Do "MEASURES" of Bank Diversification Measure Up? *

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This version: July 25, 2025

Abstract

We analyze the effectiveness of several widely-used measures of bank business segment diversification in capturing the 'diversification effect', i.e., the ability of a measure to explain variations in idiosyncratic risk over time and across banks. Given that different segment incomes are imperfectly correlated, standard portfolio theory would suggest that bank business segment diversification should be negatively correlated with idiosyncratic risk. We find that several commonly used measures of bank business segment diversification are either poorly or positively correlated with idiosyncratic risk, suggesting that they are inaccurate or misleading indicators of bank business segment diversification. We instead propose the 'Entropy' measure that accounts for both the number of businesses segments that a bank operates in, as well as the proportion of banks' incomes from these business segments. Entropy is significantly better at capturing the diversification effect and measuring bank diversification. Time-series variation in Entropy coincides with the passage of major banking legislations (such as the Gramm-Leach-Bliley Act in 1999 or the Dodd-Frank Act in 2010), providing an important validation for our measure. Using the Entropy measure, we revisit the question of how bank diversification impacts bank performance and risk and find that diversified banks exhibit better financial performance (ROA and ROE) and lower idiosyncratic and systemic risk (tail risk and MES), which is in stark contrast to findings in earlier papers that document an inconsistent relation between business segment diversification and bank performance.

JEL Codes: G20, G21, G24, G34.

Keywords: Bank diversification, non-interest income, Entropy measure of diversification.

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Introduction

Traditionally banks have engaged in two distinct activities – deposit-taking and lending. Modern banks, however, have diversified into a myriad set of business segments including trading, brokerage, investment banking, market-making, advisory, underwriting, insurance, and venture capital. Income from these diversified business segments has increased significantly and now accounts for the majority of income of all U.S. banks.[1] While many academic papers explore how bank business segment diversification impacts its valuation, risk-taking, and performance, this literature has paid surprisingly little attention to the effectiveness of the measures of bank business segment diversification itself – a starting point for all these studies. None of the papers ask what is a reasonable measure of bank business segment diversification and how well do these existing popular measures fare in terms of capturing the extent of bank business segment diversification.[2] Our paper is the first to systematically analyze the efficacy of various bank diversification measures and make a practical recommendation for regulators and researchers in this area.

We evaluate the performance of various measures of bank diversification in capturing the 'diversification effect', i.e., the ability of the measure to explain variation in idiosyncratic risk over time and across banks. Portfolio theory suggests that bank diversification should be negatively correlated with measures of idiosyncratic risk, especially if such diversification produces income streams that are imperfectly or negatively correlated with each other. Compared to an inaccurate measure of bank diversification, a true or accurate measure of bank diversification should be better at capturing the diversification effect, i.e., the true measure must be negatively correlated with the bank's idiosyncratic risk. This basic insight from modern portfolio theory forms the basis for our empirical tests.

Existing measures of bank diversification can be misleading indicators of a bank's true diversification for one simple reason – they are calculated using just two items on banks' income statements,

[1]For the aggregate U.S. bank sector, non-interest income (i.e., income from activities other than deposit-taking and lending) accounted for only 25% of total income in 1996 but was substantially higher at nearly 54% of net income by 2020.

[2]The banking literature focuses on both geographical and business segment diversification. Our paper, however, focuses only on bank business segment or "product-market" diversification. Henceforth, we use bank diversification to refer to bank business segment diversification.

namely, net interest and net non-interest income, respectively. They do not account for the fact that bank net interest and net non-interest incomes are in turn derived from a variety of business segments. Bank interest income can accrue from bank interest income and expenses obtained from loans, deposits, trading in securities, and participation in the Federal Funds market interbank markets. Similarly, bank non-interest income can stem from a variety of business segments such as trading, insurance, securities underwriting, venture capital, etc.[3]

A simple example illustrates why accounting for multiple business segments can matter. Consider two banks A and B. Bank A earns interest income from lending (\$50) and from trading securities (\$50). It also earns non-interest income from insurance (\$100) and venture capital activities (\$100). Bank B earns interest income from lending (\$100) and non-interest income from insurance (\$200). Since both banks earn \$100 in interest and \$200 in non-interest income, existing measures of bank diversification (which are simply based on the ratio of interest to non-interest income) would deem these banks to be equally diversified, despite the fact that bank A operates across twice the number of business segments as compared to bank B. While the ratio of interest to non-interest income is the same for both banks, Bank A could have lower idiosyncratic risk, especially if incomes from loans, trading debt securities, insurance, and venture capital are imperfectly correlated. Thus, in empirical tests, existing diversification measures may perform poorly as compared to measures that use more granular data when attempting to capture the diversification effect.

We consider seven different measures of bank diversification, six of which are widely used in the literature: These are (i) one minus the Herfindahl-Hirschman index of total non-interest and total interest income (Hhindex), (ii) one minus the absolute value of the difference between net interest and total non-interest income divided by the sum of net interest and total non-interest income (Absdiff), (iii) the ratio of *net* non-interest income to the sum of *net* non-interest and interest income (R-netnet), (iv) the ratio of *total* non-interest income to the sum of *total* non-interest and *net* interest income (R-totnet), (v) the ratio of *total* non-interest income to *total* non-interest and

[3]From now on, consistent with the prior literature, we use interest income and non-interest income to denote net of income over expenses.

interest income (R-tottot), and (vi) finally, the *simple* ratio of total non-interest to interest income (R-simple). These measures have been used widely in studies such as Stiroh (2004), Stiroh (2006), Stiroh and Rumble (2006), Baele, De Jonghe, and Vander Vennet (2007a), Laeven and Levine (2007), Lepetit, Nys, Rous, and Tarazi (2008a), Demirguc-Kunt and Huizinga (2010), Guerry and Wallmeier (2017), and Saunders, Schmid, and Walter (2020a), among many others.

The seventh measure of bank diversification – the one we propose as the most informative based on our empirical results – is Entropy. It is computed as the weighted sum of income that a bank derives from various business segments, where the weights are the logarithm of the inverse of the income that the bank derives from that segment. This measure was first introduced in industrial economics (Jacquemin and Berry (1979)) but has been adopted in finance to measure firm diversification by Khanna and Palepu (2000). In our bank setting, Entropy is computed using data for income that a bank derives from sixteen different categories of business segments – seven for interest income and nine for non-interest income – that are the most granular data for bank income that one can get from the publicly-available, quarterly call reports required to be filed by all U.S. bank holding companies. The Entropy measure offers a clear conceptual advantage as it not only accounts for the number of distinct business segments in which a bank operates, but also considers the distribution of a bank's total income across these business segments. For our hypothetical banks A and B above, Entropy equals to 1.33 and 0.64, respectively, indicating (correctly) that 'A' is more diversified or operates across more business segments than 'B'.

We begin our empirical analysis by documenting that at the aggregate bank sector level the six widely used measures of bank diversification exhibit low correlation with each other, despite the fact that each measure proffers to accurately assess the degree of diversification by banks into various business segments. These low correlations are surprising given that the only difference among these measures is that they use net or total interest and non-interest income to measure bank diversification. Entropy also exhibits very low correlation with all the existing measures of bank diversification; however, this is simply due to the fact that computation of Entropy relies on more granular and detailed data than the computation of the six other measures. The correlation of

Entropy with existing measures ranges from a minimum of -0.02 (with R-simple) to a maximum of 0.41 (with R-netnet). The low correlations among various measures of bank diversification provide another rationale for our study to determine the best measure of bank diversification.

Time-series plots for Entropy for the aggregate U.S. bank sector show that variation in Entropy coincides with the passage of major legislations related to banking, providing an important test. For instance, Entropy increases significantly and remains at elevated levels for all banks post-1999 – when the Gramm-Leach-Bliley (GLB) Act repealed restrictions on banking activities placed by the Glass-Steagall Act of 1933. Post-GLB, Entropy for small banks increased by 64% which is nearly two- to three-times higher than increases for large- and medium-sized banks. Pre-GLB, small banks likely faced binding constraints on activities, whereas larger banks could operate in multiple business segments via Section 20 subsidiaries.[4] Most importantly, no other measure of diversification shows a significant increase post-1999. Similarly, Entropy drops significantly and remains at low levels for all banks post 2007-2009, and especially after the passage of the Dodd-Frank Act of 2010 which places restrictions on proprietary trading and other risky activities. While all other measures also fall during 2007-2009, indicating perhaps that bank interest- or non-interest income fell during the crisis, they soon revert to their pre-crisis levels. Thus, existing measures of bank diversification suggest that commercial banks in the U.S. were as diversified after Dodd-Frank as they were before, which may not be the case.

Next, we examine at the bank-level all seven measures of bank diversification for each bank for each quarter in our sample. We systematically investigate the link between all measures of bank diversification and the diversification effect, i.e., the ability of the measure to explain variation in bank idiosyncratic risk over time and across banks. We do this by running predictive (panel) regressions, and check whether measures of bank diversification predict bank idiosyncratic risk one quarter ahead. We expect that an accurate measure of bank diversification should predict lower, i.e., be negatively correlated with idiosyncratic risk. In all our tests idiosyncratic risk is measured using the idiosyncratic volatility of bank stock returns, i.e., by the standard deviation of residuals

[4] For a detailed explanation of how Section 20 subsidiaries of large commercial banks entered the underwriting and insurance activities of investment banks, see Kim, Palia, and Saunders (2008).

obtained from regressing daily bank-level stock returns on the Fama and French (1993) 3-factor model.

Entropy emerges as the strongest (negative) predictor of idiosyncratic volatility. In univariate tests, a one standard deviation increase in Entropy at the bank-level implies that bank idiosyncratic volatility next quarter will be lower by nearly 0.18%. The average quarterly idiosyncratic volatility for the banks in our sample of 1.91% implies that higher Entropy is associated with a nearly 10% lower idiosyncratic volatility over the next quarter as compared to the sample mean. Controlling for bank-level characteristics, a one standard deviation increase in Entropy is associated with a nearly 0.08% reduction in bank idiosyncratic volatility over the next quarter (i.e., a nearly 5% reduction as compared to the sample mean).

Compared to Entropy, the ability of other measures of bank diversification to capture diversification and predict one-quarter ahead idiosyncratic volatility is either ambiguous or weak at best. After controlling for bank-level characteristics, none of the other measures appear to be related to one-quarter ahead idiosyncratic volatility. In fact, in some cases an increase in a diversification measure is associated with an increase rather than a decrease in one-quarter ahead idiosyncratic volatility.

These results survive a battery of robustness tests and changes in the empirical specification. In a horse race when including multiple measures of bank diversification in the same regression specification, Entropy is the only measure that consistently, and negatively, predicts one-quarter ahead idiosyncratic volatility across all specifications. The relation between Entropy and one-quarter ahead idiosyncratic volatility remains statistically significant in all sub-samples, and also in both normal times, and periods of recessions and financial crisis. Entropy emerges as the strongest predictor for bank idiosyncratic volatility regardless of the factor model used to estimate such volatility (CAPM, Fama-French 3-, or 5-factor models). Also, Entropy emerges as the best predictor when we use alternate market-based measure of bank diversification such as the R^2 from a regression of bank stock returns on systematic asset pricing factors (Demsetz and Strahan (1997)) as the dependent variable. Additionally, Entropy is not only the best predictor of idiosyncratic volatility just 1-quarter ahead but remains so up to 4-quarters ahead. None of the other measures of bank diversification used in the literature have any statistically significant ability to predict idiosyncratic volatility more than 1-quarter ahead.

We also estimate to what extent a market participant could have predicted one quarter ahead idiosyncratic volatility of banks in real time, using the data available to that point in time using the seven different measures of bank diversification. That is, we conduct an out-of-sample predictability test. We estimate the ability of a measure to predict out-of-sample bank idiosyncratic volatility by computing the root mean squared error, defined using the actual (i.e., realized) and predicted values of bank idiosyncratic volatility. Our results indicate that when forecasting one quarter ahead bank idiosyncratic volatility out-of-sample, the Entropy measure generally outperforms all other measures of bank diversification.

In our final test, we present a practical application which demonstrates how our study – which to our knowledge is the first to introduce the Entropy-based metric for bank diversification using the most granular data available and also the first to test which bank diversification measures accurately capture the diversification effect – can be used by regulators and researchers. In the banking literature, a significant controversy remains about how diversification affects bank performance and risk. On one hand, Stiroh (2006) and Lepetit, Nys, Rous, and Tarazi (2008a) document that diversification adversely affects market- and accounting-based measures of bank performance and risk. On the other hand, Demirguc-Kunt and Huizinga (2010) and Saunders, Schmid, and Walter (2020a) find that higher diversification is associated with higher return on equity and higher Z-scores, thus indicating improved profitability and lower bankruptcy risk for diversified banks. Our results suggest that these mixed results in the literature may partially be due to the fact that each paper uses a different or inaccurate measure to estimate bank diversification across business segments. We revisit these questions using the 'best' measure of bank diversification (i.e., Entropy).

We document a positive relation between bank diversification (as measured by Entropy) and bank performance as measured by return-on-assets and return-on-equity. Higher Entropy is also associated with lower risk for banks as measured by Z-scores, tail risk, and systemic risk (SRISK), respectively. For all banks, a one standard deviation increase in Entropy is associated with a nearly 17% increase in return-on-assets, 22% increase in return-on-equity. A one standard deviation increase in Entropy also corresponds to a nearly 5% improvement in their Z-scores, a nearly 3% reduction in tail risk, and a nearly 10% reduction in SRISK as compared to the sample means of these variables. These results are statistically and economically significant and suggest that more diversified banks benefit from higher profitability and lower bankruptcy risk. The link between other six measures of bank diversification and bank performance and risk is ambiguous. In some cases, when using current popular measures of diversification, the coefficients are sometimes positive, at other times negative, and in many cases statistically insignificant. Thus, the divergent results in the literature regarding bank diversification and bank performance may at least partly be attributed to the use of different or inaccurate measures of bank diversification. This result demonstrates how our study can be used by both regulators and researchers in this area to revisit several questions regarding the link between bank diversification and bank valuations, bank risk, and bank equity returns.

Our paper is linked to the vast literature on diversification by both financial and nonfinancial firms (see, for example, Lang and Stulz (1994), Berger and Ofek (1995), Hubbard and Palia (1999), Campa and Kedia (2002), Hann, Ogneva, and Ozbas (2013), and Kuppuswamy and Villalonga (2016), among many others). Specifically, we contribute to the literature on bank diversification and its impact on bank valuations. A comprehensive review of this vast literature is beyond the scope of this paper. This literature has explored various dimensions of bank diversification which includes both geographic diversification (Deng and Elyasiani (2008), Goetz, Laeven, and Levine (2013), Goetz, Laeven, and Levine (2016), Levine, Lin, and Xie (2021), and Gelman, Goldstein, and MacKinlay (2023)) as well as bank loan portfolio diversification (Acharya, Hasan, and Saunders (2006) and Shim (2019)). Our paper, instead, relates to the large literature on diversification by banks into multiple business segments and activities. Important papers in this area include Demsetz and Strahan (1997), Stiroh (2004), Stiroh and Rumble (2006), Baele, De Jonghe, and Vander Vennet (2007a), Laeven and Levine (2007), and Saunders, Schmid, and Walter (2020b), among many others. Our paper is different from these papers as it focuses on systematically analyzing which diversification measure for banks used in the literature is the most effective. It is also the first to construct a detailed measure of bank diversification using the most granular data for the 16 different business segments available from the quarterly call reports required to be filed by all U.S. banks. Thus, our study can help reconcile some of the divergent results in the literature regarding bank diversification – such as Demirguc-Kunt and Huizinga (2010) and Saunders, Schmid, and Walter (2020b) who find bank diversification leads to *higher* insolvency risk and Lepetit, Nys, Rous, and Tarazi (2008b) who show that diversified banks have *lower* Z-scores.

Our paper is closest to Demsetz and Strahan (1997), who compute a market-based measure of bank diversification (the R^2 from a regression of bank stock returns on systematic asset pricing factors) and relate it to bank size and risk-taking. In this paper, we use a similar approach to ask which measure of bank diversification derived from balance sheet data is the most effective at capturing the market-based diversification effect. The advantage of identifying the best measure of bank diversification derived from financial statements data is that once identified, it can be computed for both publicly-listed as well as private banks.

Our analysis only focuses on identifying which of the popular measures of bank diversification used in the extant literature are best at capturing the diversification effect. Thus, our study has nothing to say about why banks choose to diversify into a wide range of business segments, and why such diversification varies over time and across banks. The degree of business segment diversification that a particular bank chooses to undertake is of course an endogenous choice, but this question is outside the scope of our analysis.

The rest of the paper is organized as follows: Section 1 discusses our research design. In section 2 we describe our data sources and the methodology used to compute key dependent and independent variables. Section 3 presents our key empirical results and analyzes the efficacy of various bank diversification measures in capturing the diversification effect and diversification's impact on bank performance. Finally, section 4 summarizes and concludes.

1 Research design

We begin by establishing an empirical benchmark to evaluate which of the measures of diversification proposed in the literature is the 'best' measure. We do so by relying on three straightforward economic insights. The first economic insight comes from the standard leverage and capital structure invariance effect of Modigliani and Miller (1958) which allows us to relate the return on real assets for any bank to the weighted average of the return on financial assets, the weights in all cases being determined by the relative market value of each of the financial assets.

To illustrate, consider a bank i, with total assets A_i, funded by total debt of D_i and total equity of E_i. In this example, i can stand for an individual bank or the entire aggregate banking sector. Denoting the bank's return on equity and debt by $R_{i,E}$ and $R_{i,D}$, respectively, we can compute the return on bank's assets as:

$$R_{i,A} = \frac{E_i}{A_i} R_{i,E} + \frac{D_i}{A_i} R_{i,D} \tag{1}$$

Hanson, Shleifer, Stein, and Vishny (2015) show that the average bank finances nearly 80% of its assets with deposits. That is, deposits raised from customers comprises nearly all of debt financing for a typical bank. Typically, the volatility of debt is much smaller than the volatility of equity, and this is likely to be even more so for deposit financing. Further, if we assume, as is reasonable, that the correlation between debt returns (i.e., deposit rates) and equity returns is small, we can use equation (1) to relate the asset variance to the equity variance of bank i as:

$$\begin{aligned} \sigma^2_{i,A} &= \frac{E_i^2}{A_i^2} \sigma^2_{i,E} \\ \sigma^2_{i,E} &= \frac{A_i^2}{E_i^2} \sigma^2_{i,A} \end{aligned} \tag{2}$$

The above description is fairly simplistic, but it captures our core idea very well. More sophisticated models provide a more accurate description of this relationship. For e.g., in the Merton (1976) model, equity variance is related to asset variance in a non-linear manner. Nagel and Purnanandam (2020) show that the application of the Merton (1976) model can be problematic for banks given the special nature of bank assets. However, in all classes of models, the broad relation between equity variance and asset variance remains positive.

Our second economic insight comes from the arbitrage pricing theory of Roll and Ross (1984) which suggests that returns on any class of assets can be expressed as a linear combination of factors, i.e., a linear factor model. If bank equity returns follow a factor structure or a factor model, then bank equity returns and bank equity return variance can be further decomposed according to the equation below. In this equation, $\beta_{i,F}$ captures the sensitivity of stock returns for bank i to the selected factor (F), σ_F^2 is the variance of factor F, and $\sigma_{i,\epsilon}^2$ represents idiosyncratic variance:

$$\beta_{i,F}^2\sigma_F^2 + \sigma_{i,\epsilon}^2 = \frac{A_i^2}{E_i^2}\sigma_{i,A}^2 \tag{3}$$

We use a one-factor model for both equity returns and equity variance in equation (3) to show only a parsimonious representation. Advanced factor models such as, the 5-factor Fama and French (2015) model or the q-factor model of Hou, Xue, and Zhang (2015), that relate equity returns to multiple factors could easily be used, and will provide a more accurate explanation of the time-series and cross-sectional variation in equity returns and variance.

Our final economic insight comes from standard portfolio theory that allows us to decompose the asset variance of a bank that invests in a portfolio of multiple business segments using both the asset variance of each segment as well as its correlation structure with all other business segments. In other words, consider a bank that distributes its total assets A among N business segments. Let the share of bank assets invested in each segment be given by x_j with $j = 1, ..., N$. Then, we can decompose the asset variance of the bank as:

$$\begin{aligned} \sigma_A^2 &= \sum_j x_j^2\sigma_j^2 + \sum_j\sum_k x_j x_k \sigma_{j,k} \qquad (4) \\ \sigma_\epsilon^2 &= \frac{A^2}{E^2}\left(\sum_j x_j^2\sigma_j^2 + \sum_j\sum_k x_j x_k \sigma_{j,k}\right) - \beta_F^2\sigma_F^2 \end{aligned}$$

Equation (4) relates bank idiosyncratic variance directly to the extent of bank balance sheet diversification across multiple business segments. That is, controlling for bank leverage, factor volatility, and factor exposures, more diversified banks should have lower idiosyncratic variance. This relation, which we refer to as the diversification effect throughout the rest of the paper, forms the basis for all our empirical tests. In our empirical section, we compute different measures of diversification proposed by the literature to measure bank asset diversification and test how well they correlate with or predict equity idiosyncratic variance or volatility.

Note that Equation (4) suggests that the extent of diversification be measured using the market value of dollars that a bank invests in different assets i.e., the market value of assets the bank has devoted to multiple business segments. For banks, data on market value of assets devoted to multiple business segments is not readily available. For a typical bank in our sample, commercial, real-estate, and personal loans account for nearly 90% of all assets and most of these are recorded at historical book values, with no adjustment for current market value of these assets. The market value of bank loans is also extremely hard to compute given data accessible to researchers (for e.g., see Gorton and Pennacchi (1995)). Further, book values of bank asset can also be very noisy due to the accounting treatment of assets such as goodwill and investment in subsidiaries as well as variation over time in rules proposed by the Federal Reserve in how to classify certain bank assets.[5]

For all of the reasons listed above, we follow the extant banking literature and use data for income that a bank derives from multiple business segments (rather than book value of assets) to measure the extent of its diversification across multiple business segments. Measures of diversification based on income depend on the flow of earnings that a bank generates from multiple business segments, and in our view are better proxies for the market value of assets that a bank devotes to multiple business segments than historical book value of assets.

[5]See for e.g., Beatty and Liao (2014) for a comprehensive analysis of how accounting rules and regulatory regimes can impact the book value of bank assets and liabilities as well as bank behavior.

2 Data and summary statistics

In this section, we identify the set of banks used in our analysis, describe and compute the various measure of bank diversification, and presents summary statistics for these diversification measures for the cross-section as well as the aggregate U.S. bank sector. We also describe data sources and present summary statistics for all our dependent, explanatory, and control variables.

2.1 Sample selection

We collect balance sheet data from the 'Report for Condition and Income' (henceforth, the Call Report) required to be filed by all FDIC-insured bank holding companies (henceforth, banks). In the U.S., banks with total book value above $500 million file this report quarterly whereas other banks file this report semi-annually. We restrict our sample to banks which file the Call Report quarterly and are publicly listed (i.e., data for their stock returns and market capitalization is available). This restriction implies that our sample includes 560 unique banks. Our sample includes the largest banks in the U.S. that collectively account for more than 90% of total U.S. banking sector assets at any point in time. Focusing on banks with total book value above $500 million that are publicly listed is that it allows us to analyze data at the highest frequency possible. Call Report data with details for income that a bank derives from different categories starts in September 1996, and this determines the start date of our sample.[6]

A typical bank owns multiple subsidiaries that provide commercial banking or other financial services. Banks can also have stakes in non-financial firms although such ownership cannot exceed 5% of the non-financial firm's outstanding equity. For Call Reports, a bank is required to aggregate data only for subsidiaries that provide commercial banking or other financial services. Thus, by definition our data excludes non-financial subsidiaries owned by a bank, if any. A drawback of our aggregated data is that we are unable to say how diversification within an individual commercial banking subsidiary impacts its operations. However, since most banks with several subsidiaries

[6]As of March 2024, the total number of banks in the U.S. is 4,568. However, most of these banks are small or are privately-owned and stock return data is not available for them. Thus, we are unable to compute measures of idiosyncratic risk for banks that are excluded from our analysis.

manage capital centrally (Avraham, Selvaggi, and Vickery (2012)), our aggregated data provides the ideal empirical setting for our analysis. In addition, for all banks in our sample, traded equity prices reference the entire firm, and not individual subsidiaries. Were we to use data only for individual commercial banking subsidiaries, we would be unable to carry the analysis that relies on traded equity returns.

2.2 Measuring the extent of bank diversification

We begin by collecting the most granular data for income and expenses that is available across all business segments for all banks using the publicly-available, quarterly call reports required to be filed by all bank holding companies. Specifically, we collect data for income and expenses across sixteen different categories of bank business segments - seven for interest income and nine for non-interest income. The seven sources of interest income include income and expenses that a bank accrues or incurs from: (i) loans in both domestic and international branches, (ii) leases - including both direct and leveraged leases, (iii) balances at depository institutions, (iv) securities, including both U.S. Treasury and agency obligations as well as mortgage-backed securities, (v) trading assets, (vi) federal funds sold and repurchase agreements, and (vii) any other sources of fixed income. The nine sources of non-interest income include income and expenses that a bank accrues or incurs from: (i) fiduciary activities, (ii) services on domestic deposit accounts, (iii) Trading activities, (iv) activities related to securities and insurance, including brokerage services, investment banking, annuity sales, and insurance or reinsurance operations, (v) venture capital, (vi) servicing activities related to mortgages, credit cards, and other financial products, (vii) securitization, encompassing gains, losses, and fees associated with securitization and structured finance, (viii) sale of loans, leases, and real estate, and (ix) any other sources of non-interest income (for e.g., revenue from safe deposit box rentals and U.S. savings bond redemptions, etc.). Table A3 in the Appendix lists the sixteen categories of interest and non-interest income and expenses for banks and the item codes in the Call Report data used to identify them.

We separately aggregate the data for the seven sources of interest income and the nine sources of non-interest income to compute the total and net interest and non-interest incomes for each bank for each quarter. Using the aggregated values of total and net interest and non-interest incomes, we construct the six measures of bank business segment diversification widely used by practitioners, regulators, and academics to measure bank diversification: These are (i) one minus the Herfindahl-Hirschman index of total non-interest and total interest income (HHindex), (ii) one minus the absolute value of the difference between net interest and total non-interest income divided by the sum of net interest and total non-interest income (Absdiff), (iii) the ratio of *net* non-interest income to the sum of *net* non-interest and interest income (R-netnet), (iv) the ratio of *total* non-interest income to the sum of *total* non-interest and *net* interest income (R-totnet), (v) the ratio of *total* non-interest income to *total* non-interest and interest income (R-tottot), and (vi) finally, the *simple* ratio of total non-interest to interest income (R-simple). These measures have been used widely in studies such as Stiroh (2004), Stiroh (2006), Stiroh and Rumble (2006), Baele, De Jonghe, and Vander Vennet (2007a), Laeven and Levine (2007), Lepetit, Nys, Rous, and Tarazi (2008a), Demirguc-Kunt and Huizinga (2010), Guerry and Wallmeier (2017), and Saunders, Schmid, and Walter (2020a), among many others. The detailed definition of these six measures of bank diversification is listed in Table 1

In addition, we follow Jacquemin and Berry (1979) and Khanna and Palepu (2000) to define Entropy for banks. To compute Entropy, we first compute the share of income derived by bank i in quarter t from source j, namely, $(S_{j,i,t})$. That is, $S_{j,i,t}$ is simply the ratio of the income derived by bank i, in quarter t, from source j, to the total income derived from all sixteen interest and non-interest income sources listed above. In each quarter t, for each bank i, Entropy is then defined as the weighted sum of the income shares $S_{j,i,t}$, where the weight equal the natural logarithm of the reciprocal of the income share. Thus, Entropy for bank i in quarter t equals (detailed definition in the last row of Table 2.2):

$$Entropy_{i,t} = \sum_{16}^{1} S_{j,i,t} ln\left(\frac{1}{S_{j,i,t}}\right) \tag{5}$$

Entropy can range from a maximum of 2.77 to a minimum of 0 for any bank. Entropy for a bank that gets $1B from each of the 16 sources would equal 2.77. Such a bank, with income uniformly distributed across all 16 business lines, is maximally diversified as measured by Entropy. Entropy for a bank that reports $15B for one income item, $1B for another, and zero for all remaining sources would equal 0.23. Such a bank has almost the lowest level of diversification per Entropy measure. Table A4 in the Appendix shows the value of the seven measures of diversification for the five largest bank holding companies in the U.S. in 2020. Entropy values for these five banks range from 1.50 to 1.80, which compared to the maximum value of of 2.77 indicates that these banks are well-diversified. In contrast, other measures of diversification do not consistently select the bank with the most or least diversification. For example, in Column 4 of Table A4, Absdiff is lowest for Goldman Sachs (0.22) indicating it has low business segment diversification as compared to the remaining four banks. However, in Column 5, R-totnet is the highest for Goldman Sachs (0.89) indicating it is the most diversified of the five banks.[7]

Panel A of Table 2 presents summary statistics for the cross-section of banks. The average bank in our sample has an Entropy of 1.18 with a standard deviation of 0.36. The dispersion in Entropy is large as it varies from 0.95 to 1.43 for banks at the 25^{th} and the 75^{th} percentile, respectively. The maximum value of Entropy for any bank over our sample period is 2.47, compared to the maximum theoretical possible value of 2.77. Panel A also presents summary statistics for the six other measures of diversification commonly used in the literature. We observe that the means of many measures of diversification differ significantly even though there are only minute differences in their definitions. For instance, the means of R-netnet, R-totnet, and R-tottot are -0.66, 0.25 and 0.19, respectively, even though these measures only differ in whether they use total or net interest and non-interest incomes to compute the diversification measures.

Panel B of Table 2 presents summary statistics for the aggregate bank sector. To compute aggregate time-series, we start with data for individual banks. We filter the top and bottom 1-percentile of banks based on the quarterly growth rate in total book value of assets. This filter

[7] Note that the logarithm of income for any business segment is not defined for negative values of income. In these cases, which account for less than 28% of our observations, we follow Jacquemin and Berry (1979) and Khanna and Palepu (2000) and set the logarithm of income in equation 5 to 0 for all business segments which report losses in any quarter.

removes observations for those bank-quarters in which banks are involved in significant mergers. For aggregation, we require that for each quarter Call Report data for a particular bank is available for the previous and current quarters. This requirement ensures that our series are not affected by entry or exit of banks.[8] We then aggregate the income and expenses data for across each of the sixteen different categories of bank business segment listed above to obtain time-series data for the aggregate bank sector. We repeat this process for all sixteen categories, and then use the aggregated data to compute the seven measures of bank diversification listed in Table 1.

Panel B shows that there is substantial time variation in the measures of diversification for the aggregate bank sector across time. For example, Entropy for the aggregate bank sector has a mean of 2.04 with a standard deviation of 0.27. Other measures of diversification commonly used in the literature also vary over time. As was the case for the cross-section of banks, the mean values of commonly used measures differ substantially from each other. Since in Table 2 bank diversification measures have substantially different means and standard deviations, in all our empirical tests (that compare the ability of these measures to capture the diversification effect), we use standardized variables. Thus, coefficients on all diversification measures in all our regressions are directly comparable.

We plot time-series of Entropy for the aggregate U.S. bank sector in Figure 1. In this figure, the gray-shaded bars represent periods of NBER recessions or financial crisis. The time-series plot shows that variation in Entropy coincides with the passage of major legislations related to banking. For instance, Entropy increases significantly and remains at elevated levels for all banks post-1999 – when the Gramm-Leach-Bliley Act repealed the restrictions placed on banking activities by the Glass-Steagall Act of 1933. In similar plots (A1) no other measure of diversification shows a significant increase post-1999.

Similarly, Entropy drops significantly and remains at low levels for all banks post 2007-2009, and especially after the passage of the Dodd-Frank Act of 2010. While all other measures also fall during 2007-2009, indicating perhaps that bank non-interest income fell during the crisis, they soon revert to their pre-crisis levels. Thus, existing measures of bank diversification suggest that

[8]This requirement also means that the actual number of banks used in any quarter varies over time.

commercial banks in the U.S. were as diversified after Dodd-Frank as they were before, which may not be the case. The plot in Figure 1 suggests once again that the Entropy measure is best at capturing the degree of business segment diversification by banks, as it is the only measure that seemingly reacts to changes in regulations that place or remove restriction on banks' activities.

Figure 2 plots Entropy for domestic banks in the U.S. grouped by size. In each year, for each quarter, we group all banks into three size groups as measured by total book value of assets. For all banks in each group, we aggregate data for all sixteen categories of interest and non-interest income and use the aggregated time-series to compute Entropy for each group. Each panel in Figure 2 plots the time-series of Entropy for a particular group of banks. Thus, the left, middle, and right panels plot Entropy for small, medium, and large banks, respectively.Small banks are those with less than \$1.5 billion in book value of assets. Medium banks have \$1.5 – \$10 billion in book value of assets. Finally, large banks are those with more than \$10 billion in book value of assets. In each panel, the blue solid line plots Entropy. The Figure indicates that, just as was the case for the aggregate bank sector, Entropy varies over time in response to changes in banking legislations for banks of all sizes. We observe that Entropy increases post-1999 for small medium and large banks and also declines post-Dodd-Frank for all three categories of banks.

In addition, note that over 1999-2007 (i.e., just after the passage of GLB Act and till the financial crisis of 2007), entropy increases the most for small banks, followed by medium, and then large banks. For small, medium, and large banks, Entropy increases by 64%, 21%, and 34%, respectively. Thus the increase in Entropy for small banks is nearly two to three times as compared to that for medium and large banks in the post GLB era. This is consistent with the fact that prior to the passage of GLB Act, small banks were the most constrained by the Glass-Steagall Act. Pre-GLB, the Federal Reserve allowed many large and medium banks to operate in diverse business segments via Section 20 subsidiaries (Kim, Palia, and Saunders (2008)). Small banks typically found it costly to establish such subsidiaries and were mainly restricted to traditional banking activities of deposit-taking and lending. Since the activities constraint was most binding for small banks in the pre-GLB era, it not surprising that post-GLB, these banks act to diversify more than medium and large banks, which were already diversified to some extent.

Table 3 documents how various measures of bank diversifications correlate with each other. Panels A and B present correlations for the cross-section and the aggregate bank sector, respectively. A number of interesting facts emerge from this analysis. First, with few exceptions, most measures of bank diversification are positively correlated with each other, and that these correlations are statistically significant at conventional levels (1% level or better). For instance, for the cross-section of banks, as well as for the aggregate U.S. bank sector, the R-tottot and R-simple measures have a correlation of 90% or above.

Second, we note that the at the aggregate bank sector level, some widely used measures of bank diversification also exhibit low (positive) correlation with each other despite the fact that each of these measures assess the degree of bank business segment diversification. These low correlations are surprising given that the only difference among some of these measures is whether they use net or total interest and income. For e.g., the R-tottot measure has a correlation of just 0.05 (not statistically significant) with the R-netnet measure.

Finally, we note the low correlation of Entropy with all existing measures of bank diversification, which ranges from a minimum of -0.02 (with R-simple) to a maximum of 0.41 (with R-netnet). These low correlations for Entropy may be due to the fact that computation of this measure relies on much more granular and detailed data than the computation of other measures. Overall, the low correlations among various measures of bank diversification in Table 3 provide yet another rationale for our study.

2.3 Measuring bank idiosyncratic risk and data for control variables

We collect data for banks' stock prices, holding period returns including dividends, and total shares outstanding from the Center for Research on Security Prices (CRSP). For identifying banks in CRSP, we follow Gandhi and Lustig (2015) and Gandhi (2018) and select all firms with the two-digit header standard industrial classification (SIC) code of 60 or a four-digit SIC code of 6712. Several studies also define banks using four-digit SIC codes ranging from 6000–6199. Gandhi and

Lustig (2015) show this selection misses bank holding companies (listed under SIC code 6712). We match each bank in CRSP to its Call Report data (i.e., FRY9-C data) using the 'CRSP-FRB Link' provided by the Federal Reserve Bank of New York. This tool uniquely matches each RSSD IDs (a unique bank identifier allocated by the Federal Reserve for banks' regulatory reporting) with PERMCO (a unique bank identifier allocated by CRSP) and is updated frequently to account for bank mergers, acquisitions, failures, and delistings.

Next, we follow Ang, Hodrick, Xing, and Zhang (2006) and Ang, Hodrick, Xing, and Zhang (2009) and estimate the idiosyncratic volatility for each bank in our sample by regressing bank stock returns on the three Fama and French (1993) stock factors, namely the market (mkt), small minus big (smb), and high minus low (hml). While previous empirical studies suggest that there are many other cross-sectional factors that have explanatory power for the cross-section of returns, we do not directly control for all such factors. Rather, we follow Ang, Hodrick, Xing, and Zhang (2006), who argue that controlling for these additional factors only adds noise. Specifically, we estimate the following regression using daily data:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,mkt} mkt_t + \beta_{i,smb} smb_t + \beta_{i,hml} hml_t + \epsilon_{i,t} \tag{6}$$

We use daily data to estimate equation 6 for each bank for each quarter over our sample period. Idiosyncratic volatility is simply the standard deviation of the residuals (i.e., $\sigma(\epsilon_{i,t})$). Thus, at the end of this exercise, we have a time-series of quarterly idiosyncratic volatility for each bank in our sample. Note that while our primary analyses utilizes the idiosyncratic volatility derived from the Fama and French (1993) three-factor model, in robustness tests, we use idiosyncratic volatility computed using CAPM and the Fama and French (2015) five-factor model. As Section 3 shows, our results are not sensitive to the choice of a factor model.

Table 4 presents the summary statistics for idiosyncratic volatility for the cross-section of banks. Mean idiosyncratic volatility equals 1.91%. However, there is considerable variation over time and in the cross-section, as the standard deviation of idiosyncratic volatility itself is about 1.49, which is similar to the mean. The inter-quartile range (difference in the idiosyncratic volatility between the 25^{th}- and the 75^{th}-percentile) of 1.15% is also indicative of the considerable cross-section and time-series variation in idiosyncratic volatility across banks.

In all our analysis, we include data for a variety of control variables that can affect bank's idiosyncratic risk. Table 4 also presents the summary statistics for these additional control variables for the cross-section of banks. Specifically, for each bank in our sample, we collect data for log book value of assets as a control for bank size, the ratio of total capital to total book value of assets as a control for bank leverage or capitalization, the ratio of net income to total book value of assets as a control for bank profitability, the cost to income ratio computed by dividing the total and interest expenses by the total and interest income as a control for a bank's operational efficiency, the ratio of total deposits to total liabilities as a control for bank funding structure, the ratio of total loan loss provisions to total loans as a control for bank risk taking, the growth rate of total book value of assets (computed over the last three years) as a control for the growth opportunities available to a bank, the bank's Z-score as a control for bank risk-taking, and the VIX as a control for the expected market-wide volatility.

The extant literature suggests that it is important to control for the variables listed above as they can influence bank risk taking and hence its idiosyncratic risk. For instance, Laeven and Levine (2007) argue that a bank with greater capitalization (or lower leverage) may not indulge in excessive risk-taking, lowering idiosyncratic risk. Elsas, Hackethal, and Holzhäuser (2010) suggests that we should control for operational efficiency in our analysis as this too can influence idiosyncratic risk. Further, Laeven and Levine (2007) show that a bank with a higher proportion of deposits to liabilities can easily tap an inexpensive source of funding that benefits from government-subsidized deposit insurance, which can lower bank-specific (idiosyncratic) risk. In Baele, De Jonghe, and Vander Vennet (2007b), loan loss provisions are an important indicator of the amount of bank-specific credit risk. Finally, Saunders, Schmid, and Walter (2020b) document that a bank's Z-score serves as an indicator of bank risk-taking behavior and is inversely correlated with the likelihood of bank insolvency. Table A2 in the Appendix provides a summary of the definition and data sources for all control variable listed in Table 4.

3 Results

In this section, we present our main empirical results. We evaluate how well various measures of bank diversification perform in capturing the diversification effect. We begin by studying the ability of various diversification measures to predict bank idiosyncratic risk. We also directly compare the ability of various bank diversification measure to predict idiosyncratic volatility (horse races). We check if our results survive a battery of robustness tests. After documenting which of the seven measures of bank diversification is best at capturing the diversification effect, we revisit the question of how bank diversification relates to bank performance.

3.1 Bank business segment diversification and idiosyncratic volatility

In this section, we explore how various measures of bank business segment diversification relate to future idiosyncratic volatility for the cross-section of U.S. banks. In particular, we test which diversification measure is best at capturing the diversification effect. We do so by relating each bank's measure of business segment diversification measured in quarter t to the idiosyncratic volatility of its stock returns at time $t+1$ using standard panel regressions. The exact specification of our panel regression is as follows:

$$\sigma_{i,t+1} = \alpha_i + \beta_{i,DIV} DIV_{i,t} + \sigma_{i,t} + Controls + \eta_i + \gamma_t + \epsilon_{i,t} \tag{7}$$

Here, $\sigma_{i,t+1}$ is the idiosyncratic volatility of stock returns for bank i measured in quarter $t+1$, $DIV_{i,t}$ is one of the seven diversification measure for bank i at time t – Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. We control for several bank-level characteristics that influence the relation between bank diversification and bank idiosyncratic volatility. Specifically, we control for size (log book value of assets), leverage or capitalization (ratio of total capital to total book value of assets), profitability (net income to total assets), operating efficiency (cost to income ratio), funding structure (total deposits to total liabilities), growth opportunities (asset growth rate), and bank risk taking (loan loss provisions and Z-score). In addition, since idiosyncratic volatility can be highly persistent (Ang, Hodrick, Xing, and Zhang (2006)), we also control for lagged idiosyncratic volatility for bank i measured in quarter t. All regressions include bank fixed effects and time fixed effects. All right hand side variables are standardized by subtracting the mean and dividing by the standard deviation of the variables. Statistical significance is computed using standard errors clustered at the bank level. The main coefficients of interest is $\beta_{i,DIV}$, i.e., the coefficient on $DIV_{i,t}$. We expect the sign on $\beta_{i,DIV}$ to be negative for each of the seven measures of bank business segment diversification, indicating that higher bank diversification is associated with lower idiosyncratic risk (i.e., the diversification effect) as predicted by the framework in Section 1.

Table 5 presents the estimates for regression (7) and shows that the Entropy measure is best at capturing the diversification effect. Each column of this Table shows the estimates for a separate regression specification – one for each of the seven different measures of bank diversification defined in Table 1. We notice that the coefficient on Entropy is negative and statistically significant at the 1% level. The negative coefficient of -0.08 on Entropy indicates that a one-standard deviation increase in Entropy for a particular bank in a particular quarter is associated with a nearly 0.08% lower idiosyncratic volatility of daily returns for this bank over the next quarter.

The negative relation between Entropy and future bank idiosyncratic is not only statistically but economically significant as well. A one-standard deviation increase in Entropy at the bank level implies that idiosyncratic volatility will be lower by nearly 0.08% over the next quarter. Given that the average quarterly idiosyncratic volatility for the banks in our sample is 1.91%, this implies that higher Entropy is associated with nearly 4.19% lower idiosyncratic volatility over the next quarter as compared to the sample mean.

In addition, to Entropy, the coefficients on R-totnet, R-tottot, and R-simple (Columns (4), (6), and (7)) are also negative but not statistically significant, indicating that higher values of these measures are not associated with lower future idiosyncratic volatility for banks. Since all right hand side variables are standardized, the magnitude of the coefficients in columns (1) - (7) of Table 5 are directly comparable, and indicate that the Entropy measure is the best at capturing the diversification effect. While a one-standard deviation increase in R-tottot is associated with lower idiosyncratic volatility by -0.03%, the magnitude of this coefficient is at least 50% lower as compared to the coefficient on Entropy in Column (1) of Table 5. Similarly, there is no statistically significant relation between the Hhindex and Absdiff measures of bank diversification and future idiosyncratic volatility of bank stock returns. The coefficient on R-netnet is positive, indicating that higher values of diversification (as measured by R-netnet) are associated with higher rather than lower idiosyncratic volatility.

Notice also that in Table 5, the signs and significance of the coefficients on the control variables are as expected. For example, the coefficient on lagged idiosyncratic volatility is positive and statistically significant, indicating that idiosyncratic volatility is highly persistent. Similarly, the coefficient on leverage (i.e, the ratio of total capital to total book value of assets) is negative, indicating that banks with low leverage or higher capitalization have lower future idiosyncratic risk. For banks, government-guaranteed deposits are considered as a source of low risk, low cost, capital, it is not surprising that higher values of total deposits to total liabilities is also associated with lower idiosyncratic risk. Banks that are less efficient (i.e., have higher cost to income ratios) or take on more risk (as indicated by higher loan loss provisions) indeed have more future idiosyncratic risk, as indicated by the positive, statistically significant coefficients on these variables in all specifications in Table 5.

Table 6 directly compares the ability of the Entropy measure to forecast idiosyncratic volatility with each of the six other measures of bank diversification used in the literature. In other words, we conduct a horserace between Entropy and each of the six other measures of diversification. Since all diversification measures are positively correlated with each other and since some of these correlations are quite high, to avoid any issues related to multi-collinearity, in each regression specification we include only Entropy and only one of the six other measures of bank diversification. Specifically, we run a panel regression of the form:

$$\sigma_{i,t+1} = \alpha_i + \beta_{i,Entropy} Entropy_{i,t} + \beta_{i,DIV} DIV_{i,t} + Controls_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t} \tag{8}$$

Here, $Entropy_{i,t}$ is the Entropy measure for bank i measured in quarter t and $Div_{i,t}$ is one of the six other measures of bank diversification i.e., Hhindex, Absdiff, R-totnet, R-netnet, R-tottot, or R-simple. Each column in Table 6 shows the results for a different specification of the regression in equation (8). As above, in all cases we control for several bank characteristics, the lagged bank idiosyncratic volatility, and all regressions include bank fixed effects.

Table 6 shows that in all cases, Entropy still emerges as the best at capturing the diversification effect. The coefficient on Entropy is always negative and statistically significant at the 1% level. This coefficient ranges from -0.08 (when including R-simple measure of bank diversification) to -0.09 (when including the Hhindex measure of bank diversification) and the t-statistics are all above 4. Once we control for Entropy, the coefficient on most other measures of bank diversification is either positive or not statistically significant. For instance, the coefficient on Hhindex, Absdiff, R-totnet, and R-netnet are all positive and statistically significant indicating that an increase in these measures of bank diversification is associated with an increase rather than a decrease in future idiosyncratic volatility. The coefficient on R-tottot and R-simple is negative but not statistically significant, indicating that once we include the Entropy measure of bank diversification, it renders the relation between these latter measures and future bank idiosyncratic volatility meaningless. The magnitude of the coefficients on these other measures of diversification is also at best about one-third of the magnitude of the coefficient on Entropy, indicating that the Entropy measure is the best at capturing the expected negative relation between bank diversification and idiosyncratic volatility of bank stock returns.[9]

In Table 7 we test if the ability of Entropy to capture the diversification effect varies over time, i.e., do our results differ in good or bad economic times or before and after the global financial crisis. We define bad economic times as quarters of NBER recessions as well as quarters with financial crisis (failure of Long-Term Capital Management, Russian sovereign debt crisis, etc.). Quarters with recessions are identified and published by the NBER business cycle dating committee.

Table 7 shows that in both good and bad economic times as well as in the pre- and post-crisis

[9] In unreported results we also try yet another measure of bank diversification – the Herfindahl-Hirschman index of the 16 categories of bank income – and find that even this variables is not always negatively related to future idiosyncratic volatility in a statistically significant manner.

years, Entropy is significantly negatively correlated with future idiosyncratic volatility of bank stock returns. The coefficient on Entropy in this Table is -0.06 in good economic times but is nearly twice as high at -0.15 during bad economic times, indicating the ability of Entropy to capture the diversification effect in both good economic times as well as during periods of financial distress and crisis. Both these coefficients are statistically significant at the 1% level with t-statistics of -3.18 and -3.14, respectively.

Similarly, the third and fourth column of Table 7 shows that the ability of Entropy to predict lower idiosyncratic risk does not change after the global financial crisis. In both the pre- and post-crisis years, the coefficient is nearly the same (-0.08 and -0.09, respectively) and both coefficients are statistically significant with t-statistics of -3.46 and -2.18, respectively. Note that all coefficients in Table 7 are economically significant as well. For instance, in the second column, a coefficient of -0.15 on Entropy implies that a one-standard deviation increase in Entropy is associated with a -0.15% decline in idiosyncratic volatility of bank stock returns, which is nearly 7.85% of the sample mean idiosyncratic volatility of 1.91%.

3.2 Robustness tests

We carry out a series of robustness tests to ensure that the ability of Entropy to capture the diversification effect withstands any change in the design of our empirical tests. We begin by checking if our results are robust to the empirical asset pricing factor model employed to compute bank idiosyncratic risk. The results of this test are in Table 8.

Table 8 reruns the regression in Equation (8). Panels A and B of this Table uses volatility of idiosyncratic returns derived from the CAPM and the Fama and French (2015) 5-factor model as the dependent variable, respectively. Regardless of the empirical asset pricing factor model employed to estimate bank idiosyncratic risk, Entropy emerges as the best at capturing the diversification effect. The coefficient on Entropy is always negative and statistically significant at the 1% level. This coefficient ranges from -0.08 to -0.09 and the t-statistics in all cases are close to 4. In fact, the results in Table 8 are even stronger than those in Table 6. In Table 8 coefficients on most other measures of bank diversification are either positive or not statistically significant (the only exception being R-simple for which the coefficient is only marginally statistically significant). The results in Table 8 also show that controlling for market volatility (VIX) or a bank's exposure to market risk factor (β) does not impact our results and conclusion.

In an influential and highly cited paper, Demsetz and Strahan (1997), argue that the problem with using volatility of idiosyncratic returns (as we have in all our tests above) is that this variable is not only influenced by the degree of bank business segment diversification but also by individual components of its balance sheet (i.e., its assets, liabilities, off-balance sheet positions, and leverage). Demsetz and Strahan (1997) go on to suggest that one should use the $1 - R^2$ from a factor model instead of the volatility of idiosyncratic returns as an alternative market-based measure of the degree of diversification by a bank. Their suggestion is based on earlier papers such as, Barnea and Logue (1973) and Roll (1988), who advocate for the use of $1 - R^2$ from a simple factor model to measure the degree of conglomerate diversification.

Given these arguments, Table 9 repeats the analysis in Table 6, but now uses the R^2 from a factor model to measure firm-specific risk or as the dependent variable. Following the arguments in Barnea and Logue (1973), Roll (1988), and Demsetz and Strahan (1997), systematic risk factors should explain a greater proportion of variation in stock market returns (i.e., R^2 should be higher) or firm-specific risk or variation (i.e., 1 - R^2) should be lower for banks with higher business segment diversification. In other words, in this next test, we expect the coefficients on all measures of bank business-segment diversification to be positive and statistically significant.

Table 9 presents the results and again Entropy emerges as the best at capturing the diversification effect. In all cases, the coefficient on Entropy is negative and statistically significant. The coefficient on almost all other measures either has the wrong sign or these coefficients are not statistically significant at conventional levels. For instance, the coefficient on R-simple is positive and statistically significant at the 10% level, indicating higher diversification by this measure is associated with higher idiosyncratic bank risk one-quarter ahead.

Next, we check if the ability of Entropy to predict lower idiosyncratic risk and capture the diversification effect is limited to just 1-quarter ahead or whether the relation between Entropy and idiosyncratic returns is statistically significant at longer horizons as well. Table 10 presents the results of this analysis. Panels A, B, and C present the estimates for horse-races that compare the ability of various diversification measures to predict bank idiosyncratic risk 2-, 3-, and 4-quarters ahead. These results indicate that of the previous measures of business segment diversification used in the literature, Entropy is the only one that has a statistically significant (negative) correlation with idiosyncratic risk beyond a horizon of 1-quarter. In all cases, when predicting idiosyncratic risk at a horizon of 2-, 3-, or 4-quarters ahead, the coefficient on Entropy is negative and statistically significant at the 1% level with t-statistics close to or above 4. The coefficients on the six remaining diversification measures are small, statistically insignificant, and often switch sign indicating these measures are sometimes associated with higher and at other times lower idiosyncratic volatility at longer horizons. Table 10 provides yet another piece of evidence that supports Entropy as the best measure at capturing the diversification effect for banks.

In our next robustness test in Table 11 we compare the out-of-sample performance of various diversification measures to predict bank idiosyncratic volatility. Specifically, we compare the out-of-sample performance of models that (separately) use the seven diversification measures – Entropy, Hhindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple to predict bank idiosyncratic volatility. We also compare the performance of models that use these seven diversification variables by themselves (i.e., univariate regressions or a model without any control variables) as well as a model that contains each of these seven diversification variables along with all of the control variables from our baseline regression in Table 5 (i.e., multivariate regressions or a model with all control variables listed above).

For each specification and model, we measure to what extent a market participant could have predicted bank idiosyncratic volatility in real time, using the most recent data that was available to her up to that point in time. That is, we first run forecasting regressions with the selected model using data from the most recent 3-year or 5-year window. We then use the estimated parameters of this model to predict idiosyncratic volatility for one quarter following the window. For the

3-year window, our out-of-sample forecasts start in December 1999, when we first have 3 years of data to estimate the parameters of the model. Similarly, for the 5-year window, our out-of-sample forecasts start in December 2001, when we first have 5 years of data to estimate the parameters of the model. In all cases, we estimate the root mean squared error (i.e., the RMSE), which is defined as the square root of the squared differences between the actual (i.e., realized) and predicted values of idiosyncratic volatility.

Table 11 presents the results for out-of-sample forecasts for the models without (Panel A) and with (Panel B) the inclusion of all the control variables. In each panel, each row presents the RMSEs for a model that either uses a 3- or 5-year window to estimate the model parameters. The columns report the RMSEs for separate models that use one of the seven diversification measures to forecast bank idiosyncratic volatility 1-quarter ahead. For instance, the number in the first row and column of panel A of Table 11 reports the RMSE when data for Entropy is used by itself over 3-year rolling windows to predict idiosyncratic volatility 1-quarter ahead out-of-sample. In all cases, we multiply the RMSEs by 100 and express these in percentages.

Panel A of Table 11 indicates that when predicting bank idiosyncratic volatility without the use of any control variables, the model with Entropy has the lowest RMSE at both the 3- and 5-year horizons (1.4011% and 1.3160%, respectively) as compared to all other models. Models that use other diversification measures never outperform the model that uses Entropy by itself as measured by out-of-sample RMSE.

This is clear even in Panel B of this Table that shows the results for similar out-of-sample tests but now uses each of the seven diversification measures along with all control variables listed above. Again, the model that uses Entropy along with all control variables has significant predictive ability for future bank idiosyncratic volatility (lowest RMSE at 1.6795% and 1.7627% for 3- and 5-year windows, respectively).

Note that comparing the results in Panels A and B of Table 11 indicates that across all our models, the one that uses Entropy by itself (1st column of Panel A) produces the lowest RMSE, thus indicating that predicting with multiple variables (diversification measure and control variables) appears to only add noise. This result is consistent with the fact that in most out-of-sample predictive tests, it is often the most parsimonious model (such as the one with single variables) that performs well

3.3 Revisiting the relation between bank diversification and bank performance.

In this section, we present a practical application which demonstrates how our study – which to our knowledge is the first to introduce the Entropy-based metric for bank diversification using the most granular data available and also the first to test which bank diversification measures accurately capture the diversification effect – can be used practically by regulators and researchers. In banking literature, a significant controversy remains about how diversification across many business segments affects bank performance and risk.

On one hand, studies such as Stiroh (2006) and Lepetit, Nys, Rous, and Tarazi (2008a) document that diversification adversely affects bank performance and increases bank risk. Stiroh (2006) argues that bank diversification into business segments such as proprietary trading or investment banking lowers profitability and increases risk as income from these activities is more volatile and does not necessarily increase the average profits of banks. Similarly, Lepetit, Nys, Rous, and Tarazi (2008a) show that bank expansion into non-core activities leads them to mis-price loans (to encourage sales of other services to their customers) in turn leading to greater risk and poor financial performance for banks.

On the other hand, Demirguc-Kunt and Huizinga (2010) and Saunders, Schmid, and Walter (2020a) find that higher diversification is associated with higher return on equity and higher Z-scores, indicating improved profitability and lower bankruptcy risk for diversified banks. Using a sample of 1,334 banks in 101 countries, Demirguc-Kunt and Huizinga (2010) find that expansion into activities such as trading increases the rate of return on assets and offers risk diversification benefits. Saunders, Schmid, and Walter (2020a) use data for nearly 10,000 US banks over 2002–2013 and find that higher diversification is associated with higher profitability as well as lower failure probability.

Similar contradictory arguments exist for how diversification may impact bank exposure to tail and systemic risk. While some argue that diversification can increase tail and systemic risk for banks by increasing income volatility and can cause contagion (where losses in one business segment spread to other business segments) thereby contributing to institutional instability, others argue that expanding into multiple business segments allows banks to spread risk across imperfectly correlated income streams, causing them to benefit from natural hedging and reducing their overall risk exposure. The latter argument suggests that diversification can act as a hedge against downturns in any single business segment and enhance banks' stability, profitability, and resilience in the face of economic shocks.

The analysis in Ellul and Yerramilli (2013) suggests that the mixed empirical results in the literature on how diversification impacts bank performance and risk could be due to the fact that banks can use diversification into non-core activities for risk-seeking (perhaps increasing risk and lowering performance) or for hedging (focusing on trading and fee-based activities and perhaps lowering risk and improving performance). Our analysis so far suggests another cause for the divergent results in the literature regarding diversification and performance – these may partially be due to the fact that each paper uses a different (and perhaps an inaccurate) measure of bank diversification. We therefore visit the issue regarding bank diversification and performance and risk using Entropy.

Tables 12 - 16 document an unambiguous positive relation between bank diversification (when measured using Entropy) and diverse proxies for bank performance and risk such as its return on assets (ROA), return on equity (ROE), Altman Z-scores (Z-scores), tail risk, and systemic risk measures (SRISK). As measure of systemic risk, we use SRISK from Brownlees and Engle (2017), which measures the capital shortfall of a firm conditional on a severe market decline and accounts for its size, leverage and risk. The coefficients on Entropy in these table indicate that a one standard deviation increase in Entropy is associated with a 22% increase in ROA, a 17% increase in ROE, a nearly 5% increase in its Altman Z-scores, a 3% decrease in tail risk, and a

10% decrease in SRISK as compared to the sample mean over the next quarter. Thus, the positive relation between diversification and bank performance and risk is not just statistically significant but economically meaningful as well.

Columns (2) – (7) of the Tables 12 - 16 shed light on why the literature has documented conflicting results regarding the link between bank diversification and bank performance and risk. We note than when using the six other measures popular in the literature to study the link between bank diversification and performance and risk, the coefficients are sometimes positive, at other times negative, in some instances statistically significant, and in other cases either marginally or not statistically significant. For instance, Column (2) Table 12 which uses HHIndex to measure bank diversification, suggests that diversified banks suffer lower ROA and that the result is statistically significant at the 1% level. However, Column (5) of the same table which uses Rtotnet as the bank diversification measure suggests higher diversification leads to higher ROA and that the result is only marginally statistically significant. The same conclusions regarding mixed results when using different measures of diversification hold for Tables 13, 14, 15, and 16 as well. The results in these tables suggest that the divergent results in the literature regarding bank diversification and bank performance and risk may at least partly be attributed to the use of different or inaccurate measures of bank diversification.

Of course the decision of how much to diversify is an endogenous one for banks. While Tables 12 - 14 show that higher Entropy is associated with higher returns on assets and equity and lower bankruptcy risk, it is not clear if diversification leads to these benefits or if banks with better performance and lower risk choose to diversify more than other banks in the first place. To account for such endogenous decisions, we exploit a quasi-natural experiment around the passage of the GLB Act in 1999.

Specifically, we begin by showing in Table 17 that post-GLB Act, small banks increase diversification more than become more diversified than large banks as measured by Entropy. As previously mentioned, this is because prior to the passage of GLB Act, the Federal Reserve allowed many large and medium banks to operate in diverse business segments via Section 20 subsidiaries (see footnote 4). Small banks, who typically found it costly to establish such subsidiaries, were restricted to traditional banking activities of deposit-taking and lending. Since the activities constraint was the most binding for small banks in the pre-GLB era, it not surprising that post passage of GLB Act, these banks act to diversify the most and this shows up in the time-series variation of Entropy.

Figure 2 already establishes that over 1999-2007 (i.e., just after the passage of GLB Act and till the financial crisis of 2007), entropy increases the most for small banks, followed by medium, and then large banks. For small, medium, and large banks, Entropy increases by 64%, 21%, and 34%, respectively. Panel A of Table 17 confirms this result using a standard panel regression that adds several control variables for bank size, capital, asset growth, and bank and time fixed effects. The main variable of interest is the coefficient on the dummy variable $small \times post$. Small is a dummy variable that equals 1 for small banks (i.e., those with less than \$1.5 billion in total book value of assets) and post is a dummy variable that equals 1 for the five years post the passage of the GLB Act in 1999. We note that the coefficient on the interaction term of $small \times post$ is negative and statistically significant, which indicates that (as was the case in Figure 2) small banks tend to increase diversification more than other banks in the immediate aftermath of the passage of the GLB Act.

Panel B of Table 17 analyzes the performance and risk for small banks in the post-GLB period that tend to diversify the most. For this, we define another dummy variable, high. High takes the value of unity for those banks with the highest entropy in a given year. High entropy is defined as those banks for which Entropy is above the median value in a given year. We regress the measures of bank performance and risk on the triple interaction term $small \times post \times high$. That is we are interested in the effect on small banks, post-GLB, that were the most diversified. The coefficient on this variable tells us how small banks that diversified the most (as measured by Entropy) perform in the post GLB era. Panel B of Table 17 indicates that small banks that increased diversification the most in the post GLB period have high ROA, high ROE and lower tail risk.[10]

Overall this section demonstrates just one simple instance of how our study can be used by both regulators and researchers in this area to revisit several questions regarding the link between

[10] In unreported results, we also find that post-GLB, small banks that are the most diversified have higher Z-scores.

bank diversification and bank valuations, bank risk, and bank equity returns – a task we leave for future research.

4 Conclusion

Our study introduces the Entropy-based measure for bank business segment diversification, which incorporates granular information from both the number of distinct business lines and the proportion of income that a bank derives from these business lines. We find that the Entropy measure is uncorrelated with the six popular measures of bank business segment diversification used in the extant literature and is best at capturing the diversification effect both in-sample as well as in out-of-sample testing. Our results survive extensive robustness checks and hold regardless of how idiosyncratic volatility is measured, and are evident across different economic scenarios and sample periods.

Our study also highlights one practical application of our study and of our Entropy measure. The existing literature documents conflicting results regarding bank diversification and performance and risk with some studies indicating a positive, while others documenting a negative relation between bank business segment diversification and bank performance and risk. Given that we document that the Entropy measure is the 'best' measure of bank business segment diversification, we revisit these studies, and document that banks with higher business segment diversification (as measured by Entropy) not only earn higher ROA and ROE but also experience lower bankruptcy risk (as measured by their Z-scores), lower tail risk, and lower systemic risk (as measured by SRISK). The results are unambiguously economically and statistically significant in all specifications and this diverges from the mixed or ambiguous outcomes of previous research. Thus our research introduces a new perspective on the link between diversification and bank performance and risk, suggesting that unlike non-financial corporations bank business segment diversification is associated with better performance.

Since the Entropy measure can be estimated quite easily at a fairly high frequency (quarterly level) for all banks (public or private), future studies can use the Entropy measure to re-examine many of the existing studies on the impact of bank business segment diversification on bank risk-taking, executive compensation, and can serve as a practical tool for regulators and researchers.

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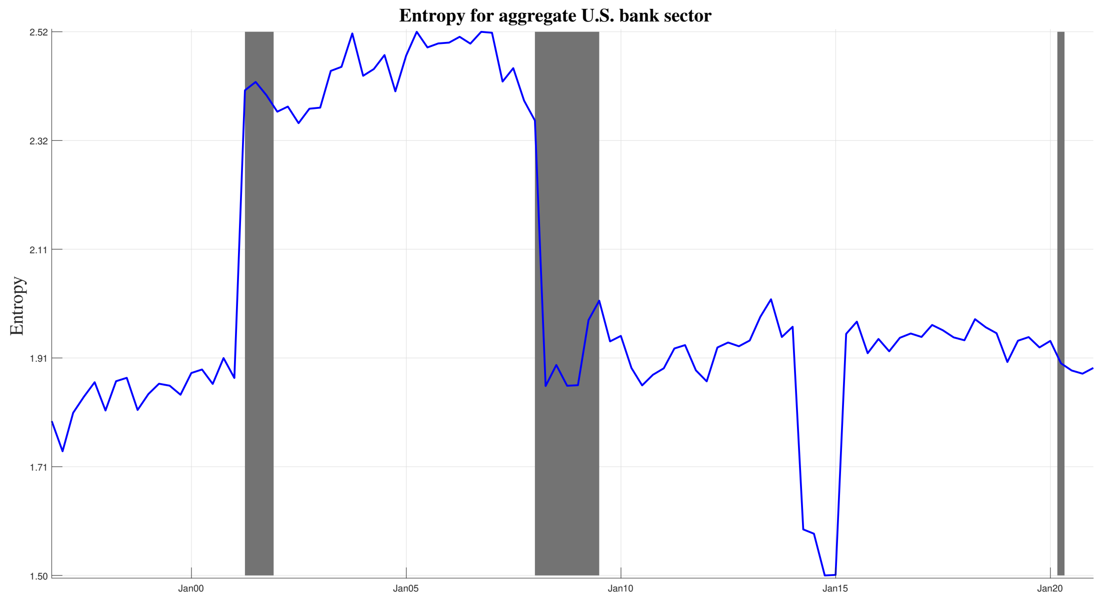

Figure 1. Time-series plot for Entropy for the aggregate U.S. bank sector

Notes: This figure plots Entropy for all domestic banks in the U.S. The blue solid line plots Entropy and the grey shaded regions represent National Bureau of Economic Research (NBER) recessions as well as periods of financial crisis. Years and months are indicated on the X-axis. The NBER recession dates are published by the NBER Business Cycle Dating Committee. Quarterly data, 1996 – 2020.

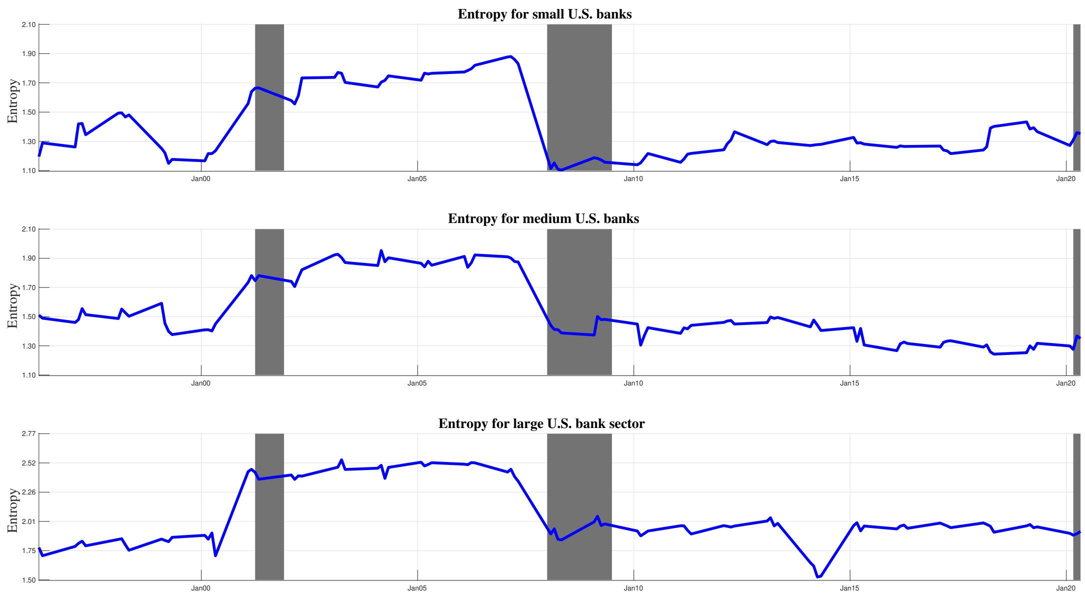

Figure 2. Time-series plot for Entropy for the aggregate U.S. bank sector

Notes: This figure plots Entropy for all domestic banks in the U.S. grouped by size as measured by total book value of assets. We group all domestic banks in the U.S. into three groups (small, medium, and large). We then aggregate data for all sixteen categories of interest and non-interest income for all banks in a particular group and use the aggregated time-series to compute Entropy for banks by asset size. Each panel in the figure plots Entropy for a separate set of banks. The left, middle, and right panels plot Entropy for small, medium, and large banks, respectively. In each panel, the blue solid line plots Entropy and the grey shaded regions represent National Bureau of Economic Research (NBER) recessions as well as periods of financial crisis. Years and months are indicated on the X-axis. The NBER recession dates are published by the NBER Business Cycle Dating Committee. Quarterly data, 1996 – 2020.

Table 1. Business line diversification measures

Notes: This table provides details regarding the construction of measures of bank diversification used in our empirical analysis. To construct these measures, we collect balance sheet data for banks from the 'Report of Condition and Income (Call Report)' required to be filed by all FDIC-insured bank holding companies in the U.S. The first column lists the mnemonic used to identify each measure of bank diversification in our empirical analysis. Column titled 'Definition of measure' provides a brief description of how the measure is constructed.

Measure	Business line diversification measure	
Entropy	$\sum_{i=1}^{16} S_i \ln \frac{1}{S_i}$ S_i is the share of each income item	This paper
HHindex	$1-[(\frac{\text{non-interest income}}{\text{Sum}})^2+(\frac{\text{Net interest income}}{\text{Sum}})^2]$ Sum = non-interest + Net interest income	Stiroh and Rumble (2006)
Absdiff	$1-\lvert\frac{\text{Net interest income - non-interest income}}{\text{Net interest income + non-interest income}}\rvert$	Laeven and Levine (2007)
R-netnet	$\frac{\text{Net non-interest income}}{\text{Net non-interest income + Net Interest income}}$	Stiroh (2004)
R-totnet	$\frac{\text{non-interest income}}{\text{non-interest income + Net Interest income}}$	Lepetit, Nys, Rous, and Tarazi (2008b)
R-tottot	$\frac{\text{non-interest income}}{\text{non-interest income + Interest income}}$	Baele, De Jonghe, and Vander Vennet (2007b)
R-simple	$\frac{\text{non-interest income}}{\text{Interest income}}$	Saunders, Schmid, and Walter (2020a)

Table 2. Summary statistics: Diversification measures

Notes: This table presents summary statistics for the key variables for the cross-section of banks. Column 1 indicates the variable for which the summary statistics is computed. Columns 2 - 6 report the mean, the standard deviation, the minimum, the 25^{th}-percentile, the median, the 75^{th}-percentile, and the maximum values for each variable. Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. Panel A shows the summary statistics for the cross-section of banks and Panel B shows the summary statistics for the aggregate U.S. bank sector. Quarterly data, 1996Q3 – 2020Q4.

Variable	Mean	σ	Min	25^{th}	Median	75^{th}	Max
Panel A: Cross-section of banks							
Entropy	1.18	0.36	0.01	0.95	1.19	1.43	2.47
HHindex	0.33	0.11	-0.03	0.26	0.35	0.42	0.50
Absdiff	0.46	0.21	-0.03	0.31	0.45	0.60	0.96
R-netnet	-0.66	0.62	-3.92	-0.81	-0.52	-0.35	1.13
R-totnet	0.25	0.15	-0.01	0.16	0.23	0.31	0.84
R-tottot	0.19	0.13	-0.01	0.11	0.17	0.24	0.75
R-simple	0.29	0.38	-0.01	0.12	0.20	0.32	2.93
Panel B: Aggregate bank sector							
Entropy	2.04	0.27	1.49	1.87	1.94	2.37	2.52
HHindex	0.49	0.02	0.37	0.49	0.50	0.50	0.50
Absdiff	0.91	0.09	0.48	0.88	0.93	0.97	1.00
R-netnet	-0.32	0.24	-1.83	-0.37	-0.25	-0.19	-0.07
R-totnet	0.46	0.05	0.24	0.44	0.47	0.50	0.54
R-tottot	0.36	0.07	0.16	0.30	0.37	0.40	0.48
R-simple	0.58	0.17	0.20	0.43	0.58	0.66	0.93

Table 3. Correlations

Notes: This table presents the correlation among the seven measures of bank diversification, i.e., Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple computed as described in Table 2.2. Panel A shows the correlations for the cross-section of banks and Panel B shows the correlations for the aggregate U.S. bank sector. Statistical significance at the 10%, 5% and 1% levels is denoted by *, **, and *** respectively. Quarterly data, 1996Q3 – 2020Q4.

Variable	Entropy	HHindex	Absdiff	R-netnet	R-totnet	R-tottot	R-simple
Panel A: Cross-section of banks							
Entropy	1.00						
HHindex	0.54***						
Absdiff	0.54***	0.97***	1.00				
R-netnet	0.14***	0.14***	0.15***	1.00			
R-totnet	0.39***	0.66***	0.70***	0.28***	1.00		
R-tottot	0.35***	0.60***	0.64***	0.19***	0.95***	1.00	
R-simple	0.17***	0.27***	0.31***	0.22***	0.84***	0.90***	1.00
Panel B: Aggregate bank sector							
Entropy	1.00						
HHindex	0.28***						
Absdiff	0.29***	0.91***	1.00				
R-netnet	0.41***	0.76***	0.65***	1.00			
R-totnet	0.33***	0.85***	0.95***	0.63***	1.00		
R-tottot	0.02	0.51***	0.64***	0.05	0.66***	1.00	
R-simple	-0.02	0.45***	0.60***	0.01	0.64***	0.99***	1.00

Table 4. Summary statistics: Control variables

Notes: This table presents summary statistics for the key variables for the cross-section of banks. Column 1 indicates the variable for which the summary statistics is computed. Columns 2 - 6 report the mean, the standard deviation, the minimum, the 25^{th}-percentile, the median, the 75^{th}-percentile, and the maximum values for each variable. Quarterly data, 1996Q3 – 2020Q4.

Variable	Mean	σ	Min	25^{th}	Median	75^{th}	Max
Idiosyncratic volatility	1.91	1.49	0.01	1.06	1.49	2.21	33.10
Log Assets	14.97	1.72	11.97	13.71	14.57	15.85	21.94
Capital/Assets	9.01	1.97	5.10	7.76	8.77	9.96	16.75
Operating Profits	0.41	0.24	-0.11	0.30	0.41	0.51	1.16
Cost/Income	74.78	12.22	48.63	67.33	73.96	80.47	131.40
Deposits/Liabilities	83.81	11.59	33.22	78.76	86.57	91.90	98.97
Loan loss provisions	0.15	0.24	-0.10	0.03	0.07	0.15	1.50
Assets growth	51.08	66.43	-26.31	13.28	32.23	64.28	393.92
Z-score	2.12	0.46	0.64	1.88	2.20	2.44	2.93
Market beta	0.68	0.49	-0.11	0.25	0.66	1.05	1.93
VIX	20.58	8.02	10.31	14.23	19.32	25.09	58.59

Table 5. Predicting idiosyncratic volatility

Notes: This table shows the estimated coefficients for the univariate forecasting regressions:

$$\sigma_{i,t+1} = \alpha_i + \beta_{i,DIV} DIV_{i,t} + \sigma_{i,t} + Controls_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t}$$

Here, $\sigma_{i,t+1}$ is the idiosyncratic volatility of bank i measured at time $t+1$. Idiosyncratic volatility is defined as the standard deviation of the residuals obtained by regressing daily bank stock returns on the three Fama and French (1993) stock return factors. We control for the lagged dependent variable (i.e., $\sigma_{i,t}$). $DIV_{i,t}$ is one of the seven diversification measure for bank i at time t – Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects and time fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Entropy	-0.08***						
	(-4.23)						
Hhindex		0.01					
		(0.14)					
Absdiff			0.01				
			(0.04)				
R-totnet				-0.02			
				(-0.72)			
R-netnet					0.01		
					(0.22)		
R-tottot						-0.03	
						(-1.53)	
R-simple							-0.03
							(-1.57)
$\sigma_{i,t}$	6.10***	6.20***	6.20***	6.20***	6.20***	6.20***	6.20***
	(18.97)	(28.80)	(28.78)	(28.75)	(28.76)	(28.74)	(28.75)
Assets	-0.25***	-0.23***	-0.23***	-0.23***	-0.23***	-0.24***	-0.23***
	(-4.33)	(-4.15)	(-4.17)	(-4.21)	(-4.26)	(-4.28)	(-4.23)
Capital/Assets	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***
	(-10.29)	(-10.14)	(-10.14)	(-10.14)	(-10.09)	(-10.13)	(-10.12)
Operating profits	-0.04*	-0.05*	-0.05*	-0.04	-0.05*	-0.03	-0.03
	(-1.69)	(-1.80)	(-1.77)	(-1.36)	(-1.92)	(-0.94)	(-1.12)
Cost/Income	0.11***	0.10***	0.10***	0.11***	0.10***	0.11***	0.11***
	(3.88)	(3.57)	(3.57)	(3.68)	(3.60)	(3.90)	(3.84)
Deposits/Liabilities	0.03	0.02	0.02	0.02	0.02	0.02	0.02
	(1.43)	(1.13)	(1.13)	(1.08)	(1.13)	(1.09)	(1.09)
Loan loss provisions	0.19***	0.19***	0.19***	0.19***	0.19***	0.19***	0.19***
	(10.21)	(10.23)	(10.26)	(10.26)	(9.98)	(10.23)	(10.26)
Asset growth	-0.02*	-0.02*	-0.02*	-0.02*	-0.02*	-0.02*	-0.02*
	(-1.74)	(-1.73)	(-1.73)	(-1.73)	(-1.73)	(-1.70)	(-1.71)
Z-Score	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***
	(-5.43)	(-5.65)	(-5.64)	(-5.69)	(-5.69)	(-5.72)	(-5.73)
VIX	0.36***	0.34***	0.34***	0.34***	0.34***	0.35***	0.34***
	(12.29)	(11.71)	(11.71)	(11.73)	(11.80)	(11.74)	(11.75)
β	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**
	(2.03)	(2.05)	(2.05)	(2.07)	(2.04)	(2.08)	(2.05)
Adjusted R^2	0.60	0.60	0.60	0.60	0.60	0.60	0.60
Bank fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Table 6. Predicting idiosyncratic volatility: Horseraces

Notes: This table shows the estimated coefficients for the forecasting regressions:

$$\sigma_{i,t+1} = \alpha_i + \beta_{i,Entropy} Entropy_{i,t} + \beta_{i,DIV} DIV_{i,t} + \sigma_{i,t} + Controls_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t}$$

Here, $\sigma_{i,t+1}$ is the idiosyncratic volatility of bank i measured at time $t+1$. Idiosyncratic volatility is defined as the standard deviation of the residuals obtained by regressing daily bank stock returns on the three Fama and French (1993) stock return factors. We control for the lagged dependent variable (i.e., $\sigma_{i,t}$). $DIV_{i,t}$ is one of the seven diversification measure for bank i at time t – Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects and time fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	(1)	(2)	(3)	(4)	(5)	(6)
Entropy	-0.09***	-0.09***	-0.08***	-0.08***	-0.08***	-0.08***
	(-4.27)	(-4.28)	(-4.10)	(-4.23)	(-3.97)	(-4.14)
Hhindex	0.03					
	(1.31)					
Absdiff		0.02				
		(1.28)				
R-totnet			0.01			
			(0.12)			
R-netnet				0.01		
				(0.32)		
R-tottot					-0.01	
					(-0.60)	
R-simple						-0.02
						(-1.11)
$\sigma_{i,t}$	0.61***	0.61***	0.61***	0.61***	0.61***	0.61***
	(18.98)	(18.97)	(18.96)	(18.95)	(18.97)	(18.96)
Assets	-0.24***	-0.24***	-0.25***	-0.25***	-0.25***	-0.25***
	(-4.18)	(-4.22)	(-4.30)	(-4.39)	(-4.33)	(-4.34)
Capital/Assets	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***	-0.17***
	(-10.25)	(-10.27)	(-10.29)	(-10.26)	(-10.28)	(-10.29)
Operating profits	-0.05*	-0.05*	-0.04	-0.04*	-0.03	-0.03
	(-1.87)	(-1.88)	(-1.54)	(-1.77)	(-1.17)	(-1.09)
Cost/Income	0.10***	0.10***	0.10***	0.11***	0.11***	0.11***
	(3.75)	(3.68)	(3.65)	(3.89)	(3.84)	(3.95)
Deposits/Liabilities	0.03	0.03	0.03	0.03	0.03	0.03
	(1.43)	(1.43)	(1.46)	(1.44)	(1.42)	(1.41)
Loan loss provisions	0.19***	0.19***	0.19***	0.19***	0.19***	0.19***
	(10.20)	(10.22)	(10.20)	(9.89)	(10.18)	(10.19)
Assets growth	-0.02*	-0.02*	-0.02*	-0.02*	-0.02*	-0.02*
	(-1.75)	(-1.73)	(-1.74)	(-1.74)	(-1.73)	(-1.72)
Z-Score	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***
	(-5.40)	(-5.40)	(-5.43)	(-5.49)	(-5.47)	(-5.50)
VIX	0.36***	0.36***	0.36***	0.36***	0.36***	0.36***
	(12.22)	(12.19)	(12.18)	(12.30)	(12.12)	(12.18)
β	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***
	(1.98)	(1.99)	(2.03)	(2.03)	(2.05)	(2.04)
Adjusted R^2	0.60	0.60	0.60	0.60	0.60	0.60
Bank fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Table 7. Predicting idiosyncratic volatility: Sub-samples

Notes: This table shows the estimated coefficients for the forecasting regressions:

$$\sigma_{i,t+1} = \alpha_i + \beta_{i,Entropy} Entropy_{i,t} + \sigma_{i,t} + Controls_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t}$$

Here, $\sigma_{i,t+1}$ is the idiosyncratic volatility of bank i measured at time $t+1$. Idiosyncratic volatility is defined as the standard deviation of the residuals obtained by regressing daily bank stock returns on the three Fama and French (1993) stock return factors. We control for the lagged dependent variable (i.e., $\sigma_{i,t}$). $Entropy_{i,t}$ is the Entropy measure of diversification computed as described in Table 2.2. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. Bad Times are periods of economic or financial sector distress and include quarters with the failure of Long-Term Capital Management (LTCM) and the Russian Crisis between the first and second quarters of 1999 and the recessions dated by National Bureau of Economic Research (NBER). Good Times are defined as all quarters not included as Bad Times. Pre-crisis is defined as the period between the third quarter of 1996 and the third quarter of 2007, and post-crisis is defined as the period between the third quarter of 2009 and the fourth quarter 2020. All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects and time fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	$Good\ times$	$Bad\ times$	$Pre-crisis$	$Post-crisis$
Entropy	-0.06***	-0.15***	-0.08***	-0.09**
	(-3.18)	(-3.14)	(-3.46)	(-2.18)
$\sigma_{i,t}$	0.48***	0.57***	0.48***	0.44***
	(19.88)	(6.00)	(12.88)	(9.31)
Assets	-0.31***	-0.21	-0.07	-0.07
	(-5.35)	(-1.23)	(-0.76)	(-0.61)
Capital/Assets	-0.17***	-0.22***	-0.10***	-0.19***
	(-10.29)	(-4.83)	(-4.76)	(-6.28)
Operating profits	-0.02	0.09	0.05	-0.13***
	(-0.96)	(0.96)	(1.11)	(-3.11)
Cost/Income	0.08***	0.35***	0.19***	-0.04
	(3.33)	(3.07)	(3.68)	(-0.89)
Deposits/Liabilities	0.01	0.12*	0.03	0.02
	(0.35)	(1.93)	(0.83)	(0.53)
Loan loss provisions	0.14***	0.30***	0.18***	0.17***
	(8.43)	(4.91)	(7.56)	(6.30)
Assets growth	-0.02*	-0.04	0.01	-0.03
	(-1.90)	(-1.26)	(0.06)	(-1.47)
Z-Score	-0.06***	-0.13**	-0.03*	-0.05***
	(-4.92)	(-2.37)	(-1.77)	(-2.75)
VIX	0.02	0.56***	0.38***	0.32***
	(0.91)	(8.56)	(10.74)	(7.31)
β	0.02	0.02	0.04**	0.01
	(1.38)	(0.22)	(2.05)	(0.22)
Adjusted R^2	0.50	0.51	0.63	0.38
Bank fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes

Table 8. Predicting idiosyncratic volatility: Alternative factor models

Notes: This table shows the estimated coefficients for the forecasting regressions:

$$\sigma_{i,t+1} = \alpha_i + \beta_{i,Entropy} Entropy_{i,t} + \beta_{i,DIV} DIV_{i,t} + \sigma_{i,t} + Controls_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t}$$

Here, $\sigma_{i,t+1}$ is the idiosyncratic volatility of bank i measured at time $t+1$. Idiosyncratic volatility is defined as the standard deviation of the residuals obtained either by regressing daily bank stock returns on the market risk factor (Panel A) or the five Fama-French Fama and French (2015) stock return factors (Panel B). We control for the lagged dependent variable (i.e., $\sigma_{i,t}$). $DIV_{i,t}$ is one of the seven diversification measure for bank i at time t – Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. In addition, we control for overall market volatility (VIX) or a bank's exposure to market risk (β). All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects and time fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: CAPM.						
Entropy	-0.09***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***
	(-4.19)	(-4.18)	(-3.96)	(-4.17)	(-3.81)	(-4.03)
Hhindex	0.02					
	(1.23)					
Absdiff		0.02				
		(1.15)				
R-totnet			-0.01			
			(-0.25)			
R-netnet				0.01		
				(0.32)		
R-tottot					-0.03	
					(-1.11)	
R-simple						-0.03*
						(-1.82)
VIX	0.38***	0.38***	0.38***	0.38***	0.38***	0.38***
	(12.69)	(12.67)	(12.67)	(12.77)	(12.65)	(12.71)
β	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***
	(3.23)	(3.24)	(3.29)	(3.27)	(3.31)	(3.29)
Adjusted R^2	0.62	0.62	0.62	0.62	0.62	0.62
Bank fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Other controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Panel B: Fama-French 5 factors.						
Entropy	-0.09***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***
	(-4.30)	(-4.32)	(-4.14)	(-4.27)	(-4.02)	(-4.19)
Hhindex	0.02					
	(1.30)					
Absdiff		0.02				
		(1.18)				
R-totnet			0.01			
			(0.15)			
R-netnet				0.01		
				(0.31)		
R-tottot					-0.01	
					(-0.56)	
R-simple						-0.02
						(-1.03)
VIX	0.36***	0.35***	0.36***	0.36***	0.36***	0.36***
	(12.54)	(12.52)	(12.50)	(12.61)	(12.44)	(12.50)
β	0.03*	0.03*	0.03*	0.03*	0.03**	0.03*
	(1.90)	(1.90)	(1.95)	(1.95)	(1.97)	(1.96)
Adjusted R^2	0.60	0.60	0.60	0.60	0.60	0.60
Bank fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Other controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Table 9. Predicting regression 1 - R^2 values: Horseraces

Notes: This table shows the estimated coefficients for the forecasting regressions:

$$1 - R^2_{i,t+1} = \alpha_i + \beta_{i,Entropy} Entropy_{i,t} + \beta_{i,DIV} DIV_{i,t} + Controls_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t}$$

Here, R^2 is defined as the R-squared value obtained from a return generating model as in Demsetz and Strahan (1997). We control for the lagged dependent variable (i.e., 1 - $R^2_{i,t}$). $DIV_{i,t}$ is one of the seven diversification measure for bank i at time t – Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects and time fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	(1)	(2)	(3)	(4)	(5)	(6)
Entropy	-0.44**	-0.45**	-0.47**	-0.45**	-0.48**	-0.49**
	(-2.14)	(-2.22)	(-2.35)	(-2.26)	(-2.41)	(-2.43)
Hhindex	-0.06					
	(-0.34)					
Absdiff		-0.02				
		(-0.08)				
R-totnet			0.11			
			(0.47)			
R-netnet				-0.14		
				(-1.14)		
R-tottot					0.17	
					(0.69)	
R-simple						0.55**
						(2.17)
VIX	-2.11***	-2.11***	-2.12***	-2.11***	-2.14***	-2.21***
	(-4.17)	(-4.18)	(-4.23)	(-4.18)	(-4.30)	(-4.45)
β	-2.47***	-2.47***	-2.48***	-2.48***	-2.48***	-2.48***
	(-10.42)	(-10.44)	(-10.42)	(-10.43)	(-10.41)	(-10.39)
Adjusted R^2	0.57	0.57	0.57	0.57	0.57	0.57
Bank fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Other controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Table 10. Predicting idiosyncratic volatility: 2- to 4-quarters ahead

Notes: This table shows the estimated coefficients for the forecasting regressions:

$$\sigma_{i,t+1} = \alpha_i + \beta_{i,Entropy} Entropy_{i,t} + \beta_{i,DIV} DIV_{i,t} + \sigma_{i,t} + Controls_{i,t} + \eta_i + \gamma_t + \epsilon_{i,t}$$

Here, $\sigma_{i,t+1}$ is the idiosyncratic volatility of bank i measured at time $t+1$. Idiosyncratic volatility is defined as the standard deviation of the residuals obtained either by regressing daily bank stock returns on the market risk factor (Panel A) or the five Fama-French stock return factors (Panel B). We control for the lagged dependent variable (i.e., $\sigma_{i,t}$). $DIV_{i,t}$ is one of the seven diversification measure for bank i at time t – Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects and time fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2 quarters ahead.						
Entropy	-0.09***	-0.10***	-0.10***	-0.09***	-0.09***	-0.09***
	(-3.78)	(-3.87)	(-4.06)	(-3.99)	(-3.88)	(-3.97)
Hhindex	0.01					
	(0.01)					
Absdiff		0.01				
		(0.24)				
R-totnet			0.03			
			(0.83)			
R-netnet				-0.02		
				(-1.09)		
R-tottot					-0.01	
					(-0.27)	
R-simple						-0.01
						(-0.60)
Adjusted R^2	0.56	0.56	0.56	0.56	0.56	0.56
Panel B: 3-quarters ahead.						
Entropy	-0.11***	-0.11***	-0.11***	-0.11***	-0.11***	-0.11***
	(-3.93)	(-3.95)	(-4.17)	(-4.24)	(-4.09)	(-4.29)
Hhindex	-0.01					
	(-0.37)					
Absdiff		-0.01				
		(-0.44)				
R-totnet			-0.01			
			(-0.06)			
R-netnet				-0.01		
				(-0.57)		
R-tottot					-0.02	
					(-0.61)	
R-simple						0.01
						(0.17)
Adjusted R^2	0.51	0.51	0.51	0.51	0.51	0.51
Panel C: 4-quarters ahead.						
Entropy	-0.10***	-0.10***	-0.09***	-0.09***	-0.09***	-0.09***
	(-3.51)	(-3.38)	(-3.45)	(-3.46)	(-3.37)	(-3.48)
Hhindex	0.02					
	(0.93)					
Absdiff		0.01				
		(0.48)				
R-totnet			0.01			
			(0.27)			
R-netnet				0.01		
				(0.51)		
R-tottot					-0.01	
					(-0.16)	
R-simple						0.01
						(0.38)
Adjusted R^2	0.49	0.49	0.49	0.49	0.49	0.49

Table 11. Predicting idiosyncratic volatility: Out of sample forecasts

Notes: This Table reports the out of sample root-mean-squared errors (RMSE) for predicting bank idiosyncratic volatility. The row headers indicate the horizon (either 3- or 5-year windows) used to estimate the model. The column headers – Entropy, Hhindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple indicate the variable used to predict idiosyncratic volatility. Panel A reports the results for the model that only uses the diversification measure without control variables and Panel B reports the results for the model that uses diversification measure along with other control variables to predict idiosyncratic volatility. The predicted values from the model for idiosyncratic volatility are compared to the realized values to compute the RMSE. Values in the table are RMSEs that are multiplied by 100 and expressed in percentages.

$H =$	Entropy	Hhindex	Absdiff	R-totnet	R-netnet	R-tottot	R-simple
			Panel A: Without control variables				
3-year window	1.4011	1.4069	1.4023	1.4058	1.4069	1.4057	1.4069
5-year window	1.3160	1.3352	1.3355	1.3340	1.3277	1.3342	1.3349
			Panel B: With control variables				
3-year window	1.6795	1.7707	1.7736	1.7723	1.7678	1.7616	1.7665
5-year window	1.7627	1.8542	1.8583	1.8572	1.8478	1.8357	1.8467

Table 12. Diversification and bank return-on-assets

Notes: This table shows the estimated coefficients for the forecasting regression:

$$ROA_{i,t+1} = \alpha_i + \beta_{i,DIV} DIV_{i,t} + Controls_{i,t} + \eta_i + \epsilon_{i,t}$$

$ROA_{i,t+1}$ is return-on-assets of bank i at time $t+1$. ROA is defined as the ratio of the net income to total assets. $DIV_{i,t}$ is one of the seven diversification measure for bank i at time t – Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Entropy	0.009***						
	(4.12)						
HHindex		-0.007***					
		(-3.21)					
Absdiff			-0.007***				
			(-3.17)				
Rnetnet				-0.007**			
				(-2.45)			
Rtotnet					0.004*		
					(1.90)		
Rtottot						-0.001	
						(-0.29)	
Rsimple							-0.002
							(-0.73)
ROA(t)	0.040***	0.041***	0.041***	0.042***	0.041***	0.040***	0.041***
	(9.50)	(9.77)	(9.79)	(9.93)	(9.79)	(9.68)	(9.81)
Log Assets	-0.040***	-0.043***	-0.043***	-0.042***	-0.042***	-0.041***	-0.041***
	(-4.67)	(-5.04)	(-5.00)	(-4.94)	(-4.85)	(-4.76)	(-4.78)
Capital to Assets	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***
	(5.11)	(4.85)	(4.84)	(4.95)	(5.01)	(5.06)	(5.09)
Cost to Income	-0.042***	-0.043***	-0.043***	-0.043***	-0.040***	-0.042***	-0.042***
	(-14.80)	(-15.04)	(-14.92)	(-14.80)	(-12.62)	(-14.76)	(-14.78)
Deposits to Liabilities	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.56)	(-0.35)	(-0.37)	(-0.52)	(-0.26)	(-0.34)	(-0.35)
Loan Loss Provisions	-0.030***	-0.030***	-0.030***	-0.030***	-0.030***	-0.030***	-0.030***
	(-10.53)	(-10.49)	(-10.39)	(-10.29)	(-10.55)	(-10.44)	(-10.41)
Assets Growth	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(5.87)	(5.82)	(5.78)	(5.80)	(5.81)	(5.83)	(5.83)
Observations	69,287	69,287	69,287	69,287	69,287	69,287	69,286
Adjusted R^2	0.331	0.331	0.331	0.330	0.330	0.330	0.330
Bank Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year-Quarter Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Table 13. Diversification and bank return-on-equity

Notes: This table shows the estimated coefficients for the forecasting regression:

$$ROE_{i,t+1} = \alpha_i + \beta_{i,DIV} DIV_{i,t} + Controls_{i,t} + \eta_i + \epsilon_{i,t}$$

$ROE_{i,t+1}$ is the return-onequity of bank i at time $t+1$. Return-on-equity is defined as the ratio of net income to total book value of equity. $DIV_{i,t}$ is one of the seven diversification measure for bank i at time t – Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Entropy	0.120***						
	(4.04)						
HHindex		-0.069**					
		(-2.16)					
Absdiff			-0.080**				
			(-2.50)				
Rnetnet				-0.456			
				(-1.42)			
Rtotnet					0.073**		
					(2.11)		
Rtottot						-0.028	
						(-0.69)	
Rsimple							-0.062
							(-1.51)
ROE(t)	0.666***	0.677***	0.678***	2.127***	0.682***	0.673***	0.677***
	(10.15)	(10.24)	(10.26)	(5.98)	(10.42)	(10.16)	(10.25)
Log Assets	-0.675***	-0.708***	-0.709***	-4.417***	-0.712***	-0.693***	-0.698***
	(-5.33)	(-5.56)	(-5.57)	(-5.00)	(-5.50)	(-5.43)	(-5.46)
Capital to Assets	-0.111***	-0.115***	-0.115***	1.619***	-0.112***	-0.112***	-0.109***
	(-2.97)	(-3.06)	(-3.08)	(6.30)	(-3.02)	(-3.00)	(-2.93)
Cost to Income	-0.500***	-0.507***	-0.506***	-5.486***	-0.457***	-0.503***	-0.503***
	(-11.56)	(-11.82)	(-11.74)	(-19.45)	(-9.23)	(-11.71)	(-11.64)
Deposits to Liabilities	-0.061*	-0.054	-0.054	-0.160	-0.050	-0.054	-0.055*
	(-1.82)	(-1.63)	(-1.64)	(-0.61)	(-1.49)	(-1.64)	(-1.65)
Loan Loss Provisions	-0.376***	-0.377***	-0.375***	-4.003***	-0.375***	-0.377***	-0.374***
	(-9.37)	(-9.36)	(-9.29)	(-14.68)	(-9.35)	(-9.27)	(-9.21)
Assets Growth	0.191***	0.190***	0.190***	0.805***	0.190***	0.190***	0.191***
	(8.25)	(8.18)	(8.15)	(5.22)	(8.16)	(8.18)	(8.18)
Observations	69,287	69,287	69,287	69,287	69,287	69,287	69,286
Adjusted R^2	0.314	0.314	0.314	0.313	0.326	0.313	0.314
Bank Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year-Quarter Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Table 14. Diversification and Z-scores

Notes: This table shows the estimated coefficients for the forecasting regression:

$$Z_{i,t+1} = \alpha_i + \beta_{i,DIV} DIV_{i,t} + Controls_{i,t} + \eta_i + \epsilon_{i,t}$$

$Z_{i,t+1}$ is the Altman Z-score of bank i at time $t+1$. $DIV_{i,t}$ is one of the seven diversification measure for bank i at time t – Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Entropy	0.005***						
	(3.69)						
HHindex		-0.000					
		(-0.21)					
Absdiff			-0.001				
			(-0.51)				
Rnetnet				-0.004***			
				(-2.92)			
Rtotnet					0.002**		
					(2.27)		
Rtottot						-0.003*	
						(-1.77)	
Rsimple							-0.004**
							(-2.48)
Z-Score(t)	0.389***	0.389***	0.389***	0.389***	0.389***	0.389***	0.389***
	(3.84)	(3.39)	(3.22)	(3.19)	(3.59)	(3.53)	(3.62)
Log Assets	-0.017***	-0.018***	-0.018***	-0.019***	-0.019***	-0.019***	-0.019***
	(-3.36)	(-3.43)	(-3.45)	(-3.63)	(-3.60)	(-3.58)	(-3.58)
Capital to Assets	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.003**
	(-2.47)	(-2.54)	(-2.54)	(-2.51)	(-2.54)	(-2.47)	(-2.39)
Cost to Income	-0.008***	-0.009***	-0.009***	-0.009***	-0.007***	-0.009***	-0.009***
	(-8.36)	(-8.39)	(-8.46)	(-8.78)	(-6.44)	(-8.51)	(-8.67)
Deposits to Liabilities	0.003**	0.004**	0.004**	0.003**	0.004**	0.004**	0.004**
	(2.18)	(2.37)	(2.37)	(2.18)	(2.43)	(2.31)	(2.26)
Loan Loss Provisions	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(-9.61)	(-9.76)	(-9.78)	(-9.80)	(-9.84)	(-9.77)	(-9.74)
Assets Growth	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(3.55)	(3.53)	(3.53)	(3.54)	(3.52)	(3.55)	(3.57)
Observations	69,287	69,287	69,287	69,287	69,287	69,287	69,286
Adjusted R^2	0.845	0.845	0.845	0.845	0.845	0.845	0.845
Bank Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year-Quarter Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Table 15. Diversification and tail risk

Notes: This table shows the estimated coefficients for the forecasting regression:

$$Tailrisk_{i,t+1} = \alpha_i + \beta_{i,DIV} DIV_{i,t} + Controls_{i,t} + \eta_i + \epsilon_{i,t}$$

$Tailrisk_{i,t+1}$ is the negative of the average CAPM residual return during the worst 5% return days over a quarter at time $t+1$. $DIV_{i,t}$ is one of the seven diversification measure for bank i at time t – Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Entropy	-0.12***						
	(-3.66)						
Hhindex		-0.02					
		(-0.74)					
Absdiff			-0.02				
			(-0.89)				
R-totnet				-0.05			
				(-1.28)			
R-netnet					-0.01		
					(-0.50)		
R-tottot						-0.07*	
						(-1.78)	
R-simple							-0.06
							(-1.60)
Tail Risk(t)	1.11***	1.12***	1.12***	1.12***	1.12***	1.12***	1.12***
	(23.89)	(24.14)	(24.14)	(24.11)	(24.07)	(24.13)	(24.12)
VIX	0.73***	0.71***	0.71***	0.71***	0.70***	0.72***	0.71***
	(12.91)	(12.49)	(12.49)	(12.49)	(12.40)	(12.54)	(12.44)
Market beta	0.06**	0.07**	0.07**	0.07**	0.06**	0.07**	0.06**
	(2.11)	(2.17)	(2.17)	(2.17)	(2.12)	(2.18)	(2.14)
Log Assets	-0.32***	-0.30***	-0.30***	-0.30***	-0.29***	-0.31***	-0.30***
	(-3.05)	(-2.97)	(-2.96)	(-2.97)	(-2.90)	(-3.04)	(-2.94)
Capital/Assets	-0.31***	-0.30***	-0.30***	-0.30***	-0.30***	-0.30***	-0.30***
	(-10.42)	(-10.34)	(-10.35)	(-10.31)	(-10.28)	(-10.28)	(-10.28)
Operating Profits	-0.08	-0.08	-0.08	-0.06	-0.08*	-0.04	-0.06
	(-1.62)	(-1.57)	(-1.52)	(-1.04)	(-1.66)	(-0.76)	(-1.00)
Cost/Income	0.19***	0.19***	0.19***	0.20***	0.18***	0.21***	0.21***
	(3.60)	(3.45)	(3.47)	(3.55)	(3.39)	(3.71)	(3.59)
Deposits/Liabilities	0.06	0.05	0.05	0.04	0.05	0.05	0.05
	(1.57)	(1.33)	(1.33)	(1.20)	(1.30)	(1.26)	(1.26)
Loan loss provisions	0.39***	0.39***	0.39***	0.39***	0.39***	0.39***	0.39***
	(13.19)	(13.26)	(13.29)	(13.29)	(13.28)	(13.26)	(13.29)
Assets growth	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-1.20)	(-1.20)	(-1.21)	(-1.20)	(-1.20)	(-1.17)	(-1.18)
Z-Score	-0.12***	-0.12***	-0.12***	-0.12***	-0.12***	-0.12***	-0.12***
	(-5.33)	(-5.53)	(-5.53)	(-5.59)	(-5.50)	(-5.61)	(-5.61)
Observations	23,783	23,783	23,783	23,783	23,783	23,783	23,783
Adjusted R^2	0.845	0.845	0.845	0.845	0.845	0.845	0.845
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year-Quarter Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Table 16. Diversification and systemic risk

Notes: This table shows the estimated coefficients for the forecasting regression:

$$S - Risk_{i,t+1} = \alpha_i + \beta_{i,DIV} DIV_{i,t} + Controls_{i,t} + \eta_i + \epsilon_{i,t}$$

$S - Risk_{i,t+1}$ is the measure of capital shortfall of a firm conditional on a sever market decline from Brownlees and Engle (2017). $DIV_{i,t}$ is one of the seven diversification measure for bank i at time t – Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple are the seven measures of diversification computed as described in Table 2.2. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Entropy	-2.25*						
	(-1.77)						
HHindex		1.77					
		(1.01)					
Absdiff			1.58				
			(0.98)				
Rnetnet				0.79			
				(0.31)			
Rtotnet					-1.74		
					(-0.99)		
Rtottot						-2.07	
						(-0.85)	
Rsimple							3.82
							(0.99)
Log Assets	10.41	11.52	11.32	11.04	11.64	10.26	11.25
	(1.47)	(1.57)	(1.56)	(1.52)	(1.63)	(1.42)	(1.58)
Capital Assets	-11.56***	-11.37***	-11.38***	-11.42***	-11.45***	-11.39***	-11.46***
	(-9.45)	(-9.41)	(-9.39)	(-9.33)	(-9.48)	(-9.33)	(-9.30)
Operating Profits	-6.16***	-6.43***	-6.40***	-6.33***	-5.88***	-5.91***	-6.65***
	(-6.62)	(-6.83)	(-6.82)	(-6.90)	(-6.82)	(-6.09)	(-8.14)
Deposits to Liabilities	0.29	-0.11	-0.08	0.06	-0.01	0.04	0.06
	(0.12)	(-0.05)	(-0.04)	(0.03)	(-0.01)	(0.02)	(0.02)
Loan Loss Provisions	4.24***	4.38***	4.35***	4.32***	4.45***	4.32***	4.29***
	(7.17)	(7.49)	(7.44)	(7.39)	(7.86)	(7.40)	(7.30)
Assets Growth	-4.23***	-4.16***	-4.15***	-4.17***	-4.14***	-4.18***	-4.18***
	(-3.56)	(-3.55)	(-3.55)	(-3.55)	(-3.52)	(-3.56)	(-3.53)
Z-Score	-1.91*	-1.95**	-1.94**	-1.94*	-1.75*	-2.06**	-1.86*
	(-1.90)	(-1.97)	(-1.96)	(-1.93)	(-1.87)	(-2.07)	(-1.82)
Observations	15,655	15,655	15,655	15,655	15,655	15,655	15,655
Adjusted R^2	0.574	0.588	0.591	0.602	0.572	0.595	0.574
Bank Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year-Quarter Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

Table 17. Diversification and performance of small banks post-GLB

Notes: This table analyzes the diversification (as measured by Entropy) and performance and risk for small banks post GLB. In panel A, the dependent variable is the Entropy at the bank level and in panel B he dependent variables are the return on assets (Column 1), return on equity (Column 2), and tail risk (Column 3). Small is a dummy variable that equals 1 for banks with less than $1.5 billion in book value of assets and post is a dummy variable that equals 1 for the 5 post GLB years from 2000 to 2005. High is a dummy variable that equals 1 for banks for which Entropy is above median value in a given year. Controls include log assets, ratio of total capital to total book value of assets, ratio of operating profits to total assets, ratio of cost to income, ratio of deposits to total liabilities, ratio of loan loss provisions to total loans, the three-year growth in total book value of assets, and the bank's Z-Score. All right-hand-side variables are standardized by subtracting the mean and normalizing by the standard deviation of the variable. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using cluster-robust standard errors with each bank as a cluster. All regressions include bank fixed effects. Quarterly data, 1996Q3 – 2020Q4.

	(1)	(2)	(3)
Panel A: Diversification (Entropy) for small banks post GLB.			
small × post	0.021***	0.034**	0.038***
	(2.46)	(2.55)	(2.85)
Assets			-0.025
			(-1.38)
Capital/Assets			-0.001
			(-0.42)
Operating profits			0.061***
			(4.76)
Deposits/Liabilities			0.002***
			(3.32)
Loan loss provisions			-0.022**
			(-2.26)
Asset growth			-0.001
			(-0.59)
Z-score			0.009
			(0.80)
Observations	46,664	46,664	45,027
Adjusted R^2	0.437	0.756	0.758
Bank FE	*No*	*Yes*	*Yes*
Year-Quarter FE	*Yes*	*Yes*	*Yes*
Panel B: Performance and risk for small banks post GLB.			
	(ROA)	(ROE)	$(Tailrisk)$
small × post × high	0.122**	0.089***	-0.283**
	(1.99)	(3.17)	(-2.12)
Assets	-0.118***	-0.136***	-0.337**
	(-3.06)	(-3.13)	(-2.18)
Capital/Assets	0.023***	-0.033***	-0.201***
	(3.37)	(-5.01)	(-6.03)
Operating profits	0.982***	0.927***	-0.385**
	(5.43)	(4.03)	(-2.30)
Deposits/Liabilities	-0.001	-0.001	0.007
	(-0.21)	(-0.38)	(0.92)
Loan loss provisions	-0.406***	-0.471***	1.225***
	(-8.69)	(-9.27)	(6.60)
Asset growth	0.001***	0.001***	-0.001
	(3.63)	(5.10)	(-0.33)
Z-score	0.202***	0.250***	-0.487***
	(6.99)	(8.04)	(-4.87)
Nobs	45,027	45,027	45,027
Adjusted R^2	0.526	0.471	0.631
Bank FE	*Yes*	*Yes*	*Yes*
Year-Quarter FE	*Yes*	*Yes*	*Yes*

Appendix
Which "MEASURE" of Bank Diversification Measure Up?

A Definitions and construction of variables

We collect balance sheet data for banks from the 'Report for Condition and Income' (henceforth Call Reports) required to be filed by all FDIC-insured bank holding companies in the U.S. This data is available at https://www.chicagofed.org/applications/bhc_data/bhcdata_index.cfm. Definitions for the variables are available at http://www.federalreserve.gov/apps/mdrm/. Banks with total book value of assets above $500 million file this report quarterly. Other banks file this report only semi-annually. We restrict our sample to banks which file the Call Reports quarterly and report a positive book value of assets. Between June 1986 and December 2020, this yields 182,038 observations. The actual number of observations in our analysis is less for several reasons. First, we eliminate data for all banks whose total capital is missing, zero, or negative. This yields a dataset with just 132,937 observations. Second, we eliminate observations if any of the control variables is missing. This leaves us with 75,020 bank-quarter observations. Third, after merging with variables constructed from CRSP, we require that the banks in our sample have at least three consecutive years (12 quarters) of data available. This leaves us with 23,785 bank-quarter observations between September 1996 and December 2020.

The data present a number of challenges in terms of creating a consistent time-series. Due to changing reporting requirements, some of the data items in the Call Reports used for the construction of key variables in our analysis are not comparable across quarters. The Chicago Federal Reserve Bank provides instructions for the construction of consistent time-series for the data in the Call Report. These instructions are available at http://www.chicagofed.org/webpages/banking/financial_institution_reports/bhc_data.cfm and are summarized in table A1.

Once we define time-series for individual banks, we also compute data for all U.S. banks (i.e. the aggregate U.S. bank sector) to report summary statistics in section 2. To compute the time-series for all U.S. banks, we start with data for individual banks. We filter the top and bottom

1-percentile of banks based on the quarterly growth rate in total book value of assets. This filter removes observations for those bank-quarters in which banks are involved in significant mergers. For aggregation, we require that in each quarter, banks included in our sample have call report data available for at least 12 previous quarters (3 years). We also require that for each quarter Call Report data for a particular bank is available for the previous and current quarters. This requirement ensures that the time-series of core, non-core, and trading incomes are not affected by entry or exit of banks. This requirement also means that the actual number of banks used in any quarter to compute the time-series for all U.S. banks varies over time.

Table A2 presents the definition for all key variables used in the paper and the data sources used to collect the data for the construction of these variables.

B Additional summary statistics

This table presents the definition for the sixteen different categories of interest and non-interest income and expenses derived from bank balance sheets to compute the Entropy measure of diversification. These sixteen categories are the most granular information on the different categories of income and expenses for banks that is available in the Call Reports required to be filed quarterly by all bank holding companies in the U.S.

Table A4 depicts the value of the seven different measures of bank diversification for the five largest bank holding companies in the U.S. The seven different measures were computed using data for 2020 (the value of the diversification measures was averaged over the four quarters of 2020).

Figure A1 This figure plots the diversification measures commonly used in the literature for all domestic banks in the U.S. Each panel depicts the time-series plot for a distinct diversification measure. The top-left panel shows the time-series plot for the HHindex, and each of the remaining panels show the time-series plot for the Absdiff, Rnetnet, Rtotnet, Rtottot, and Rsimple. In each panel, the blue solid line plots Entropy and the grey shaded regions represent National Bureau of Economic Research (NBER) recessions as well as periods of financial crisis. Years and months are indicated on the X-axis. The NBER recession dates are published by the NBER Business Cycle

Dating Committee. Quarterly data, 1990 – 2023

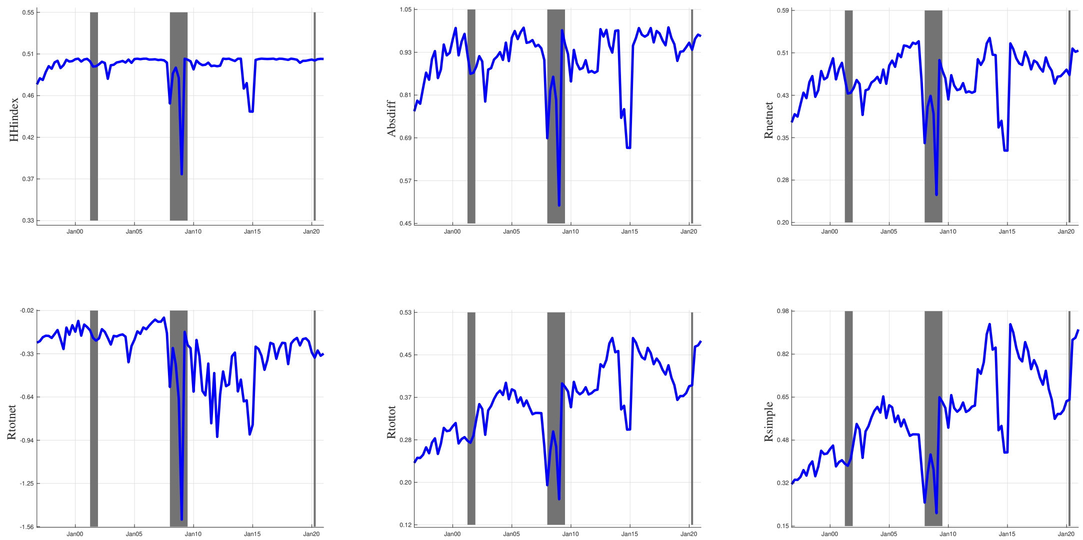

Figure A1. time-series plot for the diversification measures used commonly in the literature for the aggregate U.S. bank sector.

Notes: This figure plots the diversification measures commonly used in the literature for all domestic banks in the U.S. Each panel depicts the time-series plot for a distinct diversification measure. The top-left panel shows the time-series plot for the HHindex, and each of the remaining panels show the time-series plot for the Absdiff, Rnetnet, Rtotnet, Rtottot, and Rsimple. In each panel, the blue solid line plots Entropy and the grey shaded regions represent National Bureau of Economic Research (NBER) recessions as well as periods of financial crisis. Years and months are indicated on the X-axis. The NBER recession dates are published by the NBER Business Cycle Dating Committee. Quarterly data, 1990 – 2023.

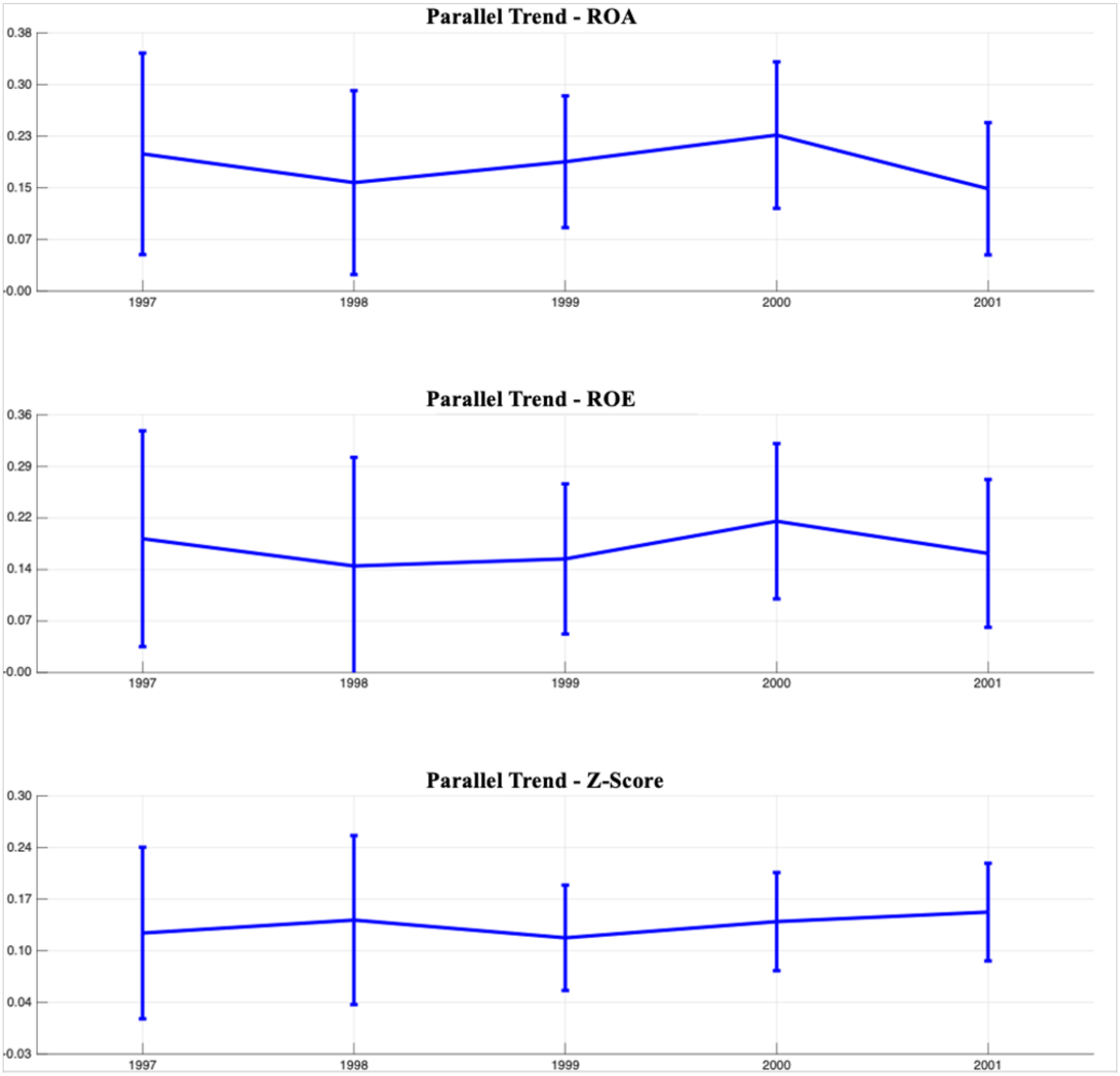

Figure A2. Parallel trends

Notes: This figure reports the regression coefficients (β_T) and 95% confidence intervals from the following regression:

$$Var_{i,t+1} = \alpha_i + \sum_{\tau}(\beta_\tau \times High_{i,t} \times Small_{i,t}) + Controls_{i,t} + \eta_i + \epsilon_{i,t}$$

Here, $Var_{i,t+1}$ is either the return on assets, return on equity, or Z-score for bank i at time $t+1$. High is a dummy variable that equals 1 for banks for which Entropy is above median in a given year. Small is a dummy variable that equals 1 for banks with less than \$1.5 billion in total assets. β_τ equals one for years 1997 – 2001, respectively. Each panel in the figure plots the results for a different dependent variable. Years are indicated on the X-axis. Quarterly data, 1997 – 2001.

Table A1. Computation of consistent time-series

Notes: This table provides details regarding the construction of key variables used in our empirical analysis. We collect balance sheet data for banks from the 'Report of Condition and Income (Call Report)' required to be filed by all FDIC-insured bank holding companies in the U.S. The first column lists the mnemonic used to identify each variable in our empirical analysis. Column titled 'Name' provides a brief description. Column titled 'Call Report Data Item' lists the exact Federal Reserve item codes used to construct each variable. Finally, column titled 'Adjustment Rules' details adjustments made to the definition of each variable to render them time-consistent.

Mnemonic	Name	Call Report Data Items	Adjustment Rules
Total assets	Book value of assets	BHCK2170	
Capital	Tier 1 Capital	BHCA8274	After 2014 use BHCA8274. Between 1996 and 2014, use BHCK8274. Before 1996 use the sum of BHCK3210, BHCK3247, BHCK3455, and BHCK3456.
	TIER 1 CAPITAL	BHCK8274	
	Total Equity Capital	BHCK3210	
	Undivided profits and capital reserves	BHCK3247	
	Unsecured long-term debt	BHCK3247	
	Mandatory convertible securities	BHCK3247	
Deposits	Domestic non-interest bearing deposits	BHDM6631	Sum of items.
	Domestic interest bearing deposits	BHDM6636	
	Foregin non-interest bearing deposits	BHFN6631	
	Foregin interest bearing deposits	BHFN6636	
	Total non-interest income	BHCK4079	
	Total interest income	BHCK4107	
	Net income	BHCK4340	
	Total liabilities	BHCK2948	
	Preferred stocks	BHCK3283	
	Net interest income	BHCK4074	
	Total interest expense	BHCK4073	
	non-interest expense	BHCK4093	
	Loan loss provisions	BHCK4230	
non-interest income	Income from fiduciary activities	BHCK4070	
	Service charges on deposits accounts in domestic offices	BHCK4483	
	Trading revenue	BHCKA220	
	Fees and commissions from securities brokerage	BHCKC886	
	Investment banking, advisory, and underwriting fees and commisions	BHCKC888	
	Fees and commissions from annuity sales	BHCKC887	
	Underwriting income from insurance and reinsurance activities	BHCKC386	
	Income from other insurance activities	BHCKC387	
	Venture capital revenue	BHCKB491	
	Net servicing fees	BHCKB492	
	Net securitization income	BHCKB493	
	Net gains (losses) on sales of loans and lease	BHCK8560	
	Net gains (losses) on sales of other real estate owned	BHCK8561	
	Net gains (losses) on sales of other assets	BHCKB496	
	Other non-interest income	BHCKB497	
Interest income	Loans secured by 1-4 family residential properties (domestic)	BHCK4435	
	All other loans secured by real estate (domestic)	BHCK4436	
	All other loans (domestic)	BHCKF821	
	In foreign offices, Edge and Agreement subsidiaries, and IBFs	BHCK4059	
	Income from lease financing receivables	BHCK4065	
	Interest income on balances due from depository institutions	BHCK4115	
	U.S. Treasury securities and U.S. government agency obligations (excluding mortgage-backed securities)	BHCKB488	
	Mortgage-backed securities	BHCKB489	
	All other securities	BHCK4060	
	Interest income from trading assets	BHCK4069	
	Interest income on federal funds sold and securities purchased under agreements to resell	BHCK4020	
	Other interest income	BHCK4518	

Table A2. Variables and data sources.

Notes: This table shows the definition for all key variables used in the paper and the data sources used to collect the data for the construction of these variables.

Variable	Description and sources
Entropy	Entropy Index of nine non-interest income and seven interest income items. FR Y-9C
Hhindex	1 - Herfindahl-Hirschman Index of non-interest income and net interest income. FR Y-9C
Absdiff	1 - the absolute value of the ratio of net interest income minus non-interest income to the sum of net interest income and non-interest income. FR Y-9C
R-totnet	Ratio of non-interest income to the sum of non-interest income and net interest income. FR Y-9C
R-netnet	Ratio of net non-interest income to the sum of net non-interest income and net interest income. FR Y-9C
R-tottot	Ratio of non-interest income to the sum of non-interest income and interest income. FR Y-9C
R-simple	Ratio of non-interest income to interest income. FR Y-9C
Idiosyncratic volatility	Standard deviation of the residuals obtained by regressing daily bank stock returns on Fama-French three factors. CRSP, Kenneth French's Data Library
Assets	Natural logarithm of total assets. FR Y-9C
Capital/Assets	Ratio of equity capital to total assets. FR Y-9C
Operating Profits	Ratio of the sum of non-interest and interest income to total assets. FR Y-9C
Cost/Income	Ratio of the sum of non-interest and interest expense to the sum of non-interest and interst income. FR Y-9C
Deposits/Liabilities	Ratio of total deposits to total liabilities. FR Y-9C
Loan loss provisions	Ratio of loan loss provisions to total loans. FR Y-9C
Assets growth	Three-year growth in total assets. FR Y-9C
Z-Score	The common logarithm of Z-score, where the Z-score is the ratio of the sum of return on assets and capital to assets ratio to the standard deviation of return on assets over a rolling window of 12 quarters. FR Y-9C
Tobin's Q	Ratio of the sum of the market value of common equity, the book value of total liabilities, and the book value of preferred stocks to the book value of total assets. CRSP, FR Y-9C

Table A3. Variables and data sources.

Notes: This table presents the definition for the sixteen different categories of interest and non-interest income derived from bank balance sheets to compute the Entropy measure of diversification. These sixteen categories are the most granular information on the different categories of income for banks that is available in the Call Reports required to be filed quarterly by all bank holding companies in the U.S. We also list the items code for the various categories of incomes in the call reports (FRY9Cs) filed by bank holding companies.

Variable	Description and sources
L01	Interest and fee income on loans (BHCK4435, BHCK4436, BHCKF821)
L02	Income from lease financing receivables (BHCK4065)
L03	Interest income on balances due from depository institutions (BHCK4115)
L04	Interest and dividend income on securities (BHCKB488, BHCK489, BHCK4060)
L05	Interest income from trading assets (BHCK4069)
L06	Interest income on federal funds sold and securities purchased under agreements to resell (BHCK4020)
L07	Other interest income Noninterest Income (BHCK4518)
L08	Income from fiduciary activities (BHCK4070)
L09	Service charges on deposits accounts in domestic offices (BHCK4483)
L10	Trading revenue (BHCKA220)
L11	Income from securities-related and insurance activities (BHCKC886, BHCKC888, BHCKC887, BHCKC386, BHCKC387)
L12	Venture capital revenue (BHCKB491)
L13	Net servicing fees (BHCKB492)
L14	Net securitization income (BHCKB493)
L15	Net gains (losses) on assets (BHCK8560, BHCK8561, BHCKB496)
L16	Other noninterest income (BHCKB497)

Table A4. Diversification measures for the five largest bank holding companies in the U.S.

Notes: This table presents the diversification measures for the five largest bank holding companies in the U.S. measured over 2020. Column 1 indicates the name of the bank, Columns 2 - 7 report the mean Entropy, HHindex, Absdiff, R-totnet, R-netnet, R-tottot, and R-simple, i.e., the seven measures of diversification computed as described in Table 2.2 for the bank over four quarters in 2020.

Bank	Entropy	HHindex	Absdiff	R-totnet	R-netnet	R-tottot	R-simple
JPMC	1.83	0.49	0.91	-0.08	0.54	0.50	1.00
BoA	1.80	0.50	0.96	-0.43	0.49	0.45	0.83
Wells	1.82	0.49	0.88	-1.43	0.44	0.40	0.68
Citi	1.70	0.48	0.82	-0.44	0.41	0.34	0.52
Goldman	1.52	0.20	0.22	0.41	0.89	0.74	3.09