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ABSTRACT

We compare the performance of unsecured personal installment loans made by traditional bank lenders with that of LendingClub, using a stochastic frontier estimation technique to decompose the observed nonperforming loans into three components. The first is the best-practice minimum ratio that a lender could achieve if it were fully efficient at credit-risk evaluation and loan management. The second is a ratio that reflects the difference between the observed ratio (adjusted for noise) and the minimum ratio that gauges the lender's relative proficiency at credit analysis and loan monitoring. The third is statistical noise. In 2013 and 2016, the largest bank lenders experienced the highest ratio of nonperformance, the highest inherent credit risk, and the highest lending efficiency, indicating that their high ratio of nonperformance is driven by inherent credit risk, rather than by lending inefficiency. LendingClub's performance was similar to small bank lenders as of 2013. As of 2016, LendingClub's performance resembled the largest bank lenders — the highest ratio of nonperforming loans, inherent credit risk, and lending efficiency — although its loan volume was smaller. Our findings are consistent with a previous study which suggest that LendingClub became more effective in risk identification and pricing starting in the 2015. Caveat: we note that this conclusion may not be applicable to fintech lenders in general, and the results may not hold under different economic conditions such as a downturn.

Keywords: marketplace lending, P2P lending, credit risk management, lending efficiency
JEL Codes: G21, L25, C58

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1. Introduction

Fintech lending has grown exponentially in recent years. LendingClub has become the largest lender in the U.S. for unsecured personal installment loans. Previous research suggests that fintech lending has changed the financial landscape and expanded credit access to consumers. Some consumers have saved a significant amount by borrowing from LendingClub to pay off their credit card balance and boost their credit scores. Jagtiani and Lemieux (2018 and 2019) show that, starting in 2015, the use of alternative data and complex algorithms have allowed fintech lenders to more accurately evaluate and price credit risk, thus being able to offer loans to more consumers at lower prices.[1] We attempt to explore LendingClub's lending efficiency compared with traditional lenders.

Using 2013 and 2016 data (before and after 2015), we compare the lending efficiency of LendingClub with U.S. bank holding companies (BHCs), focusing on unsecured consumer loans, which exclude mortgages, automobile loans, home equity loans, and home equity lines of credit.[2] We define lending efficiency based on the percent of unsecured consumer loans that are nonperforming (i.e., the sum of past-due and charged-off consumer loans).[3] In 2013, average nonperforming loan ratios are 3.84 percent for loans held by BHCs compared with 2.17 percent at LendingClub.[4] In 2016, BHCs' nonperforming rate declined from 3.84 percent to 3.00 percent, while LendingClub's nonperforming rate almost doubled from 2.17 percent to 4.16 percent. We ask whether LendingClub's higher rate of nonperformance in 2016 was a result of increased risk appetite (lending to riskier borrowers who default more often) or

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[1] See also Goldstein, Jagtiani, and Klein (2019), Jagtiani and John (2018), and Jagtiani, Vermilyea, and Wall (2018).

[2] Jagtiani, Lambie-Hanson, and Lambie-Hanson (2019) 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, probably because of the required process to qualify for conforming and Federal Housing Administration (FHA) mortgage origination standards.

[3] Since some banks are more aggressive in charging off past-due loans, we sum charged-off loans and past-due loans to eliminate bias because of the different charge-off strategies.

[4] To calculate the percentage of consumer loans that are nonperforming, we divide the sum of past due loans and gross charge-offs by the sum of consumer loans and gross charge-offs. In the Y9-C bank data, past due loans are included in the volume of consumer loans, but charge-offs are excluded.

decreased proficiency in credit analysis and risk management? Similarly, we ask whether the lower rate of BHCs' nonperformance in 2016 was the result of taking less credit risk or getting better at loan monitoring and credit risk management.

To explore these questions, we estimate the best practice ratio of consumer loans that are nonperforming for each type of lender, based on Hughes and Moon (2017). This is the minimum ratio of nonperforming consumer loans observed among all lenders in the sample, given their total volume of consumer loans to total loans, the average contractual interest rate they charge on their consumer loans (as a proxy of credit risk), and the economic conditions in their lending markets as measured by the average GDP growth rate and the local banking market concentration.

Best-Practice Ratio: The best-practice ratio indicates the minimum ratio of nonperforming consumer loans to the total consumer loans a lender could achieve if it were fully efficient at credit risk evaluation and loan management. By using stochastic frontier analysis to estimate this conditional minimum, the influence of luck (statistical noise) can be eliminated. Thus, the difference between a BHC's achieved nonperforming loan ratio, adjusted for statistical noise, and the conditional minimum ratio (the best observed-practice ratio) would gauge a lender's relative proficiency at credit risk analysis and loan management.

Controlling for Size: We divide BHC lenders into five size groups based on their consumer loan volume — largest banks (more than $10 billion), large banks ($1 billion to $10 billion), and three more groups of small banks (all less than $1 billion). LendingClub's volume of unsecured consumer lending as of 2016 makes it comparable to large bank lenders. In terms of performance, LendingClub's rate of observed nonperformance — at 4.16 percent — is similar to the median nonperforming rate for both the largest banks and the large bank groups. However, having the same nonperforming loan ratio does not necessarily imply that they all are equally efficient.

We examine whether the similarity in the nonperforming loan ratios imply that the largest banks, large banks, and LendingClub all obtain similar exposures to credit risk. In addition, lenders exposed to the same amount of credit risk may not have the same nonperforming loan ratio because some lenders could be better at credit risk analysis and management. We find that LendingClub's nonperformance ratio is similar to the median best practice rates of nonperformance for the largest bank lenders — and it is much higher than the median best practice nonperformance rate of the large bank lenders group (which is in the same size category as LendingClub). The higher best practice minimum nonperformance ratio means that the gap between the observed and the minimum ratio is smaller. Therefore, the largest bank lenders and LendingClub both exhibit higher lending efficiency than other bank lenders.

In 2013, LendingClub's rate of nonperformance ratio, which was very small at 2.17 percent, resembles the medians of smaller bank lenders (with less than $1 billion in unsecured consumer loans). Unlike in 2016, the best practice minimum nonperformance ratio was relatively low and similar across all size groups and for LendingClub. Thus, most of the observed nonperformance ratio in 2013 across all lender types seems to be caused by lending inefficiency rather than inherent credit risk. LendingClub and the largest bank lenders made significant improvement in their lending efficiency between 2013 and 2016 compared with smaller bank lenders.

The advancement in big data collection and credit risk modeling may have played an important role here. For example, Governor Lael Brainard (2018) in her speech at the Fintech and the New Financial Landscape conference at the Federal Reserve Bank of Philadelphia refers to important statistics about exponential growth in industry data collection between 2013 and 2016. Specifically, as of 2013, 90 percent of all the data in the world had been collected in the prior two years. Three years later, as of 2016, IBM estimated that 90 percent of all the global data had been collected in the prior year alone.

Caveats: Since our fintech consumer lending data in this study come from a single fintech firm, our conclusions are based solely on LendingClub's loan performance and may not be applicable to the overall fintech lending segment of the financial sector. In addition, while the efficiency metric used in this study has been well accepted, conceptually sound, and widely used in academic literature, our analysis may be subject to some data limitations. There may be factors not observed in our data set or not taken into account by this measure that, if they could be observed and taken into account, might change the measured efficiencies. An important example of such an unobserved factor is that our focus on the recent loan performance does not include performance during an economic downturn. Different results might be observed under downturn conditions, especially if the economic downturn has different impacts on delinquency rates across bank and fintech lenders. Fintech lenders do not take deposits and their funding sources could dry up quickly, and fintech borrowers may be more affected during the downturn. Finally, our evaluation of lending efficiency does not account for other aspects of efficiency, such as the management of overall profit and funding cost.

2. The Data

The sample consists of top-tier U.S. BHCs and LendingClub at year-end 2013 and 2016. The data for the BHCs are obtained from the end-of-year Y9-C reports filed quarterly with regulators. A bank's local markets are identified from the FDIC Summary of Deposits data, which allow the calculation of a bank's local market conditions that influence the performance of its consumer loans — the Herfindahl Hirschman Index (HHI) of market concentration and the 10-year average GDP growth rate. The calculation of a bank's average contractual interest rate on consumer loans relies on end-of-year Call Report data on the interest income received from consumer loans. Bank subsidiaries' data collected from the Call Reports are summed across all subsidiaries under the same BHC to the level of the consolidated BHC. Only BHCs that file quarterly Y9-C reports are included in our sample.[5]

The sample is then reduced to exclude those banks with a ratio of loans to assets of less than 0.10, those with unsecured consumer loans totaling less than $1 million, and those with a ratio of nonperforming consumer loans plus gross charge-offs to total consumer loans (plus charge-offs) that is unusually small likely due to errors (less than 0.001). The remaining 2016 sample consisting of 453 BHCs is then further reduced to 398 BHCs with bank subsidiaries that were required to submit quarterly Call Reports needed to compute the average contractual loan rate on consumer loans. The remaining 2013 sample totals 872 BHCs, 755 of which have data needed to

[5] BHCs with less than $500 million in assets are not required to file Y-9C in 2013, and BHCs with less than $1 billion in assets are not required to file Y-9C reports in 2016. The size threshold was raised in 2015. Thus, the 2016 sample contains fewer bank lenders than the 2013 sample.

calculate the average contractual loan rate. LendingClub is not a bank, and it does not file a Call Report; however, its financial statements and additional data are publicly available on its website and on the SEC website.[6]

For 2016 and 2013 data, Figure 1 and Figure 2, respectively, plot the ratio of nonperforming consumer loans to total consumer loans against the log transformation of total consumer loans (in thousands) and indicate the point representing LendingClub. 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.[7]

Figures 1A and 2A narrow the range of values of the volume of consumer loans (now from $0.44 billion to $192 billion) to magnify the individual points, which capture the largest 39 consumer lenders in 2016 and the largest 26 in 2013. The observed ratios adjusted for statistical noise (luck) are shown in red. Associated with each observed ratio is a best practice ratio, shown in blue, that depends not only on the log transformation of the volume of consumer loans but also on the volume of all loans, the average contractual interest rate on consumer loans, and the GDP growth rate and HHI market concentration in the lender's local markets.

These four figures compare each institution's observed ratio of nonperforming consumer loans (adjusted for statistical noise) with its best-practice minimum ratio. The best-practice minimum ratio represents the ratio a lender could achieve if it were fully efficient at credit-risk evaluation and loan management. As such, the best-practice ratio represents the inherent credit risk of the institution's consumer loan portfolio. And the difference between the observed ratio (adjusted for statistical noise) and the best-practice minimum ratio gauges an institution's lending inefficiency, since the

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[6] LendingClub loans are originated by WebBank, which sells loans back to LendingClub after three days. LendingClub then sells loans to the original investors who committed on the platform to funding them. When LendingClub operated purely as a peer-to-peer lender, it did not hold loans on its books. As it has started to securitize loans in recent years, it has been required by the Dodd–Frank Wall Street Reform and Consumer Protect Act to hold 5 percent of these securitized loans. Payments and losses for all loans are reported at the loan level on the LendingClub website and in its SEC reports. Losses on the loans it sells are absorbed by the investors.

[7] In reporting the volume of consumer loans, we do not include gross charge-offs.

influence of luck as well as local market conditions and the contractual interest rate have been taken into account in estimating the best-practice minimum ratio. Figures 1A and 2A point to these values for LendingClub.

3. Estimating the Best-Practice Nonperforming 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 with other lenders. Hughes and Mester (2015) explain the strategy for the inclusion of these characteristics and environmental variables in the estimating equation (p. 256): "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."

To specify the equation used to estimate the best-practice minimum ratio of nonperforming consumer loans, we define a lender's peers by including variables that are associated with the scale of its lending and lending technology, variables that characterize economic conditions in the institution's local markets, and variables that are related to the credit risk of the borrowers its lending operations attract.

First, we define a lender's peers by the scale of its lending. We include the volume of consumer loans and the volume of all loans and the squared value of each of these volumes to allow for nonlinearity. These volumes control for scale-related effects such as lending technology and the potential for diversification.

Second, we define a lender's peers in terms of the macroeconomic conditions in its local lending markets, which 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 deposits by each bank branch and the branch location. The state GDP growth rate is weighted by the proportion of a lender's deposits located in that state.

Third, we 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 in which the lender operates. The state concentration index is weighted by the proportion of the lender's deposits that are located in each 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 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 volume of consumer loans 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 volume of consumer lending with the GDP growth rate and with the index of market concentration.

Fourth, 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 since this interest rate is related to the credit risk of the borrowers it attracts. The contractual interest rate includes a credit risk premium and, itself, influences the quality of loan applicants through adverse selection.[8] Moreover, a higher rate puts

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

more financial pressure on a borrower and increases the probability of delinquency.[9] 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 also offer loan applicants superior quality services that result in a better selection of loan applicants (in terms of credit risk) for any particular contractual interest rate charged. Examples of superior quality services include speed and convenience (e.g., a geographically convenient local bank with a relationship to the borrower, a lender offering a fast and easy application process, and a lender making 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 rate of nonperformance 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. 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.[10]

We obtain the contractual rate from Call Report data by dividing the interest income received from consumer loans by the volume of consumer loans. 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 rate with the volume of

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

[10] Since LendingClub offers the convenience of consumers 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. 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.

consumer lending. To allow for the possibility that the average contractual rate's association with loan performance differs by market concentration, we interact the average contractual rate with the index of market concentration.

The specific specification of the equation to be estimated is given by

$$NP_i = \boldsymbol{X\beta} + \varepsilon_i, \tag{1}$$

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

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

x_1 = *Total consumer loans*$_i$ (100 billions),

x_2 = (*Total consumer loans*$_i$ (100 billions))^2,

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

x_4 = (*Total loans*$_i$ (100 billions))^2,

x_5 = *Total consumer loans*$_i$ (100 billions) × *Contractual consumer loan rate*$_i$,

x_6 = *Total consumer loans*$_i$ (100 billions) × *GDP growth rate across bank*$_i$*'s markets*,

x_7 = *Total consumer loans*$_i$ (100 billions) × *Herfindahl index of market concentration across bank*$_i$*'s markets*,

x_8 = *Contractual consumer loan rate*$_i$ × *Herfindahl index of market concentration across bank*$_i$*'s markets*,

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, $v_i \sim$ iid $N(0,\sigma_v^2)$, that captures statistical noise, and a term, μ_i, distributed exponentially, $\mu_i\ (> 0) \sim \theta\exp(-\theta u)$, that measures the systematic excess nonperforming loan ratio.[11] The deterministic kernel of the frontier defines the minimum (best practice) ratio:

$$\textbf{Best-Practice } \boldsymbol{NP_i} = \boldsymbol{X\beta}. \tag{2}$$

[11] We 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. We also tested whether a constant term is needed. For both 2013 and 2016, we found that, with statistical significance, the normal/exponential model is better than the normal/half-normal model. For 2013, with statistical significance the normal/exponential model with a constant term is better than the normal/exponential model without a constant term. For 2016, the normal/exponential model with a constant term is better than the normal/exponential model without a constant term, which is, however, statistically insignificant.

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

$$\textbf{\textit{Excess NP}}_{\boldsymbol{i}} = E(\mu_i|\varepsilon_i) \tag{3}$$

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

$$\textbf{\textit{Noise}}_{\boldsymbol{i}} = E(\nu_i|\varepsilon_i) = \varepsilon_i - E(\mu_i|\varepsilon_i). \tag{4}$$

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

$$\textbf{\textit{Noise-Adjusted NP}}_{\boldsymbol{i}} = NP_i - E(\nu_i|\varepsilon_i). \tag{5}$$

Thus, the estimation of equation (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:

$$\begin{aligned} NP_i &= \textbf{\textit{Best-Practice NP}}_{\boldsymbol{i}} + \textbf{\textit{Excess NP}}_{\boldsymbol{i}} + \textbf{\textit{Statistical Noise}}_{\boldsymbol{i}} \\ &= \textbf{\textit{Inherent Credit Risk}}_{\boldsymbol{i}} + \textbf{\textit{Inefficiency}}_{\boldsymbol{i}} + \textbf{\textit{Statistical Noise}}_{\boldsymbol{i}} \\ &= \boldsymbol{X\beta} + E(\mu_i|\varepsilon_i) + E(\nu_i|\varepsilon_i). \end{aligned} \tag{6}$$

Figures 1A and 2A highlight the distance between the noise-adjusted nonperforming loan ratio and the best-practice ratio for LendingClub. Rearranging equation (6) expresses this distance for any particular observation as the excess nonperforming loan ratio or inefficiency:

$$\begin{aligned} \textbf{\textit{Inefficiency}}_{\boldsymbol{i}} &= \textbf{\textit{Noise-Adjusted NP}}_{\boldsymbol{i}} - \textbf{\textit{Best-Practice NP}}_{\boldsymbol{i}} \\ E(\mu_i|\varepsilon_i) &= [NP_i - E(\nu_i|\varepsilon_i)] - \boldsymbol{X\beta}. \end{aligned} \tag{7}$$

The estimated equation (1) is described in Table 1 for 2016 and in Table 1A for 2013.

4. Evidence of Inherent Credit Risk and Lending Inefficiency

Figures 1 and 2 plot the ratio of nonperforming consumer loans to total consumer loans against the log transformation of total consumer loans (in thousands) for 2016 and 2013, respectively. Figure 1A and 2A narrow the range of values of the volume of consumer loans to magnify the individual points. Table 2 reports that the average noise-adjusted, observed ratio of nonperforming consumer loans for all lenders is 0.0300 in 2016, and Table 2A reports the value of 0.0384 in 2013. Tables 3 and 3A provide basic summary statistics for the variables as of 2016 and 2013, respectively.

Tables 4 and 4A partition lenders by the volume of their consumer lending in 2016 and 2013, respectively. Panel A in both tables summarizes the median values partitioned by the volume of unsecured consumer lending. Panel B in both tables provides all summary statistics for these partitions. As of 2016, the median noise-adjusted nonperforming consumer loan ratio ranges from 0.0181 for the group of the smallest lenders to 0.0496 for the group of the largest lenders. Larger lenders experience a higher nonperforming ratio in 2016. The difference on this ratio was even larger in 2013, ranging from 0.0244 for the smallest lenders to 0.0639 for the largest lenders.

How much of these nonperforming loan ratios reflect the inherent credit risk that lenders assume? How much of these are caused by a lack of proficiency in assessing credit risk and managing loan portfolios? The plots in Figures 1, 2, 1A, and 2A provide evidence that addresses these questions. In particular, the observed ratios adjusted for statistical noise (luck) are shown in red, and associated with each observed ratio is a best-practice ratio shown in blue. The best-practice (minimum) nonperforming ratio depends not only on the log transformation of the volume of consumer loans but also on the volume of all loans, the average contractual interest rate on consumer loans, and the GDP growth rate and the HHI market concentration in the institution's local markets — the variables that define a lender's peers. This best-practice minimum ratio gauges the inherent credit risk of a lender (i.e., the nonperforming consumer loan ratio a lender would obtain if it were fully efficient at credit-risk evaluation and loan management relative to its peers). *The difference between the noise-adjusted observed ratio and the best-practice ratio, which is the amount of the nonperforming loan ratio in excess of the best-practice minimum, gauges a lender's inefficiency in assessing credit risk and in managing loan portfolios.*

The best-practice ratio, represented by the blue points in the four plots, displays a pattern in 2016 that is similar to the pattern in 2013. The best-practice ratio appears nearly constant across the size of lenders until it starts to increase among the largest lenders. Partitioning lenders into groups by the size of their unsecured consumer lending, Table 4 (2016) and Table 4A (2013) provide summary statistics that confirm this pattern. The median values are summarized in Panel A of both tables.

In 2016, Table 4 Panel A shows that the median best-practice ratio equals 0.0015 for the three groups of small banks (with less than $1 billion of unsecured consumer loans). Larger lenders in the range of $1 billion to $10 billion exhibit a higher median best-practice ratio of 0.0024. Comparing LendingClub with bank lenders, as of 2016, while LendingClub's volume of consumer lending places it in the group size range of $1 billion to $10 billion, LendingClub obtains a much higher best-practice ratio of 0.0408 (instead of 0.0024) than its peers. LendingClub's best-practice ratio is similar to the median best-practice ratio of 0.0428 for the largest bank lenders (with more than $10 billion in consumer loans). This narrows the gap between the observed ratio and the best-practice ratio for LendingClub, relative to its peers.

In 2013, Table 4A Panel A shows that the range of median best-practice rates for the three groups of smaller institutions is very narrow at 0.0024 to 0.0025. For large bank lenders (with consumer loans totaling $1 billion to $10 billion), the median best-practice ratio is 0.0037. Unlike in 2016, LendingClub, whose loan volume falls in this range, seems to behave in a similar fashion to its peer group in 2013, with the best-practice nonperforming ratio of 0.0061. The best-practice ratio for the largest lenders (consumer loans exceeding $10 billion) is 0.0479, which is significantly higher than LendingClub's ratio.

Overall, we find that LendingClub seems to perform similarly to its peer group in 2013, but it became more efficient than its peer size group in 2016. LendingClub became as efficient as the largest bank lenders in 2016, although it belongs to the smaller-size group based on its consumer lending activities in 2016. Notably, LendingClub's inherent credit risk rose substantially from 2013 to 2016, causing the best-practice ratio to rise from 2013 to 2016, but without the same increase in the observed nonperforming ratio. In addition, our analysis suggest that the largest bank lenders were taking more inherent credit risk in both 2013 and 2016, compared with smaller lenders.

For all lenders, Tables 2 and 2A report that the average noise-adjusted, observed ratio of nonperforming consumer loans for all lenders is 0.0300 in 2016 and 0.0384 in 2013, while the median best-practice ratio is 0.0016 in 2016 and 0.0025 in 2013. The noise-adjusted ratio, represented by the red points, shows a pattern in 2016 that is similar to that in 2013. Most of the largest banks display observed ratios very close to their best-practice minimum ratios. However, for many smaller banks, the spread between the observed and best-practice ratios is much wider. This spread gauges lending proficiency — the effectiveness of credit evaluation and loan management. For all lenders, this difference, the median excess nonperforming loan ratio, is 0.0192 in 2016 and 0.0233 in 2013.

The median excess nonperforming ratio, when broken down by the consumer lending size groups, shows the pattern evident in the four plots. Specifically, the median excess nonperforming loan ratio ranges from the smallest size group to the largest size groups in 2016 is as follows: 0.0165 for the smallest bank lenders (less than $10 million); 0.0200 for bank lenders from $10 million to $100 million; 0.0212 for bank lenders from $100 million to $1 billion; and 0.0389 for large banks ($1 billion to $10 billion); and 0.0009 for the largest banks (more than $10 billion). The ratio rises as bank size gets larger but then declines dramatically as bank size increases to more than $10 billion.

As mentioned previously, for bank lenders in the range of $1 billion to $10 billion, the median excess nonperforming loan ratio increases to 0.0389; however, this excess ratio at LendingClub is only 0.0008, a much smaller ratio at LendingClub than that of its size group peers ($1 billion to $10 billion). Interestingly, the median excess ratio of the largest lenders (consumer lending that exceeds $10 billion) is only 0.0009, which is the smallest median inefficiency of all the five size group of banks — even smaller than that of the smallest size group. LendingClub's excess ratio is 0.0008, which is even smaller (but very close to) than that of the largest bank lenders. In summary, the largest bank lenders and LendingClub appear to be more proficient at consumer lending than banks in smaller size groups.

Notably, these largest lenders also assume the highest inherent credit risk measured by the median of 0.0428. The small difference, 0.0009, between the noise-adjusted observed ratio, 0.0496, and the best-practice ratio, 0.0428, provides evidence of the lending proficiency of the largest bank lenders. LendingClub resembles these largest lenders in their high rate of observed nonperformance, 0.0416, and their high best-practice rate, 0.0408, whose difference, 0.0008, reflects efficient lending. The chart in Figure 1A, which identifies the lenders in the plot, shows that LendingClub and many of the largest bank lenders exhibit similar inherent credit risk and lending efficiency. A number of papers, notably Jagtiani and Lemieux (2018 and 2019), 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. Our analysis using 2013 data suggests that LendingClub's performance was not superior to its peer size bank lenders in 2013.[12]

5. Conclusions

We apply the techniques developed by Hughes and Moon (2017) and used in Hughes, Jagtiani, Mester, and Moon (2018) to compare the performance of consumer

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[12] In 2013, the mean noise-adjusted, observed ratio of nonperforming consumer loans for all lenders is 0.0384, and the median is 0.0261. The plots in Figures 2 and 2A show that most of the largest lenders experience a nonperforming consumer loan ratio, which is very close to its best-practice ratio. Groups of smaller lenders with consumer loans totaling less than $1 billion exhibit similar median noise-adjusted and best-practice ratios. As shown in Table 4A, Panel B, their median noise-adjusted nonperforming loan ratios fall in the narrow range of 0.0244 to 0.0286. However, larger lenders with consumer loans totaling between $1 billion and $10 billion experience a much higher median noise-adjusted ratio, 0.0532, and a median best-practice ratio, 0.0037, which is larger than that of smaller banks. Their median excess nonperforming loan ratio, 0.0494, is the highest of the five size groups. The volume of LendingClub's consumer loans places it among the lenders in this group; however, its excess nonperforming loan ratio is much lower, 0.0155 -- the difference between an observed, noise-adjusted ratio of 0.0216 and a best-practice ratio of 0.0061. The largest lenders with consumer loans in excess of $10 billion exhibit a median excess ratio, 0.0039. These very large lenders take on high inherent credit risk, a median best-practice ratio of 0.0479, and experience a median observed, noise-adjusted ratio, 0.0639. Measured by the median values, the largest bank lenders experience the highest observed rate of nonperformance, the highest best-practice rate, and the lowest rate in excess of best-practice, the lowest lending inefficiency. The credit risk assumed by most of the largest bank lenders is much greater than LendingClub, while their lending proficiency is generally better. The list of lenders corresponding to the plot in Figure 2A shows that five of the six largest bank lenders obtain a very small degree of lending inefficiency.

loans made by the largest fintech consumer lending platform, LendingClub, with the performance of consumer loans made by traditional bank lenders. Stochastic frontier analysis is used 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 and, thus, answers the question — *what ratio of nonperforming consumer loans to total consumer lending could a bank achieve if 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 an observed ratio of nonperforming consumer loans, adjusted for statistical noise, and the best observed practice minimum gauges the relative proficiency of the institution at assessing credit risk and monitoring loans.

We find the largest bank lenders experience the highest median rate of nonperforming unsecured consumer loans and that this high nonperforming loan rate seems to be associated with risker loans rather than inefficiency in lending. The largest banks have the smallest inefficiency, as measured by the smallest difference between the (noise-adjusted) observed ratio and the best-practice (minimum) ratio. These largest bank lenders are, on average, the most efficient at consumer lending even though they experience the highest observed rate of nonperformance.

LendingClub's unsecured consumer lending places it in the second-largest group of consumer lenders ($1 billion to $10 billion). However, our analysis suggests that there are notable differences between these traditional lenders and LendingClub in 2016 (but not in 2013). In 2016, the median ratio of (noise-adjusted) observed nonperforming loans is similar between LendingClub and these traditional banks (in the second-largest group), but the difference between the (noise-adjusted) observed nonperformance ratio and the best-practice ratio is higher for these bank lenders than for LendingClub, indicating that LendingClub is more efficient than these large banks. LendingClub's small degree of inefficiency more closely resembles that of the largest bank lenders.

Our results suggest that, as of 2016, LendingClub's unsecured consumer lending exhibited inherent credit risk and lending efficiency that resembled the risk and efficiency of the largest traditional bank lenders; that is, higher credit risk-taking and greater lending efficiency. These results were not found as of 2013. Our findings are consistent with Jagtiani and Lemieux (2019), which suggest 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 (starting in 2015). Such advanced technology might be less accessible for smaller traditional lenders.[13]

We note that the higher inherent credit risk-taking at the largest bank lenders and at LendingClub does not necessarily imply inappropriate risk-taking. Hughes and Moon (2017) find evidence that, while greater lending inefficiency tends to erode market value at all banks, taking more inherent credit risk enhances market value at the largest banks. They conclude that additional credit risk-taking at the largest bank lenders may be motivated by market discipline through the lenders' incentive to maximize their market value.

[13] Again, while the efficiency metric used in this study has been well accepted, conceptually sound, and widely used in academic literature, our analysis may be subject to some data limitations. There may be factors not observed in our data set or not taken into account by this measure that, if they could be observed and taken into account, might change the measured efficiencies. Different results might be observed under downturn conditions, especially if the economic downturn has different impacts on delinquency rates across bank and fintech lenders.

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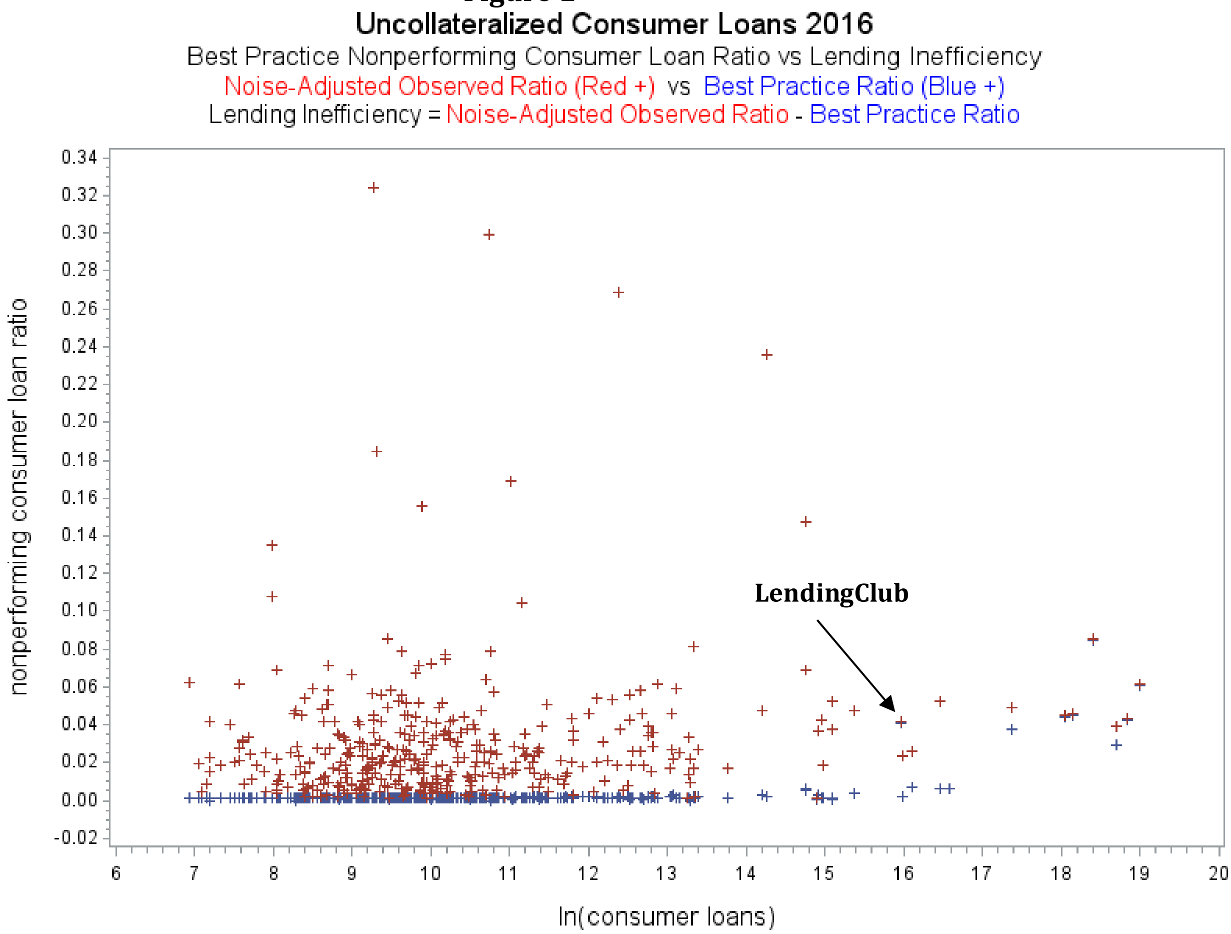
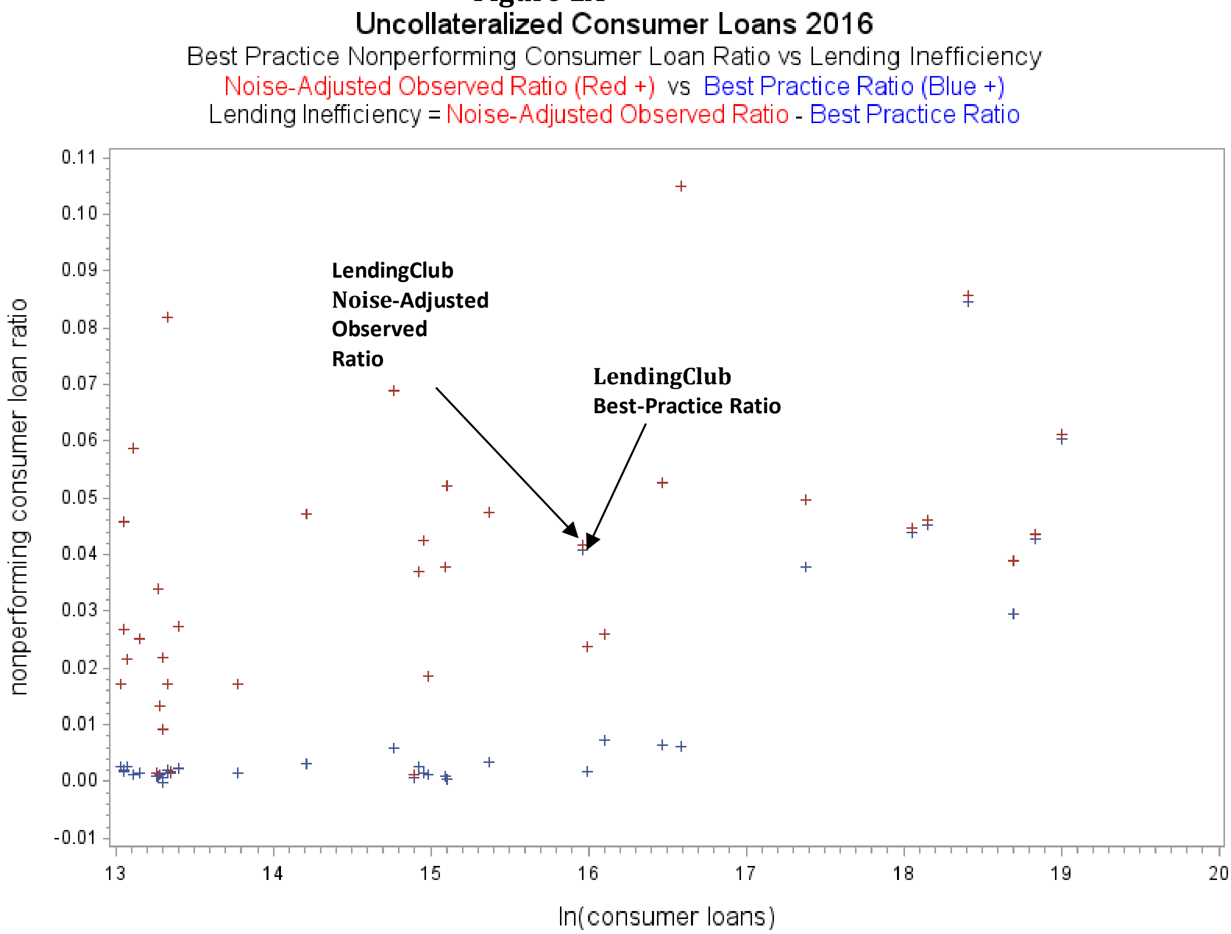
Figure 1



Loan Volume in $1000s

Figure 1A

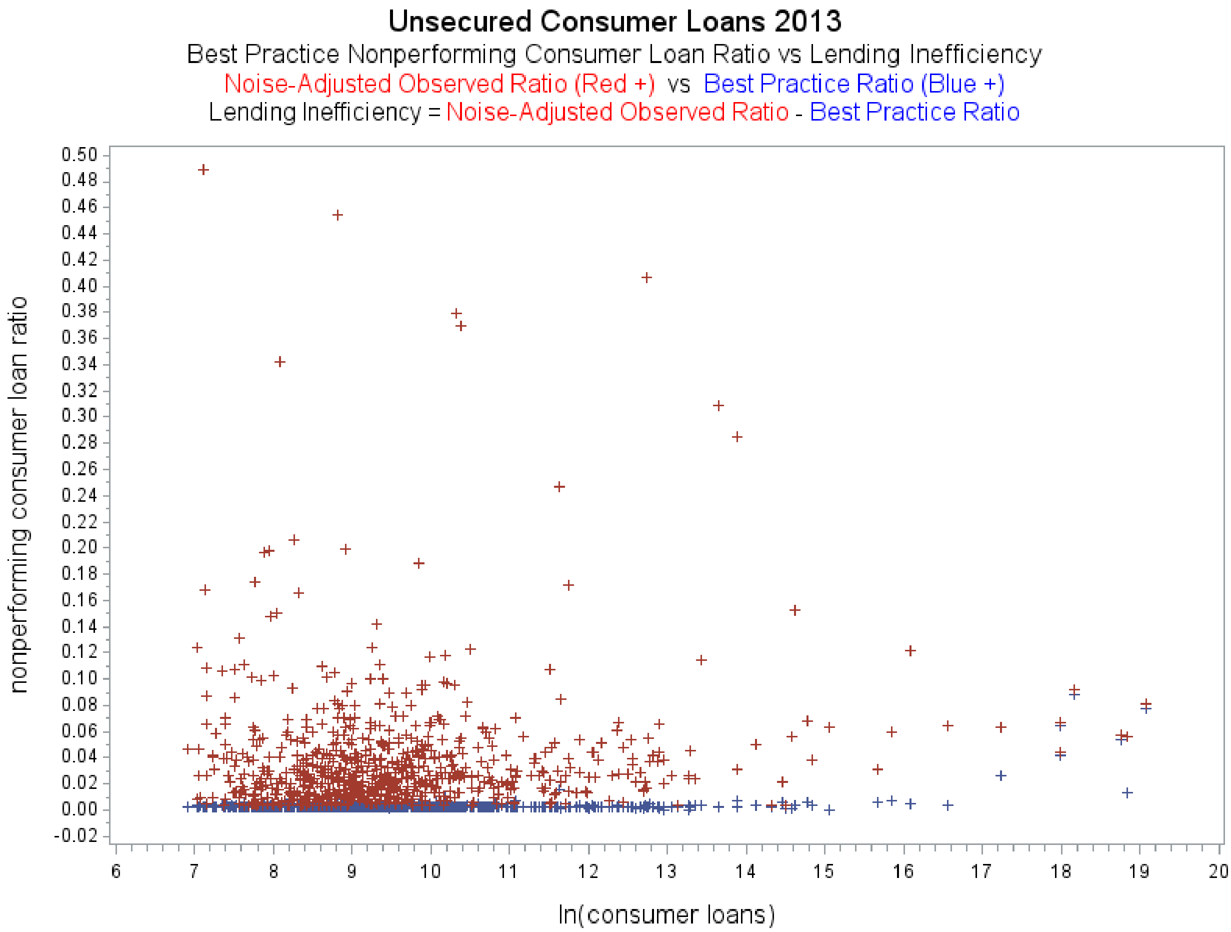


Loan Volume in $1000s

Name	Book Value of Assets	Log (Consumer Loans 1000s)	Noise-Adjusted Observed Ratio	Best-Practice Ratio	Excess Over Best Practice	Average Contractual Interest Rate
1 CITIGROUP	1,792,077,000	19.004	0.0613	0.0603	0.0010	0.1216
2 JPM CHASE	2,490,972,000	18.837	0.0436	0.0428	0.0008	0.0760
3 BANK OF AMERICA	2,189,266,000	18.700	0.0391	0.0297	0.0093	0.0672
4 CAPITAL ONE	357,158,294	18.407	0.0856	0.0847	0.0009	0.1136
5 DISCOVER FS	92,307,686	18.157	0.0461	0.0453	0.0008	0.1139
6 WELLS FARGO	1,930,115,000	18.053	0.0447	0.0438	0.0009	0.0777
7 U S BC	445,964,000	17.380	0.0496	0.0378	0.0117	0.0648
8 SUNTRUST	205,214,392	16.584	0.1051	0.0062	0.0989	0.0397
9 PNC	366,872,249	16.470	0.0527	0.0064	0.0463	0.0425
10 CITIZENS	150,022,885	16.100	0.0259	0.0073	0.0186	0.0453
11 BB&T CORP	219,276,323	15.997	0.0238	0.0017	0.0221	0.0431
12 LendingClub	**5,563**	**15.967**	**0.0416**	**0.0408**	**0.0008**	**0.1382**

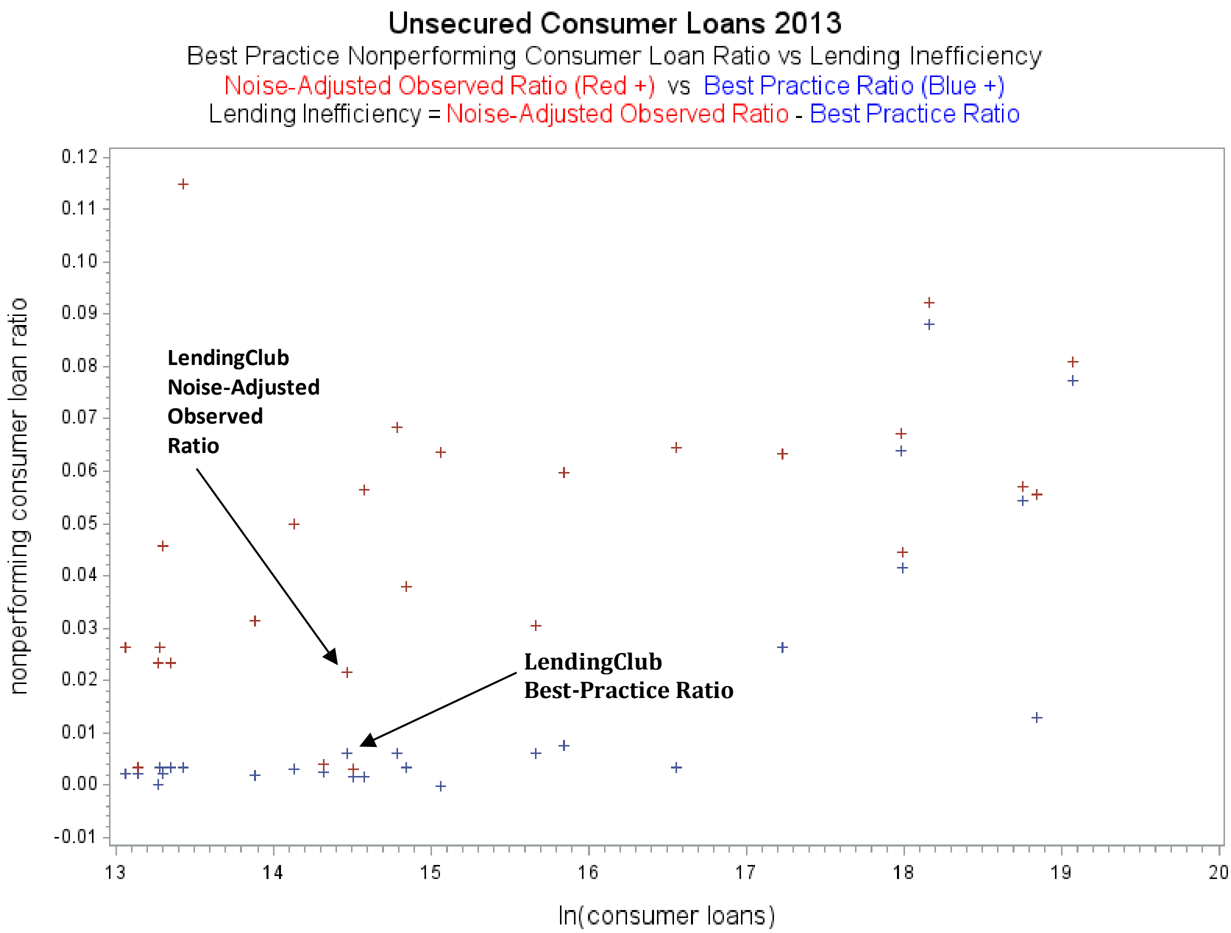
	Name	Book Value of Assets	Log (Consumer Loans 1000s)	Noise-Adjusted Observed Ratio	Best-Practice Ratio	Excess Over Best Practice	Average Contractual Interest Rate
13	KEYCORP	136,825,848	15.375	0.0475	0.0035	0.0440	0.0402
14	FIFTH THIRD	142,176,830	15.105	0.0521	0.0005	0.0516	0.0454
15	M&T	123,449,206	15.088	0.0379	0.0011	0.0369	0.0467
16	HUNTINGTON BSHRS	99,714,097	14.981	0.0186	0.0012	0.0173	0.0370
17	REGIONS FC	126,193,957	14.956	0.0425	0.0015	0.0409	0.0565
18	GOLDMAN SACHS	860,185,000	14.923	0.0370	0.0027	0.0343	0.0238
19	BANK OF NY MELLON	333,469,000	14.893	0.0011	0.0007	0.0004	0.0194
20	POPULAR	38,662,000	14.762	0.0689	0.0058	0.0631	0.1192
21	EDUCATIONAL SVC OF AMER	3,199,348	14.753	0.0473	0.0031	0.0442	0.0379
22	UNITED NAT CORP	2,489,646	14.275	0.0173	0.0014	0.0159	0.0499
23	COMMERCE BSHRS	25,659,294	14.209	0.0273	0.0024	0.0249	0.0610
24	SYNOVUS FC	30,104,002	13.779	0.0019	0.0014	0.0005	0.0456
25	ARVEST BK GRP	16,708,319	13.399	0.0172	0.0015	0.0157	0.0466
26	BANCORP	4,858,114	13.347	0.0818	0.0022	0.0796	0.0241
27	MB FNCL	19,302,317	13.335	0.0092	-.0002	0.0093	0.0409
28	FIRST BC	11,922,455	13.332	0.0217	0.0006	0.0212	0.1173
29	COMERICA	73,129,915	13.299	0.0133	0.0011	0.0122	0.0286
30	ZIONS BC	63,239,165	13.298	0.0339	0.0009	0.0329	0.0648
31	CHEMICAL FC	17,355,179	13.282	0.0015	0.0010	0.0006	0.0251
32	FIRST CITIZENS	32,990,836	13.271	0.0253	0.0014	0.0239	0.0499
33	VALLEY NAT BC	22,864,439	13.266	0.0588	0.0011	0.0577	0.0289
34	IBERIABANK CORP	21,659,190	13.151	0.0216	0.0027	0.0189	0.0652
35	HANCOCK HC	23,984,114	13.111	0.0459	0.0018	0.0441	0.0590
36	FARMERS & MRCH	3,646,580	13.074	0.0268	0.0020	0.0248	0.0323
37	NBT BC	8,867,268	13.054	0.0172	0.0025	0.0147	0.0433
38	FIRST INTRST	9,065,354	13.050	0.0436	0.0428	0.0008	0.0446
39	CULLEN/FROST BKR	30,236,088	13.035	0.0391	0.0297	0.0093	0.0393

Figure 2



Loan Volume in $1000s

Figure 2A



Loan Volume in $1000s

Obs	Name	Book Value of Assets	Log (Consumer Loans 1000s)	Noise-Adjusted Observed Ratio	Best-Practice Ratio	Excess Over Best Practice	Average Contractual Interest Rate
1	Citigroup Inc.	1,880,382,000	19.071	0.0807	0.0773	0.0034	0.1260
2	Bank of America Corporation	2,104,995,000	18.845	0.0555	0.0128	0.0428	0.0706
3	JPMorgan Chase & Co.	2,415,689,000	18.758	0.0571	0.0542	0.0029	0.0815
4	Capital One Financial Corporation	297,282,098	18.161	0.0923	0.0879	0.0043	0.1306
5	Discover Financial Services	79,339,664	17.994	0.0445	0.0416	0.0029	0.1103
6	Wells Fargo & Company	1,527,015,000	17.984	0.0671	0.0640	0.0031	0.0760
7	U.S. Bancorp	364,021,000	17.236	0.0633	0.0264	0.0369	0.0678

Obs	Name	Book Value of Assets	Log (Consumer Loans 1000s)	Noise-Adjusted Observed Ratio	Best-Practice Ratio	Excess Over Best Practice	Average Contractual Interest Rate
8	PNC Financial Services Group	320,596,232	16.560	0.0646	0.0034	0.0612	0.0407
9	Keycorp	92,991,716	15.841	0.0596	0.0076	0.0520	0.0341
10	Bb&T Corporation	183,009,992	15.663	0.0306	0.0059	0.0247	0.0627
11	Fifth Third Bancorp	129,685,180	15.065	0.0635	-.0002	0.0637	0.0529
12	M&T Bank Corporation	85,162,391	14.849	0.0380	0.0034	0.0346	0.0652
13	Popular, Inc.	35,749,000	14.782	0.0684	0.0061	0.0623	0.1180
14	Regions Financial Corporation	117,661,732	14.574	0.0565	0.0014	0.0551	0.0583
15	Bank of New York Mellon Corporation	374,310,000	14.506	0.0032	0.0015	0.0017	0.0161
16	**LendingClub**	1,943	14.466	0.0216	0.0061	0.0155	0.1350
17	Wintrust Financial Corporation	18,097,783	14.321	0.0040	0.0025	0.0015	0.0379
18	Commerce Bancshares, Inc.	23,081,892	14.135	0.0498	0.0030	0.0467	0.0694
19	Firstmerit Corporation	23,912,451	13.885	0.0315	0.0019	0.0296	0.0545
20	First Bancorp	12,656,925	13.428	0.1147	0.0034	0.1114	0.1226
21	ARVEST BK GRP	14,113,477	13.353	0.0234	0.0032	0.0201	0.0603
22	First Niagara Financial Group,	37,643,867	13.301	0.0457	0.0021	0.0436	0.0446
23	FARMERS & MRCH INV	2,915,224	13.282	0.0263	0.0033	0.0230	0.0263
24	Comerica Incorporated	65,356,580	13.270	0.0233	0.0002	0.0231	0.0269
25	City National Corporation	29,717,951	13.145	0.0032	0.0023	0.0009	0.0487
26	Zions Bancorporation	56,031,127	13.065	0.0264	0.0021	0.0243	0.0662

Table 1

2016 Unsecured Consumer Loans — Stochastic Frontier Estimation Best-Practice (Minimum)Ratio of Nonperforming Consumer Loans Including Gross Charge-Offs to the Total Amount of Consumer Loans

The data set includes LendingClub and 397 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.

Parameter	Variable	Coefficient Estimate	Pr(>|t|)
β_0	Intercept	**0.001655**	0.0000
β_1	Consumer Loans$_i$ (scaled)	0.005418	0.2300
β_2	Consumer Loans$_i$ (scaled)]^2	**−0.093679**	0.0000
β_3	Total Loans$_i$ (scaled)	**−0.005247**	0.0000
β_4	[Total Loans$_i$ (scaled)]^2	**0.000155**	0.0041
β_5	[Consumer Loans$_i$ (scaled)] × [Consumer Loan Rate$_i$]	**1.660013**	0.0000
β_6	[Consumer Loans$_i$ (scaled)] × [GDP Growth Rate$_i$]	**0.104910**	0.0000
β_7	[Consumer Loans$_i$ (scaled)] × [Herfindahl Index$_i$]	**−0.555252**	0.0000
β_8	[Consumer Loan Rate$_i$] × [Herfindahl Index$_i$]	−0.014061	0. 1900
$\sigma_\mu = 1/\theta$		**0.000336**	0.0008
σ_v		**0.027528**	0.0000

Table 2
2016 Unsecured Consumer Loans

Variable	N	Mean	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
Observed NPL Ratio	398	0.0300	0.0010	0.0110	0.0216	0.0370	0.3240
Noise-Adjusted Observed NPL Ratio	398	0.0300	0.0011	0.0110	0.0216	0.0370	0.3240
Best-Practice NPL Ratio	398	0.0025	-0.0007	0.0015	0.0016	0.0016	0.0847
Excess NPL Ratio	398	0.0275	0.0002	0.0091	0.0192	0.0340	0.3225

Table 3
2016 Unsecured Consumer Loans
by Size Groups of Consolidated Assets

ASSETS < $1 BILLION						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Observed NPL Ratio	30	0.0260	0.0142	0.0526	0.0020	0.2992
Noise_Adjusted NPL Ratio	30	0.0260	0.0142	0.0526	0.0021	0.2992
Best-Practice NPL Ratio	30	0.0029	0.0016	0.0072	0.0014	0.0408
Excess NPL Ratio	30	0.0232	0.0122	0.0527	0.0005	0.2976

ASSETS > $1 BILLION AND < $10 BILLION						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Observed NPL Ratio	302	0.0293	0.0206	0.0356	0.0011	0.3240
Noise_Adjusted NPL Ratio	302	0.0293	0.0206	0.0356	0.0015	0.3240
Best-Practice NPL Ratio	302	0.0016	0.0016	0.0003	0.0011	0.0057
Excess NPL Ratio	302	0.0277	0.0190	0.0355	0.0002	0.3225

ASSETS > $10 BILLION AND < $50 BILLION						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Observed NPL Ratio	44	0.0323	0.0268	0.0199	0.0015	0.0818
Noise_Adjusted NPL Ratio	44	0.0323	0.0268	0.0199	0.0015	0.0818
Best-Practice NPL Ratio	44	0.0013	0.0012	0.0009	-0.0007	0.0058
Excess NPL Ratio	44	0.0310	0.0252	0.0196	0.0006	0.0796

ASSETS > $50 BILLION AND < $250 BILLION						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Observed NPL Ratio	13	0.0378	0.0379	0.0243	0.0092	0.1051
Noise_Adjusted NPL Ratio	13	0.0377	0.0379	0.0243	0.0092	0.1051
Best-Practice NPL Ratio	13	0.0053	0.0012	0.0123	-0.0003	0.0453
Excess NPL Ratio	13	0.0325	0.0221	0.0249	0.0008	0.0989

ASSETS > $250 BILLION						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Observed NPL Ratio	9	0.0461	0.0447	0.0224	0.0010	0.0856
Noise_Adjusted NPL Ratio	9	0.0461	0.0447	0.0224	0.0011	0.0856
Best-Practice NPL Ratio	9	0.0343	0.0378	0.0281	0.0007	0.0847
Excess NPL Ratio	9	0.0117	0.0009	0.0170	0.0004	0.0463

Table 4
2016 Unsecured Consumer Loans
by Size Groups of Unsecured Consumer Loans

Panel A: Summary Statistics: Median Values

	< $10 M	> $10 M < $100 M	> $100 M < $1 B	> $1 B < $10 B	Lend. Club	> $10 B
Noise-Adjusted NPL Ratio	0.0181	0.0215	0.0217	0.0420	0.0416	0.0496
Best-Practice NPL Ratio	0.0015	0.0015	0.0015	0.0024	0.0408	0.0428
Excess NPL Ratio	0.0165	0.0200	0.0212	0.0389	0.0008	0.0009

Table 4 (Continued)
2016 Unsecured Consumer Loans
by Size Groups of Unsecured Consumer Loans

Panel B: Summary Statistics: All Values

< $10 MILLION IN UNSECURED CONSUMER LOANS						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Unsecured Consumer Loans*	116	5,434	5,501	2,567	1,025	9,909
Observed NPL Ratio	116	0.0236	0.0181	0.0213	0.0020	0.1354
Noise_Adjusted NPL Ratio	116	0.0236	0.0181	0.0213	0.0021	0.1354
Best-Practice NPL Ratio	116	0.0015	0.0015	0.0003	-0.0007	0.0016
Excess NPL Ratio	116	0.0221	0.0165	0.0213	0.0005	0.1339
Avg. Contractual Interest Rate	116	0.0691	0.0617	0.0347	0.0048	0.2112
> $10 MILLION AND < $100 MILLION IN UNSECURED CONSUMER LOANS						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Unsecured Consumer Loans*	202	31,492	23,534	21,964	10,006	98,584
Observed NPL Ratio	202	0.0301	0.0215	0.0380	0.0011	0.3240
Noise_Adjusted NPL Ratio	202	0.0301	0.0215	0.0380	0.0015	0.3240
Best-Practice NPL Ratio	202	0.0015	0.0015	0.0002	-0.0000	0.0020
Excess NPL Ratio	202	0.0286	0.0200	0.0380	0.0002	0.3225
Avg. Contractual Interest Rate	202	0.0597	0.0571	0.0250	0.0075	0.2204
> $100 MILLION AND < $1 BILLION IN UNSECURED CONSUMER LOANS						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Unsecured Consumer Loans*	57	333,145	287303	184,959	109,981	964,509
Observed NPL Ratio	57	0.0314	0.0218	0.0364	0.0015	0.2686
Noise_Adjusted NPL Ratio	57	0.0314	0.0217	0.0364	0.0015	0.2686
Best-Practice NPL Ratio	57	0.0015	0.0015	0.0005	-0.0002	0.0027
Excess NPL Ratio	57	0.0299	0.0212	0.0363	0.0005	0.2662
Avg. Contractual Interest Rate	57	0.0501	0.0466	0.0185	0.0191	0.1173
> $1 BILLION AND < $10 BILLION IN UNSECURED CONSUMER LOANS						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Unsecured consumer Loans*	14	4,266,418	3,167,727	2,750,465	1,482,167	9,823,886
Observed NPL Ratio	14	0.0591	0.0420	0.0609	0.0010	0.2354

Noise_Adjusted NPL Ratio	14	0.0591	0.0420	0.0608	0.0011	0.2354
Best-Practice NPL Ratio	14	0.0056	0.0024	0.0104	0.0005	0.0408
Excess NPL Ratio	14	0.0535	0.0389	0.0622	0.0004	0.2332
Avg. Contractual Interest Rate	14	0.0545	0.0453	0.0335	0.0194	0.1382

> $10 BILLION IN UNSECURED CONSUMER LOANS

Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Unsecured consumer Loans*	9	85,934,972	76,827,226	59,484,300	14,221,715	179,277,000
Observed NPL Ratio	9	0.0586	0.0496	0.0223	0.0391	0.1051
Noise_Adjusted NPL Ratio	9	0.0586	0.0496	0.0223	0.0391	0.1051
Best-Practice NPL Ratio	9	0.0397	0.0428	0.0246	0.0062	0.0847
Excess NPL Ratio	9	0.0189	0.0009	0.0334	0.0008	0.0989
Avg. Contractual Interest Rate	9	0.0797	0.0760	0.0305	0.0397	0.1216

LENDINGCLUB

NAME	**Consumer Loans (1000s)**	**Observed NPL Ratio**	**Noise-Adjusted NPL Ratio**	**Best-Practice NPL Ratio**	**Excess NPL Ratio**	**Avg. Contractual Interest Rate**
LendingClub	8,597,596	0.0416	0.0416	0.0408	0.0008	0.138154

* Measured in $1,000s

Table 1A

2013 Unsecured Consumer Loans — Stochastic Frontier Estimation
Best-Practice (Minimum) Ratio of Nonperforming Consumer Loans Including Gross Charge-Offs to the Total Amount of Consumer Loans

The data set includes LendingClub and 755 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.

Parameter	Variable	Coefficient Estimate	Pr(>|t|)
β_0	Intercept	**0.001924**	0.0002
β_1	Consumer Loans$_i$ (scaled)	**−0.234812**	0.0003
β_2	Consumer Loans$_i$ (scaled)]^2	**−0.082520**	0.0027
β_3	Total Loans$_i$ (scaled)	−0.005183	0.2392
β_4	[Total Loans$_i$ (scaled)]^2	0.000402	0.2189
β_5	[Consumer Loans$_i$ (scaled)] × [Consumer Loan Rate$_i$]	0.678566	0.2409
β_6	[Consumer Loans$_i$ (scaled)] × [GDP Growth Rate$_i$]	**0.090493**	0.0291
β_7	[Consumer Loans$_i$ (scaled)] × [Herfindahl Index$_i$]	**−0.147475**	0.0005
β_8	[Consumer Loan Rate$_i$] × [Herfindahl Index$_i$]	**0.108067**	0.0068
$\sigma_\mu = 1/\theta$		**0.001598**	0.0000
σ_v		**0.035223**	0.0000

Table 2A
2013 Unsecured Consumer Loans

Variable	**N**	**Mean**	**Minimum**	**Lower Quartile**	**Median**	**Upper Quartile**	**Maximum**
Observed NPL Ratio	755	0.0384	0.0010	0.0137	0.0261	0.0452	0.4889
Noise-Adjusted Observed NPL Ratio	755	0.0384	0.0030	0.0136	0.0261	0.0451	0.4889
Best-Practice NPL Ratio	755	0.0031	-0.0002	0.0023	0.0025	0.0027	0.0879
Excess NPL Ratio	755	0.0352	0.0006	0.0107	0.0233	0.0416	0.4870

Table 3A
2013 Unsecured Consumer Loans
by Size Groups of Consolidated Assets

ASSETS < $1 BILLION						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Observed NPL Ratio	371	0.0379	0.0268	0.0453	0.0011	0.4064
Noise_Adjusted NPL Ratio	371	0.0379	0.0267	0.0453	0.0033	0.4063
Best-Practice NPL Ratio	371	0.0027	0.0025	0.0010	0.0020	0.0159
Excess NPL Ratio	371	0.0352	0.0241	0.0451	0.0009	0.4040
ASSETS > $1 BILLION AND < $10 BILLION						
Variable	**N**	**Mean**	**Median**	**Std.Dev.**	**Minimum**	**Maximum**
Observed NPL Ratio	327	0.0371	0.0248	0.0515	0.0010	0.4889
Noise_Adjusted NPL Ratio	327	0.0371	0.0247	0.0514	0.0030	0.4889
Best-Practice NPL Ratio	327	0.0027	0.0025	0.0008	0.0018	0.0082
Excess NPL Ratio	327	0.0344	0.0221	0.0513	0.0006	0.4870
ASSETS > $10 BILLION AND < $50 BILLION						
Variable	**N**	**Mean**	**Median**	**Std Dev**	**Minimum**	**Maximum**
Observed NPL Ratio	38	0.0461	0.0372	0.0502	0.0011	0.3095
Noise_Adjusted NPL Ratio	38	0.0461	0.0371	0.0501	0.0032	0.3094
Best-Practice NPL Ratio	38	0.0025	0.0024	0.0009	0.0016	0.0061
Excess NPL Ratio	38	0.0436	0.0340	0.0501	0.0009	0.3071
ASSETS > $50 BILLION AND < $250 BILLION						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Observed NPL Ratio	11	0.0476	0.0381	0.0287	0.0213	0.1220
Noise_Adjusted NPL Ratio	11	0.0476	0.0380	0.0287	0.0213	0.1219
Best-Practice NPL Ratio	11	0.0061	0.0021	0.0120	-0.0002	0.0416
Excess NPL Ratio	11	0.0414	0.0346	0.0308	0.0029	0.1176
ASSETS > $250 BILLION						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Observed NPL Ratio	8	0.0604	0.0640	0.0264	0.0025	0.0923
Noise_Adjusted NPL Ratio	8	0.0605	0.0639	0.0262	0.0032	0.0923
Best-Practice NPL Ratio	8	0.0409	0.0403	0.0342	0.0015	0.0879
Excess NPL Ratio	8	0.0195	0.0039	0.0237	0.0017	0.0612

Table 4A
2013 Unsecured Consumer Loans
by Size Groups of Unsecured Consumer Loans

Panel A: Summary Statistics: Median Values

	< \$10 M	> \$10 M < \$100 M	> \$100 M < \$1 B	> \$1 B < \$10 B	Lending Club	> \$10 B
Noise-Adjusted NPL Ratio	0.0244	0.0260	0.0286	0.0532	0.0216	0.0639
Best-Practice NPL Ratio	0.0025	0.0025	0.0024	0.0037	0.0061	0.0479
Excess NPL Ratio	0.0220	0.0234	0.0234	0.0494	0.0155	0.0039

Table 4A (Continued)

2013 Unsecured Consumer Loans, by Size Groups of Unsecured Consumer Loans

Panel B: Summary Statistics: All Values

< $10 MILLION IN UNSECURED CONSUMER LOANS						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Unsecured Consumer Loans*	367	5,071	4,893	2,453	1,010	9,990
Observed NPL Ratio	367	0.0367	0.0245	0.0495	0.0010	0.4889
Noise_Adjusted NPL Ratio	367	0.0368	0.0244	0.0494	0.0030	0.4889
Best-Practice NPL Ratio	367	0.0027	0.0025	0.0008	0.0018	0.0082
Excess NPL Ratio	367	0.0341	0.0220	0.0494	0.0006	0.4870
Avg. Contractual Interest Rate	367	0.0753	0.0711	0.0337	0.0113	0.3854
> $10 MILLION AND < $100 MILLION IN UNSECURED CONSUMER LOANS						
Variable	**N**	**Mean**	**Median**	**Std Dev**	**Minimum**	**Maximum**
Unsecured consumer Loans*	303	25,528	18,919	18,183	10,012	94,957
Observed NPL Ratio	303	0.0358	0.0261	0.0383	0.0016	0.3793
Noise_Adjusted NPL Ratio	303	0.0358	0.0260	0.0383	0.0033	0.3792
Best-Practice NPL Ratio	303	0.0026	0.0025	0.0007	0.0016	0.0103
Excess NPL Ratio	303	0.0332	0.0234	0.0382	0.0010	0.3768
Avg. Contractual Interest Rate	303	0.0697	0.0677	0.0281	0.0159	0.2958
> $100 MILLION AND < $1 BILLION IN UNSECURED CONSUMER LOANS						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Unsecured Consumer Loans*	63	268,894	232,962	168,304	100,008	846,659
Observed NPL Ratio	63	0.0495	0.0286	0.0689	0.0011	0.4064
Noise_Adjusted NPL Ratio	63	0.0495	0.0286	0.0688	0.0032	0.4063
Best-Practice NPL Ratio	63	0.0026	0.0024	0.0018	0.0002	0.0159
Excess NPL Ratio	63	0.0469	0.0263	0.0682	0.0009	0.4040
Avg. Contractual Interest Rate	63	0.0599	0.0558	0.0355	0.0248	0.2869
> $1 BILLION AND < $10 BILLION IN UNSECURED CONSUMER LOANS						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Unsecured Consumer Loans*	14	3,288,807	2,184,047	2,658,797	1,072,278	9,718,644

Observed NPL Ratio	14	0.0704	0.0532	0.0744	0.0025	0.2850
Noise_Adjusted NPL Ratio	14	0.0704	0.0532	0.0743	0.0032	0.2850
Best-Practice NPL Ratio	14	0.0039	0.0037	0.0024	-0.0002	0.0076
Excess NPL Ratio	14	0.0665	0.0494	0.0734	0.0015	0.2779
Avg. Contractual Interest Rate	14	0.0598	0.0551	0.0319	0.0161	0.1350
> $10 BILLION IN UNSECURED CONSUMER LOANS						
Variable	**N**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
Unsecured Consumer Loans*	8	92,197,755	71,205,437	62,355,661	15,555,167	191,558,000
Observed NPL Ratio	8	0.0656	0.0640	0.0150	0.0444	0.0923
Noise_Adjusted NPL Ratio	8	0.0656	0.0639	0.0150	0.0445	0.0923
Best-Practice NPL Ratio	8	0.0459	0.0479	0.0304	0.0034	0.0879
Excess NPL Ratio	8	0.0197	0.0039	0.0236	0.0029	0.0612
Avg. Contractual Interest Rate	8	0.0879	0.0788	0.0314	0.0407	0.1306
NAME	**Consumer Loans (1000s)**	**Observed NPL Ratio**	**Noise-Adjusted NPL Ratio**	**Best-Practice NPL Ratio**	**Excess NPL Ratio**	**Avg. Contractual Interest Rate**
LendingClub	1,916,960	0.0217	0.0216	0.0061	0.0155	0.135048

* measured in 1000s