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Consumer lending efficiency: commercial banks versus a fintech lender

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Abstract

Fintechs are believed to help expand credit access to underserved consumers without taking on additional risk. We compare the performance efficiency of LendingClub's unsecured personal loans with similar loans originated by banks. Using stochastic frontier estimation, we decompose the observed nonperforming loan (NPL) ratio into three components: the best-practice minimum NPL ratio, the excess NPL ratio, and a statistical noise, the former two of which reflect the lender's *inherent credit risk* and *lending inefficiency*, respectively. As of 2013 and 2016, we find that the higher NPL ratios at the largest banks are driven by inherent credit risk, rather than lending inefficiency. Smaller banks are less efficient. In addition, as of 2013, LendingClub's observed NPL ratio and lending efficiency were in line with banks with similar lending volume. However, its lending efficiency improved significantly from 2013 to 2016. As of 2016, LendingClub's performance resembled the largest banks – consistent with an argument that its increased use of alternative data and AI/ML may have improved its credit risk assessment capacity above and beyond its peers using traditional approaches. Furthermore, we also investigate capital market incentives for lenders to take credit risk. Market value regression using the NPL ratio suggests that market discipline provides incentives to make less risky consumer loans. However, the regression using two *decomposed components* (inherent credit risk and lending inefficiency) tells a deeper underlying story: market value is significantly positively related to inherent credit risk at most banks, whereas it is significantly negatively related to lending inefficiency at most banks. *Market discipline appears to reward exposure to inherent credit risk and punish inefficient lending.*

Keywords: Fintech, Marketplace lending, P2P lending, Credit risk management, Lending efficiency, LendingClub

JEL classification: G21, L25, C58

Introduction

We investigate unsecured consumer lending by traditional U.S. bank lenders vs. LendingClub, the largest fintech personal lender in the United States. As of 2016, both LendingClub and the largest traditional bank lenders experienced the highest rate of nonperforming consumer loans (NPL) among all consumer lenders in the USA. We consider several important empirical questions regarding the NPL ratios.

First, to what extent does a high NPL ratio indicate the lender is making riskier loans that default more often and to what extent does a higher NPL ratio indicate that the lender lacks proficiency in credit assessment and loan management? We shall base our concept of lending efficiency on this proficiency rather than on the total NPL ratio.

Second, as to the large lenders experiencing a high NPL ratio and evaluating credit risk using statistical methods and algorithms, we ask whether LendingClub's loan performance is more efficient than that of the other (traditional) large bank lenders, which also use similar statistical and algorithmic methods of credit risk assessment?

Third, we investigate the Bernanke hypothesis (2011) that the in-depth local knowledge that community banks use to access credit risk "cannot be matched by models or algorithms, no matter how sophisticated." In short, we consider the Bernanke assertion that small banks are more effective at credit assessment and loan management than large lenders (both banks and LendingClub).¹ We test this hypothesis by comparing effectiveness of relationship lending (at small community banks) versus the cookie cutter approach used by large lenders.

Fourth, we investigate capital market incentives – we ask whether capital market provides potential incentives for lenders to take consumer credit risk. Specifically, we test whether the capital market distinguishes between a high NPL ratio that is due to a *lack of proficiency at credit risk assessment* vs. a high NPL ratio that results from lenders' *strategic decision to make riskier loans* (which are more likely to default)? This testing also has important implications for safety and soundness and stability in the banking system. To the extent that the capital markets punish inefficient lending, market discipline would tend to promote financial stability; however, to the extent that the capital market rewards riskier consumer lending, especially at large banks, market discipline would tend to reduce financial stability.

To address these four research questions, we apply a novel technique developed by Hughes et al. (2017, 2019) who rely on stochastic frontier estimation to decompose the observed NPL ratio into three components.

- The first is the *best-practice minimum ratio* that a lender could achieve if it were, relative to its peers, fully efficient at credit-risk evaluation and loan management. This is the inherent credit risk of the lender's loan portfolio.
- The second is a ratio that reflects the difference between the observed ratio (adjusted for statistical noise) and the minimum ratio – i.e., the observed nonperformance in excess of the best-practice minimum ratio. This difference gauges the lender's proficiency at credit assessment and loan management relative to its peers. We measure lending inefficiency as the proportion of the observed nonperforming loan ratio represented by the excess ratio. Note that this new concept of efficiency relies on the decomposition of the NPL ratio into the best-practice and excess nonperformance.
- The third is a statistical noise.

¹ Berger et al. (2021) find that the largest US banks (CCAR banks) seem to also utilize banking relationship information in their credit decisions.

This technique is uniquely suited to investigate the aforementioned four empirical questions and produces the following key findings.

First, our analysis finds that, as of 2016, both LendingClub (the largest fintech personal lender in the country) and the *largest* traditional bank lenders were more efficient than smaller lenders despite their high NPL ratio.² Thus, their high NPL ratios indicate risk-taking rather than inefficient credit risk assessment and loan management.

Second, among large lenders using algorithms and statistical methods to assess credit risk, on average, as of 2016, LendingClub's lending efficiency ratio was higher than the mean ratio of the largest bank lenders.

Third, we find some evidence consistent with the Bernanke assertion that small banks are more effective at credit assessment and loan management than large lenders. Among the smaller lenders, which are not the most efficient, the smallest lenders are the more efficient.

Fourth, we find that the NPL ratio *in aggregate* is negatively associated with the lender's market value, which suggests that higher risk-taking would be penalized by the capital market. This raises the next interesting question – why do we observe large banks taking more credit risk which results in a higher NPL ratio? Is this behavior inconsistent with the capital market incentive?

Our analysis answers this question by demonstrating that there are two distinct components within the NPL ratio besides statistical noise, and that their individual relationships with the lender's market value work in opposite directions. Therefore, it is important to consider the *components* of the NPL ratio, rather than the NPL ratio itself, when evaluating capital market incentives. While *lending inefficiency* is negatively related to market value at most banks, the other component, *inherent credit risk*, given by the best-practice ratio, is *positively related* to market value at most banks. *Market discipline appears to reward exposure to inherent credit risk and punish inefficient lending.*

The rest of the paper is organized as follows. The second section presents the review of the literature related to the empirical approach we use in this paper and the literature related to LendingClub's lending strategies. The third and fourth sections describe the approaches we take in comparing lending efficiency across lender types: small banks, large banks, and fintech (LendingClub). The data are described in the fifth section. The empirical results on the estimated best-practice ratio and on the estimated inherent credit risk and lending inefficiency are presented in the sixth and seventh sections, respectively. The influence of the capital market and market discipline on credit risk-taking is explored in the eighth section. The ninth section concludes.

² Some background on LendingClub consumer lending platform: LendingClub loans are originated by the WebBank, which sells the whole loans back to LendingClub after 3 days. LendingClub then sells the loans to the original investors who committed on the platform to funding them. When LendingClub operated purely as a peer-to-peer (P2P) lender, it did not hold loans on its books. It started to fund some loans through securitization (issuing Fintech ABS) in 2015. Payments and losses for all loans were reported at the loan level on the LendingClub website until recently – it stopped reporting these data on the website after it became a bank holding company (through its acquisition of the Radius Bank) in early 2021. Since LendingClub does not hold the loans on its balance sheet, any losses on the loans are absorbed by its P2P investors and its bondholders.

Literature review and our contribution

There are several strands of the literature that are relevant to our study – the fintech lending and lending performance literature and stochastic frontier analysis.

Fintech lending and lending performance literature

Fintech peer-to-peer and marketplace lending has grown dramatically following the 2008 financial crisis. Fintech lenders have been increasingly competing with traditional banks, especially in consumer lending. LendingClub has become the largest personal lender, with total loan origination volume of more than \$60 billion. Some believe that fintech lending could potentially improve credit access to consumers and enhance lending performance (providing faster, better, or cheaper services) in the financial system. There have also been concerns around credit risk that fintech lenders assume. Previous research studies have attempted to explore the contribution of fintech lending, by comparing traditional default prediction models with more advanced techniques using AI/ML modeling, but the results have been mixed.

Among research studies that explore fintech lending by comparing traditional default prediction models with more advanced techniques using AI/ML modeling, Jagtiani and Lemieux (2019), Goldstein et al. (2019), and Croux et al. (2020) find significant lifts in predictive ability for fintech lending, suggesting that the information asymmetry, which has been a key factor in evaluating borrower credit risks, could be overcome through AI/ML and alternative data. In contrast, Di Maggio and Yao (2021), using a consumer credit panel dataset, find that in the 15 months following origination, borrowers who take out fintech loans are more likely to default than those with a traditional loan, even after controlling for a full set of borrowers' credit characteristics, loan features, and geography. They also find that this relative underperformance persists.

Various studies focus on different types of alternative data, including information on friendship and social networks, online footprints, and text-based analysis. For example, see Iyer et al. (2016), Hildebrandt et al. (2017), Lin et al. (2013), Gao et al. (2018), Dorfleitner et al. (2016), and Berg et al. (2020). In addition to using alternative data and AI/ML to better understand a more wholistic picture of a person's financial condition, fintech lending could also allow risk pricing to be potentially more accurate. Alternative data has also been found to provide a significant lift in predicting small business performances. Kou et al. (2021) find that transactional data and payment network-based variables are useful in predicting bankruptcy even without any traditional financial (accounting) data.³ For more information on the overview of fintech lending and recent literature more broadly, see Jagtiani and John (2018), Jagtiani et al. (2018), and Allen et al. (2021).

Previous studies have also examined pricing of fintech loans. Jagtiani and Lemieux (2019) compare interest rates (APRs including the origination fees) charged by LendingClub with the interest rate that borrowers would have to pay by carrying a credit card balance. They find that the use of alternative data by LendingClub has allowed some below-prime consumers to receive credit at a much lower cost. In addition, Wang et al.

³ In addition to the use of alternative data in credit evaluation, Zhae et al. (2020) provide a review of usefulness of alternative data in other areas, including marketing, finance, e-commerce, politics, and group decision making. See also Li et al. (2021) and Kou et al. (2014) for more technical explanation of how data optimization and more complex clustering algorithms could lead to more efficient solutions to financial problems, including fraud detection and credit risk evaluation.

(2021) demonstrate that fintech lenders, using LendingClub data, could benefit from reduced lending cost through a more complex approach to credit risk evaluation and the credit rating that they assign to each loan. They conclude that more accurate credit rating and risk pricing have proved to be essential for the survival and profitability of fintech lending platforms.

Berger and Black (2011) investigate the comparative advantages of large and small banks in using different lending technologies and lending to firms of different sizes. Rather than compare lending performance with default ratios, they estimate the probability that a large bank makes the loan given the size of the borrower and the lending technology used. They interpret a significantly higher probability of a loan being made by a large bank, given the competitive conditions, as evidence that large banks experience a comparative advantage.

Using Y-14 M data on the largest U.S. banks (CCAR banks) that are subject to the DFAST/CCAR stress tests, Berger et al. (2021) find evidence that these largest banks also use information obtained from banking relationships to determine the terms of the credit-card lending to consumers and small businesses. While they note that credit card lending is transactions-based, they find that the two technologies complement one another.

Applications of stochastic frontier estimation

Applications of the stochastic frontier estimation techniques in economics are numerous and varied. Greene (2018) provides a textbook description. Surveys of applications to the performance of financial institutions are found in Hughes and Mester (2019) and Berger and Mester (1997). These applications focus on performance measured by profit, cost, and market value. Our application of stochastic frontier estimation to the decomposition of the consumer NPL ratio to compare unsecured consumer lending by a fintech and by traditional bank lenders is novel and is our important contribution to the frontier literature. Hughes et al. (2019) apply the technique we use here to study the lending efficiency of community banks in making commercial and industrial loans and commercial real estate loans. They find that large community banks are more efficient than small community banks in both types of lending.

Our use of stochastic frontier estimation to gauge a lender's potential best-practice lending performance relative to its peers and the portion of a lender's achieved performance that exceeds the best-practice minimum, the lender's inefficiency, is innovative and offers important findings on lending performance and market discipline available only by estimating best-practice lending. Specifically, it allows us to determine that the high NPL ratio experienced by LendingClub and the largest banks in 2016 resulted from assuming higher credit risk and not from a lack of proficiency in assessing credit risk and managing loans. Moreover, it allows us to identify that, as of 2016, LendingClub and the largest banks were more efficient at consumer lending than smaller banks.

In addition, it allows us to investigate the financial incentive of these lenders to assume relatively high credit risk. Our decomposition analysis adds significant value to the literature that evaluates the effect of the NPL ratio on market performance. The two components of the decomposition relate differently to the market performance measure and

enable us to explain why we observe higher NPL ratio and riskier consumer loan portfolios at the largest banks.

Our contribution to measuring lending performance based on stochastic frontier estimation

Techniques used to assess loan applicants' credit worthiness, which often differ between fintechs and traditional banks, are commonly evaluated by their associated loan performance. Banks often rely on traditional measures like FICO scores. Fintechs estimate their own ratings (or scores) based on bigger and broader datasets, which include both traditional data and alternative data. Is one approach superior to the other in terms of loan performance?

Our contribution to measuring lending performance is to decompose the NPL ratio into its distinct components. Rather than focus on the NPL ratio to evaluate lending efficiency, we distinguish the degree to which the NPL ratio may result from lending to riskier borrowers (who default more often) and the degree to which it may result from a lack of proficiency at credit evaluation and loan management. We focus on measuring lending performance by lenders' proficiency at lending.

In particular, we apply an innovative technique developed by Hughes et al. (2017, 2019) who rely on stochastic frontier estimation to decompose the observed NPL ratio into three components that are required to answer the empirical questions: first, the *best-practice minimum ratio* that a lender could achieve if it were, relative to its peers, fully efficient at credit-risk evaluation and loan management; second, a ratio that reflects the difference between the observed ratio (adjusted for statistical noise) and the minimum ratio – i.e., the observed nonperformance in excess of the best-practice minimum ratio that gauges the lender's proficiency at credit assessment and loan management relative to its peers; and, third, statistical noise.

Using this decomposition of the NPL ratio, we compare the efficiency of LendingClub's unsecured personal loans with similar loans originated by banks. The best-practice minimum NPL ratio reflects the lender's inherent credit risk while the excess ratio above the minimum best practice gauges lending inefficiency. These are novel applications and interpretations of the well-known components of the stochastic frontier applied to NPLs. Thus, we derive lending efficiency in terms of nonperformance in excess of the best practice. Using this concept of lending efficiency, our analysis finds that, as of 2016, both LendingClub and the largest traditional bank lenders were more efficient than smaller lenders despite their high NPL ratio.

This decomposition of the NPL ratio answers the important question, to what extent does a high NPL ratio indicate the lender is making riskier loans that default more often and to what extent does a higher NPL ratio indicate that the lender lacks proficiency in credit assessment and loan management? This question cannot be addressed by the usual evaluation of performance based on the ratio of nonperforming loans.

The importance of this decomposition is apparent in asking whether the capital market provides incentives for lenders to take consumer credit risk. While the negative relationship of the q ratio to the NPL ratio suggests that the capital market punishes NPLs, our new decomposition of the NPL ratio provides evidence that the capital market discourages a higher NPL ratio that is due to a *lack of proficiency at credit risk assessment*

and rewards a higher NPL ratio that results from lenders' *strategic decision to make riskier loans*. This implies that *the effect of NPL ratio as a whole is the composite of the two opposite forces, and that a casual use of NPL ratio in a q ratio estimation would not be able to capture the opposite impact from each component of the NPL ratio*. Our decomposition analysis adds significant value to the literature that evaluates the effect of the NPL ratio on market performance.

Comparing lending performance: LendingClub vs. large banks vs. small banks

The performance of unsecured consumer lending relies in part on lenders' technologies to assess and manage credit risk. Large and small lenders tend to use different methods, which may affect the performance of their loans. Small banks usually rely on their knowledge of the local economy and on information obtained from banking relationships with their customers. Among large lenders who use statistical methods in credit decisions, fintech lenders often differ from traditional large lenders by their use of alternative data and more complex AI/ML algorithms. We examine whether the choice of lending technologies would result in more effective credit risk assessment and management. Federal Reserve Chairman Ben Bernanke in a speech at the Independent Community Bankers of America National Convention, San Diego, California (March 23, 2011) made this important observation:

Community bankers live and work where they do business, and their institutions have deep roots, sometimes established over several generations. They know their customers and the local economy. Relationship banking is therefore at the core of community banking. 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.

Bernanke (2011) raises two questions. *First*, do small lenders, such as community banks, which tend to rely on *relationship banking*, tend to experience better loan performance, *ceteris paribus*, than large lenders, such as large money center banks and fintechs, which rely on statistical models and algorithms?⁴ The question broadly defines a lender's peers as potentially all lenders regardless of the credit evaluation and management techniques they use. *Second*, given a lender's methods of evaluating and managing credit risk, how well do its loans perform in relation to other lenders using the same approach to credit decisions. For example, do loans made by LendingClub perform better than loans made by traditional large banks, *ceteris paribus*? This question narrowly defines a lender's peers as lenders using the same or similar techniques of credit

⁴ Berger et al. (2021) investigate the role of banking relationships in credit card lending, but they only focus on the largest U.S. banks (CCAR banks). They do not compare the use of banking relationship in credit decisions across bank sizes (large vs. small community banks). In this paper, we do address Bernanke's question of the performance and efficiency of this relationship lending at large banks compared to smaller banks and to fintech lenders.

evaluation and management.⁵ The comparison of large banks to LendingClub focuses attention on lenders relying on “hard” information obtained from statistical methods and algorithms to evaluate credit risk.⁶

We address these two questions raised in Bernanke (2011). First, is relationship-based lending by small banks more effective than algorithmic lending by large banks? Second, among algorithmic lenders, is lending by LendingClub more effective than traditional algorithmic lending at large banks?

To evaluate these two questions, we use the technique developed by Hughes et al. (2017, 2019) to estimate the best-practice NPL ratio for each individual lender. *The best-practice NPL ratio indicates the ratio of nonperforming consumer loans to total consumer loans that a lender could achieve if it were fully efficient at credit-risk evaluation and loan management relative to its peers.* This is the *inherent credit risk* of the lender’s loan portfolio. By using stochastic frontier analysis to estimate this conditional minimum, the influence of luck (statistical noise) can be eliminated. Thus, the difference between a bank’s achieved NPL ratio, adjusted for statistical noise, and the conditional minimum NPL ratio (the best-observed-practice ratio) gauges the degree to which a lender’s NPL ratio exceeds the best-practice ratio of its peers. If this *excess ratio* is expressed as a proportion of the lender’s observed ratio, we obtain a measure of the lender’s relative *lending inefficiency*. By decomposing a lender’s NPL ratio into nonperformance due to inherent credit risk vs. due to inefficient assessment and management of credit risk, we are able to compare the lending efficiency across lenders – both for lenders using *different* lending techniques and for lenders using the *same* techniques.

Our definition of peers: peers are defined by variables that characterize the credit risk a lender adopts in its consumer loan portfolio, economic characteristics of the lender’s local markets, such as the weighted 10-year average GDP growth rate and the weighted average Herfindahl index across these markets, where the weights are bank deposit shares,⁷ the 3-year growth rate of the lender’s consumer lending,⁸ and the volume of its consumer lending. We gauge consumer loan portfolio performance by past-due consumer loans and charge-offs across lenders as a function of variables that define a lender’s peers, which are not necessarily the same type of lender, and we ask how well a lender’s consumer loan performance compares with the performance of its peers. The volume of consumer lending captures to some degree the lending technology – ranging from relationship-based lending of smaller banks through model-based and algorithmic lending of larger banks. The 3-year growth rate controls in part for loan seasoning. If a loan portfolio is growing rapidly, it has a higher share of relatively new loans compared to a portfolio that is growing more slowly. Depending on the age pattern of defaults,

⁵ It should be noted that our definition of peers also includes other controls, such as the economic conditions in the lender’s local markets and the average contractual interest rate it charges.

⁶ As mentioned earlier, Jagtiani and Lemieux (2019) find that, unlike loans that were originated prior to 2015, those loans that LendingClub originated in 2015 or later were evaluated based on alternative data and complex algorithms, resulting in more accurate assessment and pricing of credit risk.

⁷ In calculating market shares, we consider only deposits at banks. Deposits at thrifts and credit unions are not included. Market share measure is calculated at the state level.

⁸ The 3-year growth rate in consumer lending for 2016 is measured by the difference between the year-end volume of unsecured consumer lending in 2016 and 2013 expressed as a proportion of 2016 consumer lending. The difference between 2013 and 2010 is measured in terms of all consumer loans since auto loans are not reported separately in 2010. We thank William W. Lang for suggesting this control variable.

this effect can lower the default rate of a portfolio even if there is no difference in the hazard function (default probabilities at a point in the loan's lifecycle) of the individual loans. Finally, the lender's exposure to consumer credit risk depends in part on the average contractual interest rate it charges on the loans.

These variables define a lender's peers for the purpose of comparing a lender's consumer loan performance with that of comparable lenders – i.e., peers. Note that estimating a stochastic lower envelope of loan nonperformance as a function of these variables that define peers does not represent a “production function” or “cost function” of loan performance based on lenders of the same type (e.g., small community banks). Instead, the stochastic frontier constitutes a *nonstructural* representation of how well a lender's loan performance compares with that of its peers.

Alternatively, peers could be defined in terms of similar types of lenders (e.g., community banks) or in terms of different types of lenders (e.g., large commercial banks and fintech lenders). Hughes and Mester (2019) discuss the nonstructural approach and contrast it with the structural approach based on estimating a production, cost, or profit function of a single industry. The nonstructural approach asks how performance measured, for example, by Tobin's q ratio, by the z score, by a cumulative abnormal return, or by ROA is related to a firm's characteristics, such as its ownership structure, the value of its investment opportunities, and the degree of market concentration. Examples of the nonstructural approach include Caprio et al. (2007) who use Tobin's q ratio to evaluate the relationship of the characteristics of ownership and governance to firm valuation.

Brook et al. (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 et al. (1988) and McConnell and Servaes (1995) regress Tobin's q ratio on the characteristics of managerial ownership and governance, and, as is the case of many such studies, their sample includes firms from a variety of industries, excluding only financial firms and public utilities. Since production technology is not the subject of the estimation, the inclusion of firms from numerous industries is not a problem as long as the SIC codes of their industries are among the controls. Thus, in contrast to the structural approach, the nonstructural approach can be applied to samples spanning many industries.

In short, the empirical approach of this investigation accommodates combining heterogeneous firms like LendingClub and balance-sheet lenders to compare the performance of the consumer loans they make – their relative efficiency in loan performance compared with peers as defined above.⁹

⁹ We test statistically for the appropriateness of including LendingClub and traditional banks in estimating a common best-practice frontier and obtain test results supporting the common frontier. We adapt Chow's forecast test to stochastic frontier estimation. For the sample of LendingClub and traditional banks, the general model is specified as the stochastic frontier specification with the addition of a dummy variable for LendingClub to our set of regressors (which is equivalent to treating LendingClub separately from traditional banks) while the restricted model is specified as the stochastic frontier with our regressors. We conduct the likelihood ratio test. The p -values of the likelihood ratio test are 0.624 for 2016 and 0.581 for 2013, both of which are far larger than the typical significance level, 0.05.

Comparing impact of lending technology at lenders with similar size

The second question suggested by Bernanke (2011) narrowly defines a lender's peers as lenders using the same or similar techniques of credit evaluation and management. The comparative loan performance of similar lenders is estimated from a frontier that controls for loan volume. Thus, lenders with a similar loan volume constitute peers, *ceteris paribus*. By controlling for the loan volume, the best-practice frontier is estimated with respect to the loan performance of lenders with a similar volume. Thus, the best practice of lenders with a small volume is obtained from lenders with a small volume, and the best practice of lenders with a large volume is obtained from lenders with a large volume. Volume is controlling, to some extent, for the techniques of assessing and managing credit risk.

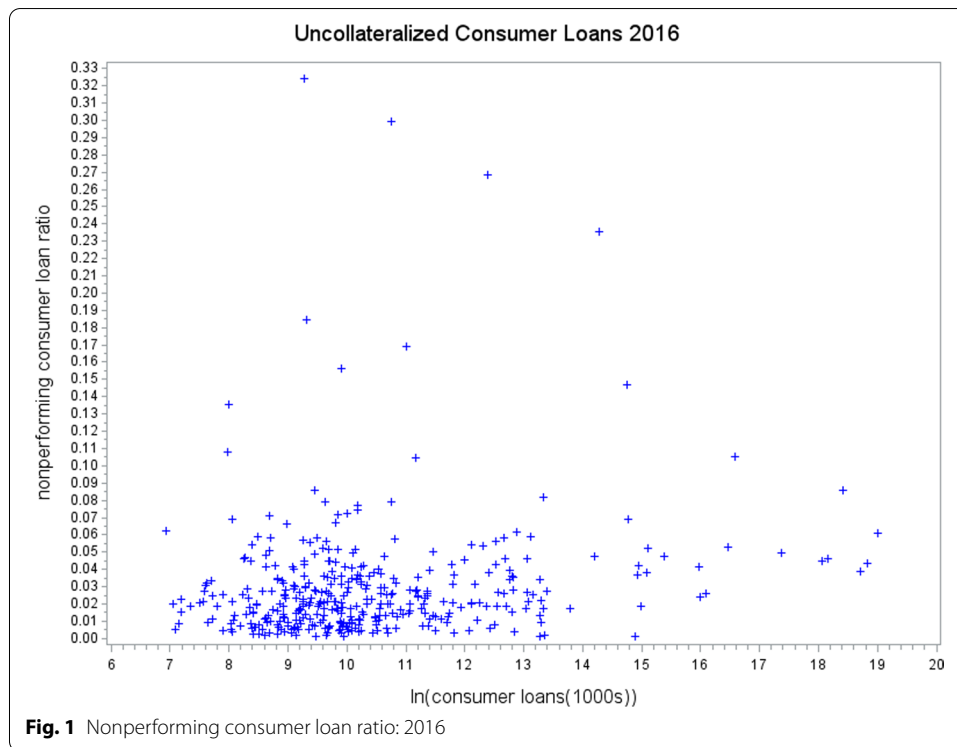
Investigating the two questions about lending efficiency raised by the Bernanke (2011) hypothesis requires different characterizations of a lender's peers that hinge on the omission or inclusion of lender's volume of consumer lending. The role of the volume of lending in the estimation of a best-practice frontier can be gleaned from several plots of the NPL ratio and the best-practice ratio on the loan volume.

Recall that we focus on unsecured consumer loans in this paper. Our loan sample does not include mortgages, automobile loans, home equity loans (HELOAN), and home equity lines of credit (HELOC).¹⁰ For *banks*, unsecured consumer loans are defined as the sum of the following Y9-C categories: BHCKB538, BHCKB539, and BHCKK207, which exclude auto loans since they are collateralized. In reporting the volume of consumer loans, we do not include gross charge-offs. We also do not include the volume of loans that a bank originated and sold or securitized – only those held on the bank's balance sheet are included in our sample. We find that the amount of consumer loans that were originated and securitized with recourse (could be put back on the bank's book if it does not perform) is very small relative to the total loan volume, and any potential loss from the securitization with recourse would not have significant impact on our results (from the regression analyses). For *LendingClub*, loan volume is measured as the outstanding loan amount at year-end. This amount consists of unpaid balances (not the initial origination amount), excluding paid-off and charge-off amounts. This outstanding amount is measured in the same way as loans outstanding are reported in Y9-C report for banking firms.

We gauge lending performance based on the proportion of unsecured consumer loans that are nonperforming (i.e., the sum of past-due and charged-off consumer loans).¹¹ In Fig. 1, we plot the noise-adjusted NPL ratio in 2016 at the end of the year against the log transformation of the loan volume (in 1000s). A cursory examination of the plot reveals that the lower bound of the NPL ratio of smaller lenders lies below the lower bound of larger lenders. The higher lower bound of larger lenders may result from their extending credit to riskier borrowers. In fact, larger lenders with over \$10 billion in unsecured consumer loans charge a higher average contractual interest rate on consumer loans, almost

¹⁰ Jagtiani et al. (2021) find that, unlike in the consumer personal lending space, alternative data do not seem to have a role to play in the fintech mortgage lending (for the period prior to 2019), probably because of the required process to qualify for conforming to Federal Housing Administration (FHA) mortgage origination standards.

¹¹ Since some banks are more aggressive in charging off past-due loans, we add gross charged-off loans to the sum of past-due loans and nonaccrual loans to eliminate bias due to the different charge-off strategies.

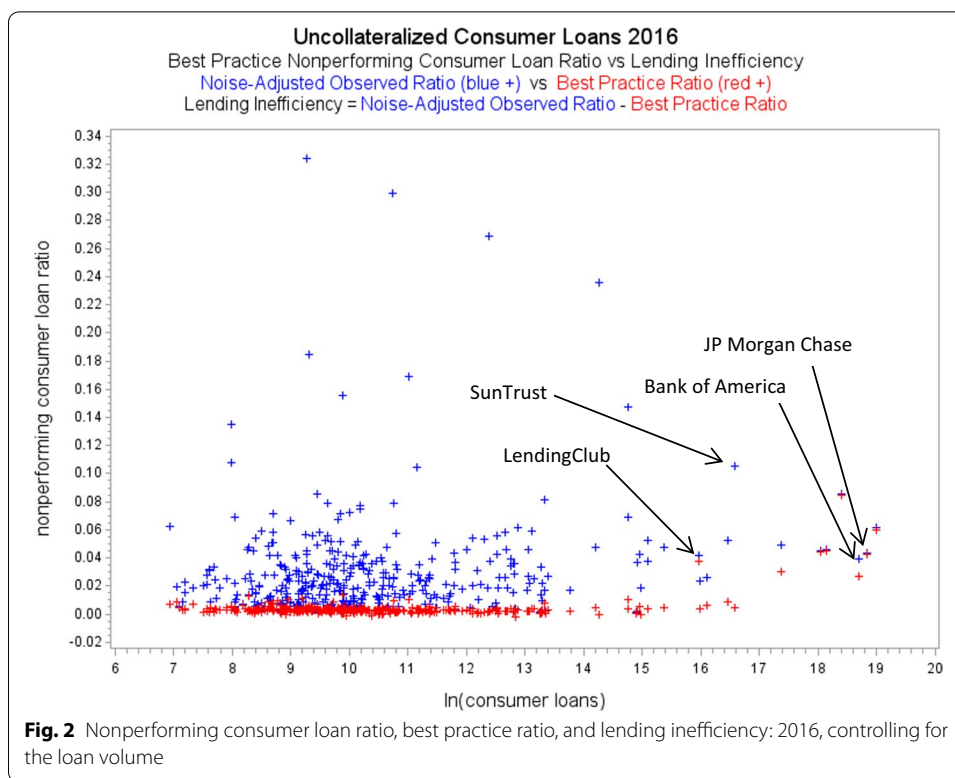


8.0 percent, compared with 6.9 percent, 6.0 percent, and 5.0 percent for lenders with less than \$1 billion in consumer loans.¹² Of course, larger lenders may also be less effective at assessing credit risk and managing loans than smaller lenders.

Figure 2 adds a best-practice NPL frontier to the plot of the NPL ratio in Fig. 1. This frontier defines a lender's peers as those with a similar volume of consumer lending, a similar average contractual interest rate, similar local market conditions, and a similar 3-year growth rate in consumer lending. Since volume is included in the specification of peers, the best practice of large lenders is obtained from the lower bound of large lenders. Consequently, the best-practice frontier in Fig. 2, which is influenced by the higher lower bound of the nonperforming loan ratio for larger lenders, bends upward for large lenders. As a result, the difference between a large lender's observed noise-adjusted ratio and its best-practice ratio, its excess nonperforming loan ratio, is reduced by the upward slope of the frontier, and the largest lenders record lower estimated lending inefficiency. The arrows point to LendingClub, Bank of America, SunTrust, and JP Morgan Chase. With the exception of SunTrust, the difference between their noise-adjusted observed NPL ratio and best-practice ratio is very small. JP Morgan Chase achieves the smallest difference of these four lenders.

If, instead, to answer Bernanke's first question, a lender's peers are only defined by lenders with a similar average contractual interest rate, similar local market conditions, and similar 3-year growth rates of consumer lending, the volume of its consumer lending will not influence the frontier. Figure 3 provides an example of such a frontier. The

¹² The specific calculation of average contractual interest rate charged on accruing consumer loans for banks and for LendingClub are described in the [Data](#) section.

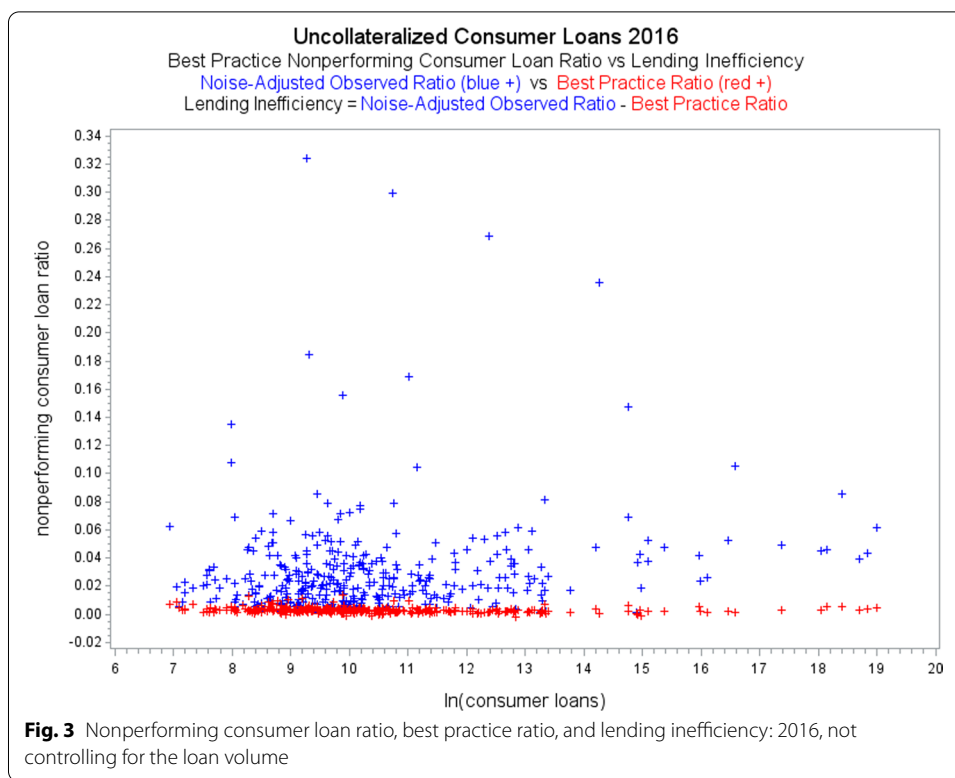


frontier is nearly flat. The performance of smaller banks largely defines the frontier across all volumes of lending. Most of the largest banks will show higher inefficiency. In other words, by not defining a lender’s peers by the volume of its loan volume, the best-practice frontier in Fig. 3 evaluates best practice over all loan volumes. It is also indicated in Fig. 3 that many of the smallest lenders experience the smallest difference between their (noise-adjusted) observed NPL ratio and their best-practice ratio, which implies that they are the most efficient at consumer lending, a result which is consistent with Bernanke (2011) about the advantages of relationship banking at small community banks.

For expository convenience, we divide lenders into five size groups based on their consumer loan volume: Group 1 is the **largest lenders** (more than \$10 billion); Group 2 is the **large lenders** (\$1 billion to \$10 billion); Groups 3, 4, and 5 are **three groups of small lenders** (all are less than \$1 billion).

Overall, our findings provide evidence supporting the Bernanke (2011) hypothesis on the efficiency of small community banks. Specifically, from the estimated frontier presented in Fig. 3 (excludes loan volume as a control from the specification defining peers), we find that as of 2016, the smallest lenders were the most efficient followed by the group of the second smallest lenders (all less than \$1 billion). As of 2013, LendingClub was the most efficient lender, followed by the smallest lenders, and then by the second smallest lenders.

When controlling for the loan volume (along with other characteristics) in defining peers, we effectively control for the lending technology – i.e., cookie-cutter approach for large volume vs. local knowledge and relationship lending for small volume. Using this approach, our results indicate that as of 2016, LendingClub and the **largest lenders** score



the highest lending efficiency, and, among the smaller lenders, which are not the most efficient, the *smallest lenders* are the most efficient.

As of 2013, the *largest lenders* were the most efficient, while LendingClub was as efficient as its peers (the *large lender* group). Again, the *smallest lenders* were the most efficient among the small lender groups.

Caveats: Since our fintech consumer lending data in this study come solely from a single fintech platform, LendingClub, our conclusions concerning LendingClub’s loan performance may not be applicable to the overall fintech lending sector. In addition, while the efficiency metric used in this study is well accepted, conceptually sound, and widely used in academic literature, our analysis may be subject to some data limitations. There may be factors not reflected in our data set or not taken into account by our measure that, if they could be reflected and taken into account, might change the measured efficiencies. Finally, our evaluation of lending efficiency does not account for other aspects of efficiency, such as the management of overall profit and funding cost.

The data

Our sample consists of top-tier U.S. bank holding companies (BHCs) and LendingClub as of year-end 2013 and 2016. The data for the BHCs are obtained from the end-of-year Y9-C Reports filed quarterly with regulators. When a specific data item is not available at the BHC level through Y9-C Reports, we collect the data at a bank subsidiary level through its Call Reports filed quarterly with regulators, and we aggregate them across all bank subsidiaries under the same BHC. For data related to the local community, we identify a bank’s local markets based on its deposit taking activities at the state level, using

the FDIC Summary of Deposits database. The overall economic conditions of the local market, such as the Herfindahl index (HHI) of market concentration and the 10-year average GDP growth rate, of a bank are calculated as a (deposit) weighted-average of the economic conditions of the states where deposits are drawn. The bank's local market conditions are expected to influence the performance of its consumer loan portfolios.

LendingClub is not a bank, and it does not file a Y-9C report; however, its financial statements and additional data were publicly available on its website (for transparency to small P2P investors) and on the SEC website (as a publicly traded company). Data on LendingClub's loan volume, contractual interest rates, nonperforming loans, and location are collected from LendingClub.com website, which reports data about each specific loan (origination date, loan amount, interest rate, maturity, location of the borrowers, etc.) and monthly payment update (including payment amount and delinquency status of each loan as of each month).

LendingClub's loans that are considered in our investigation are unsecured consumer loans. We examine the data to ensure that the mix of loans in LendingClub's portfolio falls within the range of banks' consumer portfolios observed in the paper's sample of banks. Specifically, we find that out of the 385 BHCs in the 2016 sample, the ratio of unsecured consumer loans to total consumer loans equals 1.00 at 12 BHCs. The ratio exceeds 0.95 at 72 BHCs, and it exceeds 0.90 at 102 BHCs. Hence, from the *raw data* perspective, LendingClub and the group of BHCs are comparable. In addition, as discussed earlier in footnote 9, we also test statistically for the appropriateness of including LendingClub and traditional banks in estimating a common best-practice frontier, and we obtain test results supporting the common frontier.¹³ Our empirical approach of this investigation accommodates combining heterogeneous firms like LendingClub and traditional bank lenders to compare the performance of the consumer loans they make – their relative efficiency in loan performance compared with peers.

Bank's contractual interest rates

In the Y9-C report, unsecured consumer loans are defined as the sum of the following Y9-C categories: BHCKB538, BHCKB539, and BHCKK207, which exclude auto loans, mortgages, HELOC, and HELOAN since they are collateralized. In reporting the volume of consumer loans, we do not include gross charge-offs. We then collect data on interest and fee income on unsecured consumer loans from Call Reports for individual bank subsidiaries (since these income categories are not reported on the Y9-C report). To obtain the average contractual interest rate, we sum the domestic interest and fee income received on unsecured consumer loans over the constituent subsidiaries and then divide by the sum of the subsidiaries' unsecured consumer loans.

The income from consumer loans is defined by the sum of RIADB485 (interest and fee income on credit cards) and RIADB486. In the case of RIADB486, which is income from revolving credit plans and other consumer loans, interest income from automobile loans is not separately reported. Since interest income from auto loans cannot be separated

¹³ The soundness of the comparison between types of lenders depends on the definition of lenders' peers used to specify the frontier equation. Peers are defined by variables that characterize the credit risk a lender adopts in its consumer loan portfolio, economic characteristics of the lender's local markets, such as the weighted 10-year average GDP growth rate and the weighted average Herfindahl index across these markets, the 3-year growth rate of the lender's consumer lending, and the volume of its consumer lending.

from the other components of interest income on consumer loans, the calculation of our average interest rate on consumer loans must include in the denominator, not only the sum of credit card loans (RCONB538), other revolving credit plans (RCONB539), and other single payment and installment consumer loans (RCONK207), but also the volume of automobile loans (RCONK137).

LendingClub's contractual interest rate

We first collect LendingClub's loan volume (outstanding loan amount), which is measured as the unpaid balance (not the initial origination amount), excluding paid-off and charge-off amounts as of year-end 2013 and as of year-end 2016. This outstanding amount of unsecured consumer loans is measured in the same way as the outstanding amount of unsecured consumer loans that we collect for our sample banks (from Y9-C Reports). Note that banks' consumer loans may include more educational loans than LendingClub consumer loans, which also include those for educational purposes as identified in loan applications. The bank data did not allow the separation of educational loans from other unsecured consumer loans. The average contractual interest rate of LendingClub loans is calculated as the balance-weighted-average of APR (interest and up-front origination fees included in the APR) for unsecured loans that were outstanding as of year-end 2013 and year-end 2016.

In comparing interest rates and loan performance at LendingClub vs. banks, we recognize that banks' loan portfolios generally consist of other types of loans in addition to consumer loans. One might ask whether the comparison of the performance of consumer loans in LendingClub's narrower portfolio to the performance of consumer loans in banks' generally broader portfolio of loans informative? We argue that it is. The mix of loan types found in bank portfolios may offer banks informational synergies. For example, a borrower's history taken from mortgage payments may make it easier to offer the borrower a consumer loan. The pricing of the consumer loan and its performance are likely to reflect this information. Such synergies probably improve the measured efficiency of the bank – i.e., result in performance closer to best practice. Therefore, the comparison of lenders even with heterogeneous portfolios that offer differing degrees of trust, convenience, and synergies can be informative as long as the definition of peers captures essential characteristics of credit risk.

Banks differ in ways that are not included in the definition of peers. For example, some lenders offer *convenience* that results in a better selection of loan applicants (in terms of credit risk) for any particular contractual interest rates. Examples of convenient services include geographically convenient local bank branches with a relationship to the borrower, a lender that offers an easy and fast application process, and a lender that makes speedy credit decisions.

Trust is another factor that may give a local bank or a customer's incumbent bank an advantage in lending to some customers – i.e., a better selection of loan applicants. Generally, we cannot directly measure convenience and trust, and even if they could be measured, it would not be appropriate to control for them in the specification of the frontier since doing so would too narrowly define peers so as to eliminate, for example, a convenient and speedy application process as a source of efficiency.

Bank's nonperforming loan (NPL) ratio

In calculating the NPL ratio, we collect bank data from the BHC's Y9-C Reports, where total unsecured consumer loans are the sum: BHCKB538 + BHCKB539 + BHCKK207. We then calculate dollar amount of NPL, which is the sum of past due loans, nonaccruals, and gross charge-offs. Since some banks are more aggressive in charging off past-due loans, we add gross charged-off loans to the sum of past-due loans and nonaccrual loans to eliminate bias due to the different charge-off strategies. Past due unsecured consumer loans include the following variables: BHCKB575, BHCKB576, BHCKK216, and BHCKK217. Nonaccruals on unsecured consumer loans include BHCKB577 and BHCKK218. Charge-offs on unsecured consumer loans include BHCKB514 and BHCKK205.

LendingClub's nonperforming loan (NPL) ratio

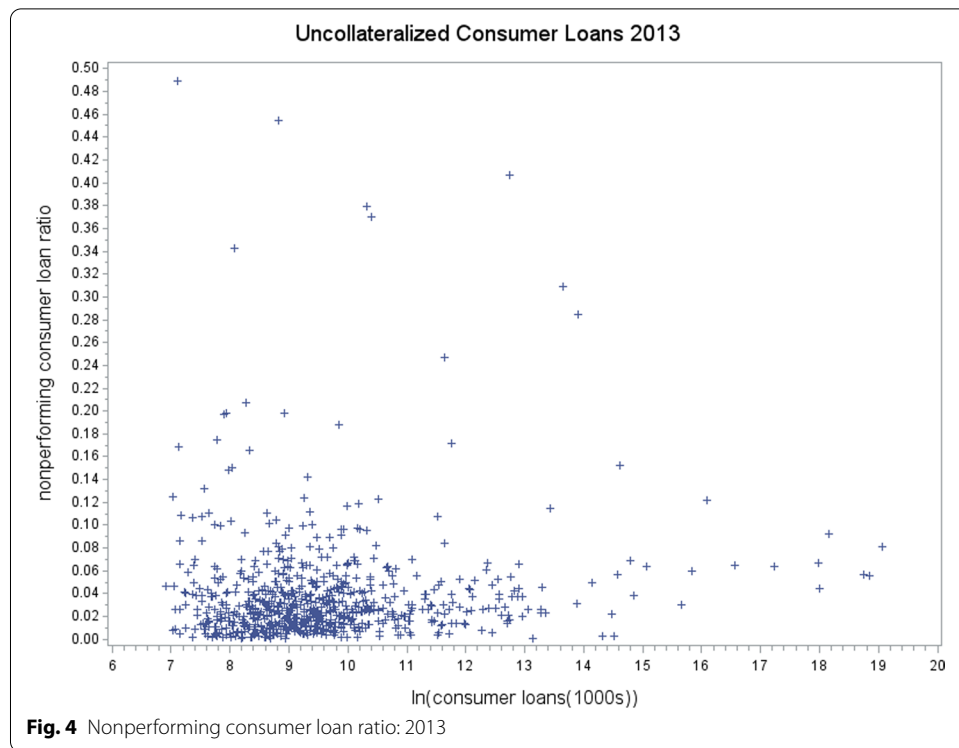
We calculate the NPL ratio for LendingClub from the loan-level monthly payment data. The volume of outstanding loans is measured as the unpaid balance (not the initial origination amount) as of year-end 2013 and year-end 2016 (excluding paid-off) plus charge-offs amount during the year 2013 and 2016, respectively. Then, the numerator (\$ amount of NPL) includes amount past due and charge-offs during the year.

As noted above, bank consumer loans may include more educational loans than LendingClub consumer loans, which include loans for educational purposes as identified in loan applications. Ideally, we would like to exclude student loans from our analysis. However, the bank data do not allow us to separate out educational loans (student loans) from the reported "other unsecured consumer loans." Our inclusion of student loans in the analysis is likely to lower the NPL ratio at banks holding such loans.

It should also be noted that there is a distinction between expected credit losses and the variability of credit losses. We define performance measure in terms of NPL ratio, which does not account for the variability of returns, because different banks are likely to follow different loss mitigation strategies. The variability of credit losses could play an important role in the lender being forced to report losses and possibly becoming insolvent.

The final sample

Our sample of BHCs include all BHCs that filed their Y9-C reports with regulators in 2013 and 2016. The filing requirement was changed in 2015, when fewer banks were required to file in 2016, as the asset size threshold for filing was raised from \$500 million to \$1 billion. Thus, the 2016 sample contains fewer small bank lenders than the 2013 sample. The sample is then further reduced to exclude those banks whose ratio of loans to assets is less than 0.10, whose unsecured consumer loans total less than \$1 million, and whose ratio of NPL plus gross charge-offs to total consumer loans (plus charge-offs) is unusually small likely due to errors (less than 0.001). The remaining 2016 sample consisting of 453 BHCs is then further reduced to 386 BHCs with data needed to compute the 3-year growth rate in consumer lending and with data from bank subsidiaries that were required to submit quarterly Call Reports needed to compute the average contractual loan rate on consumer loans. Lenders with a 3-year growth rate higher than 10 or



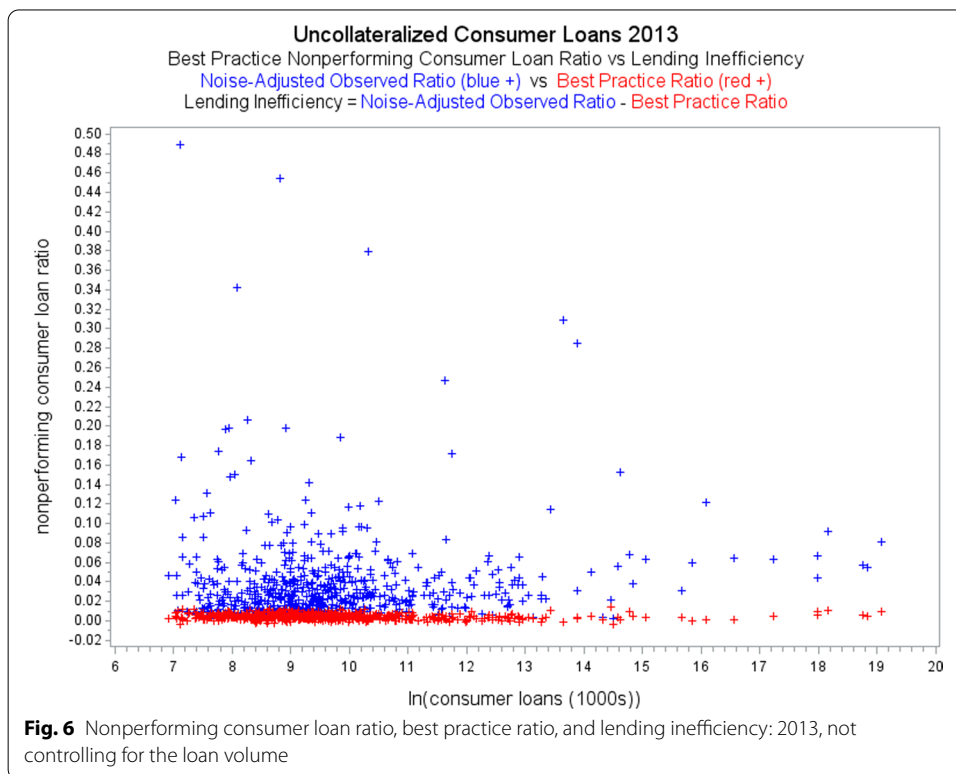
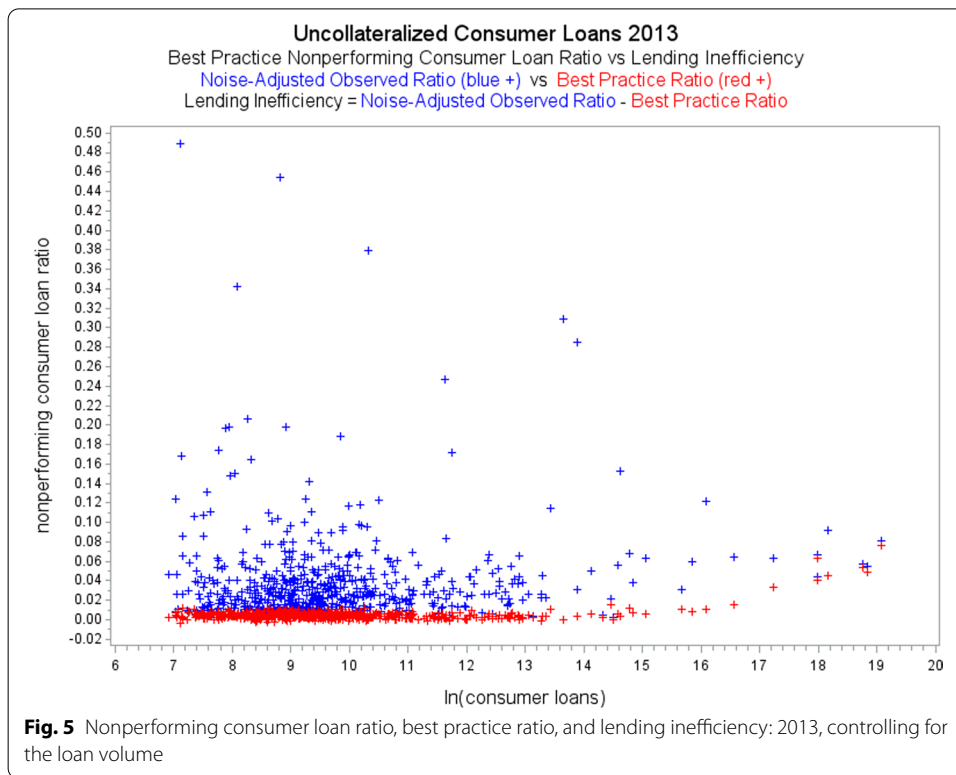
lower than -0.90 are trimmed. The 2013 sample remaining after these restrictions totals 655 lenders (including LendingClub), which have data needed to calculate the 3-year growth rate in consumer lending and the average contractual loan rate.

Figures 1 and 4 plot the ratio of NPL to total consumer loans against the log transformation of total consumer loans (in \$1000s) for 2016 and 2013, respectively. In 2013, the volume of consumer loans ranges from a minimum of \$1.01 million to a maximum of \$191.56 billion, and in 2016, the range is from \$1.03 million to \$179.28 billion.

Figure 5 overlays the 2013 best-practice frontier that controls for the volume of consumer lending in the definition of peers. Figure 6 overlays the frontier that does not control for the lending volume. These figures are qualitatively similar to those of 2016 shown in Figs. 2 and 3.

Estimating the best-practice consumer NPL ratio

The specification of the best-practice frontier in terms of environmental variables and characteristics of lenders defines an individual lender's peers for the purpose of comparing its performance to other lenders. Hughes and Mester (2019, p. 239) explain the strategy for the inclusion of these characteristics and environmental variables in the estimating equation: "These variables define the peer group that determines best-practice performance against which a particular bank's performance is judged. If something extraneous to the production process is included in the specification, this might lead to too narrow a peer group and an overstatement of a bank's level of efficiency. Moreover, the variables included determine which type of inefficiency gets penalized. If bank location, e.g., urban versus rural, is included in the frontier, then an urban bank's



performance would be judged against other urban banks but not against rural banks, and a rural bank's performance would be judged against other rural banks. If it turned out that rural banks are more efficient than urban banks, all else equal, the inefficient choice of location would not be penalized."

Bernanke (2011) hypothesis that the lending efficiency of community banks exceeds that of larger banks points to a comparison of lending technologies from those based on relationship banking to those based on statistical models and algorithms. To make such a comparison, the lender's volume of consumer loans would be excluded from the specification of peers. On the other hand, a comparison of the efficiency of lenders relying mostly on statistical models and algorithms, such as at LendingClub, and at large banks, requires defining peers in terms of the consumer loan volume. As Hughes and Mester (2019) note, "... the variables included determine which type of inefficiency gets penalized."

To specify the equation used to estimate the best-practice minimum NPL ratio, there are variables defining peers that are appropriate to include for *both* types of frontiers: variables that characterize economic conditions in the institution's local markets, variables that are related to the credit risk of the borrowers its lending operations attract, and the 3-year growth rate of consumer lending. In the case where we are considering the second question which compares lenders using similar credit assessment and loan monitoring technologies, we define a lender's peers by including the scale of its unsecured consumer lending. To compare lending across all sizes of lending, we drop the scale variable.

The macroeconomic conditions in a lender's local lending markets are captured by the 10-year average GDP growth rate obtained for the states in which the lender maintains branches and, in the case of LendingClub, for the states in which it lends. The Summary of Deposits data for the commercial banks report the amount of deposit by bank branch and the branch location. The state GDP growth rate is weighted by the share of a lender's deposits located in that state.

We also define a lender's peers in terms of the concentration of banks in its local markets. A lender operating in a concentrated local market is likely to obtain a better selection of credit applicants (in terms of credit risk) for any given contractual interest rate it charges for consumer loans. Petersen and Rajan (1995) show that, in the case of business loans, concentrated banking markets provide advantages both to the bank and to the borrower. While these advantages may not be relevant to consumer lending, we nevertheless control for market concentration in the states where the lender operates. The state concentration index is weighted by the share of the lender's deposits that are located in the state. In the case of LendingClub, the state concentration index is weighted by the volume of LendingClub's loans made in that state as a proportion of LendingClub's total consumer loans.

We include the 3-year growth rate of consumer lending to control in part for loan seasoning. If a loan portfolio is growing rapidly, it has a higher share of relatively new loans compared to a portfolio that is growing more slowly. Depending on the age pattern of defaults, this effect can lower the default rate of a portfolio even if there is no difference in the hazard function (default probabilities at a point in the loan's lifecycle) of the individual loans.

In addition, we define a lender's peers in terms of the *average contractual interest rate* it charges on its consumer loans. We include the average contractual interest rate because this interest rate is related to the credit risk of the borrowers it attracts. The contractual interest rate includes a credit risk premium and influences the quality of loan applicants through adverse selection.¹⁴ Moreover, a higher rate puts more financial pressure on a borrower and increases the probability of delinquency.¹⁵ However, the selection of borrowers by credit quality that a lender attracts at any particular contractual interest rate depends on a variety of factors in addition to the interest rate.

Lenders may offer loan applicants *convenience* that results in a better selection of loan applicants (in terms of credit risk) for any particular contractual interest rate charged. Examples of convenient services include a geographically convenient local bank with a relationship to the borrower, a lender that offers an easy and fast application process, and a lender that makes speedy credit decisions. *Trust* is another factor that may give a local bank or a customer's incumbent bank an advantage in lending to some customers. To the extent that trust and convenience give lenders a better selection of credit applicants for any particular contractual interest rate, these factors will tend to reduce the expected NPL ratio at any given contractual interest rate and enhance the measured lending efficiency of convenient and trusted lenders. Generally, we cannot directly measure convenience and trust, and even if they could be measured, it would not be appropriate to control for them in the specification of the frontier since doing so would too narrowly define peers so as to eliminate, for example, a convenient and speedy application process as a source of efficiency.¹⁶

To allow for the possibility that the association of the average contractual interest rate with loan performance differs by the size of the lender, we interact the interest rate with the volume of consumer lending. To allow for the possibility that the interest rate's association with loan performance differs by market concentration and the GDP growth rate, we interact the average contractual rate with the index of market concentration and the GDP growth rate.

We allow for the possibility that the relationship of the GDP growth rate and the concentration index to consumer loan performance can vary with a lender's volume of consumer lending. For example, the impact of the GDP growth rate on loan performance may differ for lenders with a large loan volume because their use of technologies associated with a large scale of lending may allow them to exploit growth more effectively. To account for this possibility, we interact the loan volume with the GDP growth rate and with the index of market concentration.

The specification of our stochastic frontier models is given by

¹⁴ Morgan and Ashcraft (2003) find that the interest rate banks charge on business loans predict future loan performance.

¹⁵ Jagtiani and Lemieux (2019) show that the default rate on LendingClub loans increases with the contractual rate charged on its loans.

¹⁶ Since LendingClub offers the convenience of applying entirely online and of obtaining a speedy credit decision, we test statistically for the appropriateness of including LendingClub and traditional banks in estimating a common best-practice frontier and obtain test results supporting the common frontier. Testing strategy and results are reported in Footnote 9.

$$NP_i = \mathbf{x}'\boldsymbol{\beta} + \varepsilon_i, \tag{1}$$

where NP_i =ratio of nonperforming consumer loans to total consumer loans at bank i , and $\varepsilon_i = v_i + \mu_i$ is a composite error term. The composite error term, $\varepsilon_i = v_i + \mu_i$, is formed by the sum of a two-sided, normally distributed error term, $v_i \sim \text{iid } N(0, \sigma_v^2)$, that captures statistical noise, and an one-sided, exponentially distributed error term, $\mu_i (> 0) \sim \theta \exp(-\theta u)$, that measures the systematic excess nonperforming loan ratio.¹⁷

\mathbf{x} is defined in two different ways depending on the two definitions of peers. When the definition of peers includes the volume of loans, \mathbf{x} is a vector consisting of loan volumes and control variables: $x_1 = \text{Growth Rate in Consumer Lending}$, $x_2 = \text{Total consumer loans}_i$ (100 billions), $x_3 = (\text{Total consumer loans}_i \text{ (100 billions)})^2$, $x_4 = \text{Contractual consumer loan rate}_i$, $x_5 = \text{Contractual consumer loan rate}_i^2$, $x_6 = \text{Contractual consumer loan rate}_i \times \text{GDP growth rate across bank}_i\text{'s markets}$, $x_7 = \text{Contractual consumer loan rate}_i \times \text{Herfindahl index of market concentration across bank}_i\text{'s markets}$, $x_8 = \text{Total consumer loans}_i$ (100 billions) \times $\text{Contractual consumer loan rate}_i$, $x_9 = \text{Total consumer loans}_i$ (100 billions) \times $\text{GDP growth rate across bank}_i\text{'s markets}$, $x_{10} = \text{Total consumer loans}_i$ (100 billions) \times $\text{Herfindahl index of market concentration across bank}_i\text{'s markets}$.

In contrast, when the definition of peers does not include the volume of loans \mathbf{x} , is a vector of the following variables: $x_1 = \text{Growth Rate in Consumer Lending}$, $x_2 = \text{Contractual consumer loan rate}_i$, $x_3 = \text{Contractual consumer loan rate}_i^2$, $x_4 = \text{Contractual consumer loan rate}_i \times \text{GDP growth rate across bank}_i\text{'s markets}$, $x_5 = \text{Contractual consumer loan rate}_i \times \text{Herfindahl index of market concentration across bank}_i\text{'s markets}$.

The deterministic kernel of the frontier defines the minimum (best-practice) ratio:

$$\text{Best-Practice } NP_i = \mathbf{x}'\boldsymbol{\beta}. \tag{2}$$

The best-practice ratio gauges the nonperforming consumer loan ratio a bank would achieve if it were totally efficient at credit evaluation and loan management—its inherent credit risk.

We adopt the technique of Jondrow et al. (1982) and define the bank-specific excess nonperforming loan ratio by the expectation of μ_i conditional on ε_i :

$$\text{Excess } NP_i = E(\mu_i | \varepsilon_i) \tag{3}$$

and statistical noise (luck) by the expectation of v_i conditional on ε_i :

$$\text{Noise}_i = E(v_i | \varepsilon_i) = \varepsilon_i - E(\mu_i | \varepsilon_i). \tag{4}$$

Subtracting noise from the observed nonperforming loan ratio yields the noise-adjusted observed nonperforming loan ratio:

$$\text{Noise-Adjusted } NP_i = NP_i - E(v_i | \varepsilon_i). \tag{5}$$

¹⁷ We also considered the normal distribution for the one-sided error term and conducted Vuong's (1989) test to select the better between the normal/half-normal model and the normal/exponential model. For both 2013 and 2016 and for both definitions of peers, we found with statistical significance the normal/exponential model is better than the normal/half-normal model.

Thus, the estimation of Eq. (1) yields a decomposition of the observed nonperforming loan ratio into a minimum nonperforming loan ratio that reflects inherent credit risk, the excess ratio that reflects inefficiency at evaluating credit risk and managing loans, and statistical noise:

$$\begin{aligned}
 NP_i &= \text{Best-Practice } NP_i + \text{Excess } NP_i + \text{Statistical Noise}_i \\
 &= \text{Inherent Credit Risk}_i + \text{Inefficiency}_i + \text{Statistical Noise}_i \\
 &= \mathbf{x}'\boldsymbol{\beta} + E(\mu_i|\varepsilon_i) + E(v_i|\varepsilon_i).
 \end{aligned}
 \tag{6}$$

Rearranging Eq. (6) expresses this distance for any particular observation as the excess nonperforming loan ratio:

$$\begin{aligned}
 \text{Excess } NP_i &= \text{Noise-Adjusted } NP_i - \text{Best-Practice } NP_i \\
 E(\mu_i|\varepsilon_i) &= [NP_i - E(v_i|\varepsilon_i)] - \mathbf{x}'\boldsymbol{\beta}.
 \end{aligned}
 \tag{7}$$

The excess nonperforming loan ratio can be normalized as a proportion of the observed nonperforming ratio – the **Lending Inefficiency Ratio**:

$$\text{Lending Inefficiency Ratio} = E(\mu_i|\varepsilon_i)/NP_i
 \tag{8}$$

The estimated Eq. (1) with \mathbf{x} , which includes loan volume in the specification of peers, is described in Table 1 for 2016 and in Table 3 for 2013 while the estimated Eq. (1) with \mathbf{x} , which excludes loan volume from the specification of peers, is detailed in Table 5 for 2016 and in Table 7 for 2013. These estimations yield values of the noise-adjusted observed nonperforming loan ratio, the best-practice ratio, the excess ratio, and the lending inefficiency ratio. Their summary statistics are given in Table 9.

In support of the stochastic frontier models in Tables 1, 2, 3, 4, 5, 6, 7, 8, we provide three pieces of empirical evidence. The first two are based on the OLS residuals while the third is based on the maximized log-likelihood values of the stochastic frontier model and the corresponding linear regression model. The three pieces of evidence supporting the stochastic frontier models in Tables 1, 2, 3, 4, 5, 6, 7, 8 further support the empirical results from the models reported in Table 9.

For the first and the second pieces of evidence, we firstly obtain OLS residuals from the linear regression equation using the variables composing the deterministic kernel of the stochastic frontier model as regressors and then examine these OLS residuals to confirm whether the stochastic frontier model is justified. The key point here is whether the OLS residuals are positively skewed with statistical significance. For each of Tables 1, 3, 5, 7, we present a plot of histogram and density function of the OLS residuals in the relative frequency scale,¹⁸ and the result of D’Agostino skewness test, which is asymptotically distributed as the standard normal distribution. The plots are found in Appendices 1, 2, 3, and 4.

In all four cases, the plots display highly clear positive skewness of the OLS residuals. The skewness measures reported as a part of D’Agostino skewness tests are 4.8, 4.4,

¹⁸ Relative frequency scale makes histogram and density comparable in one plot such that the sum of the heights of all individual bars of the histogram equals one while the area under the density curve equals its bandwidth.

Table 1 2016 Unsecured consumer loans–stochastic frontier estimation. Including the volume of unsecured consumer lending. Best-practice (minimum) ratio of nonperforming consumer loans

Parameter	Variable	Coefficient estimate	Pr(> t)
β_1	Growth rate in consumer lending from 2013 to 2016 _{<i>i</i>}	−0.000511	0.009747
β_2	Consumer Loans _{<i>i</i>} (100 billions)	−0.036515	0.000000
β_3	Consumer Loans _{<i>i</i>} (100 billions) ²	−0.060919	0.000000
β_4	Contractual consumer loan rate _{<i>i</i>}	0.059706	0.000000
β_5	[Contractual consumer loan rate _{<i>i</i>}] ²	0.072303	0.057154
β_6	[Contractual consumer loan rate _{<i>i</i>}] × [GDP Growth Rate _{<i>i</i>}]	−0.005834	0.167194
β_7	[Contractual consumer loan rate _{<i>i</i>}] × [Herfindahl Index _{<i>i</i>}]	−0.079739	0.000929
β_8	[Consumer Loans _{<i>i</i>} (scaled)] × [Consumer Loan Rate _{<i>i</i>}]	1.794105	0.000000
β_9	[Consumer Loans _{<i>i</i>} (scaled)] × [GDP Growth Rate _{<i>i</i>}]	0.065616	0.000000
β_{10}	[Consumer Loans _{<i>i</i>} (scaled)] × [Herfindahl Index _{<i>i</i>}]	−0.507393	0.000000
$\sigma_\mu = 1/\theta$		0.026070	0.000000
σ_v		0.000418	0.008610

The data set includes LendingClub and 387 top-tier bank holding companies at the end of 2016 with plausible values of nonperforming unsecured consumer loans and total loans exceeding 10 percent of assets

Skewness and D’Agostino skewness test of OLS residuals ($\sim N(0, 1)$ asymptotically): skewness = 4.7992 (> 0) \Rightarrow positively skewed test statistic = 16.7911 with *p*-value < 2.2E−16 \Rightarrow positively skewed with statistical significance.

Histogram and density of OLS residuals in the relative frequency scale appear in Appendix 1

Likelihood ratio test of $H_0 : \sigma_\mu^2 = 0$ vs. $H_1 : \sigma_\mu^2 > 0$ (asymptotically distributed as 50:50 mixture of $\chi_{(1)}^2$ and $\chi_{(0)}^2$): test statistic = 536.8902 with *p*-value < 2.2E−16 \Rightarrow strongly reject linear regression model (i.e., absence of inefficiency) in favor of stochastic frontier model (i.e., presence of inefficiency)

Table 2 2016 Unsecured consumer loans. Including the volume of unsecured consumer lending. Summary statistics of nonperformance derived from stochastic frontier estimation

Variable	N	Mean	Median
Observed nonperforming loan ratio	387	0.0299	0.0215
Noise-adjusted observed nonperforming loan ratio	387	0.0299	0.0215
Best-practice nonperforming loan ratio	387	0.0039	0.0028
Excess nonperforming loan ratio	387	0.0261	0.0180
Lending inefficiency ratio	387	0.7942	0.8744

4.8, and 4.3, respectively, indicating that the OLS residuals are positively skewed. The values of D’Agostino skewness tests are 16.8, 20.7, 16.8, and 20.6, respectively, and their *p*-values are practically zero, supporting positive skewness of the OLS residuals with extremely high statistical significance.

For the third piece of evidence, using the maximized log-likelihood values of the normal-exponential model and the corresponding linear regression model, we conduct a likelihood ratio test of absence of inefficiency against presence of inefficiency, that is, $H_0 : \sigma_\mu^2 = 0$ against $H_1 : \sigma_\mu^2 > 0$. Since σ_μ^2 lies at the boundary of the parameter space under the null hypothesis, the asymptotic distribution of the likelihood ratio test is a 50:50 mixture of $\chi_{(1)}^2$ and $\chi_{(0)}^2$.

The values of likelihood ratio tests are 536.9, 770.2, 511.2, and 753.3 for Tables 1, 3, 5, 7 respectively, and their *p*-values are practically zero, supporting presence of inefficiency with extremely high statistical significance.

Table 3 2013 unsecured consumer loans–stochastic frontier estimation. Including the volume of unsecured consumer lending. Best-practice (minimum) ratio of nonperforming consumer loans

Parameter	Variable	Coefficient estimate	Pr(> t)
β_1	Growth rate in consumer lending from 2010 to 2013 _{<i>i</i>}	−0.000083	0.476997
β_2	Consumer Loans _{<i>i</i>} (100 billions)	−0.187182	0.000000
β_3	Consumer Loans _{<i>i</i>} (100 billions) ²	−0.067038	0.000000
β_4	Contractual consumer loan rate _{<i>i</i>}	0.094545	0.004801
β_5	[Contractual consumer loan rate _{<i>i</i>}] ²	−0.181961	0.021239
β_6	[Contractual consumer loan rate _{<i>i</i>}] × [GDP Growth Rate _{<i>i</i>}]	−0.006107	0.181438
β_7	[Contractual consumer loan rate _{<i>i</i>}] × [Herfindahl Index _{<i>i</i>}]	0.001904	0.020190
β_8	[Consumer Loans _{<i>i</i>} (scaled)] × [Consumer Loan Rate _{<i>i</i>}]	0.663070	0.000000
β_9	[Consumer Loans _{<i>i</i>} (scaled)] × [GDP Growth Rate _{<i>i</i>}]	0.068959	0.000000
β_{10}	[Consumer Loans _{<i>i</i>} (scaled)] × [Herfindahl Index _{<i>i</i>}]	−0.117169	0.000001
$\sigma_\mu = 1/\theta$		0.031910	0.000000
σ_v		0.002098	0.061483

The data set includes LendingClub and 654 top-tier bank holding companies at the end of 2013 with plausible values of nonperforming unsecured consumer loans and total loans exceeding 10 percent of assets

Skewness and D’Agostino skewness test of OLS residuals ($\sim N(0, 1)$ asymptotically): skewness = 4.3632 (> 0) \Rightarrow positively skewed test statistic = 20.7152 with *p*-value < 2.2E−16 \Rightarrow positively skewed with statistical significance.

Histogram and density of OLS residuals in the relative frequency scale appear in Appendix 2

Likelihood ratio test of $H_0 : \sigma_\mu^2 = 0$ vs. $H_1 : \sigma_\mu^2 > 0$ (asymptotically distributed as 50:50 mixture of $\chi^2_{(1)}$ and $\chi^2_{(0)}$): test statistic = 770.2193 with *p*-value < 2.2E−16 \Rightarrow strongly reject linear regression model (i.e., absence of inefficiency) in favor of stochastic frontier model (i.e., presence of inefficiency)

Table 4 2013 unsecured consumer loans. Including the volume of unsecured consumer lending. Summary statistics of nonperformance derived from stochastic frontier estimation

Variable	N	Mean	Median
Observed nonperforming loan ratio	655	0.0364	0.0259
Noise-adjusted observed nonperforming loan ratio	655	0.0364	0.0258
Best-practice nonperforming loan ratio	655	0.0045	0.0040
Excess nonperforming loan ratio	655	0.0319	0.0220
Lending inefficiency ratio	655	0.7921	0.8423

Table 5 2016 Unsecured consumer loans–stochastic frontier estimation. Excluding the volume of unsecured consumer lending. Best-practice (minimum) ratio of nonperforming consumer loans

Parameter	Variable	Coefficient Estimate	Pr(> t)
β_1	Growth rate in consumer lending from 2013 to 2016 _{<i>i</i>}	−0.000513	0.006971
β_2	Contractual consumer loan rate _{<i>i</i>}	0.060001	0.000001
β_3	[Contractual consumer loan rate _{<i>i</i>}] ²	0.070136	0.127654
β_4	[Contractual consumer loan rate _{<i>i</i>}] × [GDP Growth Rate _{<i>i</i>}]	−0.005768	0.252876
β_5	[Contractual consumer loan rate _{<i>i</i>}] × [Herfindahl Index _{<i>i</i>}]	−0.078812	0.000650
$\sigma_\mu = 1/\theta$		0.027062	0.000000
σ_v		0.000438	0.009392

The data set includes LendingClub and 387 top-tier bank holding companies at the end of 2016 with plausible values of nonperforming unsecured consumer loans and total loans exceeding 10 percent of assets

Skewness and D’Agostino skewness test of OLS residuals ($\sim N(0, 1)$ asymptotically): skewness = 4.7958 (> 0) \Rightarrow positively skewed test statistic = 16.7863 with *p*-value < 2.2E−16 \Rightarrow positively skewed with statistical significance.

Histogram and density of OLS residuals in the relative frequency scale appear in Appendix 3

Likelihood ratio test of $H_0 : \sigma_\mu^2 = 0$ vs. $H_1 : \sigma_\mu^2 > 0$ (asymptotically distributed as 50:50 mixture of $\chi^2_{(1)}$ and $\chi^2_{(0)}$): test statistic = 511.1877 with *p*-value < 2.2E−16 \Rightarrow strongly reject linear regression model (i.e., absence of inefficiency) in favor of stochastic frontier model (i.e., presence of inefficiency)

Table 6 2016 unsecured consumer loans. Excluding the volume of unsecured consumer lending. Summary statistics of nonperformance derived from stochastic frontier estimation

Variable	N	Mean	Median
Observed nonperforming loan ratio	387	0.0299	0.0215
Noise-adjusted observed nonperforming loan ratio	387	0.0299	0.0215
Best-practice nonperforming loan ratio	387	0.0029	0.0027
Excess nonperforming loan ratio	387	0.0188	0.0271
Lending inefficiency ratio	387	0.8143	0.8795

Table 7 2013 unsecured consumer loans–stochastic frontier estimation. Excluding the volume of unsecured consumer lending. Best-practice (minimum) ratio of nonperforming consumer loans

Parameter	Variable	Coefficient estimate	Pr(> t)
β_1	Growth rate in consumer lending from 2010 to 2013 _i	−0.000067	0.802076
β_2	Contractual consumer loan rate _i	0.094798	0.003677
β_3	[Contractual consumer loan rate _i] ²	−0.185662	0.007190
β_4	[Contractual consumer loan rate _i] × [GDP Growth Rate _i]	−0.006164	0.140330
β_5	[Contractual consumer loan rate _i] × [Herfindahl Index _i]	0.011745	0.778062
$\sigma_\mu = 1/\theta$		0.032451	0.000000
σ_v		0.002119	0.044223

The data set includes LendingClub and 654 top-tier bank holding companies at the end of 2013 with plausible values of nonperforming unsecured consumer loans and total loans exceeding 10 percent of assets

Skewness and D’Agostino skewness test of OLS residuals ($\sim N(0, 1)$ asymptotically): skewness= 4.3289 (> 0) \Rightarrow positively skewed test statistic = 20.6471 with p -value < 2.2E−16 \Rightarrow positively skewed with statistical significance. Histogram and density of OLS residuals in the relative frequency scale appear in Appendix 4

Likelihood ratio test of $H_0 : \sigma_\mu^2 = 0$ vs. $H_1 : \sigma_\mu^2 > 0$ (asymptotically distributed as 50:50 mixture of $\chi^2_{(1)}$ and $\chi^2_{(0)}$): test statistic = 753.2751 with p -value < 2.2E−16 \Rightarrow strongly reject linear regression model (i.e., absence of inefficiency) in favor of stochastic frontier model (i.e., presence of inefficiency)

Table 8 2013 unsecured consumer loans. Excluding the volume of unsecured consumer lending. Summary statistics of nonperformance derived from stochastic frontier estimation

Variable	N	Mean	Median
Observed nonperforming loan ratio	655	0.0364	0.0259
Noise-adjusted observed nonperforming loan ratio	655	0.0364	0.0258
Best-practice nonperforming loan ratio	655	0.0040	0.0040
Excess nonperforming loan ratio	655	0.0325	0.0224
Lending inefficiency ratio	655	0.8014	0.8504

Empirical evidence of inherent credit risk and lending inefficiency

As reported in Table 9, the observed NPL ratio is considerably higher in 2016 and 2013 at banks larger than \$1 billion in consumer loans, the two groups of the largest banks. In 2016, the second largest group, which includes LendingClub by its volume of consumer lending, experienced an average of 5.91% and the group of the largest lenders, 5.86%. In 2016, banks under \$1 billion experienced an average ratio ranging from 2.30 to 3.14%. LendingClub at 4.16% in 2016 fell between these groups of small banks and large banks. In 2013 the three groups of the smallest lenders recorded 3.54%, 3.41%, and 4.11%

Table 9 NPL ratio and its decomposed components by size groups of unsecured consumer loans: 2016 and 2013

Year of data	2016			2013		
	Whether to control loan volume in the stochastic frontier model	No volume controls	Volume controls	No volume controls	Volume controls	
Variable	N	Mean	Mean	N	Mean	Mean
LendingClub						
Unsecured consumer Loans*	1	*8,597,596	*8,597,596	1	*1,916,960	*1,916,960
Observed NPL ratio	1	0.0416	0.0416	1	0.0216	0.0216
Noise-adjusted NPL ratio	1	0.0416	0.0416	1	0.0215	0.0215
Best-practice NPL ratio	1	0.0055	0.0376	1	0.0065	0.0089
Excess NPL ratio	1	0.0361	0.0040	1	0.0150	0.0126
Lending inefficiency ratio	1	0.8666	0.0955	1	0.6940	0.5813
Avg. contractual interest rate	1	0.1586	0.1586	1	0.1756	0.1756
< \$10 million in unsecured consumer loans						
Observed NPL ratio	111	0.0230	0.0230	300	0.0354	0.0354
Noise-adjusted NPL ratio	111	0.0230	0.0230	300	0.0355	0.0355
Best-practice NPL ratio	111	0.0035	0.0035	300	0.0042	0.0041
Excess NPL ratio	111	0.0195	0.0195	300	0.0313	0.0314
Lending inefficiency ratio	111	0.7223	0.7231	300	0.7726	0.7740
Avg. contractual interest rate	111	0.0688	0.0688	300	0.0737	0.0737
> \$10 million and < \$100 million in unsecured consumer loans						
Observed NPL ratio	196	0.0301	0.0301	273	0.0341	0.0341
Noise-adjusted NPL ratio	196	0.0301	0.0301	273	0.0341	0.0341
Best-practice NPL ratio	196	0.0028	0.0028	273	0.0039	0.0038
Excess NPL ratio	196	0.0273	0.0273	273	0.0302	0.0302
Lending inefficiency ratio	196	0.8307	0.8296	273	0.8132	0.8133
Avg. contractual interest rate	196	0.0600	0.0600	273	0.0701	0.0701

Table 9 (continued)

Year of data	2016			2013		
	Whether to control loan volume in the stochastic frontier model	No volume controls	Volume controls	No volume controls	Volume controls	
Variable	N	Mean	Mean	N	Mean	Mean
> \$100 Million and < \$1 billion in unsecured consumer loans						
Observed NPL ratio	57	0.0314	0.0314	60	0.0411	0.0411
Noise-adjusted NPL ratio	57	0.0314	0.0314	60	0.0411	0.0411
Best-practice NPL ratio	57	0.0021	0.0023	60	0.0033	0.0036
Excess NPL ratio	57	0.0293	0.0291	60	0.0377	0.0375
Lending inefficiency ratio	57	0.8913	0.8849	60	0.8567	0.8466
Avg. contractual interest rate	57	0.0501	0.0501	60	0.0600	0.6000
> \$1 Billion and < \$10 billion in unsecured consumer loans						
Observed NPL ratio	14	0.0591	0.0591	14	0.0658	0.0658
Noise-adjusted NPL ratio	14	0.0591	0.0591	14	0.0659	0.0659
Best-practice NPL ratio	14	0.0021	0.0062	14	0.0036	0.0061
Excess NPL ratio	14	0.0570	0.0529	14	0.0623	0.0599
Lending inefficiency ratio	14	0.9252	0.8184	14	0.8861	0.8146
Avg. contractual interest rate	14	0.0560	0.0560	14	0.0627	0.0627
> \$10 Billion in unsecured consumer loans						
Observed NPL ratio	9	0.0586	0.0586	8	0.0633	0.0633
Noise-adjusted NPL ratio	9	0.0586	0.0586	8	0.0632	0.0632
Best-practice NPL ratio	9	0.0036	0.0385	8	0.0048	0.0451
Excess NPL ratio	9	0.0550	0.0202	8	0.0584	0.0182
Lending inefficiency ratio	9	0.9312	0.2895	8	0.9188	0.3031
Avg. contractual interest rate	9	0.0797	0.0797	8	0.0879	0.0879

NPL ratios while the two groups of the largest lenders, 6.58% and 6.33%. LendingClub recorded 2.16%. Our empirical analysis addresses the following key questions:

1. Do the significantly higher NPL ratios in 2016 and 2013 of the two groups of the largest lenders (lenders with over \$1 billion in unsecured consumer loans) reflect lending to riskier borrowers or less efficiency in assessing credit risk and monitoring loans?
2. Does the nearly doubling of LendingClub's NPL ratio between 2013 and 2016 reflect taking on more credit risk or reduced efficiency at assessing credit risk?
3. Comparing lending efficiency without controlling for the techniques of credit-risk assessment, are small relationship-based lenders more efficient than larger lenders assessing credit risk with statistical methods and algorithms – the Bernanke (2011) hypothesis?
4. Comparing large lenders using statistical methods and algorithms, is LendingClub more efficient than large banks?

When the definition of a lender's peers includes loan volume, the best-practice frontier will be influenced by the observed higher lower bound of nonperformance for large lenders. As illustrated in Fig. 2, large lenders will experience a higher best-practice ratio, which implies higher inherent credit risk. Since the higher frontier will be closer to their observed higher rate of nonperformance, their lending inefficiency ratio will be lower.

In addition to the visual inspection of Fig. 2, a coefficient of the fitted frontiers of Eq. (1) with x , which includes loan volume in the specification of peers and gives rise to Figs. 2 and 5, provides further evidence of why controlling for volume bends the frontier upward for larger volumes. As previously noted, the average contractual interest rate charged by large lenders is much higher than that of small lenders. Inspecting the estimated frontiers, the coefficient on the interaction of loan volume and the average contractual interest rate is strikingly large: in Table 1, for 2016, it is 1.7941, and, in Table 3, for 2013, it is 0.6631. Thus, given a lender's loan volume, a higher contractual interest rate increases the lender's best-practice frontier value as a function of the relatively large amount of the coefficient, and the effect is magnified at larger loan volumes. This coefficient provides evidence that the higher frontier for large lenders resulting from controlling for loan volume results in large part from the interaction of loan volume with the relatively high contractual interest rate charged by large lenders.

With controls for loan volume, we expect the best-practice frontier to increase with loan volume. As reported in Table 9, the best-practice ratio ranges in 2016 from 0.0023 to 0.0035 at lenders with less than \$1 billion in consumer loan volume. In the category of volume greater than \$1 billion but less than \$10 billion, the average best-practice ratio increases to 0.0062. Above \$10 billion, the mean best-practice ratio is strikingly large 0.0385. This high best-practice ratio indicates higher inherent credit risk. The difference between the observed NPL ratio (adjusted for noise), 0.0586, and this ratio, 0.0385, is the excess nonperformance ratio, 0.0202. As a proportion of each lender's observed nonperformance, this mean excess ratio yields a mean lending inefficiency ratio of 0.2895, which is the lowest of all the traditional bank lenders in 2016. Hence, for these largest lenders, the high observed NPL ratio, adjusted for noise, results from risk-taking and not

lending inefficiency. While the group of the second largest lenders with consumer loans between \$1 billion and \$10 billion experiences a NPL ratio of 0.591, its inherent credit risk is only 0.0062 so that its excess ratio is relatively large. Thus, its lending inefficiency ratio is high, 0.8184, so that its high observed NPL ratio in 2016 results from inefficient lending rather than high credit risk.

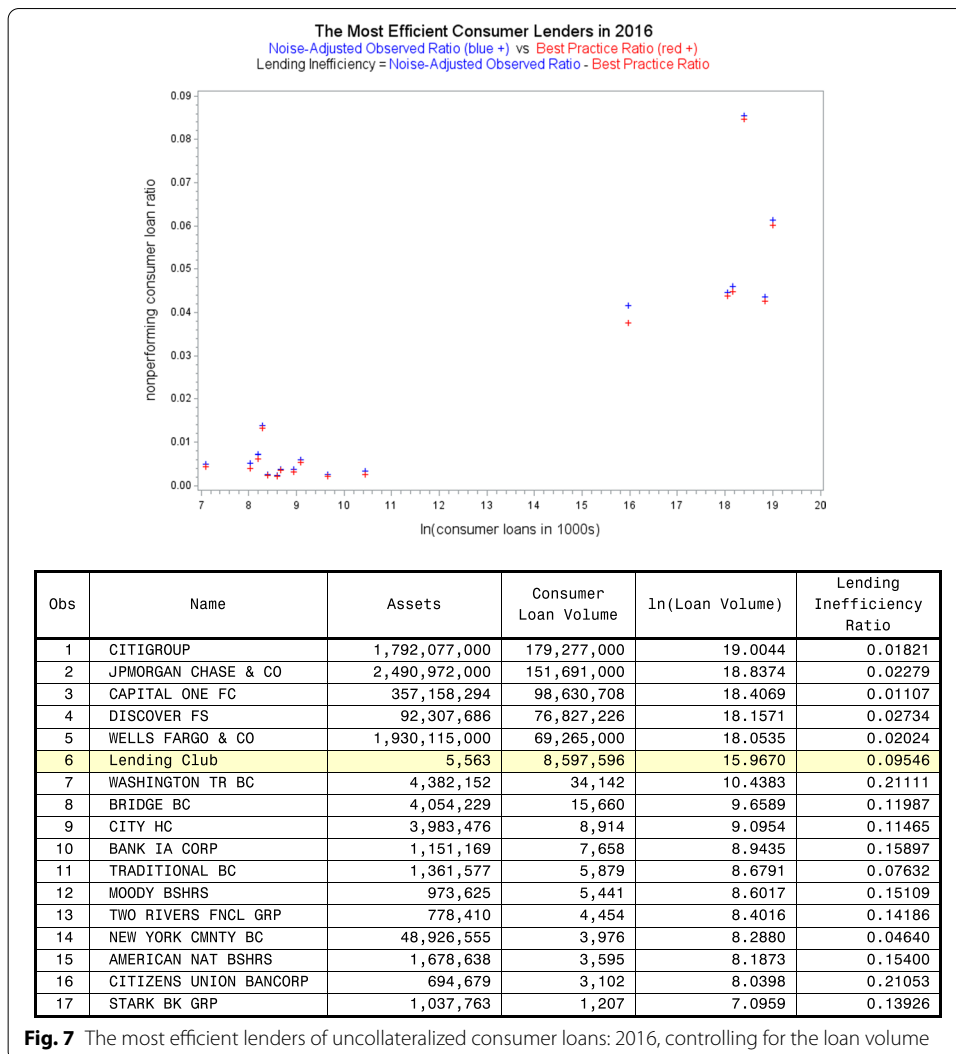
Table 9 reports that the pattern of nonperformance, inherent credit risk, and lending inefficiency observed in 2016 is also observed in 2013. The high mean ratio of nonperforming loans at the largest lenders, 0.0633, is associated with a high mean best-practice ratio, 0.0451, so that its lending inefficiency ratio is low, 0.3031. Again, its high observed nonperformance results primarily from high inherent credit risk and not lending inefficiency. The second largest lenders also experience a relatively high mean NPL ratio, 0.0658, but its mean best-practice ratio is a low 0.0061. Thus, its lending inefficiency ratio is high, 0.8146. As was the case in 2016, this group's high nonperformance in 2013 appears to result from inefficient lending rather than inherent credit risk.

In 2013, LendingClub recorded a NPL ratio of 2.16%. In 2016, the ratio increased to 4.16%. In Table 9, the evidence obtained from the best-practice frontiers including loan volume in the specification of peers indicates that LendingClub's best-practice ratio is 0.0089 in 2013 and 0.0376 in 2016. Thus, LendingClub assumed more inherent credit risk in 2016 than in 2013. Moreover, its lending inefficiency ratio is 0.0955 in 2016 as opposed to 0.5813 in 2013. Compared to 2013, LendingClub's higher NPL ratio in 2016 appears to result from an increase in inherent credit risk and not a higher lending inefficiency.

A number of papers, notably Jagtiani and Lemieux (2018, 2019) and Croux et al. (2020), have hypothesized that, starting in 2015, LendingClub's use of advanced technology in conjunction with some nontraditional data may have allowed it to identify credit risk more accurately. If so, the greater efficiency we measure in the 2016 data for LendingClub may partially reflect this lending strategy.

To compare the lending performance of large lenders using statistical methods and algorithms, we again refer to the two frontiers that include the volume of consumer lending in their specification of peers. Table 9 reports that LendingClub achieves a low inefficiency ratio, 0.0955, in 2016. The second lowest (mean) inefficiency ratio, 0.2895, is recorded by the largest traditional lenders in 2016. Thus, LendingClub appears more efficient than the largest traditional lenders. In 2013, the largest traditional lenders obtained a mean lending inefficiency ratio of 0.3031 compared to LendingClub's 0.5813. As previously noted, LendingClub's adoption of advanced technology in conjunction with some nontraditional data in 2015 may account for this improvement in lending efficiency.

Finally, when comparing lending efficiency without controlling for the techniques of credit-risk assessment, we explore whether small relationship-based lenders are more efficient than larger lenders assessing credit risk with statistical methods and algorithms. Without volume controls, Table 9 reports that the smallest lenders



achieve the lowest mean lending inefficiency, 0.7223, in 2016 and 0.7726 in 2013. In contrast, the largest lenders record the highest mean lending inefficiency: 0.9312 in 2016 and 0.9188 in 2013. LendingClub scores the lowest inefficiency, 0.6940, in 2013. In contrast, it scores a high inefficiency ratio, 0.8666, in 2016. Without controlling for volume, the relatively low NPL ratio at the smallest lenders dominates all sizes in the frontier estimation. These findings of the efficiency of the smallest lenders appears consistent with Bernanke’s observation that the advantages of relationship banking in lending dominate lending based on statistical models and algorithms. With volume controls, these small lenders are still the second most efficient following the largest banks and LendingClub.

Which individual lenders are the most efficient?

In Table 9, efficiency is identified by summary statistics for size groups of lenders. Instead of identifying the most efficient size groups by their group means, we focus on

Table 10 2016 relationship of financial performance measured by Tobin’s q to the ratio of nonperforming unsecured consumer loans to total unsecured consumer loans

Parameter	Variable	Coefficient estimate	Pr(> t)
β_0	Intercept	− 2.22050	< 0.0001
β_1	ln(book value of assets _{<i>t</i>} in 1000 s)	0.38138	< 0.0001
β_2	[ln(book value of assets _{<i>t</i>} in 1000 s)] ²	− 0.01095	< 0.0001
β_3	equity capital _{<i>t</i>} /book value of assets _{<i>t</i>}	0.31487	0.0027
β_4	unsecured consumer loans _{<i>t</i>} /total loans _{<i>t</i>}	0.12164	0.1072
β_5	nonperforming consumer loans _{<i>t</i>} /total unsecured consumer loans _{<i>t</i>}	− 0.03309	0.6860
β_6	[unsecured consumer loans _{<i>t</i>} /total loans _{<i>t</i>}] × [nonperforming consumer loans _{<i>t</i>} /total unsecured consumer loans _{<i>t</i>}]	− 2.43770	0.1140
# of entities	$\partial(q \text{ ratio})/\partial(\text{nonperforming loan ratio}) > 0$	N = 0	
	Significantly > 0	N = 0	
# of entities	$\partial(q \text{ ratio})/\partial(\text{nonperforming loan ratio}) < 0$	N = 205	
	Significantly < 0	N = 205	

The data set includes 205 top-tier publicly traded bank holding companies at the end of 2016 with plausible values of nonperforming unsecured consumer loans and total loans exceeding 10 percent of assets. Financial performance is gauged by Tobin’s q ratio. Nonperforming loans are the sum of past due and nonaccruing loans and gross charge-offs. Total unsecured consumer loans include gross charge-offs. Statistical significance is computed from robust standard errors. Bold values indicate statistical significance at stricter than 0.10. Adjusted $R^2 = 0.6626$. AIC = −1358

the most efficient individual lenders across size groups. We take the lender’s technology related to size as given and identify the most efficient lenders given their size across all sizes – those with a lending inefficiency ratio less than 0.25. We use the estimates obtained from the frontier defined in Eq. (1) for 2016 with controls for loan volume and plotted in Fig. 2. In Fig. 7 we plot only the most efficient lenders relative to their peers defined, in part, by the volume of their lending. There is a dichotomy based on lending volume. Efficient lenders are either small or large. There are 10 community banks and 6 large banks as well as LendingClub. Lenders in the mid-range of lending volume are not among these most efficient lenders.

Does market discipline reward or punish credit risk-taking?

The high mean ratios of nonperforming consumer loans for the largest lenders raise the question of how the capital market treats the investment strategies reflected by these high NPL ratios. We investigate the relationship between financial performance measured by Tobin’s q ¹⁹ and the NPL ratio and report the findings in Table 10. Our sample consists of 205 lenders. We find that the derivative of the q ratio with respect to the observed NPL ratio is negative and statistically significant for all 205 observations.

Table 11 shows the relationship of the q ratio to the two components of the NPL ratio: the best-practice ratio (inherent credit risk) and the inefficiency ratio. While the q ratio was negatively related to the aggregate NPL ratio, the relationship to the components is more complicated. Strikingly, the q ratio is *positively* related to the best-practice ratio (inherent credit risk) for 202 lenders and significantly so for 182. It is *negatively* related

¹⁹ The q ratio is defined formally by the ratio of the market value of assets to the replacement cost of assets. We use the frequently adopted proxy for the market value of assets – the sum of the market value of equity and the book value of liabilities – and the proxy for the replacement cost of assets – the book value of assets. See for examples, Demsetz et al. (1996), Pérez-González (2006), and Brook et al. (1998).

Table 11 2016 relationship of financial performance measured by Tobin’s q to the ratio of nonperforming unsecured consumer loans decomposed into the Best-Practice Ratio and the Ratio in Excess of Best Practice (Lending Inefficiency)

Parameter	Variable	Coefficient estimate	Pr(> t)
β_0	Intercept	-2.59067	< 0.0001
β_1	$\ln(\text{book value of assets}_i \text{ in } 1000 \text{ s})$	0.42633	< 0.0001
β_2	$[\ln(\text{book value of assets}_i \text{ in } 1000 \text{ s})]^2$	-0.01232	< 0.0001
β_3	Equity capital/book value of assets _{<i>i</i>}	0.32866	0.0019
β_4	Unsecured consumer loans/total loans _{<i>i</i>}	0.20179	0.1004
β_5	Best-practice nonperforming consumer loans/total unsecured consumer loans _{<i>i</i>}	1.55851	0.0647
β_6	Excess nonperforming consumer loans/total unsecured consumer loans _{<i>i</i>} (lending inefficiency)	0.04723	0.5153
β_7	$[\text{Unsecured consumer loans}/\text{total loans}_i] \times [\text{best-practice nonperforming consumer loans}/\text{total unsecured consumer loans}_i]$	-5.57497	0.0762
β_8	$[\text{Unsecured consumer loans}/\text{total loans}_i] \times [\text{excess nonperforming consumer loans}/\text{total unsecured consumer loans}_i \text{ (lending inefficiency)}]$	-11.78893	0.0094
# of entities	$\partial(q \text{ ratio})/\partial(\text{best-practice } np \text{ ratio}) > 0$ significantly > 0	N = 202 N = 182	
# of entities	$\partial(q \text{ ratio})/\partial(\text{best-practice } np \text{ ratio}) < 0$ significantly < 0	N = 3 N = 0	
# of entities	$\partial(q \text{ ratio})/\partial(\text{inefficiency ratio}) > 0$ significantly > 0	N = 33 N = 0	
# of entities	$\partial(q \text{ ratio})/\partial(\text{inefficiency ratio}) < 0$ significantly < 0	N = 172 N = 102	

The data set includes 205 top-tier publicly traded bank holding companies at the end of 2016 with plausible values of nonperforming unsecured consumer loans and total loans exceeding 10 percent of assets. Financial performance is gauged by Tobin’s q ratio. Nonperforming loans are the sum of past due and nonaccruing loans and gross charge-offs. Total unsecured consumer loans include gross charge-offs. The decomposition of the nonperforming unsecured consumer loan ratio into the best-practice ratio (inherent credit risk) and the ratio in excess of best practice (lending inefficiency) is obtained from a stochastic frontier that defines a lender’s peers as those with credit risk similar to that of the lender’s consumer loan portfolio, similar economic characteristics of the lender’s local markets, such as the weighted 10-year average GDP growth rate and the weighted average Herfindahl index across these markets, where the weights are bank deposit shares, a similar 3-year growth rate of the lender’s consumer lending, and a similar volume of its consumer lending. Statistical significance is computed from robust standard errors. Bold values indicate statistical significance at stricter than 0.10. Adjusted $R^2 = 0.6874$. AIC = -1372

but not significantly so for the remaining 3 lenders. *Lenders’ market value is significantly positively related to inherent credit risk at 182 of the 205 lenders.* Our results suggest that market discipline appears to reward exposure to inherent credit risk.

On the other hand, we also find that *lenders’ market value is negatively related to inefficient lending at 172 and significantly so at 102 lenders.* There are no lenders that experience a significant positive relationship between market value and inefficient lending. Thus, our results overall suggest that market discipline appears to reward inherent credit risk and punish inefficient lending at most lenders.

For model selection, we note that the regression relating financial performance to the traditional nonperforming consumer loan ratio exhibits AIC = -1358 and adjusted R-squared = 0.6626 while the regression relating financial performance to the two decomposed components of the traditional ratio obtains AIC = -1372 and adjusted R-squared = 0.6874. Thus, both the AIC and adjusted R-squared support that the two decomposed components obtained from stochastic frontier estimation are superior to or more informative than the traditional NPL ratio in explaining q ratio.

Between the q ratio estimation with the NPL ratio and that with the decomposition of the ratio into the best-practice ratio and the inefficiency ratio, goodness-of-fit statistics (AIC and adjusted R-squared) confirm that the latter is the better, indicating successful empirical identification of two components of the NPL ratio and showing that the two components affect the q ratio in opposite directions. This implies that the effect of NPL ratio as a whole is the composite of the two oppositely-signed effects and that use of NPL ratio as an aggregate in the q ratio estimation would have missed that there is a component of NPL ratio that impacts the q ratio positively.

Thus, the decomposition adds value compared to using the NPL ratio as an aggregate in evaluating the effect of nonperformance on market value. The effect of NPL ratio as an aggregate is in some sense the mixture of two possibly opposing effects of the decomposed components, thereby reducing the magnitude and the significance of the effect of NPL ratio. We clearly get heightened statistical significance in the two-component-related variables and in most banks the effects of the two components are opposite. The decomposition made possible by the stochastic frontier estimation shows that the two components of the decomposition relate differently to the market performance measure, and it enables us to explain why market discipline may give the largest banks the incentive to take relatively high credit risk.

Conclusions

The entire financial landscape has recently changed driven by advances in financial technology. Fintech lenders have grown and taken away market shares from the banking sector. The use of alternative data and complex modeling by fintech lenders have allowed them to evaluate credit risks more accurately and to expand credit access to those “credit invisible” consumers, without taking on excessive risks. We evaluate the impacts of fintechs on lending efficiency by comparing LendingClub (the largest lender for personal loans) with traditional banks (both large and small banks). We focus our efficiency analysis using data as of 2013 and 2016, because it has been documented in the literature that LendingClub started to fully utilize these data and AI/ML modeling for loans that were originated in 2015. We examine the lending efficiency during the period before and after 2015.

We apply a novel technique developed by Hughes et al. (2017, 2019) to compare the performance of consumer loans made by LendingClub with the performance of consumer loans made by banks. In addition, we compare the performance of consumer loans made by small banks (which tend to rely on relationship lending) to the loan performance of large banks (which tend to rely on statistical methods and algorithms in lending decisions). The Bernanke (2011) notes that “Relationship banking is therefore at the core of community banking. ... This advantage for community banks is fundamental to their effectiveness and cannot be matched by models or algorithms, no matter how sophisticated.” This is one of the hypotheses we explore in this paper.

We use the stochastic frontier analysis to estimate the conditional minimum ratio of nonperforming consumer loans while eliminating the influence of statistical noise (luck). This minimum ratio represents best-observed-practice given the conditioning variables that define lenders’ peers and, thus, answers the question, *what ratio of nonperforming consumer loans to total consumer lending could a bank*

achieve if, relative to its peers, it were fully efficient at credit-risk evaluation and loan management?

The best-practice minimum gauges the inherent credit risk of each lender's consumer loans. The difference between a lender's observed NPL ratio, adjusted for statistical noise, and its best-observed-practice minimum gauges the lender's relative proficiency at assessing credit risk and monitoring loans relative to its peers. This difference, nonperformance in excess of best practice, expressed as a proportion of a lender's observed NPL ratio represents the lender's lending inefficiency ratio. It is important to note that our measure of inefficiency of the firms' lending process is broadly defined to include not only loan risk evaluation, but also the extent to which the lenders' business model may have created increased convenience and/or trust for the borrowers.

When the specification of peers *excludes* lenders' consumer loan volume, the best-practice frontier uses the loan performance of lenders of all sizes to gauge best practice. In estimating this frontier for 2016 and 2013, we find that the smallest consumer lenders achieve the highest lending efficiency, consistent with Bernanke (2011) hypothesis.

Alternatively, when the specification of peers *includes* lenders' consumer loan volume, the loan performance frontier gauges best performance, controlling for the lender's lending volume. In this case, we find that the largest banks experience the highest mean rate of nonperforming unsecured consumer loans, and that this high mean nonperforming rate seems to be associated with riskier loans – in fact, the highest inherent credit risk (best-practice ratio) among the five size groups. Moreover, we find that these largest banks have the smallest inefficiency – i.e., the smallest difference between the observed ratio (adjusted for statistical noise) and the best-practice (minimum) ratio. Consequently, when the specification of peers includes loan volume, we find in 2016 and 2013 that these largest bank lenders are, on average, the most efficient of all banks at consumer lending even though they experience the highest observed rate of nonperformance. In both years, smaller lenders are much less efficient; however, among them, the smallest lenders are the most efficient.

While the volume of LendingClub's unsecured consumer lending places it in the second largest group of consumer lenders (in the range \$1 billion to \$10 billion) in 2016, there are notable differences between these traditional lenders and LendingClub. In 2016, LendingClub's best-practice ratio is considerably higher than the ratio of these bank lenders, which indicates that LendingClub assumes more inherent credit risk than banks do in its size group. Moreover, these bank lenders are less efficient than LendingClub. We conclude from 2016 data that LendingClub's unsecured consumer lending exhibited inherent credit risk and lending efficiency that resembled the risk and efficiency of the largest banks – that is, higher credit risk-taking and greater lending efficiency. On average, as of 2016, we find that LendingClub's lending inefficiency ratio was lower than the mean ratio of the largest bank group. We speculate that the observed greater lending efficiency may be related to a greater capacity to accurately evaluate credit risk using more advanced technology, more complex algorithms, and alternative data sources that might be less accessible

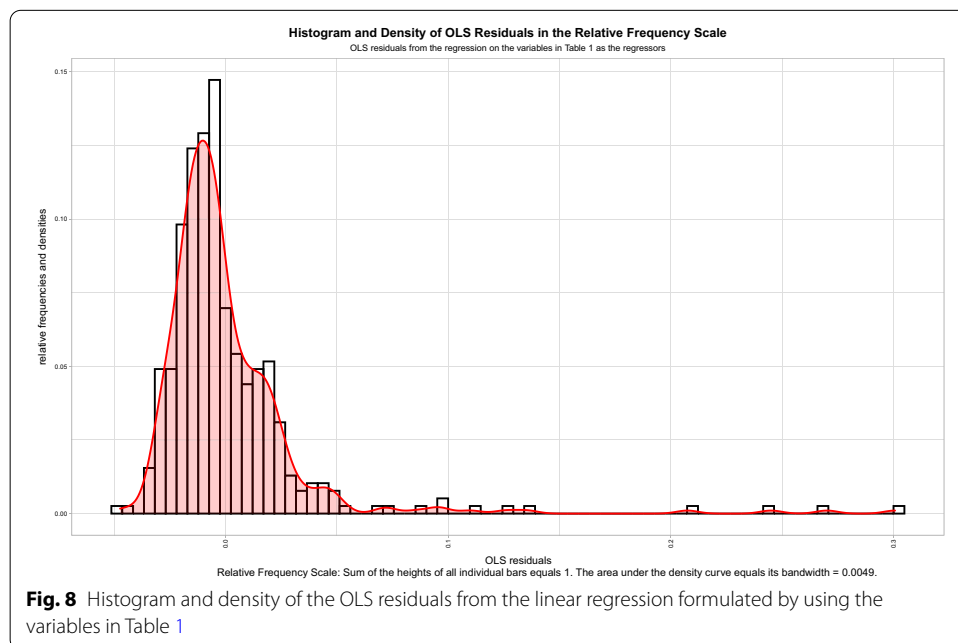
by traditional small lenders. Our results are also consistent with Kou, Akdeniz, Dincer, and Yuksel (2021) which find that fintech has made a significant contribution to the entire financial system by reducing costs, providing higher quality services, and increasing customer satisfaction.

We note that the higher inherent credit risk-taking at the largest banks and at Lending-Club does not necessarily imply inappropriate risk-taking. We find evidence that, while greater lending inefficiency tends to erode market value at most banks, taking more inherent credit risk enhances market value at most lenders. We conclude that additional risk-taking at most lenders may be motivated by market discipline through the lenders' incentive to maximize their market value.

It is also important to keep in mind that fintech lenders had not yet been through a full economic cycle and a major recession during our sample period 2013–2016. One might question whether their credit evaluation models would continue to perform as well during a recession as they did during the economic expansion periods. Unfortunately, we are not likely to learn much by updating the sample to include data during the 2019–2020 pandemic-induced recession as this is very different from the prior recessions. The combination of massive transfer payments and changes in the rules for loan forbearance means that the 2020 pandemic-induced recession did not have nearly the same effect on NPL ratios (and charge-offs) that one might have expected given the depth of the downturn. Our findings may not necessarily apply during a “normal” recession.

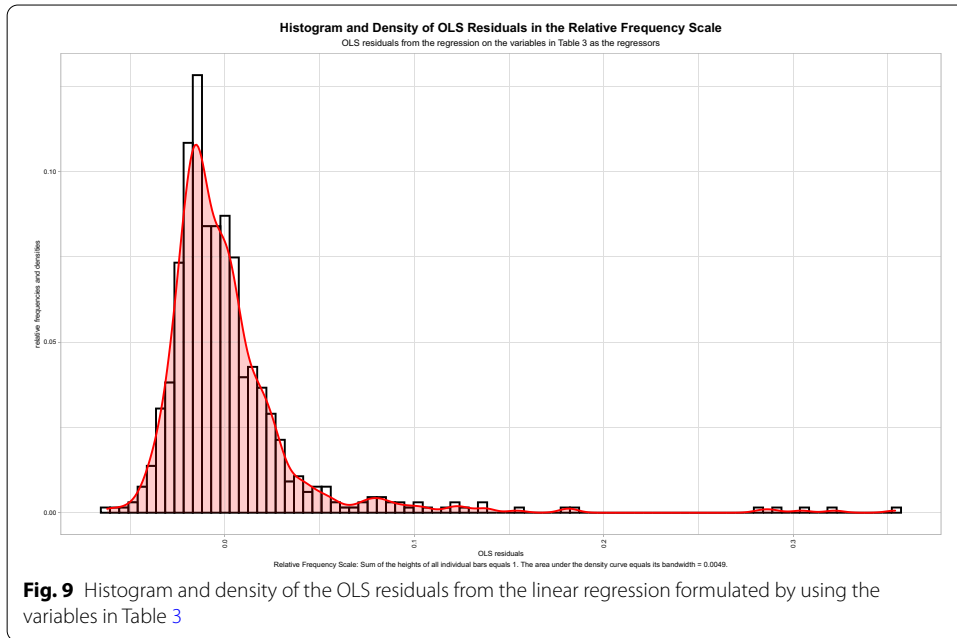
Appendix 1

See Fig. 8.



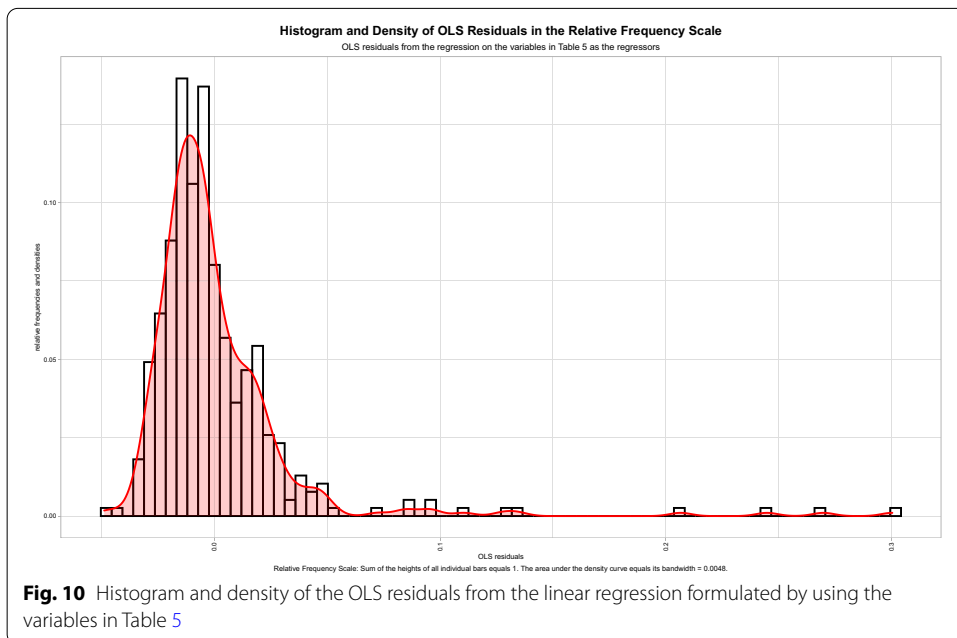
Appendix 2

See Fig. 9.



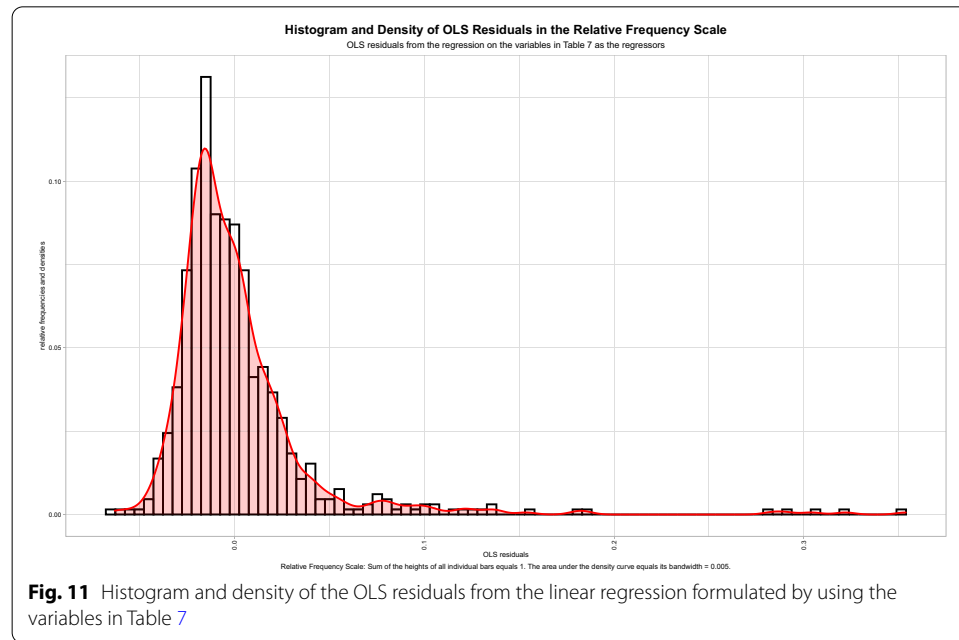
Appendix 3

See Fig. 10.



Appendix 4

See Fig. 11.



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Authors' contributions

Jagtiani provided the data on LendingClub and much of the bank data. Hughes and Moon performed the econometric analysis. All three authors contributed to writing and revising the text. All authors approved the final manuscript.

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Availability of data and materials

For the bank data, from Call Reports and Y-9C, the data are publicly available from the FDIC website. For fintech data, LendingClub made the data publicly available on its website until recently – the data are no longer released to the public as of today.

Declarations

Competing interests

The authors declare that they have no competing interests.

Disclaimer

The opinions expressed in this paper are the authors' own views and do not necessarily represent the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

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