations with missing or incomplete financial data on basis accounting variables of the main model of regression. Following Berger, El Ghoul, Guedhami, and Roman (2016), we replace all observation with ratio of total equity over total assets less than 1% by 1% to avoid distortion in ratios that contain equity, and also exclude observations with (i) gross total assets less than or equal to $25 million, or (ii) negative or no outstanding loans or deposits. Finally, our dataset contains 846,947 observations, and lasts from 1986:Q1 to 2013:Q4. All financial ratios are winsorized at 1% level on the top and bottom of their distribution to dampen the effects of outliers.

3.2 Variables

Following Stiroh and Rumble (2006), we use an adjusted Herfindahl-Hirshman index to measure diversification (DIV) that accounts for variations in the breakdown of net operating income (NOI) into two main categories: net interest income (NII) and non-interest income (NON).

$$DIV = 1 - [(SH\_NII)^2 + (SH\_NON)^2] \tag{1}$$

where $SH\_NII = \frac{NII}{NOI}$ and $SH\_NON = \frac{NON}{NOI}$ are respectively the share of NII and NON over NOI. This income-based indicator measures each banks position along two main activities: pure lending and non-lending (pure fee/trading) activities. Banks that are specialized in making loans have large proportion of NII, whereas banks that focus more on other activities such as fiduciary income, service charges, trading revenue and other sources have large share of NON. To ease interpretation, we subtract the sum of squared shares of income from unity. By definition, DIV can take value from 0 when banks focus on either pure lending or pure fee/trading activities to 0.5 when banks have a balanced mix of revenue from these two activities.

Our primary measure of bank risk-taking behavior is *ZSCORE*. Banks with high *ZS*-

CORE are more stable than banks with low *ZSCORE*. The advantage of using *ZSCORE*is the reflection of both capital level and expected earnings of banks. When banks engage in new lines of business which are riskier, *ZSCORE* is not penalized if banks hold higher capital, or if the expected returns from new lines of business more than offset the greater risks (Wall, 1987).

Following prior studies (See e.g. DeYoung and Roland (2001), Stiroh and Rumble (2006)), our control variables include the gross total assets (*SIZE*), capital ratio (*CAP*), loan ratio (*LOAN*), growth rate (*GROWTH*). Since size is highly skewed, we also control for possible non-linear relationship between size and bank risk by including the squared term of size (*SIZE2*).

[Table 1 about here.]

3.3 Descriptive statistics

In Figure 1, we plot *DIV* over the period of the study. The figures also show crisis periods, with banking crises represented by red shaded areas and market crises by light blue shaded areas [2]. We observe that on average, *DIV* is about 0.25, and banks are more likely increase *DIV* during the financial crises, except for the last subprime crisis. The sharp increase after 2000 is coincided to the Gramm-Leach-Bliley Act in 1999, suggesting that US banks diversify their income stream toward *NON*. Interestingly, we find a downward trend of *DIV* after the financial crises.

[Figure 1 about here.]

Figure 2 plots the evolution of *ZSCORE* during the period of the study. Banks have a mean of *ZSCORE* of 37.46, suggesting that banks are on average far from default. We next investigate the impacts of *DIV* on banks risk.

[Figure 2 about here.]

[Figure 3 about here.]

Figure 3 provides a graphical representation of this association. We sort our sample on 50 groups, each containing 2% of total observations in increasing order of *DIV*. We draw several remarks. First, banks with low level of *NON* can enhance their safety by diversify. Second, banks with highest level of *ZSCORE* are located between 5^{th} and 20^{th} bins of *DIV*. That is, around 16% of bank observations, corresponding to 8 groups, have the highest

[2] We use the data on crisis periods from Berger and Bouwman (2013)

level of *ZSCORE* (¿40). Interestingly, the overall relation between *ZSCORE* and *DIV* is inverted U-shaped, which means mixing income sources is related to bank safety, and this risk diversification benefits decrease with the increase of *NON* share. This finding is similar with Demirg-Kunt and Huizinga (2010) in their international sample.

[Table 2 about here.]

Table 1 reports the summary descriptive of these variables. The average of *NON* is 0.16 [3]. On average, banks hold 9.7% of equity over total assets, with nearly 60% of loans over total assets. The growth of assets (over quarter) is about 2% during our sample. Table 3 reports the correlations among these variables. Banks that are more likely to diversify and to make more loans have high risk as indicated by the negative correlation with *ZSCORE*, whereas larger and highly capitalized banks are less risky than smaller and poorly capitalized banks. Furthermore, high growth banks seem to be less risky.

[Table 3 about here.]

4 Impacts of diversification on bank risk

4.1 Model specifications

Our main econometric model aims to test the relation between bank risk and income diversification. The empirical specification we estimate is as follows:

$$\begin{aligned} RISK_{i,t-k+1,t} =& \alpha + \beta_1 DIV_{i,t-k} + \beta_2 SH\_NON_{i,t-k} \\ &+ \beta_3 CONTROL_{i,t-k} + \delta_i + \omega_t + \phi_s + \epsilon_{i,t-k} \end{aligned} \tag{2}$$

where *RISK* is measured by *ZSCORE*. *DIV* and *SH_NON* are measured by proxies described above, and *CONTROL* is vector of control variables discussed above. δ_i, ω_t, ϕ_s are respectively bank-, time- and state fixed-effects. $\epsilon_{i,t-k}$ is error term. Since banks observations are not independent over time, the standard errors are adjusted for clustering at bank level.

Following Berger et al. (2016), we measure *ZSCORE* over k=12 quarters, and use lag of k=12 quarters for all independent variables to ensure their predetermination relative to *ZSCORE* [4]. The use of lagged explanatory variables help use to mitigate the endogeneity concerns even though we address extensively this problem in *Section 5*.

[3] The (size) weighted-average of non-interest income share is 0.354. We thank Robert DeYoung for this helpful comment.

[4] In an unreported test, we use alternative windows (k=8 and 20) to compute *ZSCORE*. We also do not use lagged independent variables. In all specifications, we still have a similar result.

It is useful at this point to discuss some specifications of this model. Given $SH\_NON + SH\_NII = 1$, we then rewrite Eq. (1) as:

$$DIV = 2 * SH\_NON - 2 * (SH\_NON)^2 \tag{3}$$

Then, we replace Eq. (3) into Eq. (2), and take the first derivatives of Eq. (2):

$$\frac{\partial RISK}{\partial SH\_NON} = \beta_1 \frac{\partial DIV}{\partial SH\_NON} + \beta_2 \tag{4}$$

This deserves some discussions. First, for each appropriate value of *DIV*, we have two possible values of *SH_NON*, and each reflects different specific underlying activities of banks (either more reliance on *NON* or *NII*), then may have different effects on *ZSCORE*. Thus, we include *SH_NON* in Eq 2 to account for the potential impacts of this activities heterogeneity on *ZSCORE*. Second, since *DIV* is a quadratic function of *SH_NON*, it is clear that effects of a variation in *SH_NON* could be disentangled into direct exposure effect (β_2) and indirect exposure effect ($\beta_1 * \partial DIV/\partial SH\_NON$) as shown in Eq. 4. Finally, the dependence of DIV on SH_NON raises the question of collinearity between these two variables, which may leads to the overestimation of variance and covariance of the coefficients of DIV and SH_NON. We then use the Wald-test to examine the joint statistical significance of these two coefficients.

4.2 Empirical results

Table 4 presents estimates of Eq. 2. In Model (1), we estimate our baseline model using the bank level data, and find positive coefficient of *DIV*, and negative coefficient of *SH_NON*, both are highly statistically significant at 1%. Economically, holding all other variables constant, an increase of *DIV* from 0 to its mean value (0.25) enhances *ZSCORE* by about 5.12 (from 37.465 to 42.585), whereas banks experience higher risk (*ZSCORE* decreases by about 5 from 37.465 to 32.454) when moving from pure lending activities toward an activities generating \$0.16 of *NON* per \$1 of *NOI*. Our results remain unchanged with the inclusion of additional variables (Model (2)), with alternative samples such as BHC level data (Model (3)), annual data (Model (4)), analysis of average (Model (5)), and balanced panel data (Model (6)).

[Table 4 about here.]

Turning to the control variables, we observe that larger and well-capitalized banks are less risky than smaller and poor-capitalized banks. However, the larger the size is, the more bank is risky. Banks with high growth opportunities are more likely to be less risky than banks with low growth opportunities, consistent with Stiroh and Rumble (2006), Demirg-Kunt and Huizinga (2010). Next, banks with high share of deposits seems to be less risky than other banks. We also find evidence that *BHC* membership is related to higher *ZSCORE*, and favorable economic conditions also translate to higher *ZSCORE*.

4.3 Discussion of results

The results from Table 4 provide consistent evidences on positive (negative) correlation between *DIV* (*SH_NON*) and *ZSCORE*. These results are economically significant. For example, *ZSCORE* increases around 13% [5] with a move from 0 to mean value of *DIV*, but it decreases a quasi-similar amount when banks move from 0% to 16% of *SH_NON*.

We then find the net effect. We suggest that banks with small portion of *NON* in their revenue stream have higher potential diversification gains from moving away *NII* than banks that have initially large portion of *NON*. We evaluate, at 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile of *SH_NON*, the direct effect, indirect effect and net effect on changes in *SH_NON* on *ZSCORE*.

[Table 5 about here.]

Table 5 shows the results. Consistent with our suggestion, banks that initially focus on interest-based activities benefit more from diversification gains by having additional income from fee/trading activities. The net effect which combines both effects together shows interesting evidence. For banks with heavily concentrated in interest income (at 10^{th} of *SH_NON*), the diversification gains dominate the negative direct effects of an increase in *SH_NON*. In this case, the net effect is about 4.59, and statistically significant. This finding shows the bright side of diversification on bank riskiness, consistent with the *Diversification-Stability Channel*.

However, this positive net effect is disappeared with more reliance on *NON* as the indirect exposure effects progressively decrease, showing the dark side of diversification. At the 25^{th} and 50^{th} percentile of *SH_NON*, the net exposure effects are not statistically significant, suggesting that the direct and indirect exposure effects on *ZSCORE* come close to canceling each other out. The net effect becomes significantly negative after the 50^{th} percentile of *SH_NON*. At 90^{th} percentile of *SH_NON*, on standard deviation in *NON* induces to a jump of -1.19 in *ZSCORE*, which corresponds to 3.18% of the mean of *ZSCORE*. This evidence supports the *Diversification-Fragility Channel*.

This lack of diversification benefits could be related to the over-diversification, which is

[5] $(42.585 - 37.465)/37.465$

the diversification beyond the risk efficient levels (Sanya and Wolfe (2011)). Indeed, banks that expand to non-interest-generating activities for long period, will reach the saturation point of benefits from these activities. Further diversification brings only very marginal diversification gains that are completely dominated by negative effects, leading subsequently to higher banks risk. This reflects the double-edged nature of diversification. Additionally, banks with less risk-averse, can use up these risk mitigation gains by taking additional risks, leading consequently higher risk (Demsetz and Strahan, 1997), (Stiroh and Rumble, 2006).

In sum, the basic OLS regression results suggest that banks benefit from diversification, but these gains are quickly offset by adverse effects from reliance on more risky assets. Banks with relatively small *SH_NON* enhance their safety by relying more on *NON* activities, consistent with D*Diversification-Stability Channel*. However, with the greater reliance on *NON*, the negative effects become larger, and banks become riskier with an increase of *NON*, consistent with the *Diversification-Fragility Channel*.

5 Robustness checks

5.1 Is the choice to diversify endogenous?

The specification in Eq. 2 is based on the assumption that a banks decision to diversify is exogenous. However, diversification is not random, but is deliberate decisions of banks managers. A failure to control for factors that drive banks to diversify leads to bias econometric results (e.g. Campa and Kedia, 2002). We use the Heckman selection model, the IV approach and the matching procedures to control for any selection bias that may be present in the above estimation. The results are shown in Table 6 .

[Table 6 about here.]

We begin with the Heckman two-step approach. We obtain the inverse Mills ratio (*IMR*) from the probit selection model [6], and re-estimate Eq. 2 by including *IMR* to correct for potential self-selection biases, since *IMR* is the conditional expectation of the model selection error term, given the banks observable characteristics and the decision to diversify. Next, we thus use IV estimation, which allows us to extract the exogenous component of decision

[6]Following Laeven and Levine (2007), we classify banks into two separate groups: (i) Banks with *SH_NII* between 10% and 90% are classified as diversified banks, whereas (ii) banks with *SH_NII* either below 10% or above 90% are classified as focused (or specialized) banks. The probit diversification-choice model includes the average of diversification index, profitability, and listing status as explanatory variables, in addition of all other explanatory variables. We also add the state fixed-effects and time fixed-effects for control to environment effects.

to diversify of banks. Finally, we use propensity score matching developed by Rosenbaum and Rubin (1983) [7]. In all specifications, the results remain unchanged.

5.2 Alternative measures of bank risks and diversification

In this section, we use alternative measures of bank risks and diversification to test whether our results are still robust. The results are reported in Table 7 .

[Table 7 about here.]

First, we compose alternative measures of bank risks. Since credit risk is the most critical risk of banks (Jimnez, Lopez, and Saurina, 2013), and *ZSCORE* do not provide information on asset quality, we also use proxies reflecting risk arising from lending activities, such as ratio of non-performing loans (*NPL*), ratio of loans losses provisions (*LLP*), and ratio of loans losses allowances (*ALW*), all are normalized by total loans. Our results in Model (1)-(3) are qualitatively unchanged. Next, we compose alternative measures of diversification. First, following Stiroh (2004), Elsas, Hackethal, and Holzhuser (2010), we construct *DIV_2* using the breakdown on *NON*: (i) fiduciary income (*FID*) such as income from trust services, (ii) service charges on deposit ac-counts (*SER*), (ii) trading revenue (*TRA*) such as net gain/loss from trading, derivatives , (iv) fee and other (*FEE*) including all other *NON* not reported elsewhere. The result in Model (4) shows that the coefficient on *DIV* is still statistically positive, suggesting that banks benefit from diversification gains. These gains however, are offset by the greater reliance on *FID*, *FEE*, and especially *TRA*. The coefficient on *SER* is negative, but statistically insignificant. This may be because *SER* are incomes derived from main traditional banking activities, have low costs, and are easily adapted to demand, resulting a lower operating leverage and cost-efficiency. Therefore, an increase of *SER* does not harm to banks safety.

Following DeYoung and Torna (2013), we next decompose non-interest income into three different sets: (i) *NON* from nontraditional Stakeholder activities (*NON_STAKE*) such as proprietary trading, venture capital, investment banking, and other activities that do or

[7] We match each bank in treated group (diversified banks) with one or more banks in untreated group (specialized banks) sharing similar characteristics as reflected in their propensity scores. We use the one-to-one matching with replacement. We impose a tolerance level of 0.5% on the maximum propensity score distance allowed (caliper) to minimize the risk of bad matches. This enhances the match quality, but comes at the cost of increased variance of estimates in the case there are fewer matches can be performed as a consequence of excluding the treated units with no matches (Caliendo and Kopeinig, 2008). In unreported test, we also use one-to-one matching without replacement, nearest-neighbor matching (oversampling) with n=2 and n=3, which matches each treated banks with the two and three untreated banks with the closest propensity scores, respectively. The results remain unchanged.

may require banks to hold risky assets, (ii) *NON* from nontraditional Fee-for-service activities (*NON_FEE*) [8], including securities brokerage, insurance sales, and other activities that do not require banks to hold risky assets; (iii) *NON* from traditional Fee activities (*NON_TRADITIONAL*) such as fiduciary services, depository services. In Model (5), we still find a positive and significant coefficient of *DIV*, which means that banks can gain from diversification. However, this gain are offset by greater reliance on other non-traditional banking activities.

It worth to note that the coefficients of *TRA* (Model (4)) and *NON_STAKE* (Model (5) could reveal in some extent the destabilizing characteristics of these activities, which is in line with studies finding large losses in banks that involve in trading activities (Roengpitya, Tarashev, and Tsatsaronis (2014), Hryckiewicz and Kozowski (2016)).

5.3 How does diversification affect bank risk during the financial crises?

We use the financial crises as natural quasi-experiment to examine whether diversification affects differently banks risk. Following Berger and Bouwman (2013), we identify 5 financial crises between 1986:Q1 and 2013:Q4: (i) two banking crises - the credit crunch (1990:Q1-1992:Q4) and the subprime crises (2007:Q3-2009:Q4); and (ii) three market crises - the 1987 stock markets crash (1987:Q4), the Russian debt crisis/LTCM bailout (1998:Q3-1998:Q4) and the internet bubble (2000:Q2-2002:Q3). We first investigate whether there is a difference in the effects of diversification during the financial crises by including the interaction term *DIV*CRISES* and *SH_NON*CRISES* in Model (1). Next, in Model (2) and (3), we separately investigate the difference in the impacts of diversification during each type of crises (*BK_CRISES* and *MK_CRISES*, respectively). The results are shown in Table 8 .

[Table 8 about here.]

In Model (1), we observe that the effects of *DIV* and *NON* are attenuated during the financial crises than in normal times. The interaction term *DIV*FI_CRISES* is -4.5, suggesting that marginal effects from increased *DIV* in *ZSCORE* are 4.5% lower during financial crises than during normal times. The interaction term *SH_NON*FI_CRISES* is 8.1, indicating that marginal effects from increased exposure to *SH_NON* activities in *ZSCORE* are 8.1% lower (less negative) during financial crises than during normal time. In Models (2) and (3), when we split financial crises into banking and market crises, we obtain different results.

[8] It is worth to note that fee and other income (*FEE*) and fee-for- service activities (*NON_FEE*) are different from each other. *FEE* includes some components from *NON_FEE* (e.g. insurance fee, net gains on sales of real estate) and also from *NON_STAKE* (e.g. venture capital)

We still obtain similar effects of *DIV* and *SH_NON* during the banking crises. During market crises, the effects of *DIV* and *SH_NON* on banks risks are intensified, but interestingly, the diversification gains become larger than the negative effects during the (market) crises. Specifically, the coefficient of *DIV*MK_CRISES* is 7.6, suggesting that marginal effect of increased diversification during market crises are 7.6% higher than during normal times, whereas the coefficient of *SH_NON*MK_CRISES* is -5.5, suggesting that the marginal effect of increased non-interest income during market crises is 5.5% higher (more negative) than during normal times.

We report the net effects [9] during the crises at the end of each column in Table (8). Interestingly, the net effects are not significant during the financial crises. That is, there is no mitigated or amplified effects of diversification on bank risks during the financial crises. When we split financial crises into banking and market crises, we obtain different results. We still obtain statistically insignificant net effects during the banking crises. However, during the market crises, the net effects are positive and significant, which means that diversification helps banks to lower their risk during crises, consistent with *Diversification-Stability Channel*.

6 Why do banks diversify?

So far, the evidence suggests that diversification benefits exist, but are quickly offset by the negative effects from *NON* activities, which are inherently riskier. The results cast some doubt on the question of why banks diversify. A sizeable literature (see e.g. Denis, Denis, and Sarin (1997), Aggarwal and Samwick (2003), Laeven and Levine (2007), Goetz, Laeven, and Levine (2013)) suggests diversification could be driven by the agency problems between managers and shareholders. Managers do not fully benefit from residual claimants whereas they bear the full cost of the effort expended to maximize returns, thus they are more likely to make decision in favor of their utility. Diversification allows managers to derive private benefits, such as additional power and a more prestige career related to managing diversified banks (Jensen, 1986), a higher compensation associated to running a more complex entity (Murphy, 1985), a personal risk diversification (Morck, Shleifer, and Vishny, 1990), or management entrenchment (Shleifer and Vishny, 1989)

In this section, we examine the diversification motivations under agency problems' consideration. Specifically, we identify different circumstances that reveal the heterogeneity of agency problems within banks.

First, banks with the presence of institutional investors experience higher monitoring,

[9] Computed at median of *SH_NON*

thus suffer less agency problems Gillan and Starks (2000). These institutional investors are more reactive to bad news than individual investors since they have systems of internal risk manage-ment and are required to periodically revise their asset allocation Ben-David, Franzoni, and Moussawi (2012). The evidence in banking area remain limited: Berger et al. (2016) document that high institutional ownership is associated with lower risk whereas Mehran and Thakor (2011) suggest an opposite relationship. We obtain data on institutional ownership from Thomson Financial 13-F fillings.

The next proxies are more related to compensation [10] which is a cost-effectively device that provide incentives to managers to work in line of shareholders interest. Compensation contracts are usually link to some observable outcome variables of firms. Stock-based compensation is preferable than accounting-based compensation since the latter can be manipulated or noisy (Hlmstrom, 1979). However, compensation contracts lead managers to focus more on short-term performance, and as consequences, could induce to excessive risk-taking (Bebchuk and Fried, 2010).

We also consider the pension plan which play an important role in compensation structure. Literature suggests that pension plan induces an opportunity cost in case of leaving firms, thus reducing the mobility of workers. In addition, managers with high pension plan are more likely to manage carefully their banks in order to decrease the default probability (Sundaram and Yermack, 2007).

We consider managers age in our investigation of agency problems of diversification decisions. Yim (2013) argues that personal characteristics change with age. Bertrand and Mullainathan (2003) document the preference to quiet life of managers, and this preference increases with age. In addition, empire-building theories document the preference of acquisitions is higher in the beginning of managers career, due to high compensation associated with more complex entity.

We suggest that banks that have lower number of institutional block investors, higher compensation, lower pension plan, and younger managers experience strict agency problems. Therefore, in each quarter, we split our sample into two sub-samples: above and below median of these corporate governance variables, and create dummy variables (CG) equal to one if banks are belong to groups above median, and zero otherwise. Eq. 2 is re-estimated with the inclusion of indicator variable and its interaction with all other explanatory variables. The results of estimations are reported in Table 9. We report the net effect of the interaction terms between CG and DIV, SH_NON at the end of each column. Since the net effect for group below median ($CG = 0$) is negative, a negative (more negative) net effect for group above median (i.e. interaction terms) is associated with higher risk for the group

[10]The data related to compensation, pension plan and age is retrieved from ExecuComp database.

above median with a moving toward non-interest-generating activities, whereas a positive (less negative) net effect for group above median (interaction terms) is associated with lower risk for group above median subject to a moving toward non-interest-generating activities.

[Table 9 about here.]

Model (1) reports the results with interaction with groups above median of numbers of institutional block owners, which represent banks with lower agency problems. The coefficient of *CG*DIV* is positive and significant at the 1% level whereas the coefficient of *CG*SH_NON* is negative and significant at the 1% level. The net effect shows that banks subject to lower agency problems as reflected by the number of institutional block owners higher than median can enhance more their safety from an increase of non-interest income share than banks subject to higher agency problems. Put it differently, with an increase of *SH_NON*, banks subject to higher agency problems as reflected through lower number of institutional block owners are riskier than banks subject to lower agency problems as indicated by higher number of institutional block owners.

Model (2) reports the results with interaction with groups of banks whose executive compensation are higher than median, which are suggested face higher agency problems. Interestingly, the coefficient of *CG*DIV* is negative and significantly different from zero at the 1% level, whereas the coefficient of *CG*SH_NON* is positive and non-significant. The net effects indicate that with an increase of *SH_NON*, banks that pay higher compensation to their executive experience a higher increase in their riskiness than banks with lower executive compensation.

Model (3) documents that the coefficient of *CG*DIV* is positive and significant at the 10% level, whereas the coefficient of *CG*SH_NON* is negative and non-significant. The net effects allege that with a moving toward *NON*, banks subject to lower agency problems as reflected through higher pension plan experience a higher increase in their safety net than banks subject to higher agency problems as indicated by lower pension plans.

We end up our investigation with the estimation with interaction with groups of banks with old managers. Model (5) reports the results with interaction with groups of banks that have managers age higher than median, which are suggested face lower agency problems due to quiet life preference of managers. The coefficient of *CG*DIV* is highly positive and significant at the 1% level, whereas the coefficient of *CG*SH_NON* is negative and significant at the 1% level. The net effects are positive and statistically significant, suggesting that with an increase of *SH_NON*, banks that have managers age above median will have higher *ZSCORE* than banks with managers' age below median. That is, banks subject to higher agency problems as reflected through lower age of managers are riskier than banks subject to lower agency problems as indicated by higher managers' age.

In brief, the evidence suggest that the diversification benefits are more than offset by the costs associated with the moving toward *NON*, and this offset effects are more likely to be stronger under high agency problems circumstances.

7 Conclusion

This study investigates the impacts of functional diversification on banks risk using a large sample of US banks during the period of 1986:Q1 to 2013:Q4. Our basic regressions suggest that banks with relatively high concentration in interest income enjoy the risk diversification gains of moving toward non-interest income, consistent with *Diversification-Stability Channel.* However, at high level of non-interest income, further reliance on non-interest income increase bank's risk, consistent with *Diversification-Fragility Channel.* We obtain similar results even after estimating a battery of robustness tests by using different proxies of risk and diversification, by testing different sub-samples, by employing a variation of methods to control for endogeneity, by assessing whether impacts of diversification on risk vary with size, by analyzing bank's risk during financial crises. We finally provide explanation on why banks still diversify based on agency problems framework.

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Table 1: Variables definition

Variable	Definition
ZSCORE	A bank measure of financial risk calculated as $$\frac{CAP + \mu_{ROA}}{\sigma_{ROA}}$$ A larger value indicates lower overall bank risk; means of ROA and Equity/GTA as well as the standard deviation of ROA are computed over the previous 12 quarters (t -11 to t)
DIV	One minus the sum of the square of the share of net interest income over net operating income and the share of net non-interest income over net operating income; a larger value indicates higher diversification. $$DIV = 1 - [(SH\_NII)^2 + (SH\_NON)^2]$$
DIV_2	One minus the sum of the square of the share of net interest income over net operating income, the share of fiduciary income over net operating income, the share of service charges over net operating income, the share of trading revenue over net operating income, the share of fee and other income over net operating income; a larger value indicates higher diversification. $$1 - \left[\left(\frac{NII}{NOI}\right)^2 + \left(\frac{FID}{NOI}\right)^2 + \left(\frac{SER}{NOI}\right)^2 + \left(\frac{TRA}{NOI}\right)^2 + \left(\frac{FEE}{NOI}\right)^2\right]$$
DIV_3	One minus the sum of the square of the share of net interest income over net operating income, the share of non-interest income from stakeholder activities over net operating income, the share of non-interest income from fee-for-services activities over net operating income, the share of non-interest income from traditional banking activities over net operating income; a larger value indicates higher diversification. $$1 - \left[\left(\frac{NII}{NOI}\right)^2 + \left(\frac{NON\_STAKE}{NOI}\right)^2 + \left(\frac{NON\_FEE}{NOI}\right)^2 + \left(\frac{NON\_TRADIT}{NOI}\right.$$
NOI	Net operating income is the sum of net interest income and noninterest income
SH_NII	Net interest income / Net operating income
SH_NON	Non-interest income / Net operating income

Continued on next page

NON_STAKE	Non-interest income from stakeholder activities, such as proprietary trading, venture capital, investment banking, and other activities that do or may require banks to hold risky assets
NON_FEE	Non-interest income from fee-for-services activities, such as securities brokerage, insurance sales, and other activities that do not require banks to hold risky assets.
NON_TRADITIONAL	Non-interest income from traditional banking activities, such as fiduciary services, depository services
FID	Fiduciary income includes gross income from services rendered by the banks trust department or by any of its consolidated subsidiaries acting in any fiduciary capacity, i.e., administering investments for others.
SER	Service charges on deposit accounts include charges for maintenance of deposit accounts, failure to meet minimum balances, excess check writing, withdrawals from non-transaction accounts, early withdraw or closure fees, dormant accounts, extensive activity, ATM usage, bounced check charges, and other fees.
TRA	Trading revenue includes the net gain or loss from trading cash instruments, off-balance sheet derivative contracts, and sales of assets and other financial instruments. Also included are revaluation to carrying value of assets and liabilities due to marking to market, revaluation of interest rate, foreign exchange, equity derivative, commodity and other contracts due to marking to market, and incidental income and expense related to the purchase and sale of assets and liabilities
FEE	Fees and other income include all other non-interest income items, such as service charges, commissions, and fees not reported elsewhere. These include fees for safe deposit boxes, insurance sales, bank drafts, money orders, etc., bill collection, savings bond redemption, execution of acceptances and letters of credit, mortgage servicing fees, and notary, consulting, or advisory services), periodic credit card fees, merchant credit card charges, rental fees, and loan commitment fees. Also included here are net gains on sales of real estate, loans, or premises, data processing services, and sales of other assets, as well as non-interest income on other foreign transactions.
SIZE	The natural logarithm of gross total assets
CAP	Book value of equity over gross total assets
LOAN	Loans over gross total assets
GROWTH	Growth rate of gross total assets
SIZE2	Square term of Size
DEPO_HHI	Share of total deposits within industry

Continued on next page

SH_DEPO	Deposits over total liabilities
FED	A dummy equal to 1 if the bank is a state-chartered Federal Reserve System member, 0 otherwise
OCC	A dummy equal to 1 if the bank has a national bank charter, 0 otherwise
DUNEMP	Change in unemployment rates over the quarter
GDP	Change in GSP (gross state product) over the quarter
FI_CRISES	A dummy equal to 1 for a financial crisis period, 0 otherwise, following
BK_CRISES	A dummy equal to 1 for a banking crisis period, 0 otherwise, following
MK_CRISES	A dummy equal to 1 for a market crisis period, 0 otherwise, following
BFE	Bank fixed effects, represented by dummies for each commercial bank.
SFE	State fixed effects, represented by dummies for each state.
QFE	Time fixed effects, represented by dummies for each quarter of the sample period.

Table 2: Summary Statistics for the Main Sample

This table reports summary statistics for the main sample of U.S. commercial banks used in the analysis. The sample period is from 1986:Q1 to 2013:Q4. All financial variables are winsorized at 1% level on top and bottom of the distribution. Panel A show the summary statistics for full sample, Panel B show the summary for diversified and focused banks, and univariate test.

Variable	N	Mean	p50	sd	p25	p75
ZSCORE	674 296	37.465	30.244	29.323	16.065	50.879
DIV	846 937	0.25	0.244	0.105	0.177	0.319
SH_NON	846 064	0.162	0.143	0.101	0.099	0.2
SH_NII	846 064	0.838	0.857	0.101	0.8	0.901
SIZE	846 937	11.653	11.418	1.151	10.81	12.204
CAP	846 937	0.097	0.09	0.032	0.076	0.109
LOAN	846 937	0.589	0.606	0.151	0.495	0.698
GROWTH	828 353	0.02	0.013	0.055	-0.009	0.039
SIZE2	846 937	137.123	130.382	28.682	116.849	148.943

Table 3: Correlations among Key Variables

This table presents pair-wise correlations between *ZSCORE*, *DIV*, *SH_NON* and other important bank characteristics. Variable definitions are in Table (1).

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	ZSCORE	1							
(2)	DIV	-0.0647***	1						
(3)	SH_NON	-0.1057***	0.8626***	1					
(4)	SIZE	0.1043***	0.2761***	0.3004***	1				
(5)	CAP	0.2193***	-0.2270***	-0.1337***	-0.1149***	1			
(6)	LOAN	-0.0131***	0.0091***	-0.0201***	0.2122***	-0.1655***	1		
(7)	GROWTH	0.0276***	-0.0208***	0.0003	0.0463***	-0.0008	0.0402***	1	
(8)	SIZE2	0.0966***	0.2805***	0.3072***	0.9975***	-0.1117***	0.2037***	0.0447***	1

Table 4: Baseline Multivariate Analysis

This table reports regression estimates of the relation between diversification and banks risk. The dependent variable is *ZSCORE* and the sample period is from 1986:Q1 to 2013:Q4. The main independent variables are DIV and NON. Model (1) reports the results of our baseline model using bank level data. Model (2) includes some additional variables. Model (3) estimates the baseline model using BHC level data, and Model (4) uses the annual data. Model (5) reports the results with the analysis of average (i.e. one observation by bank). Model (6) uses the balanced panel data. All regressions include bank-, state- and time- (quarter/year) fixed effects. All financial variables are winsorized at 1% level on top and bottom of the distribution. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank/BHC level. Robust standard errors are in parentheses.

	Bank level	Bank level	BHC level	Annual data	Analysis of average	Balanced panel
	(1)	(2)	(3)	(4)	(5)	(6)
DIV	20.477***	20.062***	21.977***	17.974***	38.724***	31.870***
	(2.002)	(1.997)	(2.899)	(2.007)	(2.213)	(4.140)
NON	-30.934***	-30.379***	-29.342***	-26.519***	-48.686***	-51.152***
	(1.903)	(1.899)	(2.855)	(1.969)	(2.181)	(4.060)
SIZE	45.601***	47.275***	36.374***	44.836***	10.620***	41.576***
	(3.439)	(3.644)	(4.438)	(3.511)	(1.360)	(6.422)
CAP	164.134***	178.576***	173.170***	175.021***	-0.385***	241.044***
	(6.337)	(6.778)	(9.031)	(6.594)	(0.055)	(12.708)
LOAN	-18.486***	-18.506***	-22.576***	-18.144***	79.491***	-24.662***
	(1.196)	(1.194)	(1.682)	(1.256)	(4.149)	(2.178)
GROWTH	1.437**	1.629**	2.687***	2.680**	-20.101***	11.093***
	(0.683)	(0.684)	(0.990)	(1.255)	(0.806)	(1.361)
SZIE2	-1.761***	-1.833***	-1.359***	-1.726***	-24.714***	-1.629***
	(0.140)	(0.151)	(0.180)	(0.143)	(4.472)	(0.254)
DEPO_HHI		68.392***				
		(22.429)				
SH_DEPO		15.541***				
		(2.692)				
BHC		2.000***				
		(0.473)				
FED		1.31				
		(0.930)				
OCC		-0.545				
		(1.083)				
GDP		97.441***				
		(5.851)				
DUNEMP		-0.066				
		(0.043)				
Constant	-355.123***	-382.368***	-212.007***	-346.605***	-63.107***	-242.954***
	(21.628)	(22.621)	(27.299)	(21.890)	(8.037)	(40.383)
BFE	Yes	Yes	Yes	Yes	Yes	Yes
QFE	Yes	Yes	Yes	Yes	Yes	Yes
SFE	Yes	Yes	Yes	Yes	Yes	Yes
N	647,188	647,103	380,318	162,825	15,727	245,025
R-squared	0.116	0.118	0.115	0.114	0.214	0.153
N_clust	13378	13378	8425	13087	15727	2475
Wald test	141.74***	137.13***	54.32***	14.18***	252.28***	88.80***

Table 5: Effects of Changes in Noninterest Income on Bank Risk

This table reports estimation of first derivative of *ZSCORE* on *NON*, based on regression results reported in Table 4, Model (1) and evaluated at different values of the non-interest share based on percentile ranks (10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile). Direct effect is estimated impact of a 1% increase in the non-interest income share. Indirect effect is estimated impact of a change in revenue diversification from a 1% increase in the non-interest income share. Net effect sums the direct and indirect effects. Robust standard errors are in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Noninterest income share				
	10th	25th	50th	75th	90th
	0.067	0.099	0.141	0.197	0.268
Direct effect	-33.146***	-33.146***	-33.146***	-33.146***	-33.146***
	(-1.841)	(-1.841)	(-1.841)	(-1.841)	(-1.841)
Indirect effect	35.527***	32.876***	29.377***	24.839***	19.030***
	(3.473)	(3.214)	(2.872)	(2.428)	(1.860)
Net effect	4.593**	1.942	-1.558	-6.095***	-11.905***
	(2.278)	(2.059)	(1.786)	(1.476)	(1.209)

Table 6: Endogeneity

This table reports the results using Heckman selection model, instrumental variable (IV) regression, and PSM. The dependent variable is *ZSCORE* and the sample period is from 1986:Q1 to 2013:Q4. The main independent variables are *DIV* and *SH_NON*. The instrument variables are the average of diversification (*DIV_AVG*). F-statistics on the excluded instruments is reported at the bottom of the table in Model (2). The matching algorithms of PSM is one-to-one with replacement. All financial variables are winsorized at 1% level on top and bottom of the distribution. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank. Robust standard errors are in parentheses.

	Heckman	IV	PSM
	(1)	(2)	(3)
DIV	20.624***	71.018***	18.138***
	(2.044)	(8.289)	(3.564)
SH_NON	-30.943***	-78.082***	-27.904***
	(1.904)	(7.757)	(3.536)
SIZE	45.619***	46.132***	57.125***
	(3.440)	(0.734)	(8.176)
CAP	164.124***	172.247***	177.257***
	(6.337)	(2.093)	(12.003)
LOAN	-18.489***	-19.240***	-21.181***
	(1.196)	(0.373)	(2.264)
GROWTH	1.431**	1.665***	7.496***
	(0.683)	(0.529)	(1.439)
SIZE2	-1.762***	-1.779***	-2.407***
	(0.140)	(0.029)	(0.335)
IMR	0.151		
	(0.149)		
Constant	-355.345***	-370.292***	-284.997***
	(21.635)	(20.694)	(50.268)
BFE	Yes	Yes	Yes
SFE	Yes	Yes	Yes
QFE	Yes	Yes	Yes
Observations	647,154	647,188	151,174
R-squared	0.116	0.116	0.105
N_clust	13,378	13,378	9349
Wald test	120.22***	334.19***	5.88***
F-test		68.81***	

Table 7: Alternative Measures of Bank Risk and Diversification

This table reports regression estimates of the relation between risk and diversification. The sample period is from 1986:Q1 to 2013:Q4. Models (1)-(3) report the results with different measures of Risk as defined in Table 1. Models (4)-(5) report the results with different measures of Diversification. All regressions include bank-, state- and time- (quarter) fixed effects. All financial variables are winsorized at 1% level on top and bottom of the distribution. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank. Robust standard errors are in parentheses.

	Alternative measures of Risk			Alternative measures of DIV	
	NPL	LLP	ALW	DIV_2	DIV_3
	(1)	(2)	(3)	(4)	(5)
DIV	-0.013***	-0.003**	-0.005***	6.425***	7.626***
	(0.002)	(0.001)	(0.001)	(1.504)	(2.648)
NON	0.007***	0.001	0.004***		
	(0.003)	(0.001)	(0.001)		
NON_STAKE					-233.225**
					(98.773)
NON_FEE					-11.388***
					(3.536)
NON_TRADITIONAL					-10.285*
					(5.842)
FID				-27.991**	
				(12.063)	
SER				-0.932	
				(5.926)	
FEE				-20.646***	
				(2.229)	
TRA				-122.391**	
				(50.014)	
SIZE	0.010***	0.002***	0.004***	53.987***	87.953***
	(0.002)	(0.001)	(0.001)	(5.365)	(7.826)
CAP	0.032***	0.023***	0.010***	137.180***	101.894***
	(0.004)	(0.002)	(0.002)	(8.273)	(8.669)
LOAN	0.028***	0.010***	0.004***	-17.213***	-16.399***
	(0.001)	0.000	0.000	(1.700)	(1.905)
GROWTH	-0.006***	0.004***	-0.006***	3.482***	1.043
	(0.001)	0.000	0.000	(0.898)	(1.049)
SIZE2	0.000	0.000	0.000	-2.073***	-3.619***
	0.000	0.000	0.000	(0.213)	(0.326)
Constant	-0.058***	-0.030***	-0.035***	-311.322***	-491.432***
	(0.013)	(0.007)	(0.007)	(34.045)	(47.168)
BFE	Yes	Yes	Yes	Yes	Yes
SFE	Yes	Yes	Yes	Yes	Yes
QFE	Yes	Yes	Yes	Yes	Yes
Observations	650,332	650,333	650,795	359,211	238,127
R-squared	0.178	0.091	0.113	0.109	0.132
N_clust	13468	13468	13479	10,303	7,866
Wald tests	30.70***	12.04***	9.72***	20.53***	4.17***

Table 8: Diversification and Bank Risks During Financial Crises

This table reports regression estimates of the relation between risk and diversification. The sample period is from 1986:Q1 to 2013:Q4. The construction of the financial crisis periods follows Berger and Bouwman (2013). All financial variables are winsorized at 1% level on top and bottom of the distribution. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank. Robust standard errors are in parentheses.

	Financial crises	Banking crises	Market crises
	(1)	(2)	(3)
DIV	22.425***	23.562***	19.312***
	(2.146)	(2.061)	(2.081)
NON	-34.329***	-34.908***	-30.069***
	(2.027)	(1.966)	(1.954)
DIV*CRISES	-4.509**	-12.762***	7.556**
	(2.035)	(2.635)	(3.197)
NON*CRISES	8.111***	16.632***	-5.496**
	(1.992)	(2.619)	(2.709)
SIZE	45.706***	45.557***	45.528***
	(3.440)	(3.440)	(3.442)
CAP	164.217***	164.103***	164.173***
	(6.336)	(6.332)	(6.335)
LOAN	-18.465***	-18.510***	-18.494***
	(1.197)	(1.196)	(1.196)
GROWTH	1.444**	1.446**	1.461**
	(0.683)	(0.683)	(0.683)
SIZE2	-1.766***	-1.759***	-1.759***
	(0.140)	(0.140)	(0.140)
Constant	-356.053***	-355.251***	-354.529***
	(21.638)	(21.636)	(21.644)
BFE	Yes	Yes	Yes
SFE	Yes	Yes	Yes
QFE	Yes	Yes	Yes
Observations	647,188	647,188	647,188
R-squared	0.116	0.116	0.116
N_clust	13378	13378	13378
Wald test	80.38***	80.24***	67.20***
Net effects	0.646	-0.381	0.885**
	(0.622)	(0.477)	(0.483)

Table 9: Why Do Banks Diversify?

This table reports regression estimates of the relation between diversification and banks risk on the magnitude of agency problems (CG). The dependent variable is *ZSCORE* and the sample period is from 1986:Q1 to 2013:Q4. The main independent variables are *DIV* and *SH_NON*, and their interaction term with proxy of agency problems *CG*DIV* and *CG*NON*. CG is dummy variable that takes the value of one if banks are in groups above the median. All financial variables are winsorized at 1% level on top and bottom of the distribution. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank. Robust standard errors are in parentheses.

	Institutional Ownerships	Compensation	Pension Plan	Age Ceo
	(1)	(2)	(3)	(4)
DIV	13.780***	68.518**	50.675**	28.263
	(5.323)	(29.751)	(25.381)	(27.439)
NON	-29.297***	-89.576***	-82.752***	-63.334**
	(5.044)	(27.302)	(23.378)	(25.370)
CG * DIV	18.556***	-74.915*	160.421**	126.738***
	(6.474)	(39.971)	(81.614)	(42.247)
CG * NON	-11.625**	24.173	-37.238	-69.479**
	(4.997)	(35.023)	(66.942)	(30.419)
SIZE	59.027***	103.744***	94.246***	97.506***
	(7.512)	(23.059)	(23.081)	(22.907)
CAP	148.245***	426.193***	386.391***	355.914***
	(15.340)	(57.915)	(53.504)	(53.100)
LOAN	-15.381***	-56.428***	-51.691***	-46.645***
	(3.548)	(13.019)	(12.524)	(13.065)
GROWTH	0.554	2.89	2.514	2.467
	(1.873)	(5.692)	(5.223)	(5.277)
SIZE2	-2.106***	-4.087***	-3.649***	-3.801***
	(0.293)	(0.889)	(0.886)	(0.880)
CG	32.557	-145.774***	-46.315	-69.899**
	(39.288)	(34.627)	(84.143)	(29.397)
CG * SIZE	-5.851	10.382***	1.043	3.735
	(5.944)	(2.252)	(5.320)	(2.314)
CG * CAP	41.059**	-167.278*	-240.846	101.824
	(18.740)	(95.577)	(181.783)	(124.457)
CG * LOAN	4.148	37.541*	30.24	-34.901
	(3.562)	(22.651)	(46.600)	(21.909)
CG * GROWTH	4.464	4.797	25.306	2.637
	(3.013)	(10.958)	(24.359)	(14.848)
CG * SIZE2	0.201	-0.006	-0.008	0.003
	(0.224)	(0.017)	(0.017)	(0.018)
Constant	-356.021***	-566.040***	-515.772***	-524.841***
	(48.384)	(151.006)	(152.167)	(149.971)
BFE	Yes	Yes	Yes	Yes
SFE	Yes	Yes	Yes	Yes
QFE	Yes	Yes	Yes	Yes
Observations	105,013	24,028	24,028	24,028
R-squared	0.121	0.039	0.038	0.039
N_clust	4225	3645	3645	3645
Wald test	9.96***	3.30**	4.87***	3.34**
Net effects	3.403**	-6.742**	2.888***	8.168**
	(1.668)	(3.348)	(1.102)	(3.307)

Figure 1: Evolution of income diversification

The figure shows the evolution of diversification over our sample period. It depicts financial crisis periods in shaded areas: banking crises in blue and market crises in red. The construction of the financial crisis periods follows Berger and Bouwman (2013). For all graphs, the sample period illustrated is from 1986:Q1 to 2013:Q4. Income diversification is measured as one minus the sum of the square of the share of net interest income over net operating income and the share of net non-interest income over net operating income; a larger value indicates higher diversification. $DIV = 2 * SH\_NON - 2 * (SH\_NON)^2$.

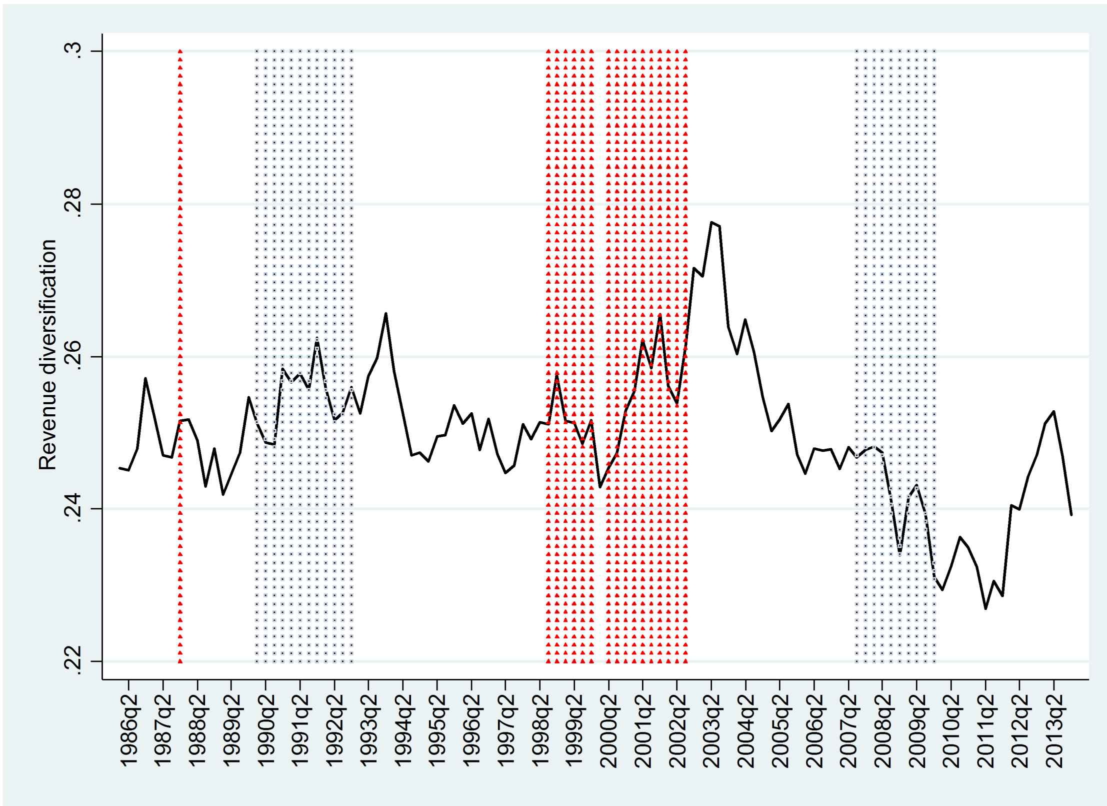

Figure 2: Evolution of ZSCORE

The figure shows the evolution of *ZSCORE* over our sample period. It depicts financial crisis periods in shaded areas: banking crises in blue and market crises in red. The construction of the financial crisis periods follows Berger and Bouwman (2013). For all graphs, the sample period illustrated is from 1986:Q1 to 2013:Q4. *ZSCORE* is defined as $(CAP + \overline{ROA})/\sigma_{ROA}$, where CAP is ratio of equity over assets, $\overline{ROA}$ is mean of ROA, σ_{ROA} is standard deviation of ROA.

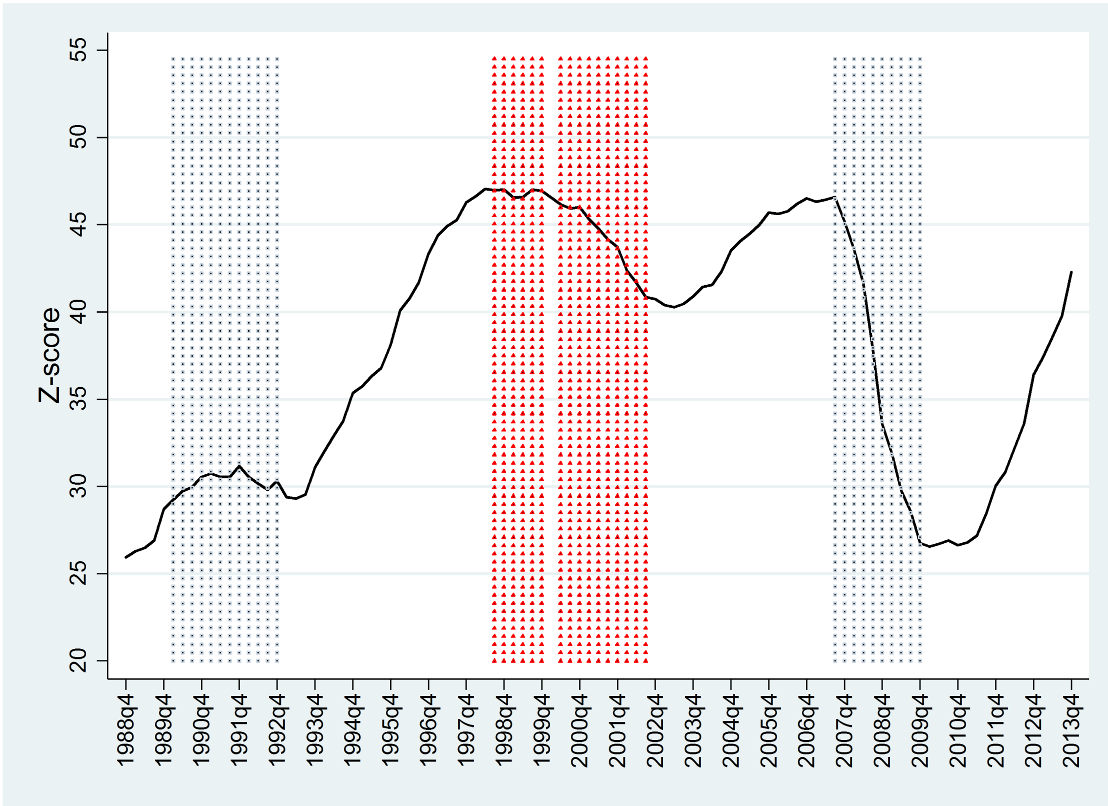

Figure 3: ZSCORE by Income Diversification

$ZSCORE$ is defined as $(CAP + \overline{ROA})/\sigma_{ROA}$, where CAP is ratio of equity over assets, $\overline{ROA}$ is mean of ROA, σ_{ROA} is standard deviation of ROA. Income diversification is measured as one minus the sum of the square of the share of net interest income over net operating income and the share of net non-interest income over net operating income; a larger value indicates higher diversification. $DIV = 2 * SH\_NON - 2 * (SH\_NON)^2$. We sort diversification into 50 bins, with each bin containing 2% of observations of diversification in increasing order.