Federal Reserve Bank of Philadelphia

Working Papers
Research Department

WP 18-11
March 2018
https://doi.org/10.21799/frbp.wp.2018.11

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ISSN: 1962-5361

DOES SCALE MATTER IN COMMUNITY BANK PERFORMANCE? EVIDENCE OBTAINED BY APPLYING SEVERAL NEW MEASURES OF PERFORMANCE*

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MARCH 2018

Supersedes Working Paper 16-15

ABSTRACT

We consider how size matters for banks in three size groups: banks with assets of less than $1 billion (small community banks), banks with assets between $1 billion and $10 billion (large community banks), and banks with assets between $10 billion and $50 billion (midsize banks). Community banks have potential advantages in relationship lending compared with large banks. However, increases in regulatory compliance and technological burdens may have disproportionately increased community banks' costs, raising concerns about small businesses' access to credit. Our evidence suggests that (1) the average costs related to regulatory compliance and technology decrease with size; (2) while small community banks exhibit relatively more valuable investment opportunities, larger community banks and midsize banks exploit theirs more efficiently and achieve better financial performance; (3) unlike small community banks, large community banks have financial incentives to increase lending to small businesses; and (4) for business lending and commercial real estate lending, large community banks and midsize banks assume higher inherent credit risk and exhibit more efficient lending. Thus, concern that small business lending would be adversely affected if small community banks find it beneficial to increase their scale is not supported by our results.

Keywords: community banking, scale, financial performance, small business lending
JEL Codes: G21, L25

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This paper supersedes "Is Bigger Necessarily Better in Community Banking?" by J.P. Hughes, J. Jagtiani, and L.J. Mester, Federal Reserve Bank of Philadelphia Working Paper 16-15, June 10, 2016.

Hughes thanks the Whitcomb Center for Research in Financial Services at the Rutgers Business School for its support of data services used in this research. We thank Raman Maingi and Leigh-Ann Wilkins for their research assistance.

1. Introduction

A body of research has shown that community banks have potential advantages in relationship lending compared with large banks, although newer research suggests that these advantages may be shrinking. In addition, community bankers often cite increased regulatory burden and the need to increase investment in technology as having raised their costs. Both of these have fixed-cost components and so may have disproportionately raised community banks' costs, with the potential to impact their ability to meet local demand or expand beyond their local communities.

We use 2013 data on 722 top-tier bank holding companies (BHCs), whose assets are consolidated across all constituent subsidiaries to investigate performance differences of banks in three size categories: small community banks (i.e., banks with assets of less than $1 billion), large community banks (i.e., banks with assets between $1 billion and $10 billion), and midsize banks (i.e., banks with assets between $10 billion and $50 billion). There are 328 small community banks, 354 large community banks, and 40 midsize banks in the sample.[2]

For the 245 publicly traded banks in the sample, we augment their financial accounting data with performance measures based on their market value. The publicly traded sample allows us to compare accounting measures of current performance with the market's expectation of discounted future profitability. Although publicly traded firms represent only about 31 percent of the community banks, this smaller sample provides important evidence of the investment incentives provided by the capital market. The performance results based on the publicly traded sample largely confirm the results from the larger sample and indicate differences in capital market incentives to make small business loans (SBLs) across the three bank size categories.

Our results indicate that small community banks experience higher overall average operating costs and higher average costs of corporate overhead, reporting and compliance, and telecommunications compared with large community banks and midsize banks. While banks of all sizes obtain essentially the same average revenue per dollar of assets, large community banks and midsize banks achieve, on average, a higher return on assets than small community banks, even when normalized for risk measured by the standard deviation of return.[3] We investigate whether this higher average return of larger banks results from more profitable investment opportunities or from greater efficiency at exploiting their investment opportunities.

We apply stochastic frontier techniques to measure efficiency as the difference between a bank's achieved return adjusted for noise (luck) and an estimate of what it could potentially achieve given its exposure to return risk. We find no statistically significant difference in the potential

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[2] The data set includes independent banks not owned by another company and the top-tier holder of institutions with multiple subsidiaries (with assets and liabilities consolidated across all constituent subsidiaries). The accounting data is from the Y-9C BHC consolidated financial statements.

[3] Stiroh and Rumble (2006) use this measure of risk to gauge risk-normalized return.

return across the three types of banks. However, we find that large community banks and midsize banks are more efficient than small community banks (i.e., they achieve more of their potential return than small community banks).

The higher average accounting return achieved by the larger banks in the full sample is confirmed by the publicly traded sample's market-value measures of performance. As in the case of the return on assets and return efficiency, the difference in Tobin's q ratios between large community banks and midsize banks is not statistically significant; however, both attain, on average, a higher Tobin's q ratio than small community banks. As in the case of the return on assets, we find that large community banks and midsize banks, on average, achieve relatively more of their potential market value than small community banks. In contrast, the relative market value of their investment opportunities is lower than that of small community banks, which suggests that these larger banks appear to exploit their investment opportunities more effectively than small community banks.

Research suggests that small community banks experience advantages in relationship lending compared with larger banks.[4] However, we find that they also have a higher ratio of nonperforming loans (NPLs) to total loans. We use data on business loans and commercial real estate loans to investigate whether the higher nonperforming loan ratio is because small community banks are lending to riskier borrowers who default more often or because they are less efficient at credit analysis and loan monitoring. For each loan category, we use stochastic frontier techniques to estimate the minimum ratio of NPLs that a bank would achieve if it were fully efficient at credit-risk evaluation and loan monitoring, controlling for the average contractual interest rate charged for this type of loan, the scale of its lending, and the economic conditions in the markets in which the bank operates. The difference in the bank's observed nonperforming loan ratio adjusted for noise (luck) and this minimum ratio reflects a bank's efficiency at credit evaluation and loan monitoring. Our analysis indicates that, compared with larger banks, small community banks' relatively higher average ratios of nonperforming business loans and commercial real estate loans reflect lower best-practice nonperforming loan ratios (i.e., lower inherent credit risk) and a relatively higher ratio of nonperformance in excess of best practice (i.e., less lending efficiency).

Finally, we investigate the incentives to make small business loans (SBLs), a product in which small banks have traditionally had a comparative advantage. Historically, community banks have served as an important source of credit for small businesses, but the SBL market and the economic landscape have significantly changed in recent years. Jagtiani and Lemieux (2016, 2018)

[4] Berger and Udell (2006) discuss the literature on small business finance.

discuss how advanced technology has allowed large banks and nonbank alternative lenders to become more important providers of SBLs since the latter part of the 2000s. The fixed cost required to invest in technology may have affected the efficiency and performance at small community banks in recent years.

Using Call Report data on SBLs (i.e., small commercial and industrial (C&I) loans) with origination amounts less than $1 million, we find no statistically significant difference in the ratio of SBL to assets at small and large community banks.[5] Accounting measures of performance indicate that financial performance is positively related to the ratio of SBLs to assets at small and large community banks, but market-value measures suggest that SBLs enhance market value at large community banks and erodes market value at small community banks.

Overall, our results suggest that on average, large community banks outperform small community banks and are more efficient at credit-risk assessment and at monitoring both business loans and commercial real estate loans and that midsize banks financially outperform community banks. Thus, there appear to be incentives for small banks to grow larger to exploit scale economies and to achieve other scale-related benefits in terms of lending efficiency. In addition, we find that SBLs are an important factor explaining large community banks' better performance compared with small community banks. Thus, the concern that small community banks would curtail their SBL if these banks decide to increase their scale is not supported by our results.

The rest of this paper is organized as follows. Section 2 provides a brief literature review. Section 3 describes the data. Section 4 discusses the accounting-based and market-value-based measures of financial performance and the empirical findings on the relationship between bank size (scale) and the various measures of performance. Section 5 considers the degree to which community banks are handicapped by costs of information technology and compliance. Section 6 explores differences in investment strategies by bank size that can influence performance. Section 7 presents results that decompose the difference in nonperformance into inherent credit risk of the borrowers to whom the bank lends and the effectiveness with which they evaluate and monitor loans to these borrowers. Section 8 investigates whether the differences in performance we found by bank size provide financial incentives for small community banks to grow larger and to change their investment strategy, in particular, lending to small businesses. Section 9 concludes.

[5] Different studies in the literature use different sources of data and therefore use different definitions of SBLs. Call Reports define SBLs as C&I loans with origination amounts less than $1 million, regardless of whether the borrowers are actually small. The Community Reinvestment Act defines SBLs as loans made to small businesses with less than $1 million in annual gross revenue. The Federal Reserve Survey of Small Business Finance defines SBLs as loans made to small businesses with fewer than 500 employees (regardless of loan size). Because of these different definitions, results may not be comparable across studies.

2. Review of the Literature on Small Business Lending by Community Banks versus Larger Banks

Previous studies, including those by Berger, Miller, Petersen, Rajan, and Stein (2005); Chakraborty and Hu (2006); Beccalli and Frantz (2013); and Kowalik (2014) have documented support for the traditional view that small community banks have advantages in monitoring their customers through personal relationships. According to this view, unlike large banks that tend to serve larger firms, on which there is more publicly available information, small community banks play a special role in supporting small businesses in their local communities because they are better able to form strong relationships with small, opaque firms.

However, this traditional view has been challenged in more recent studies. Berger and Udell (2006) find that large banks are, in fact, not disadvantaged when providing credit to informationally opaque, small firms. They explain that the conflicting evidence obtained by some studies that use international data and find that small banks have an advantage in SBL may be driven by the fact that lending technologies available in the U.S. may not be used in other countries. Studies based on U.S. data, including Berger, Frame, and Miller (2005) and Berger, Cowan, and Frame (2011), find that technologies such as small business credit scoring have somewhat replaced the traditional banking relationships and have allowed large banks to increase their SBLs at a lower cost than small community banks. Mester (1999) discusses the access to credit of small businesses and the entry of larger banks into the SBL market.

Similarly, DeYoung, Frame, Glennon, and Nigro (2011) and Peterson and Rajan (2002) note that the distance between small business borrowers and lenders has been increasing as a result of changes in lending technology, such as the adoption of credit scoring technologies by the lending banks. The motivation for this expansion is not clear; it appears that loans made to borrowers located closer to the lending bank perform better. DeYoung, Glennon, and Nigro (2008) find that borrowers at least 25 miles away from their bank lenders were 10.8 percent more likely to default on their loans, and borrowers located at least 50 miles away were 22.1 percent more likely to default on their loans. DeYoung, Frame, Glennon, McMillen, and Nigro (2008) find that, in addition to the significant movement toward automated lending technology in recent years, small businesses have increasingly relied on larger banks as their funding sources. Prager and Wolken (2008) confirm this, using the 2003 Survey of Small Business Finance data; they find that 70 percent of small businesses cite a big bank as their primary financial institution, but only 25 percent cite a community bank, and 5 percent cite a nonbank institution.

More recent studies, using data after the financial crisis, such as Berger, Goulding, and Rice (2014) and Berger, Cerqueiro, and Penas (2014), provide supporting evidence of the increasing roles that large banks play in lending to small business and to start-up firms. In addition, Jagtiani, Kotliar, and Maingi (2016) investigate bank mergers announced during the period 2000–2012 and find no adverse impact on overall SBLs even after the community bank merger targets became part of the large acquiring banks. In fact, they find that post-merger, the merged banking firm's SBLs tended to exceed the pre-merger SBLs of the target and acquirer (i.e., SBLs increased after community bank targets became larger via the merger).

In addition to small businesses obtaining more of their funding from large banks, previous studies have also shown that small businesses have increased their use of nontraditional credit, such as loans from nonbank institutions and business credit cards, funded by large banks and nonbank institutions. Mester, Nakamura, and Renault (2007) report that finance companies were responsible for an increasing share of loans to businesses over time, reaching one-third by 2006. Using a longer sample period that includes more recent data after the financial crisis, Jagtiani and Lemieux (2016, 2018) confirm that nonbank institutions have been increasing their role in the SBL market through online lending platforms.[6]

3. The Data

We use 2013 data on 722 top-tier bank holding companies to measure performance and investment strategies. Our study focuses on banking firms with assets of $50 billion or less because these firms are not considered systemically important financial institutions by the definition given in the Dodd–Frank Wall Street Reform and Consumer Protection Act. The sample consists of banks with assets ranging from $92.7 million to $47.1 billion. We define two groups of community banks: Small community banks are banks with assets of less than $1 billion, and large community banks are banks with assets between $1 billion and $10 billion. There are 328 small community banks and 354 large community banks. We contrast these two groups with the sample's 40 midsize banks (i.e., banks with assets between $10 billion and $50 billion). Among the 722 top-tier holding companies, 245 are publicly traded.

We draw on several sources for our data: market-value information from Compustat, accounting data from the end-of-year Y9-C reports filed with regulators and data used to determine the geographic reach of banks from the *Summary of Deposits* obtained from the Federal Deposit Insurance Corporation (FDIC).

Because the Y9-C data do not report SBLs at the level of the consolidated top-tier holding company, we collect data on outstanding SBLs from the end-of-year 2013 bank-level Call Reports and sum them to the top-tier holding company level using the Federal Reserve Structure Database.

[6] They also suggest ways to enhance potential cooperation, such as partnerships between large banks and community banks or between banks and nonbank lenders.

4. Financial Performance and the Value of Investment Opportunities

4.1 Accounting Measures

4.1.1 Return on Assets and Risk-Normalized Return on Assets

We base several measures of performance on accounting data. Profit is gauged by the net income component of the Y-9C Report (BHCK4301): "Income (loss) before income taxes and extraordinary items, and other adjustments." **ROA** (return on assets) is given by profit divided by consolidated assets (BHCK2170).[7] **Risk-normalized ROA** is measured by the bank's ROA divided by the standard deviation of its ROA (*ROASTD*). The standard deviation is calculated over the period 2009-2013.

4.1.2 Return Shortfall

Does a finding that the mean achieved ROA of one group of banks is higher than another reflect the first group's relatively more valuable investment opportunities, greater efficiency in exploiting investment opportunities, or both? To address this question, we estimate an upper envelope of observed ROA as a function of ROA risk to distinguish between best-practice ROA and ROA efficiency — how much of best- practice ROA is achieved after eliminating the influence of statistical noise (luck).[8] Thus, we augment the standard measures of ROA by the **best-practice ROA** and **risk-normalized best-practice ROA,** which are estimates of the value of investment opportunities available to a bank, and **ROA shortfall** and **risk-normalized ROA shortfall**, which are measures of the bank's inefficiency. For example, consider two banks — one that exhibits ROA of 3 percent and the other, 4 percent. Suppose the potential ROA of the first bank is 3.5 percent and the second bank is 5 percent. Then the ROA of the first bank is lower than that of the second bank, but it has achieved more of its potential, with a shortfall from potential of only 0.5 percentage points compared with a shortfall of 1.0 percentage points for the second bank.

To estimate the best practice and shortfall, we use stochastic frontier techniques to estimate an upper envelope of observed ROA as a quadratic function of ROA risk (*ROASTD*).[9] The frontier value estimates the best-practice ROA observed in the sample for a given value of ROA risk after eliminating noise (luck). The shortfall of a bank's actual ROA from this best-practice ROA gauges how efficient the bank is in achieving this best-practice performance.[10]

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[7] The findings based on the return on equity are qualitatively similar so we do not report them. We focus instead on the return on assets because the return on equity is substantially influenced by leverage.

[8] To be clear, this is an empirical study and we can only identify the best-practice we observe in our sample and not the theoretically best-practice.

[9] Bauer (1990) and Jondrow, Lovell, Materov, and Schmidt (1982) describe the stochastic frontier technique in detail.

[10] We use the term potential ROA, but recognize that this is the best-practice ROA observed in the sample and not necessarily the best-practice that could ever be achieved.

More specifically, we use maximum likelihood techniques to estimate a quadratic frontier:

$$ROA_i = \alpha + \beta\,(\mathrm{ROASTD_i}) + \gamma\,(ROASTD_i)^2 + \varepsilon_i\,, \tag{1}$$

where $\varepsilon_i = v_i - \mu_i$ is the sum of a two-sided, normally distributed error term, $v_i \sim$ iid $N(0,\sigma_v^2)$, that captures statistical noise, and a one-sided, positive, and exponentially distributed error term, μ_i, $\mu_i\ (> 0) \sim \theta \exp(-\theta u)$, that gauges the systematic shortfall from best practice. We measure a bank's **best-practice ROA** by,

$$\textbf{\textit{best-practice ROA}}_{\mathbf{i}} = \alpha + \beta\,(ROASTD_i) + \gamma\,(ROASTD_i)^2. \tag{2}$$

We measure a bank's **ROA shortfall** by the expectation of μ_i, the one-sided error term, conditional on $\varepsilon_{i,}$ the composite error term:

$$\textbf{\textit{ROA shortfall}}_{\boldsymbol{i}} = E(\mu_i|\varepsilon_i). \tag{3}$$

We measure **noise** by the expectation of v_i, the two-sided error term, conditional on $\varepsilon_{i,}$ the composite error term:

$$\textbf{\textit{noise}}_{\boldsymbol{i}} = E(v_i|\varepsilon_i) = \varepsilon_i + E(\mu_i|\varepsilon_i). \tag{4}$$

Thus, the frontier estimation decomposes the observed ROA into three components: the best-practice ROA, the ROA shortfall from best-practice ROA, and noise:

$$\begin{aligned} ROA_i &= \textbf{\textit{best-practice ROA}}_{\boldsymbol{i}} - \textbf{\textit{ROA shortfall}}_{\boldsymbol{i}} + \textbf{\textit{noise}}_{\boldsymbol{i}} \\ &= \alpha + \beta\,(ROASTD_i) + \gamma\,(ROASTD_i)^2 - E(\mu_i|\varepsilon_i) + E(v_i|\varepsilon_i). \end{aligned} \tag{5}$$

Statistical noise can be subtracted from ROA to obtain the noise-adjusted ROA,

$$\textbf{\textit{noise-adjusted observed ROA}}_{\boldsymbol{i}} = ROA_i - E(v_i\,|\varepsilon_i\,). \tag{6}$$

ROA shortfall, given in Equation (3), can be expressed as the difference between the best-practice ROA and the noise-adjusted observed ROA:

$$\textbf{\textit{ROA shortfall}}_{\boldsymbol{i}} = E(\mu_i|\varepsilon_i) = \alpha + \beta\,(ROASTD_i) + \gamma\,(ROASTD_i)^2 - (ROA_i - E(v_i|\varepsilon_i)). \tag{7}$$

Figure 1 illustrates achieved ROA, the best-practice ROA, the shortfall from best practice, and noise. In this example, bank *i* attains an achieved ROA of 1.08 percent. The best-practice ROA is 1.70 percent, which consists of the achieved ROA of 1.08 percent, statistical noise (luck) of −0.02 percent, and an ROA shortfall from best practice of 0.60 percent. The ROA adjusted for noise is $(ROA_i - v_i)$ = 1.08 – (–0.02) = 1.10 percent. The difference between the best-practice ROA, 1.70 percent, and the noise-adjusted observed ROA, 1.10 percent, represents the ROA shortfall, 0.60.

We can normalize the best-practice ROA and the shortfall by risk:

$$\textbf{\textit{risk-normalized best-practice ROA}}_{\boldsymbol{i}} = \textit{best-practice ROA}_i / ROASTD_i, \tag{8}$$

and

$$\textbf{\textit{risk-normalized ROA shortfall}}_{\boldsymbol{i}} = \textit{ROA shortfall}_i / ROASTD_i. \tag{9}$$

4.2 Market-Value Measures

4.2.1 Tobin's q Ratio

For the banks that are publicly traded, we also derive several measures of performance based on their market value. Market-value measures of performance offer two advantages. First, while accounting measures gauge current profitability, a firm's market value comprises not just the firm's current cash flow but also the market's expectation of the future cash flow discounted at a rate that reflects the market's assessment of the relevant risk attached to the cash flow. Second, differences in investment incentives of small and large community banks provided by the capital market can be inferred from market-value measures of performance. Nevertheless, we add the caveat that the smaller number of publicly traded banks, especially in the case of small community banks, requires caution in drawing conclusions. Hughes and Mester (2010, 2013a, 2015) provide a comprehensive discussion of methodologies to assess bank performance.

Performance based on market value is frequently measured by **Tobin's *q* ratio**, which is defined as the ratio of the market value of assets (MVA) to their replacement cost. We use a common proxy for the MVA of bank *i* (MVA_i), which is the sum of the market value of equity and the book value of liabilities. For replacement cost, we use a standard proxy, bank *i*'s book value of assets net of goodwill (BVA_i). Thus,

$$\textbf{\textit{Tobin's q ratio}} = MVA_i / BVA_i.\text{[11]} \tag{10}$$

[11] See Hughes and Mester (2010, 2015) for a review of the finance literature that uses Tobin's *q* ratio to measure performance.

4.2.2 Market-Value Inefficiency and the Value of Investment Opportunities[12]

Similar to the measures we described previously based on ROA, we use stochastic frontier techniques to gauge the market value of investment opportunities and the efficiency of banks in exploiting these investment opportunities. For efficiency measurement we ask: What is the highest market value of a bank's book-value investment in assets across all banking markets? Adjusted for statistical noise, the difference between the highest value and the achieved value measures the bank's lost market value, which can be used to gauge its efficiency. This systematic lost market value captures differences among firms in market advantages as well as differences in managerial consumption of agency goods. Because managers decide the local markets in which their firms should operate and the capital market prices differences in market advantages, we consider market advantages as components of managerial effectiveness.

As we did for the accounting measure, ROA, to obtain an estimate of the potential value, we use maximum likelihood techniques to estimate a quadratic frontier:

$$MVA_i = \alpha + \beta(BVA_i) + \gamma(BVA_i)^2 + \varepsilon_i\,, \tag{11}$$

where $\varepsilon_i = v_i - \mu_i$ is a composite error term. Statistical noise is given by $v_i \sim$ iid $N(0,\sigma_v^2)$. The systematic shortfall from bank *i*'s best-practice market value is given by μ_i. We assume that μ_i is distributed exponentially, $\mu_i\ (> 0) \sim \theta\, exp(-\theta u)$.

From the estimation of Equation (11), we obtain the best-practice market value, the market-value shortfall, and the noise component for bank *i* (all measured in dollars):

$$\textbf{best-practice MVA} = \alpha + \beta(BVA_i) + \gamma(BVA_i)^2, \tag{12}$$

$$\textbf{MVA shortfall}_{\boldsymbol{i}} = E(\mu_i|\varepsilon_i), \tag{13}$$

$$\textbf{noise}_{\boldsymbol{i}} = E(v_i|\varepsilon_i) = \varepsilon_i + E(\mu_i|\varepsilon_i). \tag{14}$$

Thus, the frontier estimation decomposes the observed MVA into three components: the best-practice MVA, the MVA shortfall from best-practice MVA, and noise:

$$MVA_i = \textbf{best-practice MVA}_{\boldsymbol{i}} - \textbf{MVA shortfall}_{\boldsymbol{i}} + \textbf{noise}_{\boldsymbol{i}}$$

$$= \alpha + \beta(BVA_i) + \gamma(BVA_i)^2 - E(\mu_i|\varepsilon_i) + E(v_i|\varepsilon_i). \tag{15}$$

By subtracting luck from the observed MVA, we obtain the noise-adjusted MVA,

[12] Hughes, Lang, Moon, and Pagano (1997) proposed these concepts, which have been applied numerous studies. See Hughes and Mester (2015) for examples.

$$\textbf{\textit{noise-adjusted observed MVA}}_i = MVA_i - E(\nu_i|\varepsilon_i). \tag{16}$$

The expression in Equation (15) can be rearranged to express the MVA shortfall as the difference between the best-practice MVA and the noise-adjusted observed MVA:

$$\textbf{\textit{MVA shortfall}}_i = E(\mu_i|\varepsilon_i) = \alpha + \beta(BVA_i) + \gamma(BVA_i)^2 - (MVA_i - E(\nu_i|\varepsilon_i)). \tag{17}$$

The shortfall is measured in dollars of lost market value. To control for size we choose to normalize the shortfall by the best-practice value to obtain the proportion of potential value systematically lost:

$$\textbf{\textit{market-value inefficiency ratio}}_i = E(\mu_i|\varepsilon_i)/[\ \alpha + \beta(BVA_i) + \gamma(BVA_i)^2]. \tag{18}$$

Figure 2 illustrates these measures. In this example, bank *i* has invested 100 in assets and achieves a market value of 106. Noise is −2, so that the MVA adjusted for statistical noise, $(MVA_i - \nu_i)$, is 108. Its best-practice market value is 120, and the shortfall from potential value, the difference between the best-practice value and the noise-adjusted observed value, is 12. Thus, the market-value inefficiency ratio is 0.10 (=12/120).

We can also use the frontier estimation to derive a measure of Tobin's *q* that is adjusted for noise:

$$\textbf{\textit{noise-adjusted Tobin's q ratio}} = [MVA_i - E(\nu_i|\varepsilon_i)]/BVA_i. \tag{19}$$

Several studies have used the market-value inefficiency ratio or the noise-adjusted Tobin's *q* ratio to measure performance.[13]

Although Tobin's *q* ratio is a standard measure in the literature, the market-value inefficiency ratio offers some advantages as a measure of financial performance. First, it removes the influence of luck on performance and measures a firm's systematic failure to achieve its best-observed-value. Since the frontier technique identifies lost market value as well as achieved market value, it gauges the extent of agency problems in an industry more directly than Tobin's *q* ratio, and it allows us to investigate the factors that contribute to firms' failure to achieve their highest potential market value. Consequently, it can uncover differences in investment incentives provided by the capital market.

We derive a second set of measures that looks at highest potential value of the bank given the markets in which it operates. This allows us to measure the market value of investment opportunities it faces in its markets, in contrast to potential value across all markets in the sample.

[13] See, for example, Habib and Ljungqvist (2005); Baele, De Jonghe, and Vander Vennet (2007); De Jonghe and Vander Vennet (2005); Hughes and Moon (2003); Hughes, Lang, Mester, and Moon (1999); Hughes, Mester, and Moon (2001); Hughes, Lang, Mester, Moon, and Pagano (2003); and Hughes and Mester (2013a, 2013b).

This highest potential value of a bank in the markets in which it operates can be considered its value in a competitive auction — its charter value. In contrast to frequently used measures of the value of investment opportunities, such as the price-earnings ratio and Tobin's q ratio, which can be biased by agency problems, this measure is independent of the managerial decisions of any specific bank.

To obtain this potential value, we amend Equation (11) by adding variables that characterize the economic opportunities of the markets in which a bank operates: the weighted average GDP growth rate ($\boldsymbol{Growth_i}$) and the weighted average Herfindahl index ($\boldsymbol{Herf_i}$) across these markets, where the weights are bank deposit shares.[14] In particular, we use maximum likelihood to estimate the frontier,

$$MVA_i = \alpha + \beta(BVA_i) + \gamma(BVA_i)^2 + \gamma_{AG}(BVA_i)(Growth_i) + \gamma_{AH}(BVA_i)(Herf_i) + \varepsilon_i\,, \tag{20}$$

where $\varepsilon_i = v_i - \mu_i$ is an error term composed of statistical noise, $v_i \sim$ iid $N(0,\sigma_v^2)$, and the systematic shortfall, μ_i. We assume that μ_i is distributed exponentially, $\mu_i\ (> 0) \sim \theta\, exp(-\theta u)$.

The best-practice value of a firm's investment opportunities in the markets in which it operates (measured in dollars) is given by this frontier value:

$$\boldsymbol{investment\ opportunities_i} = \alpha + \beta(BVA_i) + \gamma(BVA_i)^2 + \gamma_{AG}(BVA_i)(Growth_i) + \gamma_{AH}(BVA_i)(Herf_i). \tag{21}$$

This is an estimate of a bank's charter value, which is the value of its charter in a competitive auction. Franchise value, the achieved market value, differs from charter value when agency problems erode market value.

To compare the value of investment opportunities of banks of different sizes, we normalize investment opportunities by BVA to obtain:

$$\boldsymbol{investment\ opportunity\ ratio_i} = investment\ opportunities_i / BVA_i. \tag{22}$$

4.3 Results on Financial Performance

Table 1 shows the results for the performance measures based on accounting data and provides difference-in-mean tests across the three categories of banks. As shown, there are no

[14] We consider only deposits at banking institutions; deposits at thrifts and credit unions are not included in the analysis. Market share measure is calculated at the state level.

statistically significant differences in ROA, noise-adjusted ROA, and risk-normalized ROA (rows 4, 5, and 8) between large community banks and midsize banks, but these banks tend to outperform small community banks. This is a well-known result in the literature.[15] We add to this result by considering the average best-practice ROA. As shown in row 7, there is no statistically significant difference in best-practice ROA among the three size groups; however, as shown in row 9, when we normalize this best practice by risk, we find that small community banks show better potential performance per unit of risk than large community banks and midsize banks. However, using either metric of best-practice, our results show that small community banks are less efficient at achieving best practice (rows 6 and 9).

Table 2 shows the market-value performance measures for the 245 publicly traded firms in the sample. Small community banks exhibit the highest investment opportunity ratio (row 4) but achieve the lowest Tobin's q ratio among the bank size categories (rows 5 and 6). The lower Tobin's q ratio for the publicly traded small community suggests that the capital market, on average, values these banks less than publicly traded large community banks and midsize banks, which is consistent with the lower ROAs we found for small community banks. Similar to our results using ROA, we also find that small community banks are less efficient at achieving their potential MVA than for large community banks and midsize banks (i.e., on average, their market-value inefficient ratio is higher (row 7); we find that midsize banks are the most efficient at achieving their potential MVA.[16]

5. Explaining Differences in Performance: Are Community Banks Handicapped by Compliance and Information Technology Costs?

Textbooks frequently cite "spreading the overhead" as an important source of scale economies. To provide some evidence, we examine cost and revenue differences across the bank size categories. As shown in **Table 1**, while the ratio of total revenue to consolidated assets is not significantly different across size groups (row 3), there are some significant differences in costs. The ratio of noninterest expense (the cost of labor, supplies, utilities, and fixed assets) to total revenues is a measure of operating cost per dollar of revenue. We find that small community banks have significantly higher noninterest expenses to total revenue than large community banks and midsize banks (row 2), and large community banks have higher average operating costs than midsize banks.

[15] See, for example, Amel and Prager (2013) and the FDIC (2012).

[16] The relationship of Tobin's q ratio to the investment opportunity ratio and the market value inefficiency ratio is discussed at length by Hughes and Mester (2013a), pp. 29–30.

Table 3 delves deeper into the expense side and reports some components of noninterest expenses, in particular, corporate overhead costs, reporting-compliance costs, and telecommunications costs.[17] As a proportion of total revenue, corporate overhead and reporting and compliance expenses fall with larger bank size, with statistically significant differences for small versus large community banks and small community banks versus midsize banks (rows 3 and 4). Finally, telecommunications expenses also show signs of potential scale economies. The contrast between midsize banks and community banks in this ratio suggests that spreading telecommunications costs is an important advantage of a larger scale. While these revenue shares are small, the differences across banks are relatively large and point to some disadvantages of small scale.

These results on operating costs and its components are consistent with findings in the literature of scale economies in banking. However, comparing simple operating expense ratios does not account for differences in the banks' investment strategies, which can affect measures of scale economies. For example, larger banks tend to take more risk, which is costly, so comparisons of operating cost ratios may actually understate scale economies from spreading overhead costs.[18] To take account of some of these differences across bank size categories, we examine investment strategies, risk taking, and other balance sheet factors in the next section.

6. How Do Asset Portfolios Differ by Bank Size?

Table 4 describes differences in the asset components, asset quality, and off-balance sheet activities across bank size groups. While there is no statistically significant difference in the mean ratio of loans to assets or in the share of consumer loans across the three size groups (rows 2 and

[17] *Corporate overhead* consists of the sum of expenses related to accounting, auditing, advertising and marketing, and printing, as well as supplies and postage. *Reporting and compliance* comprises expenses related to legal work, accounting and auditing, and consulting.

[18] Hughes and Mester (2013b, 2015) and Hughes, Mester, and Moon (2001) contend that larger banks, which on average take more risk than smaller banks, incur higher costs because of their extra risk taking. These extra costs can obscure the technological scale economies due to better diversification and spreading operating costs over larger output if account is not taken of scale-related endogenous risk taking. Their investigations show that the scale economies predicted by textbooks often elude the standard approach to estimating scale economies for this reason. Hughes, Mester, and Moon (2001) find that the estimated scale economies index of the standard approach increases with better diversification but decreases with a variety of measures of risk taking. Kovner, Vickery, and Zhou (2014) also demonstrate that finding evidence of operating cost economies depends on controlling for the investment strategy. Without controlling for investment strategy, they find that a 10 percent increase in assets implies a 9.93 percent increase in operating costs, essentially constant returns to scale. When the authors control for asset allocation, the cost elasticity drops to 9.79 percent, and when they control for asset allocation, revenue sources, funding structure, and organizational complexity, the ratio drops further to 8.99 percent, essentially operating cost economies. They find a pattern that implies that operating scale economies increase with bank size and that the largest financial institutions obtain the largest operating cost economies.

6), small community banks hold a significantly higher proportion of real estate assets in their portfolios compared with large community banks and midsize banks (row 3). The difference is particularly pronounced for commercial real estate (CRE) loans (row 5), which can be riskier than other real estate loans, thus potentially exposing small community banks to greater credit risk than larger banks. The mean share of total business loans increases with bank size, and the differences are statistically significant across size categories (row 7).

Some loans included total business loans are SBLs, which are defined as business loans with an initial principal balance of less than $1 million. While there is no statistically significant difference in the proportion of SBLs in the portfolios of small and large community banks, these community banks hold a significantly higher proportion of SBLs than midsize banks (row 8). This is consistent with the statistics reported by Jagtiani and Lemieux (2016, 2018), although they also report that the gap in the ratio of SBLs to assets between midsize banks and community banks has become narrower over the years.

We find no significant difference in the share of liquid assets across the size categories (row 9). Liquidity is also affected by other activities not recorded as assets on the balance sheet. We use the ratio of *noninterest income* to total revenue as a proxy for off-balance sheet activities. Small community banks engage in a lower share of off-balance-sheet activities than large community banks or midsize banks (row 10). In terms of loan quality, we find that the ratio of nonperforming loans to assets is significantly higher at small community banks compared with large community banks and midsize banks (row 11).[19]

How banks price their loans also differs by bank size. The average contractual interest rate on loans declines with larger bank size (row 12). Small community banks' higher loan rate and their higher proportion of nonperforming loans may reflect higher loan risk (perhaps from their higher share of CRE and SBL lending). However, their higher nonperforming loan ratio raises the question of the degree to which they lend to riskier borrowers and the degree to which their credit analysis and loan monitoring may be less effective. We turn to this question in the next section.

7. Decomposing Loan Nonperformance into Inherent Credit Risk and Lending Inefficiency

We apply a technique developed by Hughes and Moon (2017) to distinguish nonperformance because of less effective credit evaluation and loan monitoring from

[19] Asset quality is measured by the sum of three components: (1) the amount of loans that are nonperforming, (2) the amount of loans that have been charged off, and (3) the amount of foreclosed real estate owned by the bank. Because banks differ in the aggressiveness with which they charge off nonperforming loans, our measure of nonperforming loans includes the amount of gross charge-offs in order to eliminate any bias caused by different charge-off strategies among banks.

nonperformance because of the bank's choice of the inherent credit risk of its loan portfolio. We focus on two types of loans: business loans and CRE loans. We use a stochastic frontier technique to estimate a bank's best-practice (i.e., minimum) ratio of nonperforming business loans to total business loans and best-practice ratio of nonperforming CRE loans to total CRE loans, controlling for the share of the amount held of this type of loan, the total loan volume, the average contractual interest rate charged for this type of loan, and the market concentration and 10-year average GDP growth rate in the markets in which the bank operates. The minimum ratio represents the best-observed-practice nonperformance controlling for the loan volume and other factors that, as such, capture inherent credit risk. It indicates the lowest nonperforming loan ratio the bank could achieve if it were fully efficient at credit-risk evaluation and loan monitoring. The difference between a bank's achieved nonperforming loan ratio adjusted for noise and its best-observed-practice ratio — its excess nonperforming loan ratio — gauges its efficiency at credit analysis and loan monitoring. The Appendix describes the details of the estimation.

As shown in **Table 5**, the mean share of business loans to total loans increases with bank size (row 2) and the average contractual interest rate on business loans declines with bank size (row 3). The share of nonperforming business loans to business loans also declines with bank size (row 4).

Decomposing the nonperforming business loan ratio into the best practice, the excess over the best practice, and the noise, we find that the best-practice nonperforming loans ratio increases with bank size, and the excess ratio decreases with bank size (rows 5 and 6). These results suggest that smaller banks tend to lend to less risky business borrowers, but they are less efficient at credit evaluation and monitoring, so they experience higher rates of nonperformance.

Table 6 reports the comparable results for CRE loans. The mean share of CRE loans to total loans decreases with bank size (row 2) and the average contractual interest rate on CRE loans declines with bank size (row 3). The share of nonperforming CRE loans to CRE loans is higher for small community banks than for large community banks and midsize banks (row 4).

The decomposition shows that, similar to our results for business loans, the best-practice nonperforming loan ratio for CRE loans increases with bank size, and the excess nonperforming CRE loan ratio decreases with bank size (rows 5 and 6). These results suggest that smaller banks lend to less risky CRE borrowers, but they are less efficient at credit evaluation and monitoring, so they experience higher rates of nonperformance.

Thus, both CRE and business loans exhibit the same qualitative patterns of nonperformance, inherent credit risk, and lending inefficiency. Small community banks exhibit the highest rate of nonperformance for both types of loans. While they have the lowest inherent credit risk for both, they also exhibit the highest lending inefficiency for both, resulting in their higher rates of nonperformance. This is consistent with their charging higher contractual loan rates.

8. Does Scale Affect the Financial Incentives to Lend to Small Businesses?

Given the relative performance across size categories, we explore whether a scale-related improvement in financial performance gives small community banks an incentive to become larger, and if so, whether they have an incentive to reduce the share of SBL lending in their portfolios to be comparable with larger banks.

We regress the four financial performance measures — the risk-normalized ROA, the ROA shortfall, Tobin's *q* ratio, and market-value inefficiency — on the loan-to-asset ratio, the composition of lending activities, the *ln*(total assets), the investment opportunity ratio, asset quality, and the composition of funding (the deposit ratio and the capital ratio).[20] **Table 7** and **Table 8** present the results for the accounting-based measures of performance and the market-value-based measures, respectively.

The performance equations are given by:

$$P_i = a_0 + a_1 \textit{ Total loans/Assets} + a_2 \textit{ Total business loans/Assets} \\ + a_3 \textit{ Small business loans/Assets} + \boldsymbol{X\beta} + \varepsilon_i. \qquad (23)$$

where P_i = Performance, as measured by the risk-normalized ROA, the ROA shortfall, Tobin's *q* ratio, or market-value inefficiency, and the control factors in $\boldsymbol{X}$ include: Residential real estate loans/Assets, Commerical real estate loans/Assets, Consumer loans/Assets, Liquid assets/Assets, Investment opportunity ratio (for the market-value-based regressions), *ln*(Book value of assets in $1000s), Noninterest income/Total revenue, Nonperforming loans/Assets, Deposits/(Deposits + Other borrowed funds), and (Equity + Subordinated debt + Loan loss reserves)/Assets.

By controlling for the ratio of total loans to assets, a variation in any category of loans in the regression, except SBLs, implies an equivalent change in the categories of loans omitted from the regression. These omitted categories include leases, agricultural loans, loans to nondepository institutions, and other loans.

[20] Because the performance measures are based on market values, we control for investment opportunities in these regressions. In Table 8, there is evidence that the investment opportunity ratio is positively related to financial performance for small community banks and negatively related to performance for large community banks. Hughes and Mester (2013a) find that, controlling for asset size, more valuable investment opportunities that are associated with poorer financial performance are evidence of agency problems, a point that is beyond the scope of this investigation.

SBLs constitute part of total business loans. Total business loans are the sum of SBLs (i.e., business loans with origination less than $1 million) and large business loans (i.e., business loans with origination greater than $1 million). Thus, a 1 percent increase in the ratio of SBLs to assets (an increase measured in terms of the volume of assets), holding constant the ratio of total business loans to assets, implies a 1 percent decrease (measured in terms of the volume of assets) in the ratio of large business loans to assets. Based on Equation (23), the change in financial performance associated with such a change would be $a_3 \times 0.01$. Of course, the ratio of total loans to assets is also held constant, so the variation affects only the composition of total business loans.

On the other hand, a change in the ratio of total business loans to assets (measured in terms of the volume of assets) holding constant the ratio of SBLs to assets implies an equivalent change in the ratio of large business loans to assets. Holding the ratio of total loans to assets constant, based on Equation (23),

$$\Delta P_i = \mathrm{a}_2 \times \Delta \; \textit{Total business loans/Assets}. \tag{24}$$

For example, the change in performance associated with a 1 percent increase in the ratio of total business loans to assets = $\boldsymbol{a}_2 \times 0.01$. Because we are holding constant the ratio of SBLs to assets in this calculation, this 1 percent increase in the ratio of total business loans to assets is a 1 percent increase in the ratio of large business loans to assets. And because we are holding the ratio of total loans to assets constant, this 1 percent increase in the ratio of business loans to assets implies an equivalent change in the omitted categories of loans.

If, instead, a 1 percent increase in total business loans to assets is accompanied by a 1 percent increase in the ratio of SBLs to assets, the ratio of large business loans to assets would remain constant, and the change in performance associated with such a change would be $(a_2 + a_3) \times 0.01$. Holding the ratio of total loans to assets constant, such an increase implies an equivalent change in other categories of loans omitted from the regression.

A 1 percent increase in the ratio of total business lending to assets accompanied by a 1 percent increase in the ratio of total loans to assets represents an increase in overall lending effected by large business lending; the resulting change in performance is given by $(a_1 + a_2) \times 0.01$. If the ratio of SBLs to assets is simultaneously increased by 1 percent, the change in performance is given by $(a_1 + a_2 + a_3) \times 0.01$. In the latter case, the ratio of large business loans to assets would remain constant.

The results using accounting measures of performance, in **Table 7**, point to the negative impact of nonperforming loans on financial performance, an impact whose magnitude increases with bank size. The proportion of loans to assets is positively associated with performance both at small and large community banks. A marginal increase in the proportion of SBLs to assets, holding total business loans to assets constant, implies a corresponding decrease in the large business loan ratio. This particular increase in SBLs is associated with improved accounting performance at small and large community banks. The last rows of **Table 7** report simultaneous variations in these components. Notably, a 1 percent increase in total loans and in business loans, holding SBLs constant, as well as a 1 percent increase in total loans, total business loans, and SBLs is associated with improved accounting performance at small and large community banks.

The accounting measures of performance do not account for the market's valuation of expected future performance or of risk at which expected future performance is discounted. As indicated in **Table 8**, market-value performance is, on average, negatively associated with the nonperforming loan ratio at the three groups of banks. In addition, there is evidence that small community banks have a financial incentive to *decrease* SBLs. To see this, note that a 1 percent decrease in the ratio of SBLs to assets, holding constant total business loans to assets (which implies a 1 percent increase in large business loans to assets), is associated with a statistically significant increase in Tobin's q ratio of (−0.01) × (−0.27418) = +0.0027418 = 0.27 percent. In contrast, the same increase in SBLs at large community banks is associated with an increase of 0.32 percent in Tobin's q ratio. If a 1 percent decrease in the ratio of small business loans to assets at small community banks is combined with a 1 percent increase in the ratio of total business loans to assets (which implies a 2 percent increase in large business loans to assets), the change in business lending is associated with an increase in Tobin's q ratio of [(+0.01)(0.23341)] + [(−0.01)(−0.27418)] = 0.00508, or 0.508 percent, which is significantly different from zero (with a p value of 0.052).

If the 1 percent increase in the ratio of total business loans to assets at small community banks is combined with a 1 percent increase in the ratio of total loans to assets, holding the SBL ratio constant, the associated increase in Tobin's q ratio is 0.444 percent. If, in addition, the ratio of SBLs to assets decreases by 1 percent at small community banks, the increase in Tobin's q ratio is 0.718 percent. Similar results are obtained when performance is measured by the market-value inefficiency ratio.

Overall, we find that the capital market provides small community banks a financial incentive to reduce their SBL activities and to increase their lending to larger businesses.

Unlike small community banks, we find that the capital market provides a financial incentive to large community banks to increase SBLs. For large community banks, a 1 percent increase in the SBL ratio is associated with a statistically significant +0.0032021 or 0.32021 percent increase in Tobin's q ratio. This increase holds total business lending constant and, hence, implies a reduction in large business lending. In addition, a 1 percent decrease in the total business loan ratio, holding the SBL ratio constant, is associated with a statistically significant +0.0025210 or 0.25210 percent increase in Tobin's q. A simultaneous decrease of 1 percent in the total business loan ratio and a 1 percent increase in the SBL ratio would result in a statistically significant increase of 0.572 percent in Tobin's q ratio (with p value of 0.004). This portfolio adjustment would also imply a decrease of −0.268 percent in the market-value inefficiency ratio. If this simultaneous portfolio adjustment is combined with a 1 percent decrease in the ratio of total loans to assets, the associated increase in Tobin's q ratio is 0.663 percent.

Finally, we find that midsize banks (with assets of more than $10 billion) may have an incentive to *reduce* the proportion of their assets devoted to business lending in general and SBL in particular. Although neither the coefficient, −0.02716, on the total business loan ratio nor the coefficient, −0.18834, on the SBL ratio is statistically significant, a 1 percent decrease in both ratios combined with a 1 percent decrease in the ratio of total loans to assets is associated with a statistically significant increase of 0.00338 or 0.338 percent in Tobin's q ratio and a statistically significant decrease of −0.239 percent in the market-value inefficiency ratio.

9. Conclusions

This paper uses 2013 data to investigate performance and operational efficiencies at banks with assets of less than $50 billion. We find that better financial performance is associated with larger asset size. On average, large community banks (banks with assets between $1 billion and $10 billion) exhibit better accounting-based and market-value-based financial performance than small community banks (banks with assets under $1 billion). We also find that, on average, compared to small community banks, large community banks and midsize banks (banks with assets between $10 billion and $50 billion) have less valuable investment opportunities but achieve higher proportions of their potential market value and ROA (i.e., they are more efficient). This finding suggests that the better performance is associated with better management of the relatively less valuable investment opportunities.

If such a scale-related improvement in financial performance provides an incentive for smaller banks to grow in size, an important question is whether this might also provide community banks with an incentive to reduce the proportion of their assets allocated to small business loans (SBLs) as they grow in size to achieve scale economies. We find no evidence in support of this hypothesis. There is a statistically significant positive relationship between financial performance and the ratio of SBLs to assets at large community banks, suggesting they would have financial incentives to increase their SBL share as they become larger.[21]

However, our estimates of the contribution of total business lending and SBLs to financial performance for publicly traded banks suggest that small community banks have financial incentives to shift their lending from small businesses to larger businesses, while large community banks have a financial incentive to increase lending to small businesses. The case is different for midsize banks, where we find that performance is positively related to a proportional decrease in total business lending and SBLs. This finding suggests that midsize banks have financial incentives to reduce their asset shares in overall business loans and in loans to small businesses.

In short, our evidence shows that, on average, large community banks outperform small community banks. This may reflect that the costs of regulatory compliance and technology both have a fixed cost component, which results in there being a size below which the costs outweigh any lending advantages a small community bank might have. The positive relationship between the better financial performance of large community banks and their SBL activities suggests that SBLs are an important component of large community banks' portfolio. Therefore, the concern that as small community banks become larger, they might become less effective at lending to small businesses and reduce the proportion of assets devoted to SBLs, thereby adversely affecting small businesses' access to credit, is not supported by the results in this paper.

[21] This finding is consistent with the results of Jagtiani, Kotlier, and Maingi (2015) who find that there were no adverse impacts on the overall lending to small businesses when small community banks grew larger as they became part of a larger acquiring bank. In fact, the combined banking firms increased their lending to small businesses more when the acquirers are large banks.

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Figure 1
Best-Observed-Practice Return on Assets

This figure illustrates the upper envelope of best-observed-practice ROA that is obtained by stochastic frontier estimation of the quadratic relationship between the ROA and the standard deviation of ROA (ROASTD). The error term, $\varepsilon_i = v_i - \mu_i$, is a composite term used to distinguish two-sided statistical noise, $v_i \sim$ iid $N(0,\sigma_v^2)$, from the one-sided systematic shortfall from bank *i*'s best-observed-practice ROA. We assume μ_i is distributed exponentially, $\mu_i\ (> 0) \sim \theta \exp(-\theta u)$. The quadratic specification allows the upper envelope to be nonlinear.

In this example, bank *i* achieves an ROA of 1.08 percent and its ROA adjusted for noise is $ROA_i - v_i$ = 1.08 – (–0.02) = 1.10 percent. Bank *i*'s best-practice ROA is 1.70 percent. So its ROA shortfall from best-practice is 0.60 percentage points (= 1.70 – 1.10). The standard deviation of its ROA is 2.22, so its risk-normalized best-practice ROA is 0.76 (=1.70/2.22) and its risk-normalized ROA shortfall is 0.27 (=0.60/2.22).

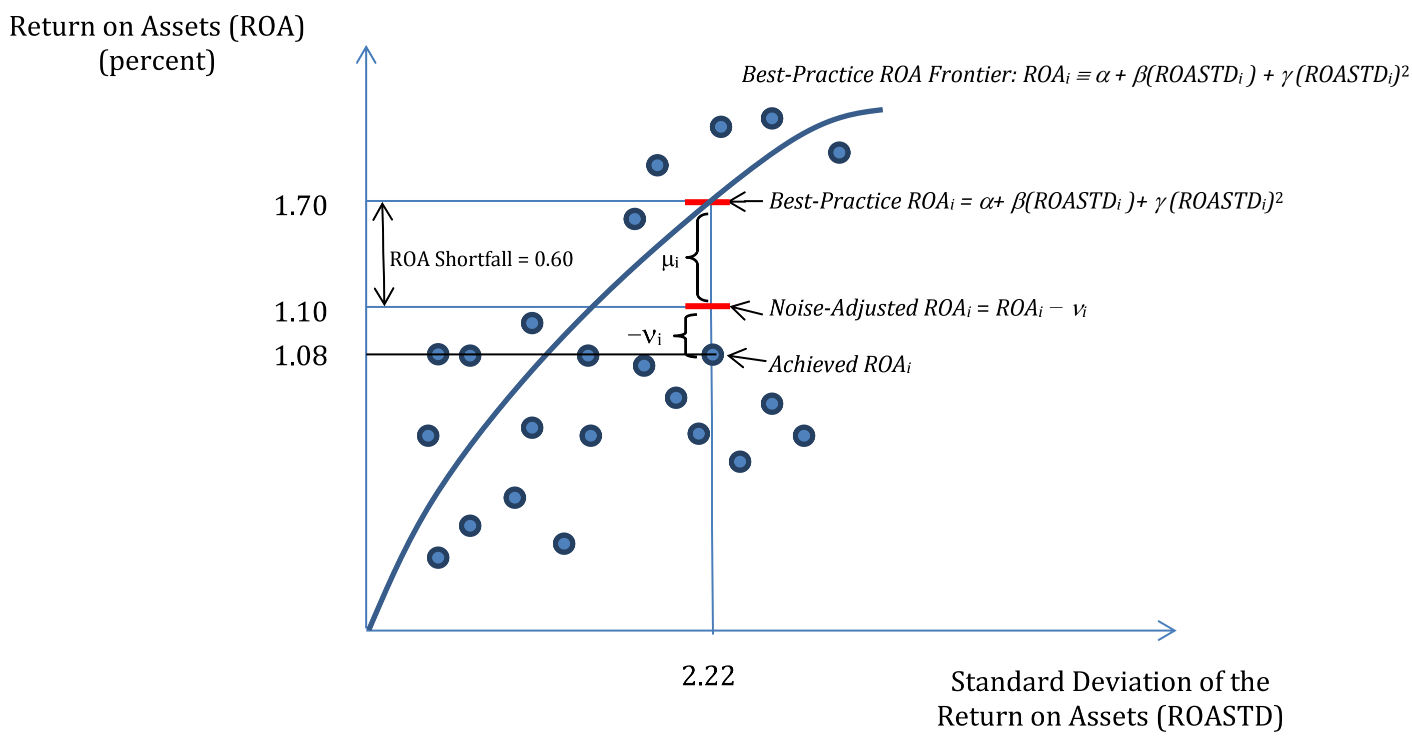


Figure 2
Market-Value Frontier

This figure illustrates the potential-value frontier that is obtained by stochastic frontier estimation of the quadratic relationship between the market value of assets (MVA) and the book value of assets net of goodwill (BVA). The error term, $\varepsilon_i = \nu_i - \mu_i$, is a composite term used to distinguish statistical noise, $\nu_i \sim$ iid $N(0,\sigma_\nu^2)$, from the systematic shortfall from bank *i*'s highest potential (frontier) market value. We assume μ_i is distributed exponentially, $\mu_i\ (> 0) \sim \theta \exp(-\theta u)$. The quadratic specification allows the frontier to be nonlinear. The potential-value frontier is the deterministic kernel of the estimated quadratic relationship.

In this example, bank *i* has invested 100 in assets (i.e., $BVA_i = 100$) and it achieves an MVA of 106. Its MVA adjusted for noise is $MVA_i - \nu_i = 106 - (-2) = 108$. Bank *i*'s best-practice MVA is 120. So its MVA shortfall from best-practice value is 12 percentage points = (120 – 108). Its market-value inefficiency ratio is 0.10 (=12/120), and its noise-adjusted Tobin's *q* ratio is 1.08 (=108/100).

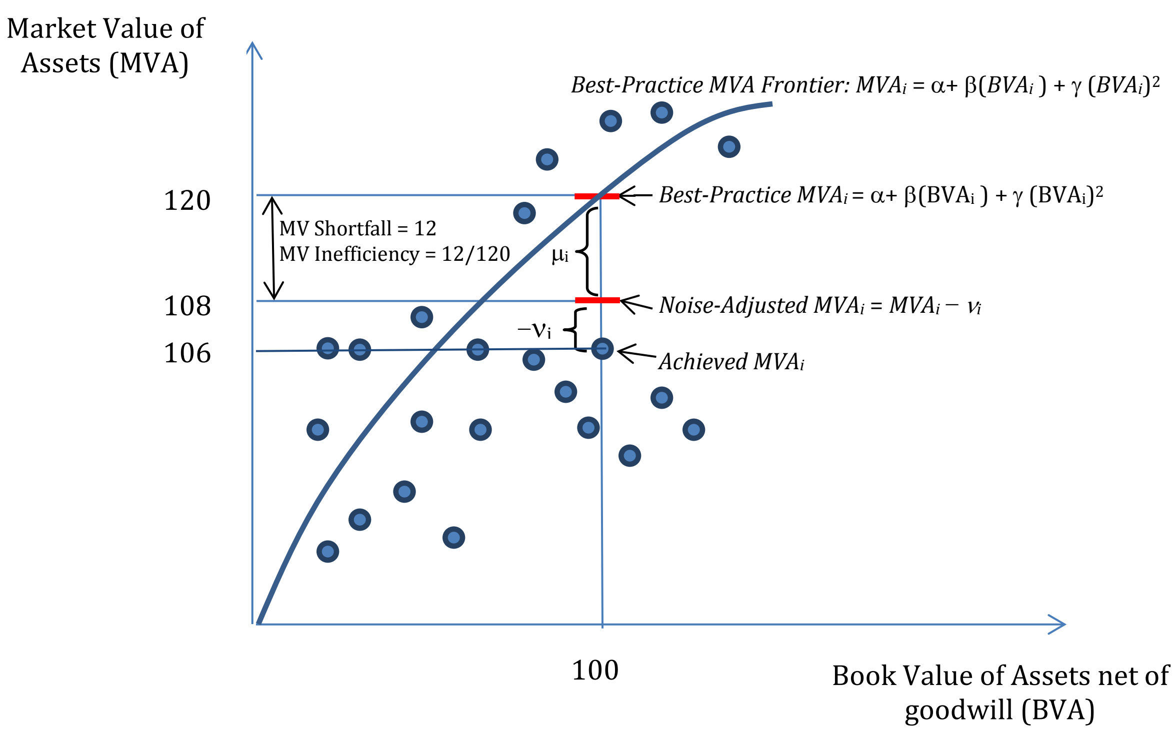


Table 1
Financial Performance
Sample Partitioned by Size Group Based on Consolidated Assets

The data set includes 722 top-tier bank holding companies at the end of 2013. *Small community banks* have consolidated assets less than $1 billion, *large community banks* have consolidated assets from $1 billion up to $10 billion, and *midsize banks* have assets between $10 billion and $50 billion. The *p* value represents the statistical significance of the comparison of means in the pairing. Pairs of means in **bold** are statistically different at stricter than $p = 0.10$.

The *best-practice ROA* is measured by the value of ROA on the estimated *best-practice frontier*, Equation (2), and the *risk-normalized, best-practice ROA*, by the *ratio of best-practice ROA to the standard deviation of ROA*, Equation (8). The ROA shortfall, Equation (7), is given the difference between the best-practice ROA and the noise-adjusted ROA, Equation (6).

	Small Community Banks vs. Large Community Banks			Small Community Banks vs. Midsize banks			Large Community Banks vs. Midsize banks		
	Small Comm Banks	Large Comm Banks		Small Comm Banks	Midsize Banks		Large Comm Banks	Midsize Banks	
	n = 328	*n* = 354		*n* = 328	*n* = 40		*n* = 354	*n* = 40	
	Mean	Mean	*p*	Mean	Mean	*p*	Mean	Mean	*p*
1. Book Value Assets (1,000s)	**671,609**	**2,628,710**	0.00	**671,609**	**20,466,676**	0.00	**2,628,710**	**20,466,676**	0.00
2. Noninterest Expense/ Total Revenue	**0.684**	**0.635**	0.00	**0.684**	**0.590**	0.00	**0.635**	**0.590**	0.05
3. Total Revenue/ Assets	0.049	0.049	0.97	0.049	0.048	0.53	0.049	0.048	0.52
4. ROA	**0.828**	**1.169**	0.00	**0.828**	**1.226**	0.00	1.169	1.226	0.58
5. Noise-Adjusted ROA	**0.913**	**1.100**	0.00	**0.913**	**1.148**	0.00	1.100	1.148	0.48
6. ROA Shortfall	**0.670**	**0.478**	0.00	**0.670**	**0.448**	0.00	0.478	0.448	0.61
7. Best-Practice ROA	1.583	1.578	0.69	1.583	1.596	0.52	1.578	1.596	0.39
8. Risk-Normalized ROA	**1.962**	**2.464**	0.00	**1.962**	**2.411**	0.00	2.464	2.411	0.80
9. Risk-Normalized ROA Shortfall	**1.344**	**0.963**	0.00	**1.344**	**0.870**	0.00	0.963	0.870	0.39
10. Risk-Normalized Best-Practice ROA	**3.540**	**3.333**	0.08	**3.540**	**3.132**	0.04	3.333	3.132	0.29

Table 2
Financial Performance of Publicly Traded Bank Holding Companies
Sample Partitioned by Size Group Based on Consolidated Assets

The data set includes 245 publicly traded top-tier bank holding companies at the end of 2013. *Small community banks* have consolidated assets less than $1 billion, *large community banks* have consolidated assets from $1 billion up to $10 billion, *midsize banks* have assets between $10 billion and $50 billion. The *p* value represents the statistical significance of the comparison of means in the pairing. Pairs of means in **bold** are statistically different at stricter than $p = 0.10$.

The *investment opportunity ratio*, equation (22), is given by the ratio of the highest potential value of assets in the markets in which the bank operates, equation (21), to the book-value of assets net of goodwill. *Tobin's q ratio* is proxied by the sum of the market value of equity and the book-value of liabilities divided by the book value of assets net of goodwill. The *noise-adjusted Tobin's q ratio* is given by Equation (19). The *market-value inefficiency ratio* is the difference between the highest potential market value of assets and the noise-adjusted achieved market value of assets divided by the highest potential value of assets, Equation (18).

	Small Community Banks vs. Large Community Banks			Small Community Banks vs. Midsize banks			Large Community Banks vs. Midsize banks		
	Small Comm Banks	Large Comm Banks		Small Comm Banks	Midsize Banks		Large Comm Banks	Midsize Banks	
	***n* = 54**	***n* = 156**		***n* = 54**	***n* = 35**		***n* = 156**	***n* = 35**	
	Mean	**Mean**	***p***	**Mean**	**Mean**	***p***	**Mean**	**Mean**	***p***
1. Book Value Assets (1,000s)	**720,540**	**3,244,643**	0.00	**720,540**	**20,489,637**	0.00	**3,244,643**	**20,489,637**	0.00
2. Noninterest Expense/ Total Revenue	**0.676**	**0.630**	0.00	**0.676**	**0.598**	0.00	0.630	0.598	0.13
3. Total Revenue/ Assets	0.050	0.048	0.40	0.050	0.048	0.29	0.048	0.048	0.77
4. Investment Opportunity Ratio	**1.742**	**1.362**	0.00	**1.742**	**1.199**	0.00	**1.362**	**1.199**	0.00
5. Tobin's *q* Ratio	**1.006**	**1.059**	0.00	**1.006**	**1.069**	0.00	1.059	1.069	0.23
6. Noise-Adjusted Tobin's *q* Ratio	**0.992**	**1.063**	0.00	**0.992**	**1.074**	0.00	1.063	1.074	0.13
7. Market-Value Inefficiency Ratio	**0.548**	**0.266**	0.00	**0.548**	**0.083**	0.00	**0.266**	**0.083**	0.00

Table 3
Operating Costs
Sample Partitioned by Size Group Based on Consolidated Assets

The data set includes 722 top-tier bank holding companies at the end of 2013. *Small community banks* have consolidated assets less than $1 billion, *large community banks* have consolidated assets from $1 billion up to $10 billion, and *midsize banks* have assets between $10 billion and $50 billion. The *p* value represents the statistical significance of the comparison of means in the pairing. Pairs of means in **bold** are statistically different at stricter than *p* = 0.10.

Corporate overhead consists of the sum of expenses related to accounting, auditing, advertising and marketing, and printing, as well as supplies and postage.[22] *Reporting and compliance* comprises expenses related to legal work, accounting and auditing, and consulting.[23]

	Small Community Banks vs. Large Community Banks			Small Community Banks vs. Midsize Banks			Large Community Banks vs. Midsize Banks		
	Small Comm Banks	**Large Comm Banks**		**Small Comm Banks**	**Midsize Banks**		**Large Comm Banks**	**Midsize Banks**	
	n **= 328**	***n*** **= 354**		***n*** **= 328**	***n*** **= 40**		***n*** **= 354**	***n*** **= 40**	
	Mean	**Mean**	***P***	**Mean**	**Mean**	***p***	**Mean**	**Mean**	***p***
1. Book Value Assets (1,000s)	**671,609**	**2,628,710**	0.00	**671,609**	**20,466,676**	0.00	**2,628,710**	**20,466,676**	0.00
2. Noninterest Expense/ Revenue	**0.68375**	**0.63494**	0.00	**0.68375**	**0.59020**	0.00	**0.63494**	**0.59020**	0.05
3. Corporate Overhead/ Revenue	**0.00145**	**0.00124**	0.00	**0.00145**	**0.00105**	0.00	0.00124	0.00105	0.11
4. Reporting-Compliance/ Revenue	**0.00118**	**0.00098**	0.01	**0.00118**	**0.00085**	0.00	0.00098	0.00085	0.20
5. Telecom-munications/ Revenue	**0.00042**	**0.00037**	0.04	**0.00042**	**0.00026**	0.00	**0.00037**	**0.00026**	0.01

[22] This category was used by Kovner Vickery, and Zhou (2014). Although not reported in the tables, corporate overhead represents, on average, 4.7 percent of operating costs for smaller community banks, 4.2 percent for larger community banks, and 3.4 percent for midsize banks.

[23] On average, reporting and compliance costs account for 4.1 percent of operating costs for smaller community banks, 3.3 percent for larger community banks, and 3.2 percent for midsize banks.

Table 4
Asset Allocation and Quality and Off-Balance-Sheet Activity
Sample Partitioned by Size Group Based on Consolidated Assets

The data set includes 722 top-tier bank holding companies at the end of 2013. *Small community banks* have consolidated assets less than $1 billion, *large community banks* have consolidated assets from $1 billion up to $10 billion, and *midsize banks* have assets between $10 billion and $50 billion. The *p* value represents the statistical significance of the comparison of means in the pairing.

Total business loans include *small business loans*, which are defined as business loans with an initial principal balance of less than $1 million. *Liquid assets* are defined as sum of cash, balances at other financial institutions, federal funds sold, securities, and securities sold under agreement to repurchase.

	Small Community Banks vs. Large Community Banks			**Small Community Banks vs. Midsize Banks**			**Large Community Banks vs. Midsize Banks**		
	Small Comm Banks	**Large Comm Banks**		**Small Comm Banks**	**Midsize Banks**		**Large Comm Banks**	**Midsize Banks**	
	***n* = 328**	***n* = 354**		***n* = 328**	***n* = 40**		***n* = 354**	***n* = 40**	
	Mean	**Mean**	***p***	**Mean**	**Mean**	***p***	**Mean**	**Mean**	***p***
1. Book Value Assets (1,000s)	**671,609**	**2,628,710**	0.00	**671,609**	**20,466,676**	0.00	**2,628,710**	**20,466,676**	0.00
2. Total Loans/Assets	0.634	0.641	0.50	0.634	0.638	0.88	0.641	0.638	0.88
3. Real Estate (RE)Loans/ Assets	**0.492**	**0.468**	0.02	**0.492**	**0.387**	0.00	**0.468**	**0.387**	0.00
4. Residential RE Loans/Assets	0.199	0.192	0.37	0.199	0.190	0.66	0.192	0.190	0.92
5. Commercial RE Loans/Assets	**0.294**	**0.276**	0.02	**0.294**	**0.196**	0.00	**0.276**	**0.196**	0.00
6. Consumer Loans/Assets	0.026	0.028	0.52	0.026	0.041	0.13	0.028	0.041	0.16
7. Total Business Loans/ Assets	**0.082**	**0.109**	0.00	**0.082**	**0.153**	0.00	**0.109**	**0.153**	0.00
8. Small Business Loans/ Assets*	0.043	0.043	0.87	**0.043**	**0.031**	0.01	**0.043**	**0.031**	0.01
9. Liquid Assets/ Assets	0.308	0.299	0.32	0.308	0.279	0.18	0.299	0.279	0.35
10. Noninterest Income/ Total Revenue	**0.195**	**0.226**	000	**0.195**	**0.259**	0.01	0.226	0.259	0.20
11. Nonperforming Loans/Assets	**0.038**	**0.024**	0.00	**0.038**	**0.022**	0.00	0.024	0.022	0.53
12. Average Contractual Interest Rate on Loans	**0.053**	**0.048**	0.00	**0.053**	**0.046**	0.00	**0.048**	**0.046**	0.08

*The sample size for data on small business loans is smaller: n=283 for small community banks, n=307 for large community banks, and n=36 for midsize banks.

Table 5
Best-Practice Commercial and Industrial Loan Performance and Lending Inefficiency
Sample Partitioned by Size Group Based on Consolidated Assets

The data set includes 619 top-tier bank holding companies at the end of 2013 with data on the average contractual loan rate on business loans and plausible values of nonperforming business loans: banks with values of nonperforming business loans to total business loans less than 0.001 and greater than 0.25 were trimmed.

Small community banks have consolidated assets less than $1 billion, *large community banks* have consolidated assets from $1 billion up to $10 billion, and *midsize banks* have assets between $10 billion and $50 billion. The *p* value represents the statistical significance of the comparison of means in the pairing. Pairs of means in **bold** are statistically different at stricter than $p = 0.10$.

The best-practice business nonperforming loan ratio is obtained from a stochastic frontier estimation of the lower envelope of business nonperforming loan ratios conditioned on the amount of business loans, the total amount of loans, the GDP growth rate, an index of market concentration, and the average contractual business loan rate. Lending inefficiency is gauged by the ratio of nonperforming business loans in excess of the best-practice ratio.

	Small Community Banks vs. Large Community Banks			Small Community Banks vs. Midsize Banks			Large Community Banks vs. Midsize Banks		
	Small Comm Banks	Large Comm Banks		Small Comm Banks	Midsize Banks		Large Comm Banks	Midsize Banks	
	n = 269	*n* = 312		*n* = 269	*n* = 38		*n* = 312	*n* = 38	
	Mean	Mean	*P*	Mean	Mean	*p*	Mean	Mean	*p*
1. Book Value Assets (1,000s)	**685,593**	**2,572,247**	0.00	**685,593**	**19,902,179**	0.00	**2,572,247**	**19,902,179**	0.00
2. Business Loans/Total Loans	**0.131**	**0.165**	0.00	**0.131**	**0.254**	0.00	**0.165**	**0.254**	0.00
3. Business Average Contractual Loan Rate	**0.057**	**0.051**	0.00	**0.057**	**0.042**	0.00	**0.051**	**0.042**	0.00
4. Nonperforming Business Loans/Business Loans	**0.033**	**0.023**	0.00	**0.033**	**0.019**	0.00	0.023	0.019	0.29
5. Best-Practice Nonperforming Business Loans/Business Loans	**0.001**	**0.002**	0.00	**0.001**	**0.005**	0.00	**0.002**	**0.005**	0.01
6. Nonperforming Business Loans in Excess of Best-Practice/Business Loans	**0.032**	**0.020**	0.00	**0.032**	**0.014**	0.00	**0.020**	**0.014**	0.05

Table 6
Best-Practice Commercial Real Estate Loan Performance and Lending Inefficiency
Sample Partitioned by Size Group Based on Consolidated Assets

The data set includes 663 top-tier bank holding companies at the end of 2013 with plausible values of nonperforming commercial real estate loans: Banks with 0 values of nonperforming commercial real estate (CRE) loans and banks whose ratios of CRE nonperforming loans exceed 0.40 were trimmed.

Small community banks have consolidated assets less than $1 billion, *large community banks* have consolidated assets from $1 billion up to $10 billion, and *midsize banks* have assets between $10 billion and $50 billion. The *p* value represents the statistical significance of the comparison of means in the pairing. Pairs of means in **bold** are statistically different at stricter than $p = 0.10$.

The best-practice CRE nonperforming loan ratio is obtained from a stochastic frontier estimation of the lower envelope of CRE nonperforming loan ratios conditioned on the amount of CRE, the total amount of loans, the GDP growth rate, an index of market concentration, and the average contractual CRE loan rate. Lending inefficiency is gauged by the ratio of nonperforming CRE loans in excess of the best-practice ratio.

	Small Community Banks vs. Large Community Banks			Small Community Banks vs. Midsize Banks			Large Community Banks vs. Midsize Banks		
	Small Comm Banks	Large Comm Banks		Small Comm Banks	Midsize Banks		Large Comm Banks	Midsize Banks	
	n =303	*n* = 322		*n* = 303	*n* = 38		*n* = 322	*n* = 38	
	Mean	Mean	*P*	Mean	Mean	*p*	Mean	Mean	*p*
1. Book Value Assets (1,000s)	**671,164**	**2,571,865**	0.00	**671,164**	**19,902,179**	0.00	**2,571,865**	**19,902,179**	0.00
2. Commercial Real Estate Loans/Total Loans	**0.466**	**0.429**	0.00	**0.466**	**0.308**	0.00	**0.429**	**0.308**	0.00
3. CRE Average Contractual Lending Rate	**0.052**	**0.049**	0.00	**0.052**	**0.047**	0.00	0.049	0.047	0.37
4. Nonperforming CRE Loans/ CRE Loans	**0.049**	**0.033**	0.00	**0.049**	**0.034**	0.01	0.033	0.034	0.95
5. Best-Practice Nonperforming CRE Loans/ CRE Loans	**0.003**	**0.004**	0.00	**0.003**	**0.012**	0.00	**0.004**	**0.012**	0.00
6. Nonperforming CRE Loans in Excess of Best-Practice/CRE Loans	**0.045**	**0.029**	0.00	**0.045**	**0.022**	0.00	0.029	0.022	0.19

Table 7

Relationship of Financial Performance Measured by Risk-Normalized ROA and ROA Shortfall to Investment Strategy and Small Business Lending

The data set includes 722 top-tier bank holding companies at the end of 2013. *Small community banks* have consolidated assets less than $1 billion, *large community banks* have consolidated assets from $1 billion up to $10 billion, *midsize banks* have assets between $10 billion and $50 billion. There are 283 small community banks, 307 large community banks, and 36 midsize banks with data on small business loans.

Risk-normalized ROA is defined as ROA divided by the five-year annual standard deviation of ROA (=ROASD). ROA shortfall is given by the stochastic ROA frontier and is the difference between the highest potential ROA for a given standard deviation and the achieved ROA. Regressions are estimated with OLS, and standard errors are heteroscedasticity consistent. Parameter estimates in **bold** are significantly different from zero at stricter than 10%.

	Dependent Variables by Size Groups					
	Small Community Banks		Large Community Banks		Midsize Banks	
	Risk-Normalized ROA	ROA Shortfall	Risk-Normalized ROA	ROA Shortfall	Risk-Normalized ROA	ROA Shortfall
Variable	Parameter Estimate (Pr > |t|)	Paramete r Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)
Intercept	**−17.71713** (0.0013)	**8.28505** (0.0002)	**−7.38380** (0.0277)	**2.35762** (0.0003)	−0.56532 (0.9708)	2.29838 (0.5049)
log (Book Value Assets (1,000s))	**0.87020** (0.0030)	**−0.35363** (0.0019)	0.09692 (0.4238)	−0.04095 (0.1559)	0.21889 (0.7522)	−0.17903 (0.3179)
Total Loans/Assets	**8.95895** (0.0193)	−2.59221 (0.1395)	**12.98854** (<.0001)	**−1.92014** (0.0005)	−0.48519 (0.9520)	1.58734 (0.3614)
Residential RE Loans/Assets	**−2.12017** (0.0807)	0.32081 (0.3064)	**−3.45890** (0.0024)	**0.52407** (0.0033)	−0.97939 (0.7723)	−0.21921 (0.7448)
Commercial RE Loans/Assets	**−4.99918** (0.0006)	0.62095 (0.1654)	**−3.62928** (0.0075)	0.28987 (0.1705)	1.93753 (0.6552)	−0.68466 (0.4552)
Consumer Loans/Assets	**−2.55907** (0.0606)	−0.14241 (0.7166)	−1.71116 (0.2300)	−0.08188 (0.7417)	9.09679 (0.2680)	−0.21995 (0.9225)
Total Business Loans/Assets	−2.19825 (0.2817)	0.54602 (0.4776)	**−6.02342** (<.0001)	**0.90324** (0.0008)	−2.00073 (0.5966)	−0.11457 (0.8888)
Small Business Loans/Assets	**6.60734** (0.0323)	**−2.27294** (0.0718)	**6.71288** (0.0019)	−0.72487 (0.1083)	3.07939 (0.7356)	−1.09722 (0.4274)
Liquid Assets/Assets	5.47971 (0.1363)	−1.99601 (0.2206)	**9.31688** (0.0001)	**−1.43127** (0.0030)	−0.15538 (0.9851)	1.55710 (0.4799)
Noninterest Income/ Revenue	0.55930 (0.4696)	**−0.62370** (0.0901)	0.51482 (0.3549)	−0.04831 (0.7028)	0.46156 (0.7368)	−0.16272 (0.6671)
Nonperforming Loans/Assets	**−10.98357** (0.0042)	**3.50920** (0.0207)	**−17.82023** (<.0001)	**5.22801** (<.0001)	**−44.30780** (0.0041)	**12.61031** (0.0350)
Deposits/(Deposits + Other Borrowed Funds)	2.28320 (0.1142)	−0.47147 (0.2113)	−0.27134 (0.8131)	0.19662 (0.4029)	1.68624 (0.4878)	−0.50427 ((0.5397)
(Equity + Sub Debt + Loan Loss Reserves)/ Assets	**7.54813** (0.0002)	**−4.04967** (<.0001)	0.29568 (0.9195)	**−1.77285** (0.0059)	−9.17303 (0.4897)	1.08475 (0.6868)

Table 7, Continued						
	Dependent Variables by Size Groups					
	Small Community Banks		**Large Community Banks**		**Midsize Banks**	
	Risk-Normalized ROA	**ROA Shortfall**	**Risk-Normalized ROA**	**ROA Shortfall**	**Risk-Normalized ROA**	**ROA Shortfall**
Variable	**Parameter Estimate (Pr > |t|)**	**Paramete r Estimate (Pr > |t|)**	**Parameter Estimate (Pr > |t|)**	**Parameter Estimate (Pr > |t|)**	**Parameter Estimate (Pr > |t|)**	**Parameter Estimate (Pr > |t|)**
+1% in Business Loans +1% in Small Business Loans	4.40908 (0.1094)	**−1.72693** (0.0809)	0.68946 (0.7616)	0.17837 (0.6153)	1.07865 (0.9129)	−1.21179 (0.4501)
+1% in Total Loans and +1% in Business Loans	**6.7607** (0.0749)	−2.04619 (0.1527)	**6.96512** (0.0034)	**−1.01690** (0.0408)	−2.48593 (0.7346)	1.47276 (0.4443)
+1% in Total Loans, +1% in Business Loans +1% in Small Business Loans	**13.368** (0.0026)	**−4.31914** (0.020)	**13.6780** (<.0001)	**−1.74177** (0.0046)	0.59346 (0.9614)	0.37554 (0.8800)
	Adj. R Sq = 0.372 F = 14.92	Adj. R Sq = 0.3977 F = 16.52	Adj. R Sq = 0.210 F = 7.79	Adj. R Sq = 0.2698 F = 10.42	Adj. R Sq = 0.328 F = 2.43	Adj. R Sq = 0.4876 F = 3.78
	n = 283	n = 283	n = 307	n = 307	n = 36	n = 36

Table 8

Relationship of Financial Performance Measured by Tobin's *q* Ratio and Market-Value Inefficiency to Investment Strategy and Small Business Lending

The data set includes 245 publicly traded, top-tier bank holding companies at the end of 2013. *Small community banks* have consolidated assets less than $1 billion, *large community banks* have consolidated assets from $1 billion up to $10 billion, *midsize banks* have assets between $10 billion and $50 billion. Market-value inefficiency is given by the stochastic frontier of the market value of assets as a function of the book value of assets and is the difference between the highest potential market value and the achieved market value adjusted for noise as a proportion of the highest potential value. Regressions are estimated with OLS, and standard errors are heteroscedasticity consistent. Parameter estimates in **bold** are significantly different from zero at stricter than 10%.

	Dependent Variables by Size Groups					
	Small Community Banks		Large Community Banks		Midsize Banks	
	Tobin's *q* Ratio	Market Value Inefficiency	Tobin's *q* Ratio	Market Value Inefficiency	Tobin's *q* Ratio	Market Value Inefficiency
Variable	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)
Intercept	−1.74032 (0.2175)	**4.60037** (<.0001)	**1.33072** (0.0002)	**1.76909** (<.0001)	**2.11641** (<.0001)	−0.23872 (0.3330)
Investment Opportunity Ratio	**0.23704** (0.0978)	**−0.06565** (0.0789)	**−0.22608** (0.0220)	**0.28211** (<.0001)	−0.14011 (0.3796)	0.09439 (0.4179)
log (Book Value Assets (1,000s))	**0.14511** (0.0666)	**−0.28360** (<.0001)	0.01025 (0.4802)	**−0.13114** (<.0001)	**−0.04870** (0.0050)	0.00988 (0.4176)
Total Loans/Assets	0.21026 (0.4568)	−0.07842 (0.3003)	−0.09115 (0.3350)	0.00631 (0.8610)	**−0.12249** (0.0021)	**0.08370** (0.0071)
Residential RE Loans/Assets	0.08898 (0.7727)	−0.02463 (0.7649)	−0.12066 (0.3196)	0.08633 (0.1285)	−0.06433 (0.5025)	0.01752 (0.7997)
Commercial RE Loans/Assets	0.03711 (0.9004)	−0.01155 (0.8806)	−0.02609 (0.8020)	0.04452 (0.3706)	**−0.19243** (0.0723)	0.11507 (0.1234)
Consumer Loans/Assets	0.05764 (0.8516)	−0.03016 (0.7117)	−0.05952 (0.6332)	0.04335 (0.4479)	0.04454 (0.8091)	−0.11066 (0.4024)
Total Business Loans/Assets	0.23341 (0.5342)	−0.07735 (0.4438)	**−0.25210** (0.0627)	**0.15269** (0.0362)	−0.02716 (0.8031)	−0.01854 (0.8220)
Small Business Loans/Assets	**−0.27418** (0.0229)	**0.10243** (0.0227)	**0.32021** (0.0400)	−0.11576 (0.2120)	−0.18834 (0.2618)	0.17425 (0.2299)
Liquid Assets/Assets	0.28173 (0.2204)	−0.09748 (0.1371)	−0.14120 (0.2650)	0.08926 (0.1394)	−0.10054 (0.2088)	0.05412 (0.3443)
Noninterest Income/ Revenue	**0.11578** (0.0070)	**−0.03845** (0.0120)	0.01639 (0.3833)	0.00477 (0.7347)	**−0.13306** (0.0152)	**0.08958** (0.0308)
Nonperforming Loans/Assets	**−0.68264** (0.0048)	**0.19023** (0.0054)	**−0.70018** (0.0029)	**0.53869** (0.0018)	**−1.07512** (<.0001)	**0.90489** (<.0001)
Deposits/(Deposits + Other Borrowed Funds)	**0.11171** (0.0316)	**−0.02923** (0.0648)	0.01855 (0.7501)	−0.04228 (0.2023)	**0.14470** (0.0178)	**−0.09534** (0.0200)
(Equity + Sub Debt + Loan Loss Reserves)/ Assets	0.16216 (0.3728)	−0.01390 (0.9806)	0.19672 (0.3059)	0.04463 (0.6202)	0.21896 (0.4352)	−0.04803 (0.7940)

Table 8, Continued						
	Dependent Variables by Size Groups					
	Small Community Banks		Large Community Banks		Midsize Banks	
	Tobin's *q* Ratio	Market Value Inefficiency	Tobin's *q* Ratio	Market Value Inefficiency	Tobin's *q* Ratio	Market Value Inefficiency
Variable	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)	Parameter Estimate (Pr > |t|)
+1% in Business Loans +1% in Small Business Loans	−0.408 (0.909)	0.025 (0.785)	0.068 (0.745)	0.037 (0.719)	−0.216 (0.184)	0.156 (0.261)
+1% in Total Loans and +1% in Business Loans	**0.444** (0.059)	**−0.156** (0.022)	**−0.343** (0.008)	**0.159** (0.029)	−0.150 (0.170)	0.065 (0.409)
+1% in Total Loans, +1% in Business Loans +1% in Small Business Loans	0.169 (0.351)	−0.053 (0.259)	−0.023 (0.910)	0.043 (0.676)	**−0.338** (0.039)	**0.239** (0.085)
+1% in Business Loans - 1% in Small Business Loans	**0.508** (0.052)	−0.180 (0.146)				
- 1% in Business Loans +1% in Small Business Loans			**0.572** (0.004)	**−0.268** (0.039)		
-1% in Business Loans -1% in Small Business Loans					0.216 (0.184)	−0.156 (0.261)
-1% in Total Loans and -1% in Business Loans			**0.343** (0.008)	**−0.159** (0.029)		
-1% in Total Loans, -1% in Business Loans -1% in Small Business Loans					**0.338** (0.039)	**−0.239** (0.085)
+1% in Total Loans, +1% in Business Loans - 1% in Small Business Loans	**0.718** (0.026)	**−0.258** (0.013)				
-1% in Total Loans, -1% in Business Loans + 1% in Small Business Loans			**0.663** (0.001)	**−0.275** (0.035)		
-1% in Total Loans, -1% in Commercial Real Estate					**0.315** (0.005)	**−0.199** (0.008)
	Adj. R Sq = 0.271 F = 2.51	Adj. R Sq = 0.981 F = 210.56	Adj. R Sq = 0.396 F = 8.82	Adj. R Sq = 0.958 F = 270.41	Adj. R Sq = 0.700 F = 7.09	Adj. R Sq = 0.676 F = 6.45
	n = 54	n = 54	n = 156	n = 156	n = 35	n = 35

Appendix A
The Effectiveness of Banks' Credit Analysis and Monitoring

A.1. Background

For each bank-size group, **Table 4** compares the ratio of nonperforming loans with total loans. Small community banks experience a rate of 0.038 in contrast to 0.024 for large community banks and 0.022 for midsize banks (row 11). What explains the higher rate of nonperformance of the small banks?

One possibility is that banks with higher levels of nonperforming loans may be electing to lend to riskier borrowers who have a higher expected level of default. Alternatively, the higher level of nonperformance may reflect less effective credit analysis and loan monitoring. Either way, as reported in **Tables 7** and **8**, the higher proportion of nonperforming loans is associated with worse financial performance.

We apply the analysis of Hughes and Moon (2017) based on stochastic frontier techniques to distinguish between nonperformance because of the degree of effectiveness of credit evaluation and monitoring and nonperformance because of the degree of inherent credit risk. We focus on business loans and commercial real estate (CRE) loans.

A.2. Best-Practice Loan Performance and the Efficiency of Credit Evaluation and Monitoring

A bank's ratio of nonperforming loans to total loans is a common ex post measure of the riskiness of the bank's loans. On the other hand, the *average contractual interest* charged on a bank's loans gauges ex ante riskiness because it contains a risk premium that reflects the loan portfolio's average ex ante credit risk, collateral, and maturity structure. Morgan and Ashcraft (2003, p. 181) make this point: "There is strong evidence that the interest rates charged by banks on the flow of newly extended Commercial & Industrial (C&I) loans predict future loan performance and CAMEL rating downgrades by bank supervisors." Moreover, the adverse selection that results from charging a higher contractual interest rate on a particular type of loan results in higher credit risk and a higher expected rate of nonperformance.

Thus, higher expected nonperformance is linked to charging a higher contractual interest rate. For any particular average contractual interest rate, the realized rate of nonperforming loans depends in part on the efficiency of credit evaluation and loan monitoring. For example, if a bank does a poor job of credit evaluation, then for any given contractual interest rate, it will have underestimated the riskiness of its loans and will experience a higher rate of nonperformance for its average contractual interest rate than a bank that accurately evaluates credit risk and lends to better credit risks at the same contractual interest rate. Or, if two banks did accurate jobs of evaluating credit risk when extending new loans, but one bank does a worse job of monitoring its loans, it will experience worse performance than the other bank. Thus, *for any given volume of a particular type of loan and average contractual interest rate charged on it, the rate of nonperforming loans varies in part with the efficiency of credit evaluation and monitoring.*

Macroeconomic conditions and market concentration in a bank's lending markets also influence the rate of nonperformance. Petersen and Rajan (1995) provide evidence that the relationship between the contractual interest rate and nonperformance depends on banks' market power in their lending markets. Banks that operate without significant competition from other lenders are able to price initial loans to new businesses at lower-than-competitive rates to reduce the probability of default. As the businesses succeed and become more experienced, the bank can make up revenue lost to the previous lower rate. That is to say, the rate falls but not as much as it would in a more competitive market.

A.3. Specifying and Estimating the Best-Practice Loan Nonperformance Frontier

We focus on the ratio of nonperforming business loans to total business loans and the ratio of nonperforming CRE loans to total CRE loans. We use stochastic frontier techniques and maximum likelihood estimation to estimate a *best-practice (minimum) frontier of the ratio of nonperforming loans to total loans* for business and CRE loans. We condition the frontier on the volume of the loan type, the total loan volume, the average contractual interest rate charged on the loan type, and macroeconomic conditions and market concentration in the bank's markets. That is,

$$NP_i = \boldsymbol{X\beta} + \varepsilon_i, \tag{A1}$$

where NP_i = ratio of nonperforming loans of a given type to total loans of that type at bank *i*,

$\boldsymbol{X}$ is a vector loan volumes and control variables,

x_1 = *Total type of loan*$_i$ (100 billions),

x_2 = (*Total type of loan*$_i$ (100 billions))^2,

x_3 = *Total loans*$_i$ (100 billions),

$x_4 = (Total\ loans_{\mathrm{i}}\ (100\ \text{billions}))^2$,

$x_5 =$ *Total type of loan*$_{\mathrm{i}}$ (100 billions) × *Contractual loan rate$_i$ on loan type*,

$x_6 =$ *Total type of loan*$_{\mathrm{i}}$ (100 billions) × *GDP growth rate across bank$_i$'s markets*,

$x_7 =$ *Total type of loan*$_{\mathrm{i}}$ (100 billions) × *Herfindahl index of market concentration across bank$_i$'s markets*,

$x_8 =$ Contractual loan rate$_{\mathrm{i}}$ on loan type × *Herfindahl index of market concentration across bank$_i$'s markets*,

and $\varepsilon_i = v_i + \mu_i$ is a composite error term.

The Herfindahl index of market concentration is a weighted average of concentration in each state in which the bank operates, and the GDP growth rate is a 10-year weighted average state GDP growth rate in the states in which the bank operates. The weights are the ratio of the deposits in the state as a proportion of total deposits across all states. The composite error term, $\varepsilon_i = v_i + \mu_i$, is the sum of a two-sided, normally distributed error term, $v_i \sim$ iid $N(0,\sigma_v^2)$, that captures statistical noise, and a term, μ_i, distributed exponentially, $\mu_i\ (> 0) \sim \theta\exp(-\theta u)$, that gauges the systematic excess nonperforming loan ratio. The deterministic kernel defines the best-practice (minimum) ratio:

$$\textbf{best-practice } \boldsymbol{NP_i} = \boldsymbol{X\beta}. \tag{A2}$$

Conditional on the control variables, the best-practice NP represents the expected best practice (i.e., *ex post* credit risk) were the bank totally efficient at credit evaluation and loan monitoring. So the best-practice NP gauges the bank's inherent credit risk.

Following Jondrow, Lovell, Materov, and Schmidt (1982), we define the bank-specific excess nonperforming loan ratio by the expectation of μ_i conditional on ε_i:

$$\textbf{excess } \boldsymbol{NP_i} = E(\mu_i|\varepsilon_i). \tag{A3}$$

Noise is given by the expectation of v_i conditional on ε_i:

$$\boldsymbol{noise_i} = E(v_i|\varepsilon_i) = \varepsilon_i - E(\mu_i|\varepsilon_i). \tag{A4}$$

Noise can be subtracted from the observed nonperforming loan ratio to obtain the noise-adjusted observed nonperforming loan ratio:

$$\textbf{noise-adjusted } \boldsymbol{NP_i} = NP_i - E(v_i|\varepsilon_i). \tag{A5}$$

Figure A.1 illustrates the deterministic best-practice nonperforming business loans frontier. In this example, bank *i* has total business loans of \$8 billion and experiences an achieved nonperforming loan ratio of 0.030; its nonperforming loan ratio adjusted for statistical noise, $NP_i - \nu_i$, equals 0.025. Measured as the difference between the noise-adjusted observed ratio of 0.025 and the best-practice minimum of 0.010, the excess nonperforming loans ratio equals 0.015 over the best-practice minimum. Alternatively, the excess ratio can be expressed as the difference between the achieved ratio of 0.030 and the stochastic frontier ratio of 0.015. (The stochastic frontier ratio is the best-practice minimum adjusted for noise, 0.010 + 0.005 (= 0.015).)

The estimated Equation (A1) provides a useful decomposition of the observed nonperforming loans ratio into a minimum nonperforming loans ratio that reflects inherent credit risk, the excess ratio that reflects inefficiency at evaluating credit risk and monitoring loans, and noise:

$$\begin{aligned} NP_i &= \textbf{\textit{best-practice NP}}_i + \textbf{\textit{excess NP}}_i + \textbf{noise}_i \\ &= \textbf{\textit{inherent credit risk}}_i + \textbf{\textit{inefficiency}}_i + \textbf{\textit{luck}}_i \\ &= \boldsymbol{X \bullet \beta} + E(\mu_i|\varepsilon_i) + E(\nu_i|\varepsilon_i) \end{aligned} \tag{A6}$$

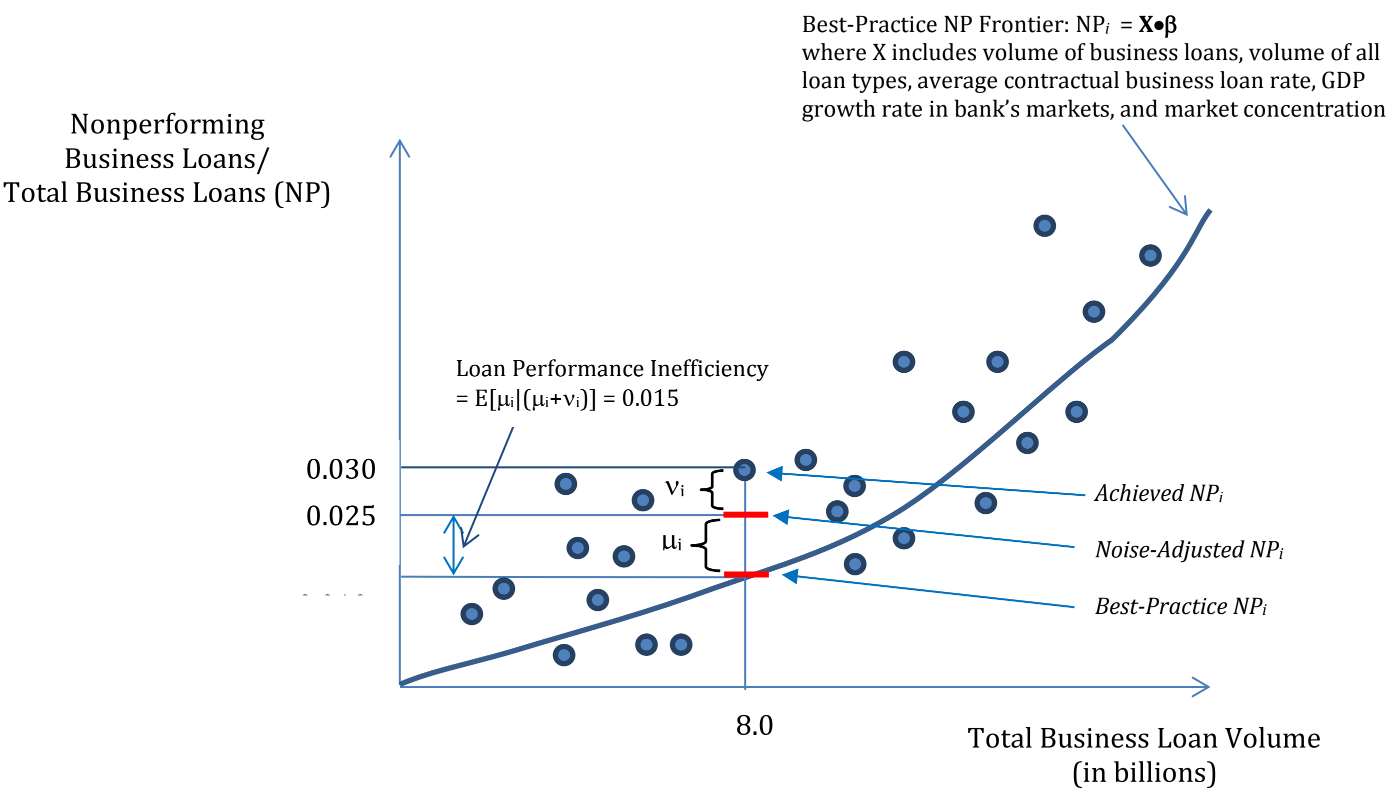
The frontier specified in Equation (A1) is estimated for business loans and commercial real estate (CRE) loans. The parameters of each loan type are provided in **Table A1** and **Table A2**. Based on robust standard errors, parameter estimates significantly different from zero at the 10 percent or stricter are in **bold**. The parameter estimates appear sensible. Note, in both fitted frontiers, that the negative coefficient, β_7, on the interaction of market concentration with business loans and with CRE loans is consistent with the hypothesis of Petersen and Rajan (1995): Greater market power in local lending markets allows banks to price business loans lower initially over the length of lending relationship to reduce the probability of default among new businesses. Thus, higher market concentration for any given volume of the loan type is associated with a lower best-practice rate of nonperformance. In both fitted frontiers, the negative coefficient, β_6, on the interaction of the volume of the loan type and the GDP growth rate indicates that better macroeconomic conditions in local lending markets improve best-practice nonperformance for any given volume of the loan type. The positive coefficient, β_5, on the interaction of the volume of the loan type with the contractual interest rate on the loan type indicates that higher loan rates are associated with riskier borrowers and higher best-practice nonperforming loan rates. And the positive coefficient, β_8, on the interaction of the Herfindahl index with the contractual interest rate on the loan type suggests that a higher contractual interest rate attracts riskier borrowers for any degree of market concentration and raises the best- practice loan nonperformance rate.

For each of the three size groups and the two types of loans, we report the decomposition of the mean observed nonperforming loans ratio into its mean inherent credit risk and its mean excess nonperforming loans ratio. As noted in Equation (A6), the sum of the inherent credit risk, the excess nonperforming loans ratio, and the noise equals the observed nonperforming loans ratio. We report the values of the first two components in **Table 5** for commercial and industrial loans and in **Table 6** for commercial real estate loans.

Figure A.1
Best-Practice Business Loan Nonperformance Frontier[24]

This figure illustrates the best-practice minimum ratio of nonperforming business loans to total business loans that is obtained by stochastic frontier estimation of the relationship between the nonperforming business loan ratio and total business loans (expressed in 100 billions), controlling for the volume of business loans, the volume of all loan types, the average contractual loan rate on business loans, and the GDP growth rate and market concentration in the bank's markets. The error term, $\varepsilon_i = \nu_i + \mu_i$, is a composite term used to distinguish statistical noise, $\nu_i \sim \text{iid } N(0,\sigma_\nu^2)$, from the term, μ_i, which is distributed exponentially, $\mu_i\ (> 0) \sim \theta \exp(-\theta u)$, that measures the systematic excess business nonperformance from bank *i*'s best-practice minimum business nonperforming loan ratio. The best-practice minimum nonperforming loan ratio is given by the value on the deterministic kernel of the stochastic frontier.

In this example, bank *i* has total business loans of $8 billion and experiences an observed nonperforming business loan ratio (NP_i) of 0.030. Its NP_i adjusted for statistical noise is $NP_i - \nu_i$ = 0.025, which is an excess of 0.015 over its best-practice minimum of 0.01.



[24] Adapted from Hughes and Moon (2017).

Table A1
Stochastic Frontier Estimation
of Commercial and Industrial Loan Nonperformance

The data set includes 619 top-tier bank holding companies at the end of 2013 with data on the average contractual loan rate on business loans and plausible values of nonperforming business loans; Banks with values of nonperforming business loans to total business loans less than 0.001 and greater than 0.25 were trimmed.

Parameter	Variable	Coefficient Estimate	Pr(>|t|)
β_1	Business Loans_i (scaled)	**−0.582107**	0.000051
β_2	[Business Loans_i (scaled)]^2	**2.245355**	0.035777
β_3	Total Loans_i (scaled)	**0.125135**	0.000007
β_4	[Total Loans_i (scaled)]^2	**−0.195548**	0.022056
β_5	[Business Loans_i (scaled)] × [Business Loan Rate_i]	**11.686910**	0.008653
β_6	[Business Loans_i (scaled)] × [GDP Growth Rate_i]	−0.013310	0.130716
β_7	[Business Loans_i (scaled)] × [Herfindahl Index_i]	**−1.847575**	0.000071
β_8	[Business Loan Rate_i] × [Herfindahl Index_i]	**0.197388**	0.001387
$\sigma_\mu = 1/\theta$		**0.025025**	0.000000
σ_v		**0.001044**	0.001338

Table A2
Stochastic Frontier Estimation
of Commercial Real Estate Loan Nonperformance

The data set includes 663 top-tier bank holding companies at the end of 2013 with plausible values of nonperforming commercial real estate loans; banks with 0 values of nonperforming commercial real estate (CRE) loans and banks whose ratios of CRE nonperforming loans exceed 0.40 were trimmed.

Parameter	Variable	Coefficient Estimate	Pr(>|t|)
β_1	CRE Loans_i (scaled)	**0.747581**	0.000000
β_2	CRE Loans_i (scaled)]^2	−0.189158	0.901903
β_3	Total Loans_i (scaled)	−0.006967	0.229286
β_4	[Total Loans_i (scaled)]^2	−0.021185	0.896806
β_5	[CRE Loans_i (scaled)] × [CRE Loan Rate_i]	**16.582116**	0.000000
β_6	[CRE Loans_i (scaled)] × [GDP Growth Rate_i]	**−0.189680**	0.000000
β_7	[CRE Loans_i (scaled)] × [Herfindahl Index_i]	**−5.107528**	0.000000
β_8	[CRE Loan Rate_i] × [Herfindahl Index_i]	**0.550731**	0.000190
$\sigma_\mu = 1/\theta$		**0.036006**	0.000000
σ_v		**0.002386**	0.000000