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How bad is a bad loan? Distinguishing inherent credit risk from inefficient lending (Does the capital market price this difference?)

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ABSTRACT

Small community banks and the largest banks experience higher ratios of nonperforming loans than other sizes of banks. To what extent does their nonperformance result from lending to riskier borrowers, and to what extent does it result from a lack of proficiency at loan making? Does market discipline punish or reward credit risk and lending proficiency? Using stochastic frontier estimation, we develop a technique to decompose banks' ratio of nonperforming loans to total loans into three components: the best-practice ratio representing the inherent credit risk of the loan portfolio, the excess ratio representing lending inefficiency, and statistical noise. We apply the decomposition technique to data from 2010, 2013, and 2016 on top-tier U.S. bank holding companies. The largest banks with consolidated assets exceeding $250 billion experience the highest ratio of nonperformance among the five size groups. Our decomposition shows that the high ratio of nonperformance of the largest banks appears to result from lending to riskier borrowers, not inefficiency at lending. Restricting the sample to publicly traded bank holding companies, we find that the nonperformance ratio is negatively related to market value except at the largest banks. When the two components of the nonperformance ratio are used instead, we uncover a more informative underlying story: taking more inherent credit risk enhances market value at many more large banks and the value-enhancing effect increases sharply from 2010 to 2016, whereas lending inefficiency is negatively related to market value at all banks and more so from 2010 to 2016. Market discipline appears to reward riskier lending at large banks and discourage lending inefficiency at all banks – incentives that are both increasing over time.

1. Introduction

The ratio of nonperforming loans to total loans a bank experiences reflects both the inherent credit risk the bank targets and the bank's proficiency at evaluating credit risk and monitoring the loans it has made. In all three years of our data on U.S. banks – 2010, 2013, and 2016 – we find that small community banks and the largest financial institutions on average experience the highest ratios of nonperforming loans. How much of this nonperformance is due to inherent credit risk and how much, to their proficiency at loan making?

To answer this question, we develop a novel technique based on stochastic frontier estimation and apply it to data on large as well as small banks to compare their lending performance. The ratio of banks' nonperforming loans is decomposed into three components:

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first, a minimum ratio that represents best-practice lending given the volume and composition of a bank's loans, the average contractual interest rate charged on these loans, and market conditions such as the average GDP growth rate and market concentration; second, luck or statistical noise, which should be removed from the bank's observed ratio of nonperforming loans; and, third, the bank's excess nonperforming loan ratio, which equals the difference between the bank's observed nonperforming loan ratio adjusted for luck and its best-practice minimum ratio, and which represents the bank's proficiency at loan making. The best-practice ratio of nonperforming loans represents the inherent credit risk of the loan portfolio – the nonperforming loan ratio a bank would experience if it were fully efficient at credit evaluation and loan monitoring. This best-practice minimum is obtained by estimating a stochastic lower envelope of nonperforming loan ratios conditioned on variables associated with inherent credit risk. The stochastic frontier estimation eliminates the influence of luck, statistical noise, and gauges systematic failure to achieve the best-practice minimum.

A major contribution of our innovative decomposition of the nonperforming loan ratio is to show that the nonperforming loan ratio in aggregate may provide a misleading or biased gauge of bank risk-taking because it fails to distinguish nonperformance due to lack of proficiency at credit risk assessment from nonperformance due to lending to riskier applicants. The largest financial institutions with assets exceeding $250 billion experienced the highest mean nonperforming loan ratio of all size groups in our three years of data. In 2010, they recorded a mean of 0.1167; in 2013 a mean of 0.0610; and in 2016 a mean of 0.0372. In contrast the group of the second largest banks with assets between $50 billion and $250 billion recorded smaller nonperformance: in 2010 a mean of 0.0866, in 2013, 0.0307, and in 2016, 0.0294. What can we infer about the lending strategy of the largest banks that experience a nonperforming ratio in 2016 of 0.0372 in comparison with the second largest banks that record a ratio of 0.0294? Are the largest banks lending to riskier applicants who are more likely to default? How much of these ratios result from a lack of proficiency in assessing credit risk and managing loans rather than riskier lending?

To the extent that the ratios reflect lending strategy rather than lending skill, we would expect that banks' market value, reflected in their Tobin's *q* ratio, would tend to be positively related to their nonperforming loan ratio. To the extent that the ratio reflects a lack of skill in assessing credit risk and managing loans, we would expect the *q* ratio to tend to be negatively related to nonperformance. A negative relationship punishes a lack of lending skill and discourages taking greater credit risk. In fact, in 2010 we find that Tobin's *q* ratio is significantly negatively related to the nonperforming loan ratio at 213 out of 218 banks, in 2013 at 235 out of 244 banks, and in 2016 at 278 out of 285 banks. This negative relationship between market value and the nonperforming loan ratio suggests that market discipline discourages taking increased credit risk at most banks and punishes lack of lending proficiency. What explains the high mean nonperforming loan ratio of the largest institutions?

Of the 10 banks in the group with more than $250 billion in assets, the derivative of the *q* ratio with respect to the nonperforming loan ratio of the four largest institutions in 2016 is positive but not statistically significant. The remaining 6 banks exhibit a negative derivative where 3 of the 6 are significantly negative. All 18 banks in the group with assets between $50 billion and $250 billion exhibit a significant negative derivative. Based on the evidence related to the nonperforming ratio, the capital market does not appear to provide the largest banks with a clear incentive to take increased credit risk.

An important contribution of our innovative decomposition of the nonperforming loan ratio consists of distinguishing nonperformance due to a lack of lending proficiency from nonperformance due to borrowers' credit risk, which allows us to infer the credit risk assumed by lenders from their nonperforming loan ratios. When the nonperforming loan ratio, adjusted for statistical noise, is decomposed into the inherent credit risk (the best-practice minimum ratio) and the lending inefficiency ratio, a positive relationship is found between Tobin's *q* ratio and inherent credit risk at 4 banks in 2010 where none are statistically significant. In contrast, the relationship between Tobin's *q* ratio and the inherent credit risk is negative at 211 smaller banks and significantly negative at 206.

In 2013, a positive relationship is found between Tobin's *q* ratio and inherent credit risk at 95 large banks where none are statistically significant. And it is negative at 150 banks and significant at none.

However, in 2016, Tobin's *q* ratio is positively related to inherent credit risk at 262 banks where, strikingly, 156 are significantly positive, and notably there are no banks where the relationship is negative. Thus, market discipline appears increasingly to favor efficient credit risk.

In contrast to the weak evidence provided by the relationship of the *q* ratio to the nonperforming loan ratio, in 2016 all the banks in the groups with assets exceeding $250 billion and $50 billion exhibit a statistically significant positive relationship between the *q* ratio and inherent credit risk, which is much stronger for the banks larger than $250 billion. Thus, these large banks experience a significant financial incentive to increase their exposure to credit risk, which is consistent with their high nonperforming loan ratio. Hence, the measure of inherent credit risk obtained from the decomposition appears to gauge banks' credit risk more accurately than the nonperforming loan ratio.

The evolution of these incentives over time suggests that the capital market is increasingly rewarding credit risk. The evidence that the capital market rewards higher credit risk at the largest banks is consistent with their higher ratio of nonperformance and suggests that market discipline may not enhance financial stability through the lending channel at these large banks, which highlights the importance of heightened supervision and capital standards at large institutions. On the other hand, the capital market penalizes lending inefficiency at banks of all sizes and in doing so tends to promote financial stability.[1]

[1] Hughes, Mester, and Moon (2016) find a similar relationship between the equity capital ratio and financial performance based on market value measures. At the margin, the largest financial institutions improve financial performance by increasing financial leverage while smaller institutions, by reducing leverage.

2. Contributions to the literature

This novel decomposition of the nonperforming loan ratio into inherent credit risk and lending inefficiency contributes significantly to the literature on measuring risk and lending performance using the nonperforming loan ratio in aggregate by separating nonperformance due to lending to riskier borrowers from nonperformance due to a lack of proficiency at assessing credit risk and managing loans. In addition, it provides a new, innovative application of stochastic frontier analysis to gauge lending performance.

2.1. Lending performance

A number of studies of fintech lending have focused on loan default to compare lending by fintechs with traditional lending by commercial banks. In contrast to traditional bank lending that relies on information obtained from banking relationships and from credit scoring models such as FICO, fintechs rely on alternative data and on more advanced techniques using AI and ML modeling. Jagtiani and Lemieux (2019), Goldstein, Jagtiani, and Klein (2019), and Croux, Jagtiani, Korivi, and Vulanovic (2020) find enhanced credit assessment at fintechs. In contrast to comparisons of lending performance based on default, which do not separate default resulting from lending skill from risk-taking, Hughes, Jagtiani, and Moon (2022) apply our decomposition to identify and compare the lending efficiency and inherent credit risk of a large fintech, LendingClub, with commercial banks. Focusing on unsecured consumer lending in 2013 and 2016, they find that the high nonperforming loan ratio of large banks results from high inherent credit risk, not from lending inefficiency. In 2013 the nonperforming loan ratio and the lending efficiency of LendingClub resembled commercial banks with a similar volume of loans. By 2015 LendingClub had increased its use of alternative data and AI/ML to assess credit risk. In 2016 LendingClub's efficiency and inherent credit risk had increased and resembled that of the largest consumer lenders.

In short, our decomposition of the nonperforming loan ratio contributes to the literature on lending performance by distinguishing lending skill from inherent credit risk, and uncovers improved lending efficiency resulting from using alternative data and credit risk modeling based on AI/ML.

2.2. Stochastic frontier estimation of firm performance

Greene (2018), Kumbharkar and Lovell (2000), and Coelli, Prasada Rao, and Battese (1998) provide detailed general discussions of stochastic frontier estimation. Estimation of stochastic frontiers gauges firms' best-practice performance and their failure to achieve it. The ratio of lost performance to best-practice performance measures a firm's inefficiency. Frontiers fitted to data as upper envelopes include those where performance is based on profit, on the market value of assets, and on the return on assets. Alternatively, frontiers can be fitted as lower envelopes where performance is measured in terms of cost. Hughes and Mester (2019) and Berger and Mester (1997) review applications of these frontiers to banking and financial economics.

The best-practice nonperforming loan frontier fits the data as a lower bound. It represents a new application and interpretation of frontier estimation. The performance metric is the nonperforming loan ratio. A lender's nonperforming loan ratio is compared to that of its peers to ask: How well does the lender's ratio compare with that of other lenders deemed peers? Best practice gauged by the frontier represents the nonperformance a bank would experience if it were fully efficient at credit-risk evaluation and loan monitoring relative to its peers. The difference between a lender's nonperforming loan ratio and its best-practice ratio – the lender's failure to achieve best practice – measures the lender's inefficiency at lending.

3. The data

We obtain balance-sheet and income statement data from the Y9-C report which bank holding companies file quarterly with their regulators. We draw these data from the end-of-year reports for 2010, 2013, and 2016. Because the reporting requirements were relaxed for banks with assets under \$1 billion after 2014, many (but not all) small community banks drop out of the reports in subsequent years, which handicaps our 2016 sample. Hence, we focus on 2013 and use 2010 and 2016 to confirm that the generality of the findings obtained in 2013.

To estimate the 2013 frontier, we start with data on 807 top-tier holding companies at year-end. The 807 companies are obtained after dropping one company with no nonperforming loans and all companies without data on small business loans (commercial and industrial loans with an origination amount under \$1 million). The data on small business loans are obtained by summing the loan amounts of subsidiaries of the top tier company from the Call Report data.[2] In this section, we provide details on trimming the full sample in 2013 to achieve a sample of banks whose focus on lending is sufficient to allow the estimation of a stochastic best-practice loan performance frontier. A similar procedure is applied to 2010 and 2016.

In 2013 the average ratio of total loan volume to consolidated assets is 0.636, bounded by a minimum of 0.055 and a maximum of 0.962. The 4 companies with the smallest loan ratios, less than 0.15, are not focused on the loan-making function of commercial banks and, thus, are trimmed from the data used to estimate best-practice loan making.

In addition, some companies exhibit unusually large ratios of nonperforming loans to total loans. Nonperforming loans include loans past due less than and more than 90 days plus nonaccruing loans, lease financing receivables, placements, and other assets

[2] These data were constructed by Quinn Maingi of the Federal Reserve Bank of Philadelphia.

(BHCK525 +BHCK5524 +BHCK5526)[3]; gross charge-offs (BHCK4635); and other real estate owned (BHCK2150). Since some banks are more aggressive in charging off past-due loans and, consequently, would appear to have a lower ratio of past-due loans, gross charge-offs are added to past-due loans to eliminate distortions caused by differences among banks in charge-off strategies. We trim banks with unusually high and low ratios of nonperforming loans.

The final 2013 sample is restricted to holding companies with a loan volume that exceeds 15% of consolidated assets and nonperforming loans, broadly defined, that are at least 1% and no more than 15% of the total loan volume. In addition, data on small business lending obtained from the Call Reports of subsidiaries of the holding company must be available. These restrictions yield a sample of 710 bank holding companies. We apply a similar procedure to the other two years of data which generates 776 companies in 2010 and 474 in 2016.[4] The log transformation of the volume of nonperforming loans (measured in 1,000s) is plotted in Fig. 1 against the log transformation of the volume of total loans (in 1,000s) for the trimmed samples in 2010, 2013, and 2016. In Fig. 2**,** where the ratio of nonperforming loans to total loans is plotted against the log transformation of total loans (measured in 1,000s), a higher ratio of nonperformance for the largest banks is evident, especially in 2013 and 2016. In addition, the smallest banks also exhibit higher ratios of nonperformance in all three years.

Table 1 shows for 2013 that banks in all but the largest category have similar mean and median values of the ratio of loans to assets. Banks in the largest group, whose consolidated assets exceed $250 billion, allocate on average 51.74% of their assets to loans while banks in the other size groups allocate on average 63.22–66.78% of their assets to loans.

As suggested in Fig. 2, the mean ratio of nonperforming loans to total loans is higher in the smallest size group, community banks with assets less than $1 billion, and in the largest size group, banks whose consolidated assets exceed $250 billion. In 2013, on average 4.61% of loans at these small community banks are nonperforming while loans at the largest banks exhibit a mean nonperformance rate of 6.10%. In contrast, loans in the next largest group (assets between $50 billion and $250 billion) default at 3.07%. Table 2 shows the details of nonperformance in 2013 for the banks whose consolidated assets exceed $50 billion. As Table 4 reports, this pattern is also found in 2010. In 2016, the relatively high nonperforming loan ratio of small community banks exceeds that of large community banks and midsize banks, but not that of larger banks. Unfortunately, the reduced number of small community banks caused by the change in reporting requirements in 2015 makes drawing conclusions about these banks in 2016 less reliable than conclusions drawn in 2010 and 2013.

The strikingly higher average ratio of nonperformance among the largest banks and, to some degree, among the small community banks, raises the question of whether these banks are on average less efficient at credit evaluation and loan monitoring or whether they may be lending to riskier borrowers who have a higher expected rate of default.

4. Best-practice loan performance and the efficiency of lending

We use stochastic frontier techniques to distinguish between nonperformance due to less effective credit evaluation and loan monitoring and nonperformance due to the bank's choice of the overall credit risk of its loan portfolio. Our performance metric is the nonperforming loan ratio for lending, and we compare a lender's nonperforming loan ratio to that of its peers to ask: How well does the lender's ratio compare with that of other lenders deemed peers? Best practice gauged by the frontier represents the nonperformance a bank would experience if it were fully efficient at credit-risk evaluation and loan monitoring relative to its peers. The difference between a lender's nonperforming loan ratio and its best-practice ratio – the lender's failure to achieve best practice – measures the lender's inefficiency at lending.

Efficiency is often measured relative to a frontier. The estimation of a production, cost, or profit function intends to capture the technology – often to gauge economies of scale. Estimated as a frontier, it seeks to gauge the best practice production, cost, or profit based on the assumption of optimizing behavior. Hughes and Mester (2019) refer to this strategy as the structural approach to modelling bank production and efficiency. They contrast this approach to the nonstructural approach, which investigates how measures of performance such as the *z* score, ROA, the Sharpe ratio, Tobin's *q* ratio, the ratio of operating costs to revenue, and a cumulative abnormal return, are related to, for example, firms' investment strategies, their ownership and governance structure, and their corporate control environment. Thus, the nonstructural approach, which can be formulated in terms of a frontier, does not intend to estimate production, cost, or profit technology.

Examples of the nonstructural approach include Caprio, Laeven, and Levine (2007) who use Tobin's *q* ratio to evaluate the relationship of the characteristics of ownership and governance to firm valuation. Brook, Hendershott, and Lee (1998) regress the cumulative abnormal return to banks resulting from the deregulation of interstate branching on factors related to the probability of takeover due to deregulation: prior financial performance and evidence of managerial entrenchment. Morck, Shleifer, and Vishny (1988) and McConnell and Servaes (1995) regress Tobin's *q* ratio on characteristics of managerial ownership and governance.

In contrast to the more commonly estimated frontiers based on structural approaches, Hughes, Lang, Moon, and Pagano (1997) use frontier methods in a non-structural approach to estimate a proxy for Jensen and Meckling's agency cost: a frontier of the market value of assets fitted as a potentially nonlinear function of the book-value investment in assets and the book value of assets squared. This frontier gives the highest potential value *observed* in the sample for any given investment in assets. For any bank, the difference

[3] The BHCK numbers refer to categories in the Y9-C regulatory reports filed by bank holding companies.

[4] After 2014, the Y9-C reporting requirements were relaxed for most banks with less than $1 billion in assets so that the 2016 sample has fewer of these banks than in 2010 and 2013: 35 in 2016 while 419 in 2010 and 364 in 2013. That is, the small community bank group in 2016 may not be highly comparable to those in 2010 and 2013.

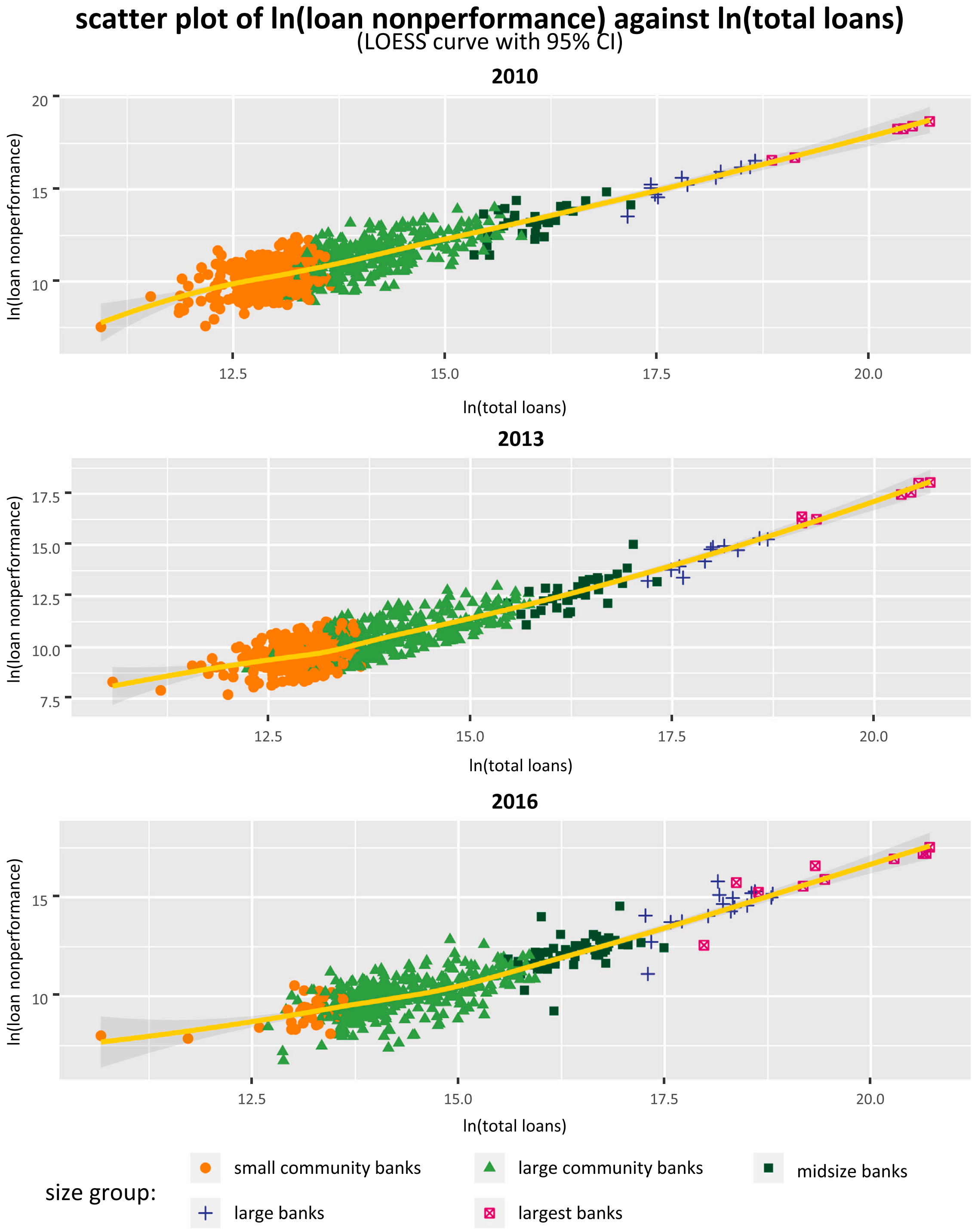

Fig. 1. Scatter plot of ln(loan nonperformance) against ln(total loans). The log transformation of nonperforming loans (measured in 1,000s) is plotted against the log transformation of total loan volume (measured in 1,000s) for 776 top-tier bank holding companies at the end of 2010, 710 companies in 2013, and 474 in 2016. While it appears that, for any given volume of loans, the degree of nonperformance is wide, it is important to remember that some of this wide variation in nonperformance is due to differences in the average contractual interest rate, the composition of the loan portfolio, the GDP growth rate, and market concentration. LOESS curve (the thick curve in the above figure) and its 95% confidence interval (the shaded band) are included. LOESS is short for locally estimated scatterplot smoothing, which fits local polynomial regression model to scatter points. LOESS is one of the most popular local smoothing methods and is robust to a long-tailed error distribution while it is highly effient when the error distribution is normal.

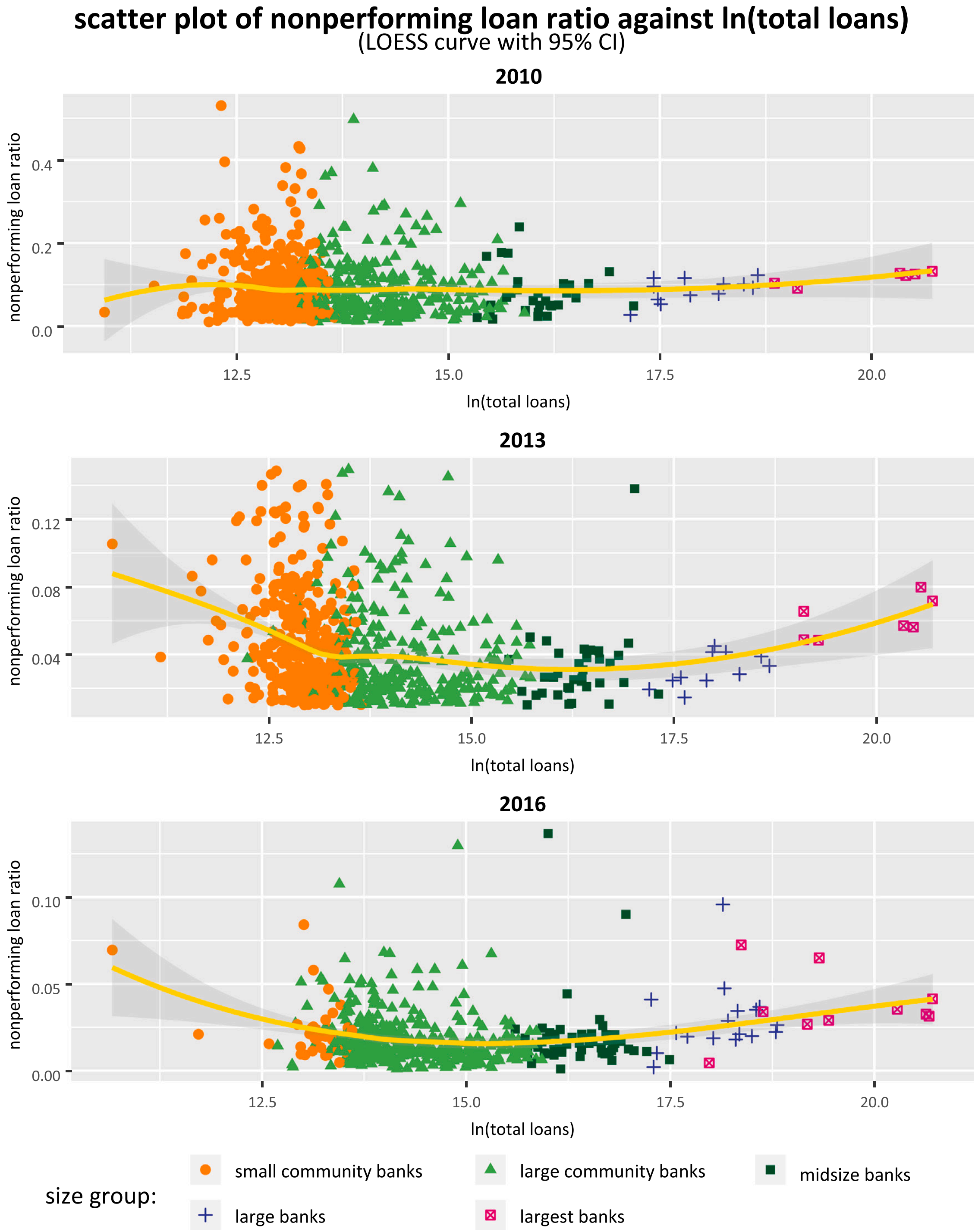

Fig. 2. Scatter plot of nonperforming loan ratio against ln(total loans). The ratio of nonperforming loans as a proportion of total loans is plotted against the log transformation of total loan volume (measured in 1,000s) for 776 top-tier bank holding companies at the end of 2010, 710 companies in 2013, and 474 in 2016. While it appears that, for any given volume of loans, the degree of nonperformance is wide, it is important to remember that some of this wide variation in nonperformance is due to differences in the average contractual interest rate, the composition of the loan portfolio, the GDP growth rate, and market concentration. LOESS curve (the thick curve in the above figure) and its 95% confidence interval (the shaded band) are included. LOESS is short for locally estimated scatterplot smoothing, which fits local polynomial regression model to scatter points. LOESS is one of the most popular local smoothing methods and is robust to a long-tailed error distribution while it is highly efficient when the error distribution is normal.

Table 1
Summary Statistics of Top-Tier Bank Holding Companies at Year-End 2013.

	N	Mean	Median	Std. Dev.	Minimum	Maximum
Panel A: Small Community Banks (Consolidated Assets < $1 Billion)						
Book Value Assets (1,000s)	364	662,973	654,468	167,443	92,694	998,762
Loans /Assets	364	0.6400	0.6558	0.1267	0.2838	0.9142
(Nonperforming Loans) / Loans	364	0.0461	0.0370	0.0310	0.0100	0.1485
Panel B: Large Community Banks ($1 Billion < Consolidated Assets < $10 Billion)						
Book Value Assets (1,000s)	293	2,600,335	1,853,823	1,918,892	1,000,668	9,641,427
Loans /Assets	293	0.6414	0.6537	0.1229	0.1653	0.9216
(Nonperforming Loans) / Loans	293	0.0383	0.0280	0.0277	0.0100	0.1492
Panel C: Large Banks ($10 Billion < Consolidated Assets < $50 Billion)						
Book Value Assets (1,000s)	35	21,161,256	18,473,488	9,330,543	10,989,286	47,138,960
Loans /Assets	35	0.6322	0.6588	0.1366	0.3856	0.9621
(Nonperforming Loans) / Loans	35	0.0312	0.0264	0.0219	0.0102	0.1379
Panel D: Very Large Banks ($50 Billion < Consolidated Assets < $250 Billion)						
Book Value Assets (1000 s)	11	104,276,621	92,991,716	43,640,904	56,031,127	183,009,992
Loans /Assets	11	0.6678	0.6958	0.1388	0.2854	0.8290
(Nonperforming Loans) / Loans	11	0.0307	0.0283	0.0099	0.0146	0.0449
Panel E: Largest Banks (Consolidated Assets > $250 Billion)						
Book Value Assets (1000 s)	7	1,272,854,333	1,527,015,000	923,465,518	297,282,098	2,415,689,000
Loans /Assets	7	0.5174	0.5501	0.1409	0.3167	0.6656
(Nonperforming Loans) / Loans	7	0.0610	0.0569	0.0118	0.0483	0.0798

The data set includes 710 top-tier bank holding companies at the end of 2013. Nonperforming loans include past due loans less than and more than 90 days plus nonaccruing loans, lease financing receivables, placements, and other assets (BHCK525 +BHCK5524 +BHCK5526); gross charge-offs (BHCK4635); and other real estate owned (BHCK2150). Banks whose nonperforming loans exceed 15% of total loans as well as those whose nonperforming loans are less than 1% of total loans are dropped. And banks with total loans less than 15% of consolidated assets are dropped. These restrictions reduce the initial sample of 807 banks to 710.

Table 2
The Largest Banks and Their Loan Performance at Year-End 2013.

	Name of bank holding company	Book value of total assets (1,000s)	(Nonperforming loans) / (Total loans)	(Nonperforming loans + gross charge-offs) / (Total loans)	(Nonperforming loans + Gross charge-offs + Other real estate owned) / (Total loans)
1	JPMorgan Chase & Co.	2,415,689,000	0.042777	0.052537	0.056131
2	Bank Of America Corporation	2,104,995,000	0.058744	0.069468	0.071591
3	Citigroup Inc.	1,880,382,000	0.033841	0.056329	0.056944
4	Wells Fargo & Company	1,527,015,000	0.067471	0.075102	0.079751
5	U.S. Bancorp	364,021,000	0.036162	0.044326	0.048340
6	PNC Financial Services Group,	320,596,232	0.037558	0.045575	0.048626
7	Capital One Financial Corp	297,282,098	0.037057	0.064881	0.065447
8	BB&T Corp	183,009,992	0.028152	0.036616	0.038728
9	Suntrust Banks	175,380,779	0.024413	0.031124	0.033224
10	Fifth Third Bancorp	129,685,180	0.017885	0.024993	0.028333
11	Regions Financial Corp	117,661,732	0.027746	0.039622	0.041359
12	Northern Trust Corporation	102,947,333	0.016903	0.018918	0.019324
13	Keycorp	92,991,716	0.018109	0.024203	0.024622
14	M&T Bank Corp	85,162,391	0.036329	0.040286	0.041329
15	Discover Financial Services	79,339,664	0.018484	0.044931	0.044931
16	Comerica Inc	65,356,580	0.010943	0.014293	0.014566
17	Huntington Bancshares Inc	59,476,344	0.018639	0.025698	0.026335
18	Zions Bancorporation	56,031,127	0.020123	0.023459	0.024635

Holding companies whose consolidated assets exceed $50 billion are listed below. Nonperformance is measured by the following data from the Y9-C report at year-end 2013 divided by Total Loans (BHCK2122). Nonperforming = past due loans less than and more than 90 days plus nonaccruing loans, lease financing receivables, placements, and other assets (BHCK525 +BHCK5524 +BHCK5526); Nonperforming loans + Gross Charge-offs (BHCK4635); Nonperforming Loans + Gross Charge-offs + Other Real Estate Owned (BHCK2150).

Table 3
Estimation of Stochastic Best-Practice Loan Nonperformance Frontier.

Parameter	Variable	2010 Coefficient estimate	2013 Coefficient estimate	2016 Coefficient estimate
α_0	Intercept	**− 0.051846**	− 0.008948	**− 0.007746**
α_1	Total loans$_i$ (100 billons)	**0.012543**	**0.005276**	**0.002340**
β_1	Contractual lending rate$_i$	**0.470863**	**0.368182**	**0.308503**
β_2	Herfindahl index of market concentration$_i$	0.006347	− 0.000805	**− 0.012501**
β_3	GDP growth rate$_i$	**− 0.006347**	**− 0.000669**	**− 0.001035**
β_4	(Small business loan volume$_i$) / (Total loan volume$_i$)	0.003207	− 0.014782	− 0.000355
β_5	(Total business loan volume$_i$) / (Total loan volume$_i$)	**0.028802**	0.002404	0.004670
β_6	(Consumer loan volume$_i$) / (Total loan volume$_i$)	**0.044054**	**0.014150**	**0.023073**
β_7	(Residential real estate volume$_i$) / (Total loan volume$_i$)	**0.026825**	0.008028	**0.005293**
β_8	(Commercial real estate volume$_i$) / (Total loan volume$_i$)	**0.079318**	0.009189	− 0.000652
σ_v	Two-sided, normally distributed error term, $\nu_i \sim \text{iid}N(0,\sigma_\nu^2)$	**0.008056**	**0.002858**	**0.002152**
$\sigma_\mu \equiv \frac{1}{\theta}$	Positive, exponentially distributed error term, $\mu_i \sim$ iid with $\theta\exp(-\theta\mu)$ as the pdf, that gauges excess nonperformance[a]	**0.064384**	**0.028071**	**0.012860**

The data set includes 776 top-tier bank holding companies at the end of 2010, 710 companies in 2013, and 474 in 2016. Nonperforming loans include past due loans less than and more than 90 days plus nonaccruing loans, lease financing receivables, placements, and other assets (BHCK525 +BHCK5524 +BHCK5526); gross charge-offs (BHCK4635); and other real estate owned (BHCK2150). Stochastic frontier techniques are used to estimate the best-practice minimum ratio of nonperforming loans to total loans for any given amount of total loans, expressed in 100 billions, controlling for the composition of the bank's loan portfolio, the average contractual interest rate charged on its loans, the ten-year average GDP growth rate and market concentration in the states in which the bank operates, where each state's datum is weighted by the proportion of the bank's total deposits located in the state. See Eq.(1). Parameters significantly different from zero at 10% or stricter are given in bold.

[a] Compared to the normal-half-normal model, the normal-exponential model with a constant term is the best by AIC (BIC) employed for comparing models in the same family of distributions and Vuong's test employed for comparing non-nested models for each of the three years.

Table 4
Best Practice Nonperformance and Lending Inefficiency.

Variable	Size groups					
	Full sample Mean	Small community banks < \$1 B Mean	Large community banks \$1 B − \$10 B Mean	Midsize banks \$10 B − \$50 B Mean	Large banks \$50 B − \$250 B Mean	Largest banks > \$250 B Mean
Avg. Contractual Loan Interest Rate						
2010	**0.0594**	0.0609	0.0578	0.0544	0.0589	0.0587
2013	**0.0508**	0.0525	0.0494	0.0458	0.0453	0.0538
2016	**0.0441**	0.0492	0.0438	0.0407	0.0497	0.0432
Nonperforming Loans / Loans						
2010	**0.0885**	0.0907	0.0861	0.0793	0.0866	0.1167
2013	**0.0421**	0.0461	0.0383	0.0312	0.0307	0.0610
2016	**0.0195**	0.0241	0.0181	0.0193	0.0294	0.0372
Best-Practice Nonperformance						
2010	**0.0242**	**0.0251**	**0.0227**	**0.0169**	**0.0220**	**0.0797**
2013	**0.0140**	**0.0143**	**0.0131**	**0.0118**	**0.0154**	**0.0442**
2016	**0.0066**	**0.0072**	**0.0059**	**0.0059**	**0.0148**	**0.0193**
Lending Inefficiency						
2010	**0.0644**	**0.0656**	**0.0635**	**0.0618**	**0.0637**	**0.0367**
2013	**0.0281**	**0.0318**	**0.0252**	**0.0194**	**0.0153**	**0.0167**
2016	**0.0129**	**0.0168**	**0.0122**	**0.0132**	**0.0145**	**0.0178**

The data set includes 776 top-tier bank holding companies at the end of 2010, 710 companies in 2013, and 474 in 2016. Nonperforming loans include past due loans, gross charge-offs, and other real estate owned. Stochastic frontier techniques described in Eq. (1) are used to estimate the best-practice minimum ratio of nonperforming loans to total loans for any given amount of total loans, controlling for the composition of the bank's loan portfolio, the average contractual interest rate charged on its loans, the ten-year average GDP growth rate and market concentration in the states in which the bank operates, where each state's datum is weighted by the proportion of the bank's total deposits located in the state. Lending Inefficiency is measured as the difference between the noise-adjusted actual ratio and the best-practice minimum ratio of nonperforming loans to total loans. See Eqs. (2) through (6).

between its highest potential value and its noise-adjusted achieved value represents its lost market value – a proxy for agency cost. Several studies have used either this systematic lost market value or the resulting noise-adjusted *q*-ratio to measure performance: Baele, De Jonghe, and Vander Vennet (2007), Hughes et al. (2003), De Jonghe and Vander Vennet (2005), Hughes and Moon (2003), Hughes (1999), Hughes, Mester, and Moon (2001), Hughes & Mester (2013a), (2013b), Hughes et al. (2016). Habib and Ljungqvist

(2005) specify an alternative market-value frontier as a function of a variety of managerial decision variables, including size, financial leverage, capital expenditures, and advertising expenditures. Instead of modeling production technology or investment strategy based on optimization, this study adopts the nonstructural approach defined by Hughes and Mester (2019).

We gauge lending performance by the ratio of past-due loans and charge-offs across a variety of lenders as a function of variables that define a lender's peers, which are not necessarily the same type of lender, and we decompose performance into best practice and excess nonperformance (inefficiency) to ask how well a lender's consumer loan performance compares with the performance of its peers. We include gross charge-offs as well as past-due loans to capture the initial nonperformance of loans. While this *ex post* measure does not account for the subsequent developments regarding the disposition of nonperforming loans such as curing and recoveries, it is appropriate for the comparison of how well lenders' loan performance compares to their peers (before further action on nonperformance occurs or is taken). In contrast to this *ex post* measure, an *ex ante* measure of credit risk, which would be appropriate in a risk-expected-return formulation, would not gauge the initial nonperformance of loans.

Peers are defined by variables that characterize the credit risk a lender adopts in its loan portfolio, economic characteristics of the lender's local markets, such as the GDP growth rate and market concentration, and the volume of its lending. The volume of lending captures to some degree the lending technology − ranging from relationship based lending of smaller lenders to algorithmic lending of larger lenders. Default probabilities differ by the type of loan, and so it is important to include variables that characterize the composition of the loan portfolio. In addition, the contractual interest rate charged on a loan includes a credit risk premium and, itself, influences the quality of loan applicants through adverse selection.[5] In addition, conditions in the markets in which a bank lends, such as the macroeconomic growth rate and the bank's market power, influence loan performance. Petersen and Rajan (1995) find that a bank with market power is able to price a loan to a young business at a lower-than-competitive rate to reduce the probability of default. As the firm gains experience and continues to borrow from the bank, the bank recovers its implicit subsidy by lowering the loan rate but not as much as would occur in a competitive market. Thus, the degree of market concentration can influence loan performance. These variables define a consumer lender's peers for the purpose of comparing a lender's loan performance with that of comparable lenders − i.e., peers.

The stochastic lower envelope of nonperforming loan ratios takes into account the observed loan performance of all banks in the sample and eliminates the influence of luck, statistical noise, on loan performance. It estimates observed best practice, the minimum ratio of nonperforming loans a bank could obtain relative to its peers if it were fully efficient at credit evaluation and loan monitoring given its loan volume, the composition of its loan portfolio, its average contractual lending rate and the economic conditions in its local lending markets.

The choice of specifying the frontier in terms of the ratio of nonperforming loans to total loans is motivated by the need to obtain an unbiased estimate of the best-practice minimum ratio of nonperforming loans to total loans, which will be used to gauge inherent credit risk. If the log transformation of the amount of nonperforming loans or the log transformation of the ratio were used as the dependent variable in the frontier estimation, an unbiased estimate of the degree of inefficiency can be obtained; however, the estimate of the minimum ratio of nonperforming loans to total loans computed from the log transformation is not unbiased. Thus, we avoid the log transformation.

Defining the frontier in terms of the ratio of nonperforming loans provides two important advantages. First, it gives an unbiased estimate of inherent credit risk; and, second, it decomposes the nonperforming loan ratio, adjusted for statistical noise, into two ratios capturing inherent credit risk and lending inefficiency.

We use maximum likelihood to estimate a *best-practice loan performance frontier* that determines the minimum nonperforming loan ratio conditional on the total loan volume (expressed in 100 billions), the average contractual interest rate, macroeconomic conditions and market concentration in the bank's markets, and the composition of the loan portfolio. That is,

$$\mathrm{NP}_i = \alpha_0 + \alpha_1(\text{Total loans}_i\ (100\ \text{billions})) + \mathbf{x}_i'\boldsymbol{\beta} + \varepsilon_i \tag{1}$$

where NP_i = observed ratio of nonperforming loans to total loans at bank i,

and $\mathbf{x}_i$ is a vector of other control variables:

$x_{1,i}$ = Contractual lending rate_i,

$x_{2,i}$ = Herfindahl index of market concentration across bank_i's markets,

$x_{3,i}$ = GDP growth rate across bank_i's markets,

$x_{4,i}$ = Small business loan volume_i / Total loans_i,

$x_{5,i}$ = Total business loan volume_i / Total loans_i,

$x_{6,i}$ = Consumer loan volume_i / Total loans_i,

$x_{7,i}$ = Residential real estate loan volume_i / Total loans_i,

$x_{8,i}$ = Commercial real estate loan volume_i / Total loans_i,

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

The average contractual interest rate is interest and fee income on loans divided by total loans. The Herfindahl index of market concentration is a weighted average of banking market concentration in each state in which the bank operates. The weights are the proportions of deposits located in each state. 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 same as those used to compute the Herfindahl index. The composite error term, $\varepsilon_i = \nu_i +$

[5] Morgan and Ashcraft (2003) find that the interest rates charged by banks on business loans predict future loan performance.

μ_i, is the sum of a two-sided, normally distributed error term, $\nu_i \sim \text{iid}N(0,\sigma_\nu^2)$, that captures statistical noise, and a term, $\mu_i\langle\rangle 0)$, which is a one-sided, positive, and exponentially distributed error term, $\mu_i \sim$ iid with $\theta\exp(-\theta\mu)$ as the pdf, that gauges systematic excess nonperformance.[6]

The best-practice (minimum) nonperforming loan ratio is given by the deterministic kernel of the frontier:

$$\textbf{best practice NP}_i = \text{FNP}_i = \alpha_0 + \alpha_1(\text{Total loans}_i\ (100\ \text{billions})) + \mathbf{x}_i^{'}\boldsymbol{\beta}. \tag{2}$$

The bank's excess nonperforming loan ratio, μ_i, cannot be directly measured so, following Jondrow, Lovell, Materov, and Schmidt (1982), we define bank-specific excess nonperformance or lending inefficiency by the expectation of μ_i conditional on ε_i, the two-sided error term,

$$\textbf{excess}\ NP_i = E(\mu_i|,\varepsilon_i), \tag{3}$$

while luck is measured by statistical noise, the two-sided error term,

$$\textbf{luck}_i = E(\nu_i|\varepsilon_i) = \varepsilon_i - E(\mu_i|\varepsilon_i). \tag{4}$$

Thus, the frontier estimation decomposes the observed nonperforming loan ratio into three components: the best-practice (minimum) nonperforming loan ratio, the excess nonperforming loan ratio (over best-practice), and luck:

$$\text{NP}_i = \alpha_0 + \alpha_1(\text{Total}\ loans_i\ (100\ \text{billions})) + \mathbf{x}_i^{'}\boldsymbol{\beta} + E(\mu_i|,\varepsilon_i) + E(\nu_i|,\varepsilon_i)$$

$$= \textbf{best practice NP}_i + \textbf{excess NP}_i + \textbf{luck}_i \tag{5}$$

The 'expected' best-practice nonperforming loan ratio, conditional on the values of the control variables is the ratio that would be achieved were the bank totally efficient at credit evaluation and loan monitoring. As such, it represents the inherent credit risk of the bank's loan portfolio. The excess nonperforming loan ratio, which measures the effectiveness of the bank's credit evaluation and loan monitoring, can be expressed as the difference between the observed nonperforming loan ratio adjusted for noise, $(\text{NP}_i - \nu_i)$, and the frontier value of the nonperforming loan ratio:

$$\textbf{lending}\ \textit{inefficiency}_i = \textbf{excess}\ NP_i = E(\mu_i|,\varepsilon_i) = [\text{NP}_i - E(\nu_i|,\varepsilon_i)] - \text{FNP}_i. \tag{6}$$

Greene (2018) addresses the identification of the inefficiency term defined in (6): "Modeling in the stochastic frontier setting is rather unlike what we are accustomed to up to this point, in that the inefficiency part of the disturbance, specifically *u*, not the model parameters, is the central focus of the analysis. The reason is that in this context, the disturbance, *u*, rather than being the catchall for the unknown and unknowable factors omitted from the equation, has a particular interpretation—it is the firm-specific inefficiency."[7]

Fig. 3 illustrates the frontier and these components of the decomposition of the nonperforming loan ratio. The hypothetical bank whose loan performance is illustrated in this figure has total loans of 0.08 (expressed in 100 billions[8]) and experiences a nonperforming loan ratio adjusted for statistical noise, $(\text{NP}_i - \nu_i)$, of 0.025. The 'expected' best-practice minimum ratio equals 0.01. Its noise-adjusted ratio, 0.025, exceeds the best-practice minimum, 0.01, by 0.015. Thus, its *lending* inefficiency is 0.015.

Fig. 4 shows these estimated values for a portion of the sample in 2013. For illustration, the four banks with the largest volume of loans, Bank of America, Wells Fargo, JP Morgan Chase, and Citibank, are highlighted. For a given volume of loans, the noise-adjusted observed nonperforming loan ratio is indicated in blue while the best-practice (minimum) ratio, in red. The difference between these ratios is the excess nonperforming loan ratio, an indication of the proficiency of the bank in lending.

4.1. The estimation of the best-practice loan performance frontier

Table 3 shows for each of the three years the estimated parameters of the frontier specified in Eq. (1). We find consistently across the three years that, for any given volume of loans, a higher contractual interest rate is associated with a higher best-practice nonperforming loan ratio, while a higher GDP growth rate is associated with a lower best-practice ratio of nonperforming loans. The significantly positive coefficient on the proportion of total loans made up of consumer loans across the three years implies a positive relationship of consumer loans with the nonperforming loan ratio.[10] The coefficient on the ratio of residential real estate loans is significantly positive in 2010 and 2016. The significantly negative coefficient on the Herfindahl index of market concentration in 2016 is consistent with the hypothesis of Petersen and Rajan (1995).

[6] The AIC (BIC) employed for comparing models in the same family of distributions and Vuong's test employed for comparing non-nested models favor the exponential distribution of the one-sided error term over the half-normal distribution for the frontier of each of the three years.

[7] Greene adds to his discussion of the identification of the inefficiency term (p. 927): "Most theoretical treatments of inefficiency as envisioned here attribute it to aspects of management of the firm. It remains to establish a firm theoretical connection between the theory of firm behavior and the stochastic frontier model as a device for measurement of inefficiency."

[8] The Y9-C data report amounts in 1000 s, and so 0.08 (in 100 billions here) corresponds to 8000,000 (in thousands) in the Y9-C data report.

[10] Since the proportion of assets allocated to lending is one of the control variables, a variation in any category of loans implies an offsetting variation in the omitted categories of loans. The exception is a variation in small business loans since the proportion of total business loans is a control variable. These omitted categories include leases, agricultural loans, loans to nondepository institutions, and other loans.

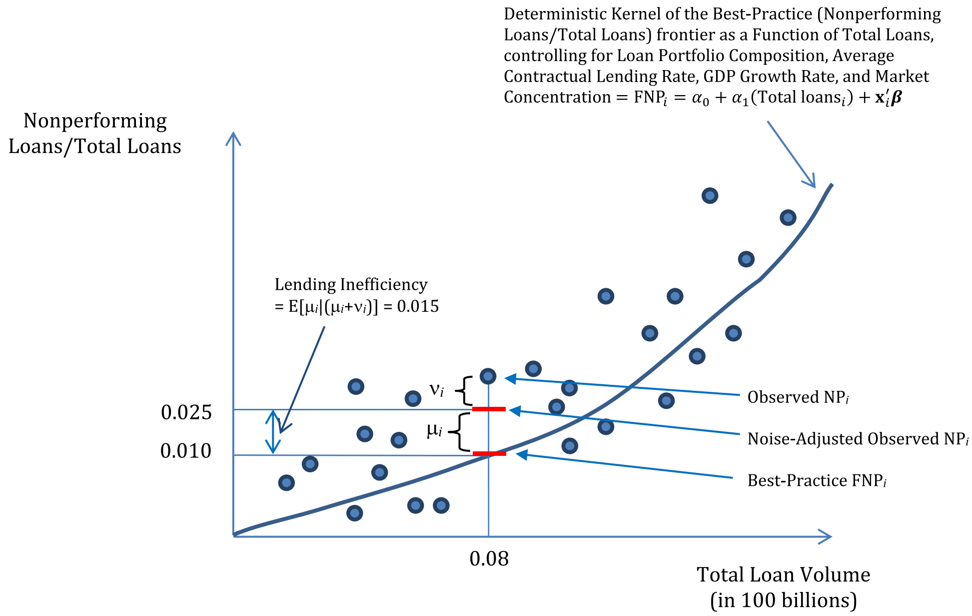

Fig. 3. Best-Practice Loan Nonperformance Frontier**.** This figure illustrates the best-practice minimum ratio of nonperforming loans to total loans that is obtained by stochastic frontier estimation of the relationship between the nonperforming loan ratio and total loans (expressed in 100 billions), controlling for the loan portfolio composition, the average contractual lending rate, and the GDP growth rate and market concentration in the bank's market. 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, $\mu_i(\rangle 0)$, which is a positive, half-normal error term, $\mu_i \sim$ iid with $\theta\exp(-\theta\mu)$ as the pdf, that measures the systematic excess nonperformance from bank *i*'s best-practice minimum nonperforming loan ratio. The 'expected' best-practice minimum nonperforming loan ratio is given by the deterministic kernel of the estimated function. In this example, bank *i* has total loans of 0.08 ($8 billions[91]) and experiences a nonperforming loan ratio adjusted for statistical noise, $(\text{NP}_i - \nu_i)$, of 0.025, which is an excess of 0.015 over the 'expected' best-practice minimum, FNP_i, of 0.010. Thus, its *lending* inefficiency is 0.015.

The positive relationship of consumer loans to inherent credit risk raises the question of the influence of large banks that undertake a large amount of credit card lending. Since only about 36% of banks in our sample have credit card lending, we created a dummy variable to identify them and added it to the frontier estimation for 2016. It makes no difference in the results – and its parameter estimate has a p-value of about 0.20. We then created a dummy for the 7 largest credit card banks. This dummy was highly significant, but it hardly influenced the results. Moreover, the summary statistics for the group of the largest banks were not much affected by the control for credit card lending.[11]

In Table 4, the sample is partitioned into five size groups. Summary statistics for each group in each of the three years are reported for the observed ratio of nonperforming loans, which is divided into the best-practice minimum ratio and the difference between the observed ratio, with statistical noise eliminated, and the best-practice ratio – the measure of lending inefficiency.

4.2. *Credit risk and lending inefficiency at community banks*

In Table 4 the mean values of the ratio of observed nonperforming loans to total loans in 2010 and 2013 are larger at small community banks (under $1 billion in assets) than at the groups of larger banks with assets less than $250 billion (although these differences are not statistically significant in 2010 at 0.10). In 2016, this ratio, 0.0241, at small community banks is on average statistically larger than at large community banks, 0.0181 ($p = 0.025$ for the difference) and smaller than at the largest banks, 0.0372 ($p = 0.0431$ for the difference). In 2013 the mean 0.0461 at these small banks exceeds the value 0.0383 at large community banks ($p = 0.0007$ for the difference), 0.0312 at banks with assets between $10 billion and $50 billion ($p = 0.0006$ for the difference), and 0.0307 at banks with assets between $50 billion and $250 billion ($p = 0.0003$ for the difference). All these differences in means in 2013 are statistically significant as indicated by the *p* values. The contrast of loan performance at small community banks with that at larger banks under $250 billion raises the question of whether these small banks are lending to riskier borrowers or whether they are less efficient at lending.

The inherent credit risk of loans can be gauged by the value of the nonperforming loan ratio on the deterministic frontier – the best practice ratio of nonperforming loans given the volume of loans, their composition, their average contractual interest rate, and the GDP growth rate and concentration in banks' local markets. The mean value of inherent, best-practice credit risk at small community banks

[11] Details of these investigations are available upon request.

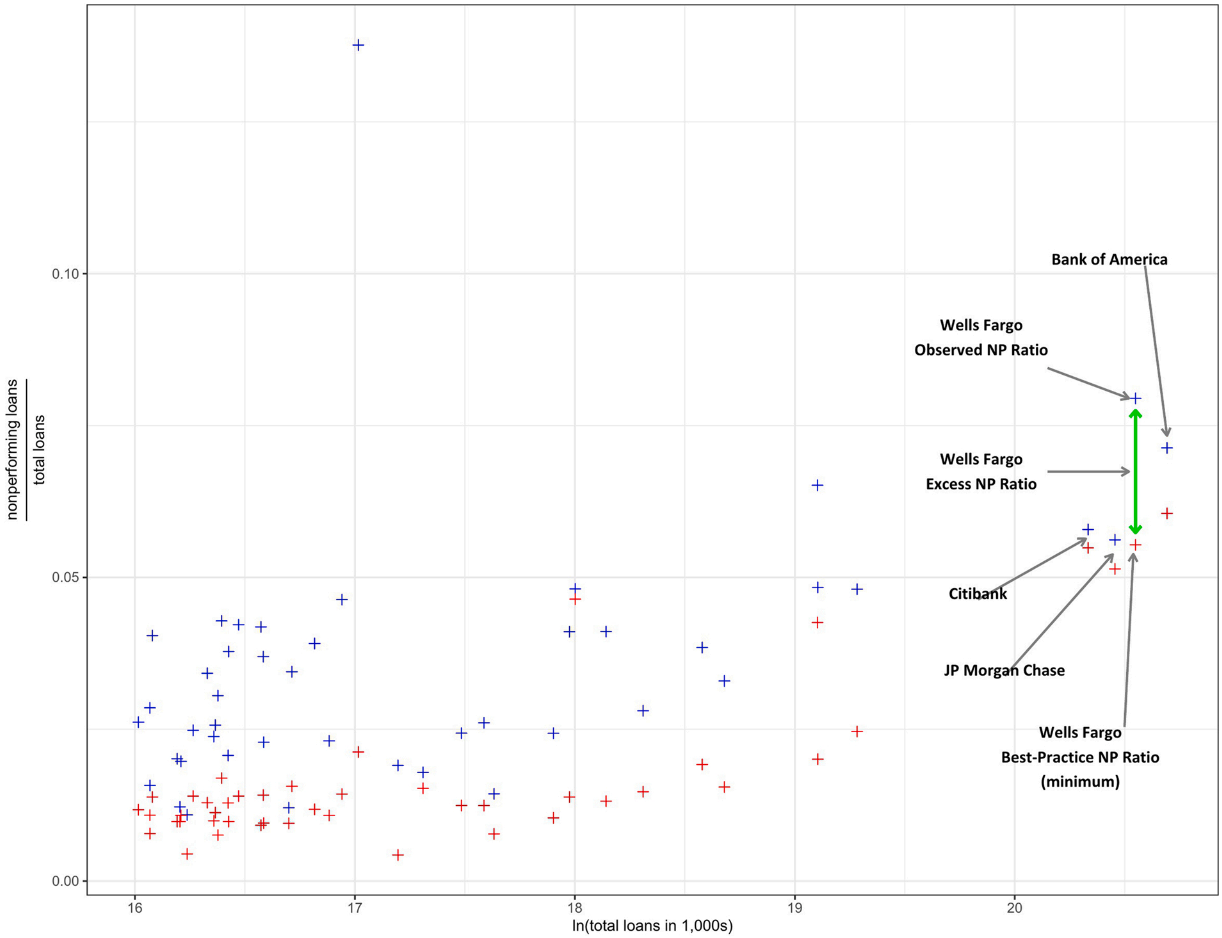

Fig. 4. Best-Practice and Observed Nonperforming Loan Ratios in 2013. This figure illustrates for banks with total loans between $8.9 billion and $967.3 billion in 2013. The estimated best-practice minimum ratio of nonperforming loans to total loans is obtained by stochastic frontier estimation of the relationship between the nonperforming loan ratio and total loans, controlling for the loan portfolio composition, the average contractual lending rate, and the GDP growth rate and market concentration in the bank's market. The 'expected' best-practice minimum nonperforming loan ratio is given by the deterministic kernel of the estimated function, which gauges inherent credit risk. The excess nonperforming loan ratio, a measure of a bank's proficiency at credit risk assessment and loan monitoring, is given by the difference between the noise-adjusted observed ratio (**blue** +) and the best-practice minimum (**red** +). These values are indicated for the four largest financial institutions.

in 2013, 0.0143, is higher than the mean value, 0.0131 ($p = 0.0001$ for the difference), at large community banks and 0.0118 ($p = 0.0003$ for the difference) at banks in the range $10 billion to $50 billion. All these differences are statistically significant. These patterns are also found in 2010 and 2016 where the differences are statistically significant at stricter than $p = 0.0001$ for the three comparisons in 2010 – 0.0251 at small community banks, 0.0227 at large community banks, and 0.0169 at banks between $10 billion and $50 billion in assets. In 2016, they are significant at $p = 0.060$ between small (0.0072) and large (0.0059) community banks and $p = 0.084$ between small community banks (0.0072) and banks between $10 billion and $50 billion in assets (0.0059).

The distance of the observed noise-adjusted ratio of nonperformance from the minimum, best-practice ratio on the deterministic frontier constitutes lending inefficiency − the nonperforming loan ratio in excess of the best-practice ratio. In 2013, the mean inefficiency, 0.0318, of these small community banks exceeds 0.0252 ($p = 0.002$ for the difference) at large community banks, 0.0194 ($p = 0.001$ for the difference) at banks in the range $10 billion to $50 billion, 0.0153 ($p < 0.0001$ for the difference) at banks from $50 billion to $250 billion, and 0.0167 ($p = 0.007$ for the difference) at banks whose assets exceed $250 billion. As noted, all these differences in means are statistically significant. A similar pattern is observed in 2010 and in 2016; however, the differences in means are not statistically significant. Thus, in general, small community banks appear on average less efficient at lending than larger banks in 2013.

[9] 0.08 (in 100 billons, here) = 8000,000 (in thousands in the Y9-C data report) = 8 billions.

4.3. Credit risk and lending efficiency at the largest banks

The seven largest banks with consolidated assets exceeding $250 billion experience the highest mean ratio of nonperformance in each of the three years. For example, in 2010 the largest banks exhibit on average a nonperformance rate of 0.1167; in 2013, 0.0610; and in 2016, 0.0372 The average inherent credit risk attained by these largest banks is similarly high: in 2010, 0.0797; in 2013, 0.0442; and in 2016, 0.0193. The difference between the nonperforming loan ratio, adjusted for statistical noise, and the inherent credit risk is their inefficiency at lending. In 2010, it is 0.0367, which is the smallest degree of inefficiency and statistically different at stricter than 0.10 except for the size group between $10 billion and $50 billion. In 2013, their mean inefficiency at lending, 0.0167, is the second lowest among the five where the difference is statistically significantly smaller than that of the two groups of community banks. Banks in the range from $50 billion to $250 billion exhibit a lower inefficiency ratio of 0.0153 but the difference is not statistically significant. In 2016, the inefficiency rate for these largest banks is the highest of the five groups but none of the differences in means is statistically significant.

Table 5 shows the values of lending inefficiency, the best-practice ratio of nonperforming loans measuring inherent credit risk, and the observed ratio of nonperforming loans for large banks with consolidated assets greater than $50 billion at year-end 2013. Nonperforming loans as a percentage of total loans range from 7.98% for Wells Fargo to 1.46% for Comerica. The best-practice percentage spans from 6.06% for Bank of America to 0.40% for Northern Trust. The lending inefficiency ranges from 2.83% for PNC to 0.17% for Discover Financial Services.

4.4. Relationship lending versus statistical and algorithmic lending

Small banks usually evaluate credit risk using soft information obtained from relationship banking. Large banks instead usually rely on statistical methods and algorithms to evaluate credit risk. Former Federal Reserve Chairman Ben Bernanke in a speech at the Independent Community Bankers of America National Convention, San Diego, California, March 23, 2011, asserted that community banks are more effective lenders: “. The largest banks typically rely heavily on statistical models to assess borrowers’ capital, collateral, and capacity to repay, and those approaches can add value, but banks whose headquarters and key decision makers are hundreds or thousands of miles away inevitably lack the in-depth local knowledge that community banks use to assess character and conditions when making credit decisions. This advantage for community banks is fundamental to their effectiveness and cannot be matched by models or algorithms, no matter how sophisticated.”

As noted in Section 4.2, small community banks appear on average less efficient at lending than larger banks. Fig. 5, plotting the observed and best-practice nonperforming loan ratios for 2016, shows that the observed lower bound of the nonperforming loan ratio is lower for small banks than for large banks. The best-practice points on the lower bound for small banks suggest that these banks experience very low inherent credit risk while the observed ratios for many small banks indicate considerable lending inefficiency

Table 5
Best Practice Nonperformance and Lending Inefficiency at Year-End 2013 for Banks with Consolidated Assets Greater Than $50 Billion.

	Name of bank holding company	Book value of total assets (1,000s)	Lending inefficiency	Best-practice nonperformance	(Nonperforming loans) / (Total loans)
1	JPMorgan Chase & Co.	2,415,689,000	0.0048	0.0514	0.0561
2	Bank Of America Corporation	2,104,995,000	0.0107	0.0606	0.0716
3	Citigroup Inc.	1,880,382,000	0.0031	0.0548	0.0569
4	Wells Fargo & Company	1,527,015,000	0.0241	0.0554	0.0798
5	U.S. Bancorp	364,021,000	0.0235	0.0245	0.0483
6	PNC Financial Services Group,	320,596,232	0.0283	0.0200	0.0486
7	Capital One Financial Corp	297,282,098	0.0225	0.0426	0.0654
8	BB&T Corporation	183,009,992	0.0193	0.0191	0.0387
9	Suntrust Banks, Inc.	175,380,779	0.0176	0.0153	0.0332
10	Fifth Third Bancorp	129,685,180	0.0135	0.0146	0.0283
11	Regions Financial Corporation	117,661,732	0.0280	0.0130	0.0414
12	Northern Trust Corporation	102,947,333	0.0150	0.0040	0.0193
13	Keycorp	92,991,716	0.0141	0.0102	0.0246
14	M&T Bank Corporation	85,162,391	0.0272	0.0139	0.0413
15	Discover Financial Services	79,339,664	0.0017	0.0467	0.0449
16	Comerica Incorporated	65,356,580	0.0066	0.0077	0.0146
17	Huntington Bancshares Inc	59,476,344	0.0137	0.0123	0.0263
18	Zions Bancorporation	56,031,127	0.0119	0.0125	0.0246

The values of lending inefficiency, the best-practice ratio of nonperforming loans measuring inherent credit risk, and the observed ratio of nonperforming loans are shown for large banks with consolidated assets greater than $50 billion. Nonperforming loans include past due loans, gross charge-offs, and other real estate owned. Stochastic frontier techniques are used to estimate the best-practice minimum ratio of nonperforming loans to total loans for any given amount of total loans, controlling for the composition of the bank’s loan portfolio, the average contractual interest rate charged on its loans, the ten-year average GDP growth rate and market concentration in the states in which the bank operates, where each state’s datum is weighted by the proportion of the bank’s total deposits located in the state.

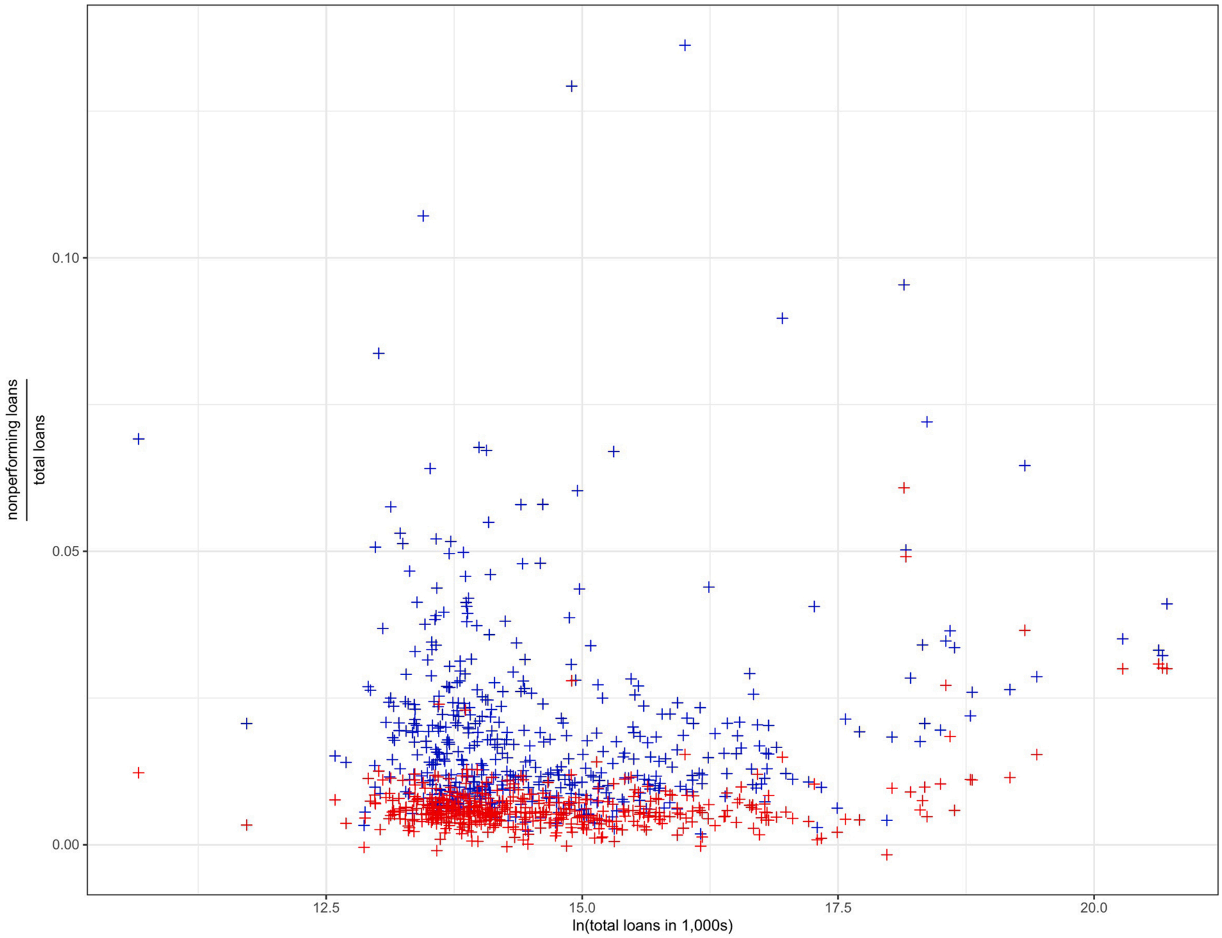

Fig. 5. Best-Practice and Observed Nonperforming Loan Ratios, and Lending Inefficiency in 2016. Noise-Adjusted Observed Ratio (blue +) vs Best-Practice Ratio (red +). Lending Inefficiency = Noise-Adjusted Observed Ratio − Best-Practice Ratio.

described in Section 4.2. Nevertheless, it is clear that many small banks have a ratio very close to the best-practice ratio, which suggests they may be efficient lenders.

To find efficient lenders, we normalize lending inefficiency by the proportion of nonperforming loans to obtain a lending inefficiency ratio – lending inefficiency as a proportion of nonperforming loans – and we limit the sample to relatively efficient banks with a lending inefficiency ratio less than 0.25. Fig. 6 shows these relatively efficient lenders – 22 banks – and reveals a size dichotomy: these relatively efficient banks are either small or large. There are 5 large lenders with assets between $92 billion and $2.5 trillion. The other 17 banks are community banks, one with $8 billion in assets and the other 16 with less than $5 billion. Lenders holding assets in the midrange do not exhibit such efficiency. The relatively large number of small banks suggests that soft information can be used to evaluate credit risk and to lend efficiently, which is consistent with the Bernanke hypothesis.

4.5. Factors that influence lending inefficiency

Using 2013 data, factors that potentially explain a bank's lending inefficiency are explored in Table 6 in regressions specified by the general-to-specific modeling strategy, which is a well-grounded method to search for the best model specification.[12] Maddala (2001) aptly describes this approach as "intended overparametrization with data-based simplification." We first define the general specification reflecting existing literature and our presumptions. In turn, our general specification defines the pool of candidate specifications, which are the specifications generated by all possible combinations of regressors in the general specification. The pool includes the general specification among many others. Hence, model selection from all candidate specifications is characterized in econometrics as *model selection within the same family of distributions*, for which we can use AIC or BIC in search of the best specification.

Our model search is based on the AIC criterion. Both AIC and BIC are based on Kullback-Leibler information distance from the

[12] Hendry (1983) provides the first complete application, and Campos, Ericsson, and Hendry (2005) survey this technique.

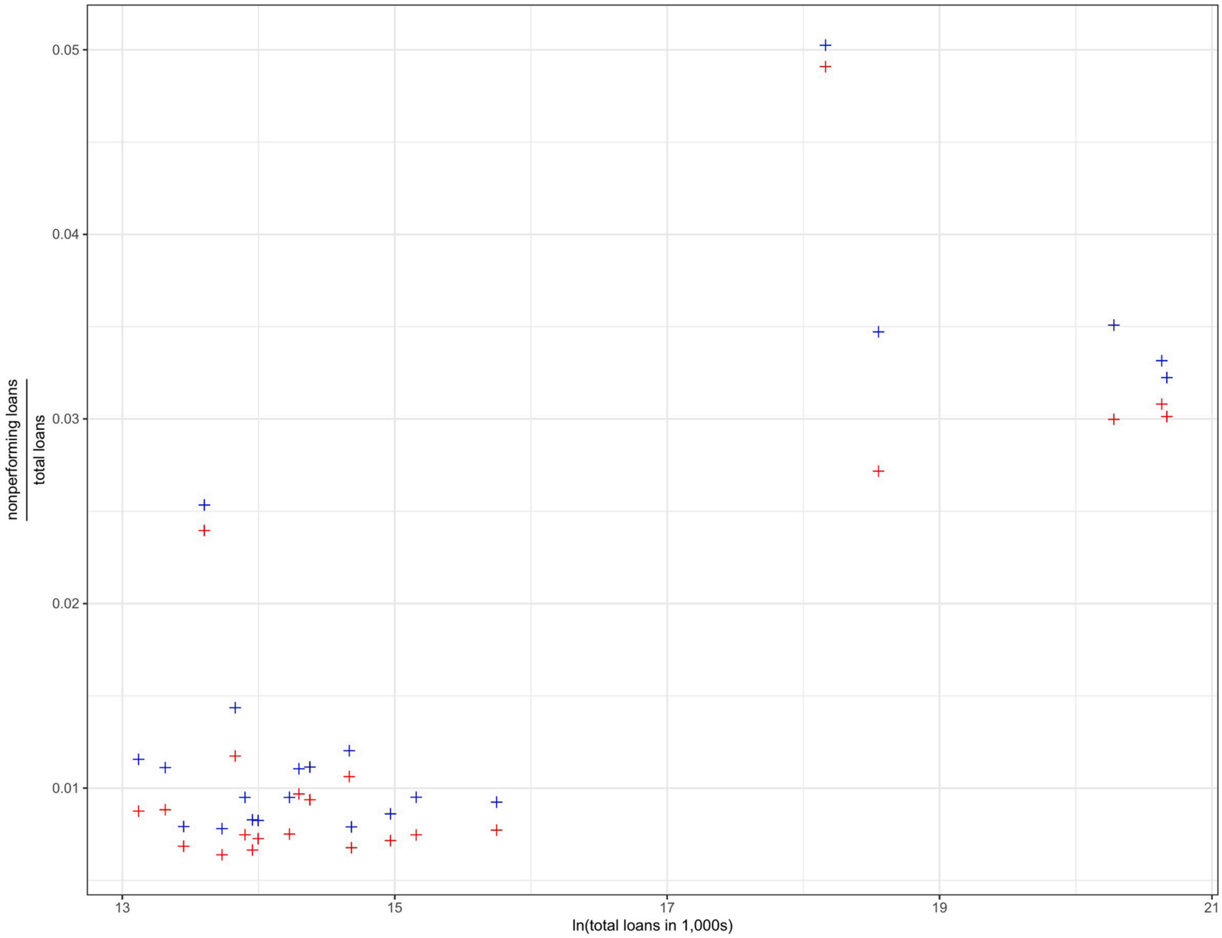

Fig. 6. The Most Efficient Lenders in 2016 Noise-Adjusted Observed Ratio (blue +) vs Best-Practice Ratio (red +). Lending Inefficiency = Noise-Adjusted Observed Ratio − Best-Practice Ratio.

(unknown) true specification. According to (econometric and statistical) theory BIC is superior to AIC, since BIC is consistent while AIC is short of being consistent. However, it is well known in econometrics and statistics through extensive Monte Carlo study that AIC performs better than BIC in finite samples. Hence, our model selection is based on AIC.

While overfitting is a legitimate concern when model search is based on goodness-of-fit measures (such as R^2 or adjusted R^2), our model selection is not related to goodness-of-fit measures. We report adjusted R^2 in the tables of estimation results as an indication of overall goodness-of-fit, but we do not use adjusted R^2 for model selection.[13]

In the general specification we account for the asset size of the bank, which influences the diversification of credit risk and the techniques used to evaluate and monitor credit risk. We characterize size, first, by the log transformation of consolidated assets and its square and, second, by the number of states in which the bank operates and by the interaction of the number of states and the total number of branches. The economic conditions in a bank's lending markets are described by the 10-year weighted average growth rate of state GDP and by a weighted average of banking market concentration in each state in which the bank operates where the weights are the proportions of deposits located in each state. Additionally, we account for the proportion of total assets allocated to loans, which accounts in part for a bank's focus on lending and the lending experience it is likely to have developed. We include the ratio of Tier 1 equity capital to consolidated assets to account for the cushion protecting a bank from loan losses and, hence, a component of the opportunity cost of loan losses. Since the credit analysis and monitoring of some types of loans are more difficult than other types, we control for important categories of loans as proportions of total loans in the general specification. Moreover, we include the average contractual interest rate on loans to account for a bank's choice of credit risk. We find that it is important to allow for size effects and flexibility in the specification of the average contractual rate so we include the rate, the rate squared, and the interaction of the rate and the log transformation of assets, the interaction of the rate squared and the log transformation of assets, the interaction of the rate and

[13] Model selection based on R^2 *always* declares a larger specification better than a smaller specification. Adjusted R^2 *still tends to* declare a larger specification better than a smaller specification, albeit less so than R^2 does.

Table 6
Factors Affecting Lending Inefficiency in 2013.

Variable	General specification		Specific specification	
	Parameter estimate	Pr > |t|	Parameter estimate	Pr > |t|
Intercept	− 1.14308	0.2318	**− 0.07184**	0.0002
log(Book Value Assets (1,000s))	0.13893	0.2544		
[log(Book Value Assets (1,000s))]^2	− 0.00441	0.2525		
Total Loans / Assets	**− 0.02370**	0.0026	**− 0.02477**	0.0011
Equity Capital / Assets	**− 0.13998**	0.0035	**− 0.14383**	0.0023
Contractual Interest Rate on Loans	42.07329	0.1619	**2.79361**	< 0.0001
(Contractual Interest Rate on Loans)^2	− 329.47919	0.1591		
[Contractual Interest Rate on Loans] × [log (Book Value Assets (1,000s))	− 5.07481	0.1878		
[Contractual Interest Rate on Loans]^2 × [log (Book Value Assets (1,000s))	41.53939	0.1682	**− 1.01937**	< 0.0001
[Contractual Interest Rate on Loans] × [log (Book Value Assets (1,000s))]^2	0.16054	0.1903		
[Contractual Interest Rate on Loans]^2 × [log (Book Value Assets (1,000s))]^2	− 1.34726	0.1636		
Consumer Loans / Total Loans	**0.05615**	0.0286	**0.05883**	0.0311
Total Business Loans / Total Loans	**0.04152**	0.0153	**0.03972**	0.0132
Small Business Loans / Total Loans	**− 0.11546**	< 0.0001	**− 0.11125**	< 0.0001
Commercial RE Loans / Total Loans	**0.05934**	< 0.0001	**0.05963**	< 0.0001
Residential RE Loans / Total Loans	**0.03673**	0.0053	**0.03679**	0.0055
GDP Growth Rate	**-0.00401**	< 0.0001	**− 0.00414**	< 0.0001
Number of States	**0.00255**	0.0226	**0.00227**	0.0016
[Number of States] × [Number of Branches]	**− 3.451E-7**	0.0065	**− 3.22982E-7**	0.0125
Market Concentration	− 0.01829	0.1411		

The data set includes 710 top-tier bank holding companies at the end of 2013. Stochastic frontier techniques are used to estimate the best-practice minimum ratio of nonperforming loans to total loans specified in (1).
Lending Inefficiency, defined by (6), is measured as the difference between the observed noise-adjusted ratio and the best-practice minimum ratio of nonperforming loans to total loans.
The regression is estimated with OLS, and standard errors are heteroscedasticity consistent. Parameter estimates in bold are significantly different from zero at 10% or stricter.
We apply the general-to-specific modeling strategy to identify the best specification for the lending inefficiency equation. The regressors of the general specification are given in the first column. The specific specification is obtained through a full AIC-based search over all possible specifications with all combinations of regressors derived from the general specification.

the squared log transformation of assets, and the interaction of the squared rate and the squared log transformation of assets. The parameter estimates of all regressors in the general specification are reported in the second column of Table 6. The general specification is narrowed with an AIC-based search that estimates all possible specifications with all combinations of the above-mentioned regressors. The fourth column shows the parameter estimates of the regressors that survive the AIC-based search and define the specific specification.

The best specific specification reported in the fourth column of Table 6 for 2013 data provides evidence that higher ratios of loans to assets and equity capital to assets as well as a higher GDP growth rate are associated with lower lending inefficiency. The magnitude of the coefficient estimate on the capital ratio is notable. The median capital ratio of the full sample is 0.0960, and the median inefficiency, 0.0189. Hence, an increase of 0.01 in the capital ratio is associated with a decrease of 0.0014383 in the inefficiency ratio, which is a 7.6% decline in lending inefficiency. On the other hand, lending inefficiency is positively related to the number of states in which a bank operates. While operating in more states may tend to diversify credit risk, it also increases organizational complexity and makes managerial control more difficult. An increase by 1.0 in the number of states on average increases lending inefficiency by 0.00227, which is an increase of 14.3% over the median value of inefficiency, 0.0189. Increasing the number of branches, controlling for the number of states, is associated with reduced lending inefficiency, but the effect is quite small in magnitude and does not seem *economically* significant. While an increase in total business loans as a proportion of total loans is associated with increased lending inefficiency, an increase in the proportion of small business loans, holding the proportion of total business loans constant, is associated with reduced lending inefficiency – this is a substitution of small business loans for larger business loans. The magnitude of these loan composition effects is small. For example, increase of 0.01 in the proportion of business loans implies an increase of 0.0003972 in lending inefficiency while a like increase in small business loans, a decrease of 0.0011125 in lending inefficiency. Given the median value of lending inefficiency for the full sample, 0.0189, the 0.01 increase in the business loan ratio implies an increase of 2.1% of the median inefficiency and the 0.01 increase in the small business loan ratio, a 5.9% decrease in the median inefficiency. The association of the average contractual interest rate with lending inefficiency is given by the derivative of inefficiency with respect to the interest rate.[14] This derivative is positive for 704 of the 710 banks and statistically significant for all 704; and, it is negative for 6 banks and statistically significant for all 6. As shown in the frontier estimations reported in Table 3, a higher contractual interest rate is associated with a higher best-practice nonperforming loan ratio − i.e., higher inherent credit risk. And, a higher contractual interest rate is also

[14] From Table 9, the derivative is given by ∂(lending inefficiency)/∂(contractual interest rate) = 2.79361 + 2[−1.01937][contractual interest rate][log(Book Value Assets(1,000 s)].

associated with higher lending inefficiency at most banks, which suggests these loans involving higher credit risk are in general more difficult to make and to monitor.

5. Do capital markets distinguish between inherent credit risk and lending efficiency?

To obtain evidence on whether capital markets price inherent credit risk and lending inefficiency, we focus on 2013 data, and, in Table 7**,** we compare lending characteristics and financial performance between banks in the halves of the sample with lower and higher observed ratios of nonperforming loans. The half that experiences lower ratios of nonperformance holds on average less total assets, makes more loans as a proportion of assets, charges a lower average contractual rate on loans, takes on lower inherent credit risk, and is more efficient at lending. The higher mean Tobin's q at these banks suggests capital markets price these lower ratios of nonperformance.

We evaluate financial performance with Tobin's q ratio, which takes into account a bank's current profit and its discounted future expected profit. A higher stream of profit, given market-priced risk, implies higher market value. Credit risk generally produces a stream of profit (loss). However, credit risk may not be rewarded. While it is likely associated with a higher contractual interest rate, the higher revenue associated with the higher rate will be reduced by the associated loan losses due to higher defaults resulting from lending to higher credit risks. To the extent the higher credit risk increases current and future cash flow, market value will tend to be increased. On the other hand, the increased losses will increase the probability of financial distress, which may result in insolvency and the loss of valuable investment opportunities, which will tend to reduce market value. To account for future as well as current profit and for the effects of potential financial distress, we prefer to measure financial performance by Tobin's q ratio.

In Panels A and B of Table 8**,** the two groups of banks with lower and higher ratios of nonperforming loans are further divided into the more and less efficient at lending. In both groups, the more efficient experience significantly lower ratios of overall nonperformance; however, strikingly, there is little difference in the magnitudes of the mean inherent credit risk and the contractual lending rate between the more and less efficient subsamples in each group although, as reported in Table 7 that compares means between the sample partitioned into higher and lower rates of nonperformance, the group with a higher mean ratio of nonperformance is exposed to higher inherent credit risk and charges on average a higher contractual lending rate. In Table 7**,** publicly traded banks in the half of the sample with lower ratios of nonperformance on average experience a higher Tobin's q ratio, and, in Table 8**,** banks in the more efficient partitions on average obtain a higher Tobin's q ratio than those in the less efficient partitions.

These differences in the mean Tobin's q ratio raise the question of whether capital markets simply penalize differences in nonperformance or whether these markets distinguish and price differently inherent credit risk and lending proficiency. Before investigating this issue, we compare the efficient halves of the banks with lower and higher ratios of nonperformance in Panel C of Table 8**.** The efficient banks with a higher ratio of nonperformance are on average larger than the efficient banks with a lower ratio of nonperformance. Moreover, they assume higher inherent credit risk and charge a higher average contractual lending rate, and, while belonging to the more efficient half of the group with higher overall nonperformance, their mean lending inefficiency is significantly higher than that of the efficient half of the group with lower overall nonperformance. The lower q ratio in the efficient half of the group with a higher ratio of nonperformance suggests that nonperformance is penalized by capital markets.

5.1. Relationship of financial performance to nonperforming loans

To obtain evidence on whether the capital market prices inherent credit risk and lending inefficiency, we restrict the samples of 2010, 2013, and 2016 to publicly traded, top-tier holding companies. Financial performance is measured by the market value of assets, expressed by Tobin's q ratio. Tobin's q ratio is given by the ratio of the market value of assets to the replacement cost of assets, whose commonly used proxy is the sum of the market value of equity and the book value of liabilities to the book value of assets.[15]

Market value has the advantage over accounting measures of performance in capturing the market's expectation of the discounted value of the firm's current and future cash flow where the discount rate reflects the market's assessment of the relevant risk attached to the cash flow. In addition, market values permit investigation of investment incentives provided by the capital market.

Credit risk generally produces a stream of profit (loss) realized over time. Higher credit risk may not be rewarded. While it is likely associated with a higher contractual interest rate, the higher revenue associated with the higher rate will be reduced by the associated loan losses due to higher defaults resulting from lending to higher credit risks. To the extent the higher credit risk increases current and future cash flow, market value will tend to be increased. On the other hand, the increased losses will increase the probability of financial distress, which may result in insolvency and the loss of valuable investment opportunities, which will tend to reduce market value. To account for future as well as current profit and for the effects of potential financial distress, we prefer to measure financial performance by Tobin's q ratio.

We first investigate the relationship of Tobin's q ratio to the nonperforming loan ratio. From Table 4, we learned that small community banks and the largest banks on average charge relatively high contractual loan rates and exhibit relatively high ratios of nonperformance compared to the other three size groups. Are these high average ratios of nonperformance associated with better financial performance, which is to ask if the higher average contractual interest rate associated with the riskier lending results in a higher discounted cash flow that more than compensates for higher expected loan losses. After answering this question, we investigate

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

Table 7
Best Practice Nonperformance, Lending Inefficiency, and Financial Performance in 2013.

	N	Mean	Median	Std. Dev.	Minimum	Maximum
Panel A: Half of the Sample with a Lower Ratio of Nonperforming Loans to Total Loans						
Book Value Assets (1,000s)	355	**4,152,644**	1,098,991	12,251,316	280,370	129,685,180
(Nonperforming Loans) / Loans	355	**0.0208**	0.0206	0.0061	0.0100	0.0325
Best-Practice Nonperformance	355	**0.0120**	0.0120	0.0025	0.0037	0.0245
Lending Inefficiency	355	**0.0090**	0.0085	0.0053	0.0010	0.0230
Average Contractual Loan Interest Rate	355	**0.0476**	0.0475	0.0059	0.0253	0.0750
Loans / Assets	355	**0.6543**	0.6735	0.1211	0.1892	0.9621
Tobin's *q* Ratio	129	**1.0564**	1.0554	0.0475	0.9580	1.3129
Panel B: Half of the Sample with a Higher Ratio of Nonperforming Loans to Total Loans						
Book Value Assets (1,000s)	355	**29,089,290**	864,288	214,309,437	92,694	2,415,689,000
(Nonperforming Loans) / Loans	355	**0.0634**	0.0549	0.0278	0.0325	0.1492
Best-Practice Nonperformance	355	**0.0160**	0.0149	0.0064	0.0066	0.0606
Lending Inefficiency	355	**0.0471**	0.0380	0.0271	0.0017	0.1375
Average Contractual Loan Interest Rate	355	**0.0540**	0.0525	0.0110	0.0366	0.1404
Loans / Assets	355	**0.6246**	0.6431	0.1297	0.1653	0.9216
Tobin's *q* Ratio	116	**1.0360**	1.0258	0.0621	0.9506	1.3058

The data set consists of 710 top-tier bank holding companies, of which 244 are publicly traded, at year-end 2013. The sample is partitioned into the halves with the lower and higher ratios of observed nonperforming loans to total loans. Mean values in bold print are significantly different at 10% or stricter.

Table 8
Comparison of Means between Groups Partitioned by Nonperforming Loans Ratio and Lending Inefficiency in 2013.

	Panel A			Panel B			Panel C		
	Banks with lower ratios of nonperforming loans to total loans			Banks with higher ratios of nonperforming loans to total loans			(Nonperforming loans) / (Total loans)		
							Lower ratio	Higher ratio	
	More efficient at lending	Less efficient at lending		More efficient at lending	Less efficient at lending		*More* efficient at lending	*More* efficient at lending	
	$n = 178$	**$n = 177$**		**$n = 178$**	**$n = 177$**		**$n = 178$**	**$n = 178$**	
	$n^* = 61$	**$n^* = 68$**		**$n^* = 77$**	**$n^* = 39$**		**$n^* = 61$**	**$n^* = 77$**	
	Mean	**Mean**	***p***	**Mean**	**Mean**	***p***	**Mean**	**Mean**	***p***
Book Value Assets (1,000s)	3,171,816	5,139,013	0.13	**56,605,738**	**1,417,381**	0.02	**3,171,816**	**56,605,738**	0.02
(Nonperforming Loans) / Loans	**0.0158**	**0.0258**	< 0.01	**0.0432**	**0.0837**	< 0.01	**0.0158**	**0.0432**	< 0.00
Best-Practice Nonperformance	0.0122	0.0118	0.18	0.0162	0.0158	0.57	**0.0122**	**0.0162**	< 0.00
Lending Inefficiency	**0.0044**	**0.0136**	< 0.01	**0.0268**	**0.0676**	< 0.01	**0.0044**	**0.0268**	< 0.00
Average Contractual Loan Interest Rate	**0.0482**	**0.0469**	0.03	0.0532	0.0549	0.15	**0.0482**	**0.0532**	< 0.00
Loans / Assets	0.6544	0.6542	0.99	**0.6374**	**0.6116**	0.06	0.6544	0.6374	0.21
Tobin's *q* Ratio*	**1.0669**	**1.0470**	0.02	**1.0471**	**1.0141**	0.01	**1.0669**	**1.0471**	0.05

The data set consists of 710 top-tier bank holding companies, of which 244 are publicly traded, at year-end 2013. The sample is partitioned into the halves with the lower and higher ratios of observed nonperforming loans to total loans. Each of these halves is then partition into the more and less efficient halves by lending efficiency. The *p*-value represents the statistical significance of the comparison of means in the pairing. Pairs of means in bold are statistically different at $p = 0.10$ or stricter.

the relationship of financial performance to the decomposition of the nonperforming loan ratio into inherent credit risk and lending inefficiency. We are particularly interested in answering the question, is the higher inherent credit risk of the largest banks associated with higher market value.

The relationship of Tobin's *q* ratio to the nonperforming loan ratio in 2010, 2013, and 2016 is reported in Table 9. In the regressions in Table 9 we include among the regressors the log transformation of the book value of assets and the square of this variable to control for differences among banks related to size, such as the potential for economies of scale due to better diversification, network economies, and spreading overhead costs. In addition, we account for the importance of lending in the business model of the bank by controlling for the ratio of loans to assets. We account for capital structure by adding the ratio of equity capital to assets and it square to allow for nonlinearity. We include the interaction of the ratio of nonperforming loans to total loans with the log transformation of assets since size-related diversification may influence the risk associated with any given nonperforming loans ratio. To capture the potential for dichotomous credit risk strategies for maximizing value that differ between larger and smaller banks, we add an indicator variable for very large banks, and we interact it with the product of the nonperforming loan ratio and the log of assets. To define this indicator variable, we see from Table 1 that, in 2013, banks in the largest size group with assets exceeding $250 billion exhibit a much

Table 9
2010, 2013, and 2016: Regression Analysis of Financial Performance with the Nonperforming Loans Ratio and the Mega Bank Dummy.

Year:	2010		2013		2016	
Dependent variable:	Tobin's q Ratio	Market value inefficiency ratio	Tobin's q ratio	Market value inefficiency ratio	Tobin's q ratio	Market value inefficiency ratio
Variable	Parameter estimate	Parameter estimate	Parameter estimate	Parameter estimate	Parameter estimate	Parameter estimate
Intercept	− 0.1221 (0.7063)	**5.4820**(<0.0001)	**− 1.5183** (<0.0001)	**10.1143**(<0.0001)	**− 0.8369** (0.0200)	**10.8289**(<0.0001)
log(Book Value Assets (1,000s))	**0.1482** (0.0004)	**− 0.6511** (<0.0001)	**0.32467** (<0.0001)	**− 1.1699** (<0.0001)	**0.2246** (<0.0001)	**− 1.1718** (<0.0001)
[log(Book Value Assets (1,000s))]^2	**− 0.0043** (0.0013)	**0.0193**(<0.0001)	**− 0.0100** (<0.0001)	**0.0339**(<0.0001)	**− 0.0067** (<0.0001)	**0.0319**(<0.0001)
Loans / Assets	**− 0.0756** (0.0082)	0.0340(0.1165)	**− 0.0592** (0.0496)	**0.0348**(0.0522)	− 0.0431 (0.1732)	− 0.0016(0.9336)
Equity Capital / Assets	**− 0.8727** (0.0183)	**0.7231**(0.0093)	0.3250 (0.7452)	0.0287(0.9610)	**1.5278** (0.0177)	− 0.4539(0.1421)
(Equity Capital / Assets)^2	**5.7544** (0.0042)	**− 3.9000**(0.0126)	− 0.6878 (0.8736)	− 0.2027(0.9381)	− 3.9736 (0.1097)	1.2303(0.2882)
(Nonp. Loans / Loans) [log(BVA (1,000s))]	**− 0.0212** (<0.0001)	**0.0155**(<0.0001)	**− 0.0390** (<0.0001)	**0.0233**(0.0006)	**− 0.0626** (0.0015)	**0.0404**(0.0002)
(Mega Bank) (Nonp. Loans / Loans)	**8.0970** (<0.0001)	**20.7537**(<0.0001)	**− 14.5593** (0.0022)	**58.3395**(<0.0001)	**− 17.8959** (0.0569)	**88.3836**(<0.0001)
(Mega Bank) (Nonp. Loans / Loans) [log (BVA (1,000s))]	**− 0.3542** (<0.0001)	**− 1.1357** (<0.0001)	**0.8419** (0.0005)	**− 3.1593** (<0.0001)	**0.9206** (0.0622)	**− 4.4953** (<0.0001)
Mega Bank = 1 when assets >	**300 Billion**	**170 Billion**	**170 Billion**	**170 Billion**	**170 Billion**	**170 Billion**
n: ∂(*q ratio*)/∂(*np loan ratio*) > 0	**5 largest banks**		**9 largest banks**		**4 largest banks**	
n: significantly > 0	**1**		**7**		**0**	
n: ∂(*q ratio*)/∂(*np loan ratio*) < 0	213		235		281	
n: significantly < 0	213		235		278	
n: ∂(*in_ratio*) /∂(*np ratio*) < 0		**7 largest banks**		**9 largest banks**		**7 largest banks**
n: significantly < 0		**6**		**9**		**6**
n: ∂(*in_ratio* /∂(*np ratio*)> 0		211		235		278
n: significantly > 0		211		235		275
Adjusted R Square	0.348	0.894	0.376	0.978	0.264	0.984
N	218	218	244	244	285	285

The data set includes 218 publicly traded top-tier bank holding companies at the end of 2010, 244 at the end of 2013, and 285 at the end of 2016. The dependent variables are a proxy for Tobin's q ratio and the market-value inefficiency ratio, which is the difference between the best-practice, maximum value of assets derived by stochastic frontier estimation and the observed market value of assets, adjusted for statistical noise. Regressions are estimated with OLS, and standard errors are heteroscedasticity consistent. Probability values are reported in parentheses. Parameter estimates in bold are significantly different from 0 at 10% or stricter.

higher average ratio of nonperformance than smaller banks in the other four size groups. When 2013 banks are sorted by asset size, the largest 9 banks range in size from $175.4 billion to $2.4 trillion. The next largest bank is $129.7 billion. Thus, we set the lower bound on the indicator variable at $170 billion, and we interact it with variables involving the nonperforming loan ratio and add these variables to the general specification.

Based on the parameter estimates associated with banks in 2013, the derivative of Tobin's q ratio with respect to the nonperforming loan ratio is given by.

$$\partial \text{Tobin's } q/\partial(\text{nonperforming loan ratio}) = -0{\cdot}0390[\log(\text{Book Value Assets (1,000s)})]$$

$$-\ 14{\cdot}5593(\text{Indicator Variable Assets} > \$170 \text{ billion})$$

$$+\ 0.8419(\text{Indicator Variable Assets} > \$170 \text{ billion})[\log(\text{Book Value Assets (1,000s)})]\cdot \tag{7}$$

The third term in the derivative is positive when banks hold assets in excess of $170 billion, and it increases with the volume of assets. The rows near the bottom of Table 9 report the number of banks exhibiting positive and negative derivatives. The rows highlighted in red represent the incentive to take more credit risk. For the nine largest banks, the derivative is positive, and for 7 of the 9 banks, the derivative is statistically significant at 10% or stricter. Thus, the relatively high average observed ratio of nonperforming loans among these banks is associated with a higher market value. In the case of these very large banks, market discipline appears to encourage greater risk-taking in lending and, in this respect, tends to work against financial stability. For the remaining 235 smaller banks, the statistically significant negative sign of the derivative suggests that a higher ratio of nonperformance is associated with poorer financial performance. In the case of these smaller banks, market discipline appears to discourage risky lending.

This derivative evaluated using the parameter estimates in the 2010 and 2016 regressions yield less statistically significant results for the positive valued derivative. In 2010, the derivative is positive for 5 of the largest banks and statistically significant for 1. In 2016, it is positive but not significant at 4 largest banks. On the other hand, 213 banks in 2010 obtain a statistically significant negative derivative and, in 2016, 281 banks where 278 are significantly negative.

To obtain evidence on the robustness of these dichotomous capital-market investment incentives, we use an alternative market-value measure of performance based on the stochastic frontier analysis. The second measure of financial performance yields stronger results in terms of statistical significance. This measure employs stochastic frontier techniques to estimate the highest potential (observed) market value of assets for any given book-value investment in assets.[16] The difference between the highest potential value and the observed market value, adjusted for statistical noise, is systematically lost market value. Such a loss can result from, for example, suboptimal managerial performance, poor locational decisions, and agency problems. (We add the caveat that the highest potential value is obtained as the stochastic upper envelope of observed values and, thus, is not necessarily the highest technologically possible value.) When the lost market value is normalized by the associated highest potential value, we obtain the market-value inefficiency ratio, the lost market value as a proportion of potential value.[17] Table 9 reports that in all three years, the derivative of the market-value inefficiency ratio is positively related to the nonperforming loan ratio for most banks; however, for the largest banks, it is negatively related. In 2010, the largest 7 banks exhibit a negative relationship between the inefficiency ratio and credit risk where 6 of the 7 are statistically significant; in 2013, the largest 9 banks where all 9 are statistically significant; and in 2016, the largest 7 banks where 6 of the 7 are statistically significant. This evidence of a dichotomous effect on market-value inefficiency of credit risk mirrors the evidence obtained from Tobin's q ratio. In the case of these large banks, an increase in credit risk reflected in a higher nonperforming loan ratio is associated with a higher market value that is closer to the highest potential value given the size of the bank − a lower market-value inefficiency.

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

where $\varepsilon_i = \nu_i - \mu_i$ is a composite error term. Statistical noise is given by $\nu_i \sim$ iid $N(0,{\sigma_\nu}^2)$. The systematic shortfall from bank i's best-practice market value is given by μ_i. We assume that μ_i is distributed exponentially, $\mu_i\ (> 0) \sim$ iid with $\theta\ exp(-\theta\mu)$ as the pdf, which is confirmed by Vuong's tests. From the estimation of Equation (a), we obtain the highest potential market value, the market-value shortfall, and the noise component for bank i (all measured in dollars):

$$\boldsymbol{Highest\ Potential\ MVA_i} = \alpha + \beta(\mathrm{BVA_i}) + \gamma\ (BVA_i)^2, \tag{b}$$

$$\boldsymbol{MVA\ Shortfall_i} = \mathrm{E}(\mu_i|\varepsilon_i), \tag{c}$$

$$\boldsymbol{Noise_i} = \mathrm{E}(\nu_i|\varepsilon_i) = \varepsilon_i + \mathrm{E}(\mu_i|\varepsilon_i). \tag{d}$$

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

$$\boldsymbol{Market\text{-}Value\ Inefficiency\ Ratio_i} = E(\mu_i|\varepsilon_i)/[\alpha + \beta(BVA_i) + \gamma(BVA_i)^2]. \tag{e}$$

We have evaluated the evidence of a positive association between financial performance and credit risk at the largest financial institutions in terms of a standard of statistical significance at 10% or stricter. Hence, a positive association between performance and loan default with a higher probability value will be deemed not statistically different from 0. However, the investment incentive to take more credit risk may nevertheless be present at banks with a higher probability than 10% − which suggests that financial stability could be undermined by credit-risk-taking at more banks than those with a stricter probability value. Thus, from the supervisors' focus on safety and soundness, a "supervisory standard" of statistical significance may be less strict than that of 10%. With that caveat in mind, we suggest that our focus on the 10% criterion may be too strict.

5.2. Relationship of financial performance to inherent credit risk and lending inefficiency

The regressions in Table 9 provide evidence that the capital market rewards at the margin a lower nonperforming loan ratio at most banks and a higher ratio at the very largest banks. In Table 10, we investigate the degree to which the capital market distinguishes nonperformance due to inherent credit risk from that due to lending inefficiency. In the regression specifications, we substitute variables involving inherent credit risk and lending inefficiency for those involving the nonperforming loan ratio. We include among the explanatory variables lending inefficiency and both inherent credit risk and the interaction of inherent credit risk with the log of asset size.

Lending inefficiency is punished by the capital market in all three years. The negative association between the q ratio and lending inefficiency strengthens from − 0.2239 in 2010 to − 0.5878 in 2013 to − 1.7138 in 2016. In a similar pattern, the association between the market-value inefficiency ratio and lending inefficiency strengthens from 0.1761 in 2010–0.3716 in 2013–0.8010 in 2016. In short, lending inefficiency is penalized at all banks.

Inherent credit risk, measured by the best-practice nonperforming loan ratio, also exhibits a striking evolution over these three

[16] Hughes et al. (1997) proposed these concepts, which have been applied in numerous studies. See Hughes and Mester (2019) for examples and Hughes et al. (2016).

[17] We obtain the potential market value of assets (*MVA*) by specifying a quadratic function of the book value of assets (*BVA*) net of goodwill and by applying maximum likelihood techniques to estimate the frontier:

Table 10
2010, 2013, and 2016: Regression Analysis of Tobin's *q* Ratio with the Best-Practice Nonperforming Loans Ratio and Lending Inefficiency as the Main Factors for the Construction of Regressors.

Year:	2010		2013		2016	
Dependent variable:	Tobin's *q* ratio	Market value inefficiency ratio	Tobin's *q* ratio	Market value inefficiency ratio	Tobin's *q* ratio	Market value inefficiency ratio
Variable	Parameter estimate	Parameter estimate	Parameter estimate	Parameter estimate	Parameter estimate	Parameter estimate
Intercept	0.2547(0.3891)	**4.3574**(<0.0001)	**− 1.0376**(0.0006)	**9.2527**(<0.0001)	**− 1.0302**(<0.0001)	**9.7454**(<0.0001)
log(Book Value Assets (1,000s))	**0.1080**(0.0061)	**− 0.5166**(<0.0001)	**0.2662**(<0.0001)	**− 1.0752**(<0.0001)	**0.2580**(<0.0001)	**− 1.0504**(<0.0001)
[log(Book Value Assets (1,000s))]^2	**− 0.0033**(0.0102)	**0.0153**(<0.0001)	**− 0.0083**(<0.0001)	**0.0315**(<0.0001)	**− 0.0079**(<0.0001)	**0.0284**(<0.0001)
Loans / Assets	**− 0.0600**(0.0329)	**0.0472**(0.0384)	**− 0.0566**(0.0596)	**0.0409**(0.0534)	**− 0.1009**(0.0006)	**0.0616**(0.0012)
Equity Capital / Assets	**− 0.7161**(0.0289)	**0.6459**(0.0172)	0.4212(0.6857)	− 0.2109(0.7652)	**1.6329**(0.0127)	**− 0.6339**(0.0983)
(Equity Capital / Assets)^2	**5.1718**(0.0045)	**− 3.4664**(0.0226)	− 1.2289(0.7868)	1.1979(0.7044)	**− 4.6411**(0.0575)	2.0709(0.1458)
Best-Practice Nonperformance	**− 5.4496**(0.0004)	**9.1830**(<0.0001)	**− 7.3131**(0.0107)	**24.3369**(<0.0001)	− 3.2279(0.4240)	**19.7467**(0.0006)
(Best-Practice Nonperformance) [log(BV Assets (1,000s))]	**0.2664**(0.0033)	**− 0.5745**(<0.0001)	**0.4810**(0.0042)	**− 1.6663**(<0.0001)	0.2980(0.1973)	**− 1.1623**(0.0005)
Lending Inefficiency	**− 0.2239**(0.0001)	**0.1761**(0.0006)	**− 0.5878**(0.0002)	**0.3716**(0.0190)	**− 1.7138**(<0.0001)	**0.8010**(0.0007)
n: ∂(*q ratio*)/∂(*best-practice np ratio*) > 0	**4 largest banks**		**95 larger banks**		**262 banks**	
n: significantly > 0	**0**		**0**		**156**	
n: ∂(*q ratio*)/∂(*best-practice np ratio*) < 0	211		150		0	
n: significantly < 0	206		0		0	
n: ∂ (*in ratio*)/∂(*best-practice np ratio*) < 0		**47 largest banks**		**129 larger banks**		**46 largest banks**
n: significantly < 0		**27**		**94**		**27**
n: ∂ (*in ratio*)/∂(*best-practice np ratio*) > 0		168		115		216
n: significantly > 0		143		61		175
Adjusted R Square	0.358	0.879	0.360	0.974	0.359	0.975
N	215	215	244	244	262	262

The data set includes 215 publicly traded top-tier bank holding companies at the end of 2010, 244 at the end of 2013, and 262 at the end of 2016. The dependent variables are a proxy for Tobin's *q* ratio and the market-value inefficiency ratio, which is the difference between the best-practice, maximum value of assets derived by stochastic frontier estimation and the observed market value of assets, adjusted for statistical noise. Regressions are estimated with OLS, and standard errors are heteroscedasticity consistent. Probability values are reported in parentheses under the parameter estimates. Parameter estimates in bold are significantly different from zero at 10% or stricter.

Table 11
2016 Estimates of Derivatives of Tobin's q Ratio with Respect to Inherent Credit Risk, Individually for the Largest 25 Banks.

	Name	Book-value assets (1,000s)	∂ (Tobin's q ratio)/∂ (best-practice nonperforming loans ratio)	p-value
1	JPMORGAN CHASE & CO	2,490,972,000	3.21857	0.00495
2	BANK OF AMER CORP	2,189,266,000	3.18010	0.00449
3	WELLS FARGO & CO	1,930,115,000	3.14256	0.00407
4	CITIGROUP	1,792,077,000	3.12045	0.00384
5	GOLDMAN SACHS GROUP THE	860,185,000	2.90176	0.00198
6	MORGAN STANLEY	813,049,000	2.88497	0.00187
7	U S BC	445,964,000	2.70604	0.00098
8	PNC FNCL SVC GROUP	366,872,249	2.64787	0.00078
9	CAPITAL ONE FC	357,158,294	2.63987	0.00076
10	BANK OF NY MELLON CORP	333,469,000	2.61943	0.00070
11	CHARLES SCHWAB CORP	223,383,000	2.50005	0.00044
12	BB&T CORP	219,276,323	2.49452	0.00043
13	SUNTRUST BK	205,214,392	2.47477	0.00040
14	ALLY FNCL	163,728,000	2.40748	0.00032
15	AMERICAN EXPRESS CO	158,885,000	2.39854	0.00031
16	CITIZENS FNCL GRP	150,022,885	2.38144	0.00030
17	FIFTH THIRD BC	142,176,830	2.36543	0.00028
18	KEYCORP	136,825,848	2.35400	0.00028
19	REGIONS FC	126,193,957	2.32990	0.00026
20	NORTHERN TR CORP	123,926,854	2.32450	0.00026
21	M&T BK CORP	123,449,206	2.32335	0.00026
22	HUNTINGTON BSHRS	99,714,097	2.25973	0.00023
23	DISCOVER FS	92,307,686	2.23673	0.00022
24	SYNCHRONY FNCL	90,244,879	2.23000	0.00022
25	COMERICA	73,129,915	2.16734	0.00022

The derivative of Tobin's q ratio with respect to the best-practice nonperforming loans ratio is derived from the 2016 estimation of Table 10: ∂(Tobin's q ratio)/∂(best-practice nonperforming loans ratio) $= -3.22786 + (0.29795)$ [log(Book Value Assets (1,000s))].

years. The rows near the bottom of Table 10 report the number of banks exhibiting positive and negative derivatives of Tobin's q ratio with respect to inherent credit risk (best-practice nonperformance). The rows highlighted in red represent the incentive to take more credit risk. For example, in 2010 Tobin's q is positively related to best-practice nonperformance at the 4 largest banks where none are statistically significant, at the 95 largest banks in 2013 where none are statistically significant, and at 262 banks where 156 are significant in 2016. Equally striking is the number of banks exhibiting a negative association between the q ratio and best-practice nonperformance: in 2010, 211 banks where 206 are negatively significant, in 2013, 150 banks where none are statistically significant, and in 2016, strikingly, where no banks exhibit a negative derivative. The evolution of this incentive over time suggests that the capital market is increasingly rewarding credit risk.

The market-value inefficiency ratio gauges the distance between a bank's highest potential market value of assets and its observed market value, adjusted for statistical noise. Tobin's q ratio follows directly from the market value of assets. Consequently, the association between the market-value inefficiency ratio and best-practice nonperformance in Table 10 exhibits a more complicated pattern than that of the q ratio: in each of the three years, the negative association between market-value inefficiency and inherent credit risk is at the largest banks. The number of these banks, 129 where 94 are statistically significant, is greatest in 2013 compared to 47 in 2010 where 27 are significant and 46 in 2016 where 27 are significant.

In Table 11, we investigate the 25 largest banks in 2016 where making riskier loans is associated with a higher Tobin's q ratio with statistical significance at 10% or stricter. To evaluate the economic significance of these derivatives, consider the largest value, 3.21857, obtained by JPMorgan Chase. From Table 8, the value of JP Morgan's inherent credit risk is 0.030807. An increase of 0.00329 in this value, about 10%, is associated with an increase of 0.0059, about 1.04%, in its q ratio, 1.04160. This incentive to make riskier loans is strongest for the four largest banks.

The decomposition of the noise-adjusted nonperforming loan ratio into inherent credit risk and lending inefficiency shows that the credit market rewards inherent credit risk at the largest banks and penalizes lending inefficiency at all banks.

In sum, the value effect of the inherent credit risk suggests a dichotomous lending strategy to maximize value that differs between the larger banks and smaller banks. Inherent credit risk is positively related to value at the largest banks and negatively related at smaller banks. The evidence of a dichotomous lending strategy that differs between the largest financial institutions and smaller institutions is similar to evidence of dichotomous capital strategies found by Hughes et al. (2016), which also differs between large banks that at the margin improve value by reducing their capital ratio and smaller banks that at the margin improve value by increasing their capital ratio.

Marcus (1984) and Herring and Vankudre (1987) demonstrate that pursuing a low-risk investment strategy to minimize the probability of financial distress maximizes value at banks with high-valued investment opportunities while adopting a high-risk investment strategy to exploit the option value of explicit and implicit deposit insurance maximizes value at banks with low valued investment opportunities. Hughes et al. (2016) show that smaller banks experience higher valued investment opportunities than larger banks. McConnell and Servaes (1995) find similar results for nonfinancial firms which they interpret as capital structure that addresses the overinvestment problem at firms with low valued investment opportunities and the underinvestment problem at firms with high valued investment opportunities.

Koehn and Santomero (1980) and Kim and Santomero (1988) demonstrate that restrictions on banks' capital ratio to control risk-taking can lead to more, not less risking-taking. Herring (2018) notes that large financial institutions respond to reform of capital restrictions by arbitrage of the new requirements to achieve higher expected yield. In turn, regulators revise the restrictions to eliminate the arbitrage, but banks adapt their arbitrage strategies to maintain a higher expected yield. Behn, Haselmann, and Vig (2016) contend that large banks game capital regulations through internal models to take more risk. A similar finding is obtained by Plosser and Santos (2014). Laeven and Levine (2009) provide evidence that large banks with more powerful owners tend to take more risk. Cheng, Hong, and Scheinkman (2015) show that riskier firms offer higher compensation to induce risk-averse managers to take more risk and that these firms are more likely to be held by institutional investors who are able to influence compensation. While a number of studies have found that risk-taking incentives at large financial institutions influence capital structure, our evidence suggests that they also apply to credit risk.

6. Summary and conclusions

We develop a novel technique to analyze nonperforming loans and apply it to data on top-tier bank holding companies at year-end 2010, 2013, and 2016. The ratio of banks' nonperforming loans to their total loans is decomposed into three components: first, a minimum ratio that represents the best-practice nonperforming loans ratio given the volume and composition of a bank's loans, the average contractual interest rate charged on these loans, and market conditions such as the average GDP growth rate and market concentration; second, a ratio, which is the difference between the bank's observed ratio of nonperforming loans adjusted for statistical noise and the best-practice minimum ratio, that represents the bank's inefficiency at lending; third, statistical noise. The best-practice ratio of nonperforming loans represents the inherent credit risk of the loan portfolio.

Bank holding companies are divided into five size groups. The largest banks with consolidated assets exceeding $250 billion experience the highest ratio of nonperformance among the five groups. Moreover, the inherent credit risk of their lending is the highest among the five groups. On the other hand, their inefficiency at lending is one of the two lowest among the five in 2010 and 2013. In 2016, it is the lowest when considering inefficiency as a proportion of the nonperforming loan ratio. Thus, the high ratio of nonperformance of the largest financial institutions appears to result from lending to riskier borrowers, not from inefficiency at lending.

When the sample is restricted to publicly traded bank holding companies, market values can be used to gauge how financial performance is related to nonperforming loans. In contrast to accounting measures of performance, market value reveals the market's expectation of future as well as current cash flows discounted by market-priced risk. The ratio of nonperforming loans to total loans is negatively related to financial performance except at the largest institutions, which suggests a dichotomous credit risk strategy for maximizing value that differs between the largest banks and smaller banks. The decomposition of the noise-adjusted nonperforming loan ratio into inherent credit risk and lending inefficiency shows that market discipline rewards riskier lending at large banks and discourages inefficient lending at all banks – incentives that grow stronger from 2010 to 2016.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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