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Activity Strategies, Information Asymmetry, and Bank Opacity

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Abstract: Using a large panel of US bank holding companies from 2001 to 2015, we investigate the association between functional diversification and bank earnings management. We document a positive relationship between bank earnings management and bank diversification. Our findings are consistent with the hypothesis that diversification increases the asymmetric information of banks, leading to greater discretionary power by bank managers. This effect is most prevalent in smaller banks and non-dividend paying banks. The impact of diversification on earnings management is less pronounced during the crisis. Our study is of interest to regulators and other stakeholders who examine factors which affect behavior of bank managers.

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1. Introduction

Banks are inherently more opaque than other firms due to their ability to keep both loans and assets off the balance sheet and their ability to hold complicated financial assets. The costs outside investors must bear to serve as adequately monitor banks are greater than the costs to monitor industrial firms. When banks manipulate their reported numbers, this manipulation exacerbates information asymmetry between the bank and its stakeholders, leading to greater opportunities for managerial expropriation.

The goal of this study is to determine the impact bank operational diversification has on earnings management. Lim, Thong, and Ding (2008), Chin, Chen, and Hsieh (2009), Rodríguez-Pérez and van Hemmen (2010), and Farooqi, Harris, and Ngo (2014) note that increases in non-financial firm diversification increase the information asymmetry between firms and shareholders and can lead to an increase in earnings management. Other researchers, like Jiraporn, Kim, and Mathur (2008) and El Mehdi and Seboui (2011) note firms which diversify operations face additional monitoring from analysts, ratings agencies and regulators which could result in a decrease in the incentive to manage earnings. Using a sample of 2,482 bank holding companies (BHC), we determine whether the empirical evidence supports either of these hypotheses: the “monitoring” hypothesis or the “information asymmetry” hypothesis.

Our empirical analysis indicates diversified bank holding companies engage in greater earnings management through discretionary loan loss provisions (*DLLP*). Our baseline model indicates that a one standard deviation increase of scaled non-interest income (*NII*), which is our primary measure of bank diversification, leads to a 9.1% increase in *DLLP*. These results indicate the net effect of an increase in diversification is an increase in earnings management and that

agency problems subsume the benefits of monitoring from external agents. Our evidence supports the asymmetric information hypothesis and appears to reject the monitoring hypothesis.

We provide a battery of sensitivity tests ascertain our findings are robust. First, we perform our analysis with the inclusion of additional variables to deal with potential omitted variables. We also use alternative samplings, like only fourth quarter data, since managers are more likely to engage in earnings management during the fourth quarter rather than other fiscal quarters. We also use average analysis and find consistent results (using only one observation by bank). We also perform Newey-West and Fama-MacBeth procedures. In all specifications, our findings remain quantitatively similar. The results of our robustness tests lend support to the asymmetric information hypothesis.

We use quantile regression in further regressions to test the robustness of the relationship between bank diversification and earnings management. The relationship between *NII* and *DLLP* is uniform in sign (positive) in each quantile, and also increases in magnitude with the increase of quantiles. These results provide further evidence against the monitoring hypothesis since larger firms (firms in higher quantiles) should exhibit a more negative relationship between diversification and earnings management.

Next, we re-estimate the analysis with alternative measures of earnings management and diversification. Our first alternative measure of bank earnings management is the natural logarithm of *DLLP*, which should mitigate the effects of outliers. Our second measure involves only negative *DLLP*. We choose negative *DLLP* as our second because positive *LLP* can convey private information about bank's future prospects, involving a transparency-enhancing accounting discretion rather than earnings management (Tran and Ashraf, 2018). Next, we calculate industry-adjusted *DLLP* for each bank for each quarter. We also compute excess earnings management

following the “chop-shop” approach in the spirit of Laeven and Levine (2007), Lang and Stulz (1994). Finally, we rely on other models of bank discretionary LLP as suggested by Beatty and Liao (2014). Regardless of the measure of bank earnings management, we continue to document a positive relationship between diversification of operations and earnings management at banks. Our positive relationship between diversification of activities and earnings management persist when we follow Stiroh and Rumble (2006) and Laeven and Levine (2007) and proxy for diversification using trading income.

The decision to diversify is an endogenous one. Bank managers make the decision deliberately and can be expected to diversify when their firm derives greater benefits than costs from such an action (Campa and Kedia (2002)). The underlying costs and benefits which lead a manager to diversify could also influence the degree to which a manager manipulates earnings. We address this endogeneity using a battery of tests. We first use propensity score matching to assign a focused bank to each diversified bank and examine the difference in earnings management between these two banks. Next, we use a Heckman two-step model and instrumental variables approach to examine whether the private information of the decision to diversify is correlated with the propensity to use discretion in financial reporting. In each of our tests, our findings remain quantitatively similar to our initial evidence.

We take our examination of the relationship between bank diversification and earnings management further and investigate whether the association between diversification and earnings management is more or less pronounced under particular conditions. Prior authors indicate bank size strengthens the relationship between these two variables (Demsetz and Strahan (1997), De Jonghe, Diepstraten, and Schepens (2015)). We find that earnings management is more pronounced in diversified banks which are of small and medium size. Moving into non-interest

generating activities could create greater discretionary incentives for smaller banks, but not for larger banks. These findings indicate that the agency problems caused by diversification are prevalent for smaller banks. Our results are consistent with the findings of Flannery, Kwan, and Nimalendran (2004), who show small banks are more opaque and tend to engage in value-destroyed projects.

Next, we investigate whether specific financial policies can minimize the effect diversification of activities has on bank earnings management. Tran and Ashraf (2018) notes that paying dividends induces banks to engage in less earnings management when compared with non-payers. Dividends could mitigate the increased information asymmetry and agency problems caused by diversification of activities because dividends are a costly signal which remove cash from the firm and constrain the discretion of managers. Our findings indicate increases in non-interest generating activities could create greater discretionary incentives for non-paying banks, but not for dividend-paying banks. These results are consistent with Jensen (1986) and the findings of Tran and Ashraf (2018).

Finally, we investigate whether diversification affects bank earnings management differently during financial crises. We compare bank earnings management during the crisis with earnings management in the pre-crisis period. We regress our baseline model for the pre-crisis period and use the estimated coefficients to predict *DLLP* of banks during the crisis. By comparing the predicted *DLLP* with actual *DLLP* during the crisis, we create a measure of abnormal *DLLP*. We regress our abnormal *DLLP* measure on our measure of diversification and a series of controls. While the use of discretionary accruals by the banking industry as a whole increased during the crisis, diversified banks decreased their *DLLP*. Our evidence suggests that complex banks faced more scrutiny from external agents during the crisis and responded by reducing earnings

management.

Our study contributes to the literature in several ways. First, our study provides the first investigation of the impact of functional diversification on the quality of bank information disclosures. Existing literature on this relationship in non-financial firms yields mixed results. Lim, Thong, and Ding (2008), Rodríguez-Pérez and van Hemmen (2010), Chin, Chen, and Hsieh (2009), Farooqi, Harris, and Ngo (2014) lend support for our information asymmetry hypothesis, whereas Jiraporn, Kim, and Mathur (2008) support the monitoring hypothesis.

We contribute to the literature by using tests which allow us to examine both the information asymmetry and monitoring hypotheses at once and determine which effect dominates the other. Our investigation is the first to compare different theories of how bank diversification affects managerial discretion. We show increases in non-interest generating activities increase managerial discretion. This evidence supports our information asymmetry hypothesis and indicates greater diversity of operations does not lead to an improvement in the monitoring of banks.

Second, our study provides evidence of the effects of diversification over the entire range of the earnings management distribution. The traditional inference approach (i.e. the ordinary least squares) reflects the mean behavior of the sample due to the assumption of the homogeneity in the relationship between diversification and earnings management. However, we show that this relationship is heterogeneous and therefore other methods are more applicable to examining the relationship across the entire industry. Rather than relying on a single description of the central behavior of the sample, we employ the quantile approach. This approach explores a range of conditional quantile functions, which allows us to explore potential forms of conditional heterogeneity (Tran, Hassan, and Houston (2018)). We show the positive relationship between

diversification and *DLLP* increases in bank size.

Our evidence should be of interest to regulators and policymakers. After the last financial crisis, initiatives like the Vickers Report (UK) and the Dodd-Frank Act (US) proposed narrower banking policies which limited some of the permissible activities of banks (Tran, 2017). It is important to understand the factors which increased bank opacity and increased bank risk-taking prior to the Great Recession because the banking sector represents a large portion of the U.S. economy and has recently been successful in deconstructing much of the Dodd-Frank Act.¹ Our evidence suggests that there might be a previously-unexamined cost to allowing large banks to expand into non-interest generating activities. Increased diversification could increase information asymmetry between banks and their stakeholders.

The next section describes our hypotheses. Section 3 introduces our data and variables. We report our main results and alternative tests in Section 4. We report additional robustness tests in Section 5. We discuss our conclusions in Section 6.

2. Hypotheses

Little is known about the impact of diversification on the earnings management of banks. U.S. deregulation of the banking sector, which began during 1970s, allowed banks to operate with fewer constraints and expand into highly volatile and complex non-bank activities such as trading and market-making (Tran, 2017). The entrance into these industries increased the complexity of banks' balance sheets (Financial Crisis Inquiry Commission, 2011). The result of this expansion was an increase in information asymmetry at diversified banks. The casino-style gambling on Wall

¹ As of 2006, the financial sector represented approximately 6% of U.S. GDP: <http://cepr.net/blogs/cepr-blog/the-growth-of-finance-in-graphs>

Street, failures of large numbers of financial institutions, and the financial crisis in 2008-2009 led many Americans to blame banks for job losses and slow economic growth over the past decade.

The incentive to engage in earnings management could be exacerbated by diversification. Demsetz and Strahan (1997) note diversification leads to greater agency problems between top management and divisional managers and between opportunistic managers and shareholders. Top management of diversified banks could possess limited knowledge of each bank division, while division managers have special information or expertise concerning their particular sphere of activity. Their incentives could differ from those of top management (Harris, Kriebel, and Raviv (1982)), which leads to greater agency costs. Senior managers of banks which are less diversified should be more effective monitors of their divisional managers.

Banks which have diverse operations often require a large board with the ability to oversee the bank's operations, which could result in greater agency costs and allow management to gain private benefits. The complexity of modern banking requires board members with diverse backgrounds in order to monitor the firm's operations. While this large board provides valuable expertise to the bank, it could increase the agency costs between the board and shareholders and between the board and management. Yermack (1996) finds firms with large boards are poor monitors of management. Bank CEOs could gain greater private benefits from diversification of operations as the board increases in size. When a bank has a diverse set of operations and its board is unable to provide effective compensation or monitoring of management, managers have greater discretion to increase their power and prestige (Jensen (1986)), increase their managerial compensation (Jensen and Murphy (1990)), or mitigate their idiosyncratic risk (Amihud and Lev (1981)). An ambitious CEO could also direct the bank into new, profitable activities.

If a CEO decides to diversify bank operations, this action could also increase information asymmetry between the bank and its stakeholders. Lim, Thong, and Ding (2008), Chin, Chen, and Hsieh (2009), Rodríguez-Pérez and van Hemmen (2010), and Farooqi, Harris, and Ngo (2014) document a positive relation between diversification and discretionary accruals for non-financial firms. The effect of diversification on the willingness of management to manipulate accruals could be even stronger in the banking industry, where the board is unable to properly monitor or incentivize them. Therefore, we hypothesize:

H1: The information asymmetry hypothesis: Earnings management is more severe in diversified banks.

Other authors suggest a countervailing mechanism could mitigate asymmetric information in diversified banks. Diversification, along with increased complexity and bank size, could lead to increased scrutiny from regulators, financial analysts and rating agencies. With their substantial industry knowledge and interaction with management, financial analysts and rating agencies can glean new information about firm operations. They can express their concerns about a bank through research reports, recommendations, ratings, etc. (Yu, 2008). If bank management believes these information channels will provide transparency about risk-taking behavior, this belief could prevent them from engaging in behavior which would be viewed unfavorably by shareholders. Based on this argument, we posit our second, “monitoring” hypothesis. The monitoring hypothesis predicts greater diversification in activities is associated with a lower degree of earnings management because the managers of these firms face greater scrutiny from investors and other stakeholders. This hypothesis is supported by Jiraporn et al. (2008), who note corporate diversification reduces earnings management. El Mehdi and Seboui (2011) argue that industrial diversification mitigates accrual manipulation while global diversification exacerbates it.

H2: The monitoring hypothesis: Earnings management is less severe in diversified banks.

3. Data, and variables

3.1 Sample banks

We examine U.S. banks from 2001:Q1 to 2015:Q4. We rely on quarterly Y-9C regulatory reports filed by bank holding companies (BHC) with assets of \$150 million and greater. We remove any bank-quarter observations with missing or incomplete accounting variables in the main regression model. Following Berger and Bouwman (2013), we replace all observations with the ratio of total equity over total assets less than 1% to avoid distortion in ratios that contain equity. We also exclude observations with negative or nonexistent outstanding loans or deposits. Our dataset contains 54,821 observations for 2,482 BHCs. We winsorize all financial ratios at the 1% level at both the top and bottom of their distributions to dampen the effects of outliers.

3.2. Measures of Bank Opacity

Following Jiang, Levine, and Lin (2016) and Tran and Ashraf (2018), we first measure bank earnings management by focusing on loan loss provisions (LLP). Loan loss provisions (LLP) are the most critical accruals for banks (Ryan, 2012; Beatty and Liao, 2014). They are large relative to net income and equity capital (Healy and Wahlen, 1999) and provide signals of bank health for stakeholders such as creditors or regulators (Bushman and Williams (2012)). LLP reflect information asymmetry because the amounts reported depends on the judgment of the managers. We use the model of Beatty and Liao (2014) in our main analysis since there is no consensus on how to ideally model discretionary provisions.¹ This model allows us to separate the normal LLP,

¹ There is a large body of literature on earnings management which focuses on shaping an underlying model to capture the LLP characteristics. For example, see McNichols and Wilson (1988) or Healy and Wahlen (1999).

which reflect adjustments in a banks' fundamental performance, from the abnormal LLP that are due in part to managerial discretion. We calculate abnormal LLP as a proxy of bank earnings management.

$$llp_{it} = \alpha + dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + alw_{it-1} + cho_{it} + size_{it} + dloan_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \epsilon_{it} \quad (1)$$

$dnpl_{it}$ is the change in non-performing loans over the quarter, divided by total loans at the beginning of the quarter. alw_{it} is the loan loss allowance as a percentage of lagged total loans. cho_{it} represents the adjusted charge-off as a percentage of lagged total loans. $size_{it}$ is the natural logarithm of gross total assets. $dloan_{it}$ is the change in total loans over the quarter, divided by total loans at the beginning of the quarter. $csret_{it}$ is the return on the Case-Shiller Real Estate Index over the quarter. We measure $dgdp_{it}$ as the change in GSP (gross state product) over the quarter. $dunemp_{it}$ represents the change in unemployment rates over the quarter.

Once model (1) is estimated, we calculate the difference between the predicted and the actual values of LLP as discretionary LLP (Tran and Ashraf, 2018). We define non-discretionary LLP as the predicted value of LLP. We compute the absolute value of both positive and negative residuals and refer to this as our measure of discretionary accruals. This discretionary portion of LLP ($DLLP$) reflects the degree of earnings management. A greater (absolute) value of abnormal LLP ($DLLP$) reflects greater discretion by bank management, which reduces the ability of outside investors to accurately assess firm performance and valuation.

3.2. Diversification strategy and control variables

Following prior works by Stiroh and Rumble (2006), De Jonghe, Diepstraten, and Schepens (2015), and Tran (2017), we measure the diversification strategy of banks using bank

income structure, which is the ratio of non-interest income over the net operating income (*NII*).² We control for various bank-specific characteristics. These characteristics include bank size (*SIZE*), the capital ratio (*CAPITAL*), bank performance (*DUMMY LOSS*, and *EARNINGS*), and the total asset growth rate (*GROWTH*). See Table 1 for definitions.

In Table 2, we report the descriptive statistics of our sample. We find a positive correlation between DDLP and NII. Large firms are more diversified than smaller firms. Large firms engage in greater levels of earnings management.

4. Do activity strategies affect bank opacity?

4.1. Main findings

In this section, we conduct multivariate analysis to formally investigate the effect of diversification on earnings management. The empirical specification we estimate is as follows:

$$Y_{it} = \alpha + NII_{it-1} + Z_{it-1} + \mu_i + \theta_t + \varepsilon_{it} \quad (2)$$

where Y_{it} is the measure of *DLLP* of bank i at time t . Our variable of interest is *NII*, which is the ratio of non-interest incomes over the net operating incomes. Z_{it} is the vector of control variables described above. We include bank fixed-effects, μ_i , to take into account the unobservable bank invariant characteristics such as corporate culture, bank management, etc. We include time-fixed effects, θ_t , to control for time effects which can affect the risk profile of banks. ε_{it} is the error term. To mitigate the possibility of reverse causality, all bank-level control variables are lagged by one period in all regressions. We cluster standard errors at the bank level since *DLLP* is likely to be correlated within a bank over time.

² The use of other measures of diversification leads to quantitatively similar results.

We present our main results in Table 3. Model (1) reports our baseline model. The coefficient on our main variable of interest, *NII*, is positive and significant, suggesting diversified banks engage in greater earnings management than their more focused counterparts. This positive relationship between bank diversification and earning management is also economically significant. A one standard deviation increase of *NII* (*ceteris paribus*) is associated with an increase in *DLLP* of 0.0003 (i.e. the coefficient on *NII*, 0.002, times the standard deviation of *NII*, 0.137). With a mean of 0.003 and a standard deviation of 0.006, this is equivalent to a 9.1% increase in *DLLP*. This evidence is consistent with our asymmetric information hypothesis, which suggests that earnings management is more prevalent in diversified banks. Our evidence is consistent with the findings of Lim, Thong, and Ding (2008), Chin, Chen, and Hsieh (2009), Farooqi, Harris, and Ngo (2014), all of whom examine non-financial firms. Unlike Lim, Thong, and Ding (2008), we rely on a bank-specific measure of discretionary accruals.

In Model (2), we extend our baseline model by controlling for the effect of asset structure as measured by the ratio of loans to total assets (*LOAN*), the funding structure as measured by the ratio of deposits over assets (*DEPOSITS*), and the payout policy (*DUMMY DIVIDEND*). Again, we observe diversified banks experience larger *DLLP* than other banks. In Models (3) through (5), we use other econometric methods to test the relationship between bank diversification and bank opacity. In Model (3) we use alternative econometric methods such as Newey-West (Model (3)). In Model (4) we use Fama-MacBeth regression. In Model (5), we perform our baseline model with a single cross-sectional regression (average analysis) to deal with the potential error-dependence problem. By performing this time-series mean regression (one observation per bank), we eliminate the problem of serially correlated errors. This estimation still keeps the heterogeneity across banks but does not exploit the time-series variation in the observations (Tran, Hassan, and

Houston, 2018). Our findings in Models (3) through (5) are comparable to our results in the baseline model.

In Model (6), we re-perform our baseline model with only fourth quarter data. This specification is motivated by prior literature suggesting that managers are more likely to engage in earnings management during the fourth quarter than during other fiscal quarters (Liu, Ryan, and Wahlen (1997)). Again, we find diversified banks engage in greater earnings management than other banks. It is worth noting that the coefficient on *NII* is similar in every specification, suggesting the relationship between diversification and bank earnings management is quite robust.

Earnings management appears to be associated with other bank characteristics. We document that well-capitalized and fast-growing banks are less likely to engage in earnings management than other banks. The evidence also shows that highly profitable banks experience lower *DLLP* than other banks, but the coefficient is statistically insignificant. Additionally, banks experiencing losses have higher *DLLP* than other banks. We observe that large banks are more likely to engage in earnings management. However, this coefficient is not statistically significant.

³ In brief, our findings support the asymmetric information hypothesis. Diversification makes banks more complex, increases information asymmetry, and facilitates the discretionary behavior of management.

³ In an unreported test, we use alternative measures of bank size. First, since size is, to a large extent, an outcome of bank decision making, then is highly correlated with other independent and dependent variables, we decompose bank size with respect to all other independent variables into two components: an organic growth component that is measured by the fitted value, and a historical size component that equals to residual. Orthogonalizing size allows us to derive the pure effects of size (De Jonghe, (2010). Second, we also check for the nonlinear relationship between earnings management and size by including size-decile fixed effects to control for unobserved heterogeneity across banks in different size categories as suggested in Ellul and Yerramilli (2013). We obtain similar results.

4.2. Quantile regressions

In Table 4, we perform quantile regression – a generalization of median regression analysis to other quantiles – to assess whether the interplay between diversification and earnings management differ across risk quantiles. The traditional inference approach (i.e. ordinary least squares) used in earlier sections describes the average behavior of the sample with the assumption of a homogeneous relationship between diversification on bank earnings management. However, when heterogeneity is suspected in a sample, the use of the traditional OLS might not be ideal. Rather than relying on a single description of the central behavior of the sample, the quantile approach explores a range of conditional quantile functions. This approach allows us to explore potential conditional heterogeneity (Tran, Hassan, and Houston, 2018). Furthermore, the quantile regression approach avoids the restrictive assumption that the error terms are identically distributed for different levels of bank earnings management (Klomp and Haan, 2012).

The coefficients on *NII* in Models (1) - (3) show the impact of diversification on bank earnings management is indeed uniform in sign (positive) but increases significantly in magnitude with the increase of quantiles. Our empirical findings indicate diversification not only affects the conditional average *DLLP*, but also influences the *DLLP* distribution.

4.3. Alternative measures of earnings management

In Panel A of Table 5, we re-conduct our baseline model with alternative measures of bank earnings management. In Model (1), we use the natural logarithm of *DLLP* to mitigate the effect of outliers. Next, we follow Foos, Norden, and Weber (2010) and use the deviation of *DLLP* of bank *i* at time *t* from the contemporaneous industry average *DLLP* as a measure of bank earnings management in Model (2). In all specifications, our main findings are unchanged.

In Model (3), we compute excess earnings management following the “chop-shop”

approach of Lang and Stulz (1994) and Laeven and Levine (2007), which assumes the stand-alone *DLLP* of each division in financial conglomerates can be approximated as the average *DLLP* of specialized banks. We compare the *DLLP* of each bank with the *DLLP* which would result if the bank were “chopped” into separate pure-activity “shops”, each focused on a particular financial activity (i.e. either traditional activities or non-traditional activities). $DLLP^{1*}$ is the earnings management of a bank focused on traditional banking, whereas $DLLP^{2*}$ is the earnings management of a bank focused on non-traditional banking. The activity-adjusted *DLLP* for a bank with a_{it} is the ratio of non-interest incomes over the net income:

$$Activity - adjusted\ DLLPs_{it} = a_{it} * DLLPs_{it}^{1*} + (1 - a_{it}) * DLLPs_{it}^{2*} \quad (3)$$

$$Excess\ DLLPs_{it} = DLLPs_{it} - [a_{it} * DLLPs_{it}^{1*} + (1 - a_{it}) * DLLPs_{it}^{2*}] \quad (4)$$

We follow Laeven and Levine (2007) to classify focused and diversified banks and define specialized banks as banks that receive 90% of their income from one activity. $DLLP^{1*}$ equals the mean *DLLP* of banks whose net interest income represents more than 90% of their net operating income. Our tests relying on this measure yield findings consistent with those in earlier tables.

We re-estimate Equation (2) using only negative *DLLP* in Model (4). Because positive *DLLP* could represent a signal managers are sending to the markets, positive *DLLP* could enhance the quality of information of the firms⁴ (Tran and Ashraf, 2018). We show our results using only negative *DLLP* because managers are likely to use negative *DLLP* to manage earnings. Our results in Model (4) indicate a positive relationship between *NII* and this measure of discretionary accruals, which supports the asymmetric information hypothesis.

⁴ See e.g. Beaver et al. (1989), Wahlen (1994), Beaver and Engel (1996), Liu and Ryan (1995), Liu, Ryan, and Wahlen (1997) who find positive reactions of stock markets with discretionary accruals when future cash flow prospects improve. In contrast, Ahmed, Takeda, and Thomas (1999) do not find support for the signaling incentives in banks whereas Kanagaretnam, Lobo, and Yang (2004) find less consistent evidence.

Finally, we use three alternative models from Beatty and Liao (2014) to compute the *DLLP*. We include these measures of *DLLP* as the dependent variables in Models (5)-(7). We describe each of these models of *DLLP* in Table 1. Our results in Models (5)-(7) confirm our earlier findings that diversified banks engage in greater earnings management than non-diversified banks.

4.4. Alternative measures of diversification

In Panel B of Table 5, we re-run our baseline model with alternative measures of bank diversification. In Model (1), we report our results with the most controversial type of non-interest income: trading income. Following Gandhi, Kiefer, and Plazzi (2016), we sum trading revenues, interest income from trading assets, and the realized gains or losses from held-to-maturity and available-for-sale securities. Using this measure allows us to mitigate the concern that non-interest incomes may include income derived from traditional activities.

Following Stiroh and Rumble (2006), we use an adjusted Herfindahl-Hirschman index to measure diversification (*DIV_1*). *DIV_1* accounts for variations in the breakdown of net operating income (*NOI*) into two main categories: net interest income (*NII*) and noninterest income (*NON*).

$$DIV_1 = 1 - [(SH_{NII})^2 + (SH_{NON})^2] \quad (5)$$

where $SH_{NII} = NII/NOI$ and $SH_{NON} = NON/NOI$ are respectively the share of *NII* and *NON* over *NOI*. Following Laeven and Levine (2007), we compute an additional measure income diversity (*DIV_2*).

$$DIV_2 = 1 - |SH_{NII} - SH_{NON}| \quad (6)$$

where $SH_{NII} = NII/NOI$ and $SH_{NON} = NON/NOI$ are respectively the share of *NII* and *NON* over *NOI*.

Finally, we use the ratio of loans over total assets as a proxy of functional diversification (LOAN). In contrast with other measures, this measure is interpreted as an inverse diversification measure, since higher values of this loan ratio indicate a bank is focused on traditional banking activities.

Our results in Panel B of Table 5 confirm our findings from Table 3. Increased bank diversification is associated with increased earnings management. It is worth noting that the coefficient on *TRADING* (Model (1)) is larger than the coefficients in Table 3, suggesting that a move toward trading activities increases bank discretionary behavior.

4.5. Endogeneity concerns

The specification in Equation (1) of Table 3 is based on the assumption that a bank's decision to diversify is exogenous. However, the decision to diversify is deliberately made by bank managers. Managers could choose to diversify when they believe the bank will derive more benefits than costs from diversification (Campa and Kedia (2002)). However, the same characteristics that led the bank to diversify could also affect discretionary behavior of the bank (Laeven and Levine (2007)). This means our results could be driven by some unobservable characteristic of bank management which simultaneously affects the decision to diversify and the use of earnings management. If true, this possibility indicates the OLS framework is inappropriate for our analysis. Thus, we complement our OLS estimation with different approaches: a Heckman selection model, the instrumental variables approach and propensity score matching. These procedures should control for any selection bias in the estimation. Our results are tabulated in Table 6.

We first employ the propensity score matching (PSM) method developed by Rosenbaum and Rubin (1983) and extended by Heckman et al. (1997). We separate the full sample into two

groups: diversified (treated) and focused (untreated) banks. We measure the propensity of undergoing treatment (i.e. the probability of diversification) by using a logit model for both treated and untreated samples. Our dependent variable in this logit model is a binary variable which equals 1 if the bank is classified as diversified bank, and equals zero otherwise.⁵ We match each diversified bank with one focused banks sharing similar characteristics as reflected in their propensity scores.⁶ We use one-to-one matching without replacement. We find a positive relationship between diversification and DLLP. Our result in Model (1) supports our earlier finding: the incentive to manipulate earnings are stronger at diversified banks than non-diversified banks.

The matching estimator presented above mitigates the selection bias, but there could be unobservable factors causing banks to diversify operations. In Models (2) and (3) of Table 6, we use the Heckman two-step approach to eliminate the bias due to unobservable variables. We first model the selection of diversification by using the logit selection model. Then we obtain the inverse Mills ratio (IMR). Following Laeven and Levine (2007), we use the average non-interest income of other banks as an instrumental variable. We then estimate the diversification-choice using a logit model and calculate the IMR. The IMR is the conditional expectation of the model selection error term, given the banks' observable characteristics and decision to diversify. In the second stage, we re-estimate Equation (1) by including IMR as an additional control variable to correct for potential self-selection biases. Models (2)-(3) report the maximum likelihood estimates of the logit diversification-choice and our baseline model augmented by IMR. Consistent with our

⁵ We detail the first-stage in Section 5.2.

⁶ We retain only untreated observations whose propensity scores fall inside the interval defined for the treated group. We impose a tolerance level of 0.5% on the maximum propensity score distance allowed (caliper), to minimize the risk of bad matches.

core findings, we document a positive and significant coefficient of *NII*. Our results continue to support the information asymmetry hypothesis.

We conclude our inquiry into the endogeneity of the diversification decision with an instrumental variables (IV) approach. As in Model (2), the instrument is the average non-interest income of other banks. We report first-stage and second-stage IV regression results in Models (4) and (5) of Table 6. Our results in the second stage also support our earlier findings. We observe the coefficient on *NII* in the IV estimation is much larger than the coefficient from our OLS estimation. This finding lends support for the possibility of reverse causality and indicates we are justified in using an IV approach to identify the impact of going public on bank risk (Tran, Hassan, and Houston (2018)). The OLS estimation might yield coefficient estimates of the impact of *NII* on *DLLP* that are biased toward zero, whereas the IV estimation yields the more accurate (and larger) impact of *NII* on *DLLP*. It is worth noting that in Models (2) and (4), our instrumental variable is positively associated with the decision to diversify. This relationship confirms the relevance of our instrumental variables approach.

5. Additional tests

5.1. The effects of size

We take our examination further and investigate whether the association between diversification and earnings management is more or less pronounced under particular conditions. We first address the question related to the scale effect. Demsetz and Strahan (1997) and De Jonghe et. al (2015) note a positive relationship between diversification and firm size. It is widely accepted that larger regional or national banks are less focused on traditional bank lending and also face tighter prudential supervision and regulatory constraints given their systemic importance within banking sector (Tran, Hassan, and Houston, 2018). These constraints affect the incentive

to manipulate earnings by decreasing the information asymmetry between the firm and other stakeholders, such as investors, analysts, and regulators. To alleviate the concern that a few large banks are influencing our results, we exclude the top ten largest banks in Model (1). In Model (2), we exclude too-big-to-fail entities, defined as banks with assets greater than \$100B. Banks with more than \$100B in assets are subject to stress tests or the Supervisory Capital Assessment Program (SCAP) and the first Comprehensive Capital Analysis and Review (CCAR) during our sample period. We continue to find diversified banks are more likely to engage in earnings management, suggesting that our main result is not driven by too-big-to-fail or the largest banks.

Next, we report results by bank size to investigate whether our core finding is concentrated in a particular size class. In Models (3) – (5), we find that for small and medium banks (i.e. assets under \$1Bn, and \$5Bn respectively), earnings management is more pronounced in diversified banks. However, for large banks (i.e. assets over \$5Bn), we document an inverse association between diversification and earnings management incentives. It appears that amongst the largest banks, the incentive for managing earnings decreases as diversification increases.⁷ This result suggests that the monitoring effect subsumes the information asymmetry effect for larger banks.

Next, we interact bank size with diversification as a robustness check of the relationship between bank size, diversification, and bank earnings management. In Model (6) the coefficient on the interaction term ($NII*SIZE$) is negative and statistically significant. The coefficient on NII remains positive and significant. This finding indicates an increase in the percentage of non-interest income could create greater discretionary incentives for small banks. For example, a one

⁷ We also check for the nonlinear relationship between risk and size by including size-decile fixed effects to control for unobserved heterogeneity across banks in different size categories as suggested in Ellul and Yerramilli (2013). We obtain similar results. Additionally, since size is, to a large extent, an outcome of bank decision making, then is highly correlated with other independent and dependent variables, we decompose bank size with respect to all other independent variables into two components: an organic growth component that is measured by the fitted value, and a historical size component that equals to residual. Orthogonalizing size allows us to derive the pure effects of size (De Jonghe (2010)). The result is unchanged.

standard deviation increase in non-interest income for a bank at the 5th percentile (SIZE=12.231, i.e total assets of \$205 M) could lead to an increase in *DLLP* of 0.0012. The average *DLLP* in our sample is 0.0034. Therefore, this one standard deviation increase in *NII* corresponds to a 35.2% increase of *DLLP*.⁸ This effect is economically significant.

For banks within the 85th – 96th percentile based on size, (corresponding to a size range of [14.733-16.885], or a total asset range of [\$2.5Bn-\$21.5Bn]), an increase in *NII* would be negligible. The impact of *NII* becomes negative and statistically significant above the 97th percentile. In other words, for 84% of banks in our sample, an increase in non-interest income-generating activities would result in an increase of *DLLP*. For only the largest 3% of banks, this increase would lead to a decrease of *DLLP*. A one standard deviation increase of non-interest income for a bank in the 97th size percentile would lead to a 7.5% decrease in *DLLP*. We represent the marginal effect of *NII* on *DLLP* in Figure (1). Our results provide some further, limited support of the monitoring effect. However, the information asymmetry effect still dominates the monitoring effect for all but the largest 3% of banks.

Small and medium banks could lack sufficient experience, tools, or knowledge of how to minimize the agency costs of diversification into new financial products. This explanation is consistent with that of De Jonghe, Diepstraten, and Schepens (2015), who find small banks which increase non-interest income are increasingly exposed to systemic risk. Large banks are more experienced at managing risk and face greater scrutiny from external agents. This scrutiny inhibits their discretionary behavior. This finding partially supports our monitoring hypothesis and highlights the monitoring role of various disciplining stakeholders. Increased monitoring

⁸ The 5th size percentile is 12.231, the standard deviation of non-interest income is 0.137. Using the coefficient in Model (6), we have: $0.137 \times (0.021 - 0.001 \times 12.231) = 0.0012$.

incentivizes managers at large banks to refrain from discretionary behaviors which do not benefit shareholders.

5.2. The effects of dividend policy

Dividends are considered to mitigate information asymmetry and agency problems, since paying dividends is a costly signal to convey information and is used to discipline managers. Recently, Tran and Ashraf (2018) document that paying dividends induces banks to engage in lower levels of earnings management relative to non-dividend-paying firms. Dividend-paying banks may be subject to closer scrutiny from outsiders due to more frequent recapitalization from the market. More frequent bond and stock issuances should decrease the ability of managers to misrepresent information to investors since the bank would need to provide a large amount of information to potential bondholders and stockholders.

Diversification makes banks more complex, strengthening the asymmetric information problems in financial conglomerates. We investigate whether dividend policy would mitigate the asymmetric information in diversified banks. We add to our baseline model the indicator of dividend policy, *DUMMY DIVIDEND* (= 1 if banks pay dividends at time t , and = 0 otherwise) and the interaction *DUMMY DIVIDEND*NII*. Model (7) provides our results. We observe a positive and significant relationship between *NII* and earnings management. The interaction term, *DUMMY DIVIDEND*NII*, is negative and statistically significant. This negative relationship means that the increase in earnings management caused by bank diversification is reduced by the payment of dividends. This result is consistent with the information asymmetry hypothesis, since dividend-paying banks are subject to greater scrutiny by stakeholders and therefore have the incentive to avoid too much discretionary activity.

5.3. The effects of the crisis

One could argue that disciplinary forces acting on management are increased by the public's heightened awareness of bank risk. Diversified banks which are usually larger, more complex, and have important roles in the real economy. Diversified banks also face greater monitoring pressure from external agents than their non-diversified counterparts. This monitoring pressure could lead banking conglomerates to decrease financial statement manipulation during crisis periods. Organizational complexity makes it difficult for conglomerate banks to rapidly respond to crises. They might also rely on risky funding sources (e.g. wholesale funding, capital markets, etc.) which become more volatile during crises. At the same time, prior literature indicates moral hazard as a result of government intervention at the start of the crisis could decrease the discipline of large banks. These factors could either increase or decrease discretionary behaviors at conglomerate banks during crisis periods.

In Model (8) of Table 7,⁹ we investigate whether the association between *NII* and *DLLP* changes during crisis periods. We identify the last crisis from 2007:Q3-2009:Q2 following Cornett et al. (2011). We re-run Equation (1) by adding the interaction of the crisis dummy with *NII* (*NII*CRISIS*). The coefficient on the interaction term (*NII*CRISIS*) is negative and statistically significant, indicating that diversified banks decreased their *DLLP* during the crisis.

6. Conclusions

In this study, we provide one of the first large-sample investigations of the effects of operational diversification on bank earnings management. We exploit a dataset which allows us to examine firms with a high degree of information asymmetry. We show that diversification

⁹ We do not use crisis dummies as stand-alone since they are subsumed by the time fixed-effects. However, replacing time fixed-effects by crisis dummies do not change our results.

increases earnings management behavior. However, this effect is mitigated by bank size. We also document the mitigating role of dividend policy on the association between diversification and earnings management. During the crisis, diversified banks were less likely to manipulate their earnings, indicating the effectiveness of the monitoring forces from external agents. Our results are robust to a battery of sensitivity tests.

We examine whether the net effect of diversifying bank operations is an increase or a decrease in earnings management. These two possibilities are consistent with our information asymmetry hypothesis and our monitoring hypothesis, respectively. We find strong evidence that an increase in non-interest income leads to greater use of earnings management, and thus decreases transparency of the bank's operations. Only for the largest banks (top 3%) does diversification of operations have a net negative effect on the use of earnings management.

Our results should be of interest of regulators and policymakers. These results indicate managers of banks with focused operations have less incentive than managers of other banks to manipulate financial statements. The increase in opacity which results could make it difficult for shareholders to correctly value a bank or make it difficult for bondholders to know how much risk they are assuming when they buy the bank's bonds. As regulators in the U.S. examine whether to overturn regulations imposed after the financial crisis, it is important to remember the costs of such information opacity.

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Figure 1. Marginal effect of non-interest income on bank's earnings management

Table 1. Variables Definitions

This table presents definitions of all main variables used in the analysis.

Variables	Definitions
<i>Dependent variables</i>	
DLLP	Absolute value of residuals from: $llp_{it} = dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + alw_{it-1} + cho_{it} + size_{it} + dloan_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \epsilon_{it}$
LN(DLLP)	Logarithm of absolute value of residuals from: $llp_{it} = dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + alw_{it-1} + cho_{it} + size_{it} + dloan_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \epsilon_{it}$
Deviation DLLP	$DLLP_{i,t} - \text{Average } DLLP_{i,t} \text{ of the industry}$
Excess DLLP	$Excess\ DLLPs_{it} = DLLPs_{it} - [\alpha_{it} * DLLPs_{it}^1 + (1 - \alpha_{it}) * DLLPs_{it}^2]$ Where DLLP ¹ is the earnings management of a bank focused on traditional banking, whereas DLLP ² is the earnings management of a bank focused on non-traditional banking
NDLLP	Absolute value of negative residuals from: $llp_{it} = dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + alw_{it-1} + cho_{it} + size_{it} + dloan_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \epsilon_{it}$
DLLP_1	Absolute value of residual from: $llp_{it} = dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + size_{it} + dloan_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \epsilon_{it}$
DLLP_2	Absolute value of residual from: $llp_{it} = dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + size_{it} + dloan_{it} + alw_{it-1} + csret_{it} + dgdp_{it} + dunemp_{it} + \epsilon_{it}$
DLLP_3	Absolute value of residual from: $llp_{it} = dnpl_{it+1} + dnpl_{it} + dnpl_{it-1} + size_{it} + dloan_{it} + cho_{it} + csret_{it} + dgdp_{it} + dunemp_{it} + \epsilon_{it}$
<i>Components of dependent variables</i>	
NPL	Nonperforming assets over the quarter, scaled by total loans at the beginning of the quarter
DNPL	Change in NPL over the quarter, divided by total loans at the beginning of the quarter
LOAN	Total loans over the quarter
DLOAN	Change in total loans over the quarter, divided by total loans at the beginning of the quarter
ALW	Loan loss allowance as a percentage of lagged total loans
CHO	Adjusted charge-off as a percentage of lagged total loans
RSGL	Realized security gains and losses as a percentage of total assets (includes realized gains and losses from available-for sale securities and held-to-maturity securities)
URSGL	Unrealized security gains and losses (includes only unrealized gains and losses from available-for-sale securities) as a percentage of total assets;
SIZE	The natural logarithm of gross total assets
CSRET	The return on the Case-Shiller Real Estate Index over the quarter
DUNEMP	Change in unemployment rates over the quarter
DGDP	Change in GSP (gross state product) over the quarter
<i>Variable of interest</i>	
NII	Non-interest incomes over the net operating incomes
TRADING	Including trading revenues, interest income from trading assets and the realized gains or losses from the held-to-maturity and available-for-sale securities
DIV_1	$DIV_1 = 1 - [(SH_NII)^2 + (SH_NON)^2]$
DIV_2	$DIV_2 = 1 - SH_NII - SH_NON $

<i>Control variables</i>	
CAPITAL	Book value of equity over gross total assets
DUMMY LOSS	A dummy variable that equals one if net income is negative, and zero otherwise
EARNINGS	Income before taxes, provisions recognized in income over gross total assets
CRISIS	A dummy equal to 1 for a financial crisis period, and 0 otherwise.
BFE	Bank fixed effects
QFE	Time fixed effects, represented by dummies for each quarter of the sample period.

Table 2. Summary Statistics

This table reports summary statistics for the main sample of U.S. commercial banks used in the analysis. The sample period is from 2001:Q1 to 2015:Q4. All financial variables are winsorized at 1% and 99% levels.

Variable	N	Mean	Standard deviation	Min	Max	Correlation					
						DLLP	NII	SIZE	EQUITY	EARNINGS	GROWTH
DLLP	55,543	0.003	0.006	0.000	0.074	1.000					
NII	75,718	0.227	0.137	0.000	0.814	0.065***	1.000				
SIZE	75,175	13.695	1.345	12.089	19.109	0.046***	0.381***	1.000			
EQUITY	77,153	0.092	0.031	0.019	0.220	-0.006	0.067***	0.051***	1.000		
EARNINGS	76,757	0.015	0.009	-0.020	0.051	-0.147***	0.140***	0.066***	0.260***	1.000	
GROWTH	74,106	0.019	0.045	-0.085	0.229	-0.093***	-0.005	0.013***	-0.058***	0.106***	1.000
DUMMY LOSS	76,773	0.087	0.282	0.000	1.000	0.435***	0.013***	0.058***	-0.138***	-0.491***	-0.133***

Table 3. Baseline Multivariate Analysis

This table reports regression estimates of the relation between DLLP and NII. The sample period is from 2001:Q1 to 2015:Q4. The main independent variable is NII. Models (1) presents our baseline model. Model (2) augments additional variables. Model (3)-(4) use different econometric methods. Model (5) presents the average analysis (one observation by bank). Model (6) uses only 4th quarter observations. All regressions include time (quarter) fixed effects, and bank fixed effects. All financial variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics.

	Dependent variable = DLLP					
	Baseline	Additional variables	Newey-West	Fama-MacBeth	Average analysis	4th quarter
	(1)	(2)	(3)	(4)	(5)	(6)
NII	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002* (0.001)
SIZE	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000*** (0.000)	0.000** (0.000)	0.001 (0.000)
EQUITY	-0.007** (0.003)	-0.007** (0.003)	0.010*** (0.002)	0.009*** (0.002)	0.005** (0.002)	-0.007 (0.006)
EARNINGS	-0.008 (0.007)	-0.003 (0.007)	0.027*** (0.007)	0.051*** (0.005)	0.027*** (0.010)	0.015 (0.013)
GROWTH	-0.003*** (0.001)	-0.003*** (0.001)	-0.006*** (0.001)	-0.005*** (0.002)	-0.019*** (0.003)	-0.005*** (0.001)
DUMMY LOSS	0.003*** (0.000)	0.003*** (0.000)	0.006*** (0.000)	0.005*** (0.000)	0.004*** (0.000)	0.005*** (0.000)
LOAN		-0.002*** (0.001)				
DEPOSITS		-0.002** (0.001)				
DUMMY DIVIDEND		-0.000*** (0.000)				
Constant	0.001 (0.003)	0.006* (0.003)	0.001** (0.000)	0.004*** (0.001)	0.001 (0.001)	-0.004 (0.006)
Bank F.E.	Yes	Yes	Yes	Yes	No	Yes
Quarter F.E.	Yes	Yes	Yes	Yes	No	Yes
Obs.	54,821	54,633	54,821	54,821	2,483	13,196
Adj R ²	0.128	0.131	0.128	0.073	0.209	0.145
Number of_clusters	2482	2482	.	.	.	2287

Table 4. Quantile regression

This table reports regression estimates of the relation between DLLP and NII using quantile regressions. The sample period is from 2001:Q1 to 2015:Q4. All financial variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics.

	Q25	Q50	Q75
	(1)	(2)	(3)
NII	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)
SIZE	0.000*** (0.000)	0.000*** (0.000)	0.000** (0.000)
EQUITY	-0.001*** (0.000)	-0.001* (0.001)	0.008*** (0.001)
EARNINGS	-0.009*** (0.000)	-0.028*** (0.006)	-0.045*** (0.003)
GROWTH	-0.001*** (0.000)	-0.002*** (0.001)	-0.003*** (0.000)
DUMMY LOSS	0.001*** (0.000)	0.003*** (0.000)	0.007*** (0.000)
Constant	-0.000 (0.000)	0.001*** (0.000)	0.002*** (0.000)
Bank F.E.	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes

Table 5. Alternative Measures of Earnings management and Diversification

Panel A reports regression estimates of the relation between NII and alternative measures of earnings management. Panel B reports estimates using alternative measures of diversification. The sample period is from 2001:Q1 to 2015:Q4. All financial variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics.

Panel A: Alternative measures of earnings management

	ln(DLLP)	Deviation DLLP	Excess DLLP	Negative DLLP	DLLP_1	DLLP_2	DLLP_3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NII	0.411*** (0.130)	0.002*** (0.001)	0.004*** (0.001)	0.003*** (0.001)	0.002** (0.001)	0.002*** (0.001)	0.002*** (0.001)
SIZE	-0.131** (0.052)	0.000 (0.000)	-0.000 (0.000)	-0.001** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.000 (0.000)
EQUITY	0.083 (0.576)	-0.007** (0.003)	-0.007** (0.003)	-0.014*** (0.004)	-0.007 (0.005)	0.000 (0.005)	-0.007** (0.003)
EARNINGS	-3.347** (1.312)	-0.008 (0.007)	-0.010 (0.007)	-0.026*** (0.008)	-0.006 (0.010)	-0.027*** (0.009)	-0.007 (0.007)
GROWTH	-0.328** (0.137)	-0.003*** (0.001)	-0.003*** (0.001)	-0.002*** (0.001)	-0.005*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
DUMMY LOSS	0.478*** (0.030)	0.003*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.006*** (0.000)	0.005*** (0.000)	0.003*** (0.000)
Constant	-4.867*** (0.702)	-0.001 (0.003)	0.000 (0.003)	0.011*** (0.004)	-0.019*** (0.004)	-0.015*** (0.004)	0.001 (0.003)
Bank F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	54,821	54,821	54,821	31,830	54,821	54,821	54,821
Adj R ²	0.103	0.033	0.041	0.110	0.161	0.156	0.128
Number of clusters	2482	2482	2482	2388	2482	2482	2482

Panel B: Alternative measures of diversification

	Trading	Diversification_1	Diversification_2	Loan
	(1)	(2)	(3)	(4)
NII	0.003*** (0.001)	0.001* (0.001)	0.001** (0.000)	-0.003*** (0.001)
SIZE	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
EQUITY	-0.009*** (0.003)	-0.008** (0.003)	-0.008** (0.003)	-0.009*** (0.003)
EARNINGS	-0.010 (0.007)	-0.004 (0.007)	-0.004 (0.007)	-0.003 (0.007)
GROWTH	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
DUMMY LOSS	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Constant	0.003 (0.003)	0.002 (0.003)	0.002 (0.003)	0.004 (0.003)
Bank F.E.	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes
Obs.	55,494	54,821	54,821	55,542
Adj R ²	0.132	0.128	0.128	0.131
Number of_clusters	2,483	2,482	2,482	2,483

Table 6. Endogeneity concerns

The table reports regression estimates of the relation between NII and DLLP. The sample period is from 2001:Q1 to 2015:Q4. Models (1) reports results from one-to-one matching PSM. Models (2)-(3) present estimations of Heckman selection model. Models (4)-(5) present estimations of IV estimations. All financial variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics.

	PSM	Heckman selection		Instrument variables	
	(1)	1st step	2nd step	1st step	2nd step
	(1)	(2)	(3)	(4)	(5)
NII	0.003** (0.002)		0.003** (0.001)		0.032*** (0.009)
SIZE	0.000 (0.001)	0.144*** (0.020)	-0.000*** (0.000)	0.036*** (0.003)	-0.001*** (0.000)
EQUITY	-0.006 (0.007)	-1.449* (0.750)	0.007 (0.006)	0.208 (0.128)	0.001 (0.005)
EARNINGS	-0.007 (0.015)	-1.599 (2.533)	0.045** (0.021)	1.433*** (0.397)	0.027 (0.020)
GROWTH	-0.004*** (0.001)	-1.350*** (0.236)	-0.004*** (0.001)	0.006 (0.025)	-0.002** (0.001)
DUMMY LOSS	0.003*** (0.000)	-0.484*** (0.049)	0.005*** (0.000)	0.042*** (0.007)	0.005*** (0.000)
AVERAGE DIVERSITY		5.660*** (0.526)		0.067*** (0.025)	
IMR			-0.000*** (0.000)		
Constant	-0.002 (0.007)	-5.449*** (0.571)	0.005*** (0.001)	-0.365*** (0.040)	0.013*** (0.002)
Bank F.E.	Yes	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Obs.	10,866	69,050	52,858	59,659	47,224
Adj R ²	0.136		0.146	0.175	0.141
Number of_clusters	1,395	2934	2407	2780	2300

Table 7. The effects of size, dividend policy and the crisis

Table 7 reports regression estimates of the relation between DLLP and NII. The sample period is from 2001:Q1 to 2015:Q4. Models (1), (2) excludes top 10th largest banks, and TBTF banks. Models (3)-(5) report results with different size range. Models (6)-(8) reports results with interaction with size, dividend policy and crisis. All financial variables are winsorized at the 1% and 99% levels. ***, **, * indicate significance at the 1%, 5%, and 10% level respectively. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics.

	Excluded top 10th largest	Excluded TBTF	Assets <\$1B	\$1B < Assets < \$5B	Assets > \$5B	Interaction with size	Interaction with dividend	Crisis
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NII	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.002* (0.001)	-0.003** (0.001)	0.021*** (0.005)	0.003*** (0.001)	0.002*** (0.001)
NII*SIZE						-0.001*** (0.000)		
NII*DUMMY DIVIDEND							-0.002** (0.001)	
NII*CRISIS								-0.002** (0.001)
SIZE	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)	-0.001 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
EQUITY	-0.005 (0.003)	-0.007** (0.003)	-0.009** (0.004)	0.001 (0.007)	-0.015 (0.014)	-0.007** (0.003)	-0.006* (0.003)	-0.008** (0.003)
EARNINGS	-0.010 (0.007)	-0.008 (0.007)	-0.013 (0.009)	0.003 (0.013)	0.026* (0.015)	-0.008 (0.007)	-0.007 (0.007)	-0.007 (0.007)
GROWTH	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.004*** (0.001)	-0.002 (0.002)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
DUMMY LOSS	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
DUMMY DIVIDEND							-0.000 (0.000)	
Constant	0.000 (0.004)	0.001 (0.003)	0.002 (0.005)	0.001 (0.008)	0.014 (0.010)	-0.003 (0.004)	0.000 (0.003)	0.002 (0.003)
Bank F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	50,033	54,821	36,851	13,520	4,450	54,821	54,633	54,821
Adj R ²	0.127	0.128	0.114	0.130	0.157	0.129	0.129	0.129
Number of_clusters	2374	2482	2110	602	162	2,482	2,482	2482