CONSUMER LENDING EFFICIENCY: COMMERCIAL BANKS VERSUS A FINTECH LENDER

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ABSTRACT

Using 2013 and 2016 data, we compare the performance of unsecured consumer loans made by U.S. bank holding companies to that of the fintech lender, LendingClub. We focus on the volume of nonperforming unsecured consumer loans and apply a novel technique developed by Hughes and Moon (2017) that decomposes the observed rate of nonperforming loans into three components: a best-practice minimum ratio, a ratio that gauges nonperformance in excess of the best-practice (reflecting the relative proficiency of credit analysis and loan monitoring), and the statistical noise. Stochastic frontier techniques are used to estimate a minimum rate of nonperforming consumer loans conditioned on the volume of consumer loans and total loans, the average contractual lending rate on consumer loans, and market conditions (GDP growth rate and market concentration).

This minimum gauges best-observed practice and answers the question, *what ratio of nonperforming consumer loans to total consumer lending could a lender achieve if it were fully efficient at credit-risk evaluation and loan management?* The frontier estimation eliminates the influence of luck (statistical noise) and gauges the systematic failure to obtain the minimum ratio. The conditional minimum ratio can be interpreted as a measure of **inherent credit risk**. The difference between the observed ratio, adjusted for statistical noise, and the minimum ratio gauges **lending inefficiency**.

In 2013 and 2016, the largest bank holding companies with consolidated assets exceeding $250 billion experience the highest ratio of nonperforming consumer loans among the five size groups constituting the sample. Moreover, the inherent credit risk of their consumer lending is the highest among the five groups, but their lending efficiency is also the highest. Thus, the high ratio of consumer nonperformance of the largest financial institutions appears to result from assuming more inherent credit risk, not from inefficiency at lending.

In 2016, LendingClub's scale of unsecured consumer lending is slightly smaller than the scale of the largest banks. And like these large lenders, its relatively high nonperforming loan ratio is the result of a higher best-practice ratio of nonperforming consumer loans – i.e., higher inherent credit risk. As of 2016, LendingClub's lending efficiency is similar to the high average efficiency of the largest bank lenders – a conclusion that may not be applicable to other fintech lenders.

While the efficiency metric is well-accepted, widely used, and conceptually sound, it may be subject to some data limitations. For example, our data do not include lending performance during an economic downturn when delinquency rates would be higher and when lenders more experienced with downturns might achieve higher efficiency.

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1. Introduction

Using 2013 and 2016 data, we compare the lending efficiency of U.S. bank holding companies (BHCs) with the fintech lender, LendingClub. We consider their unsecured consumer loans, which exclude automobile loans, home equity loans, and home equity lines of credit. To measure lending efficiency, we focus on the volume of nonperforming loans, which we define as the sum of past-due and charged-off consumer loans.[1] In 2013 we find that on average 3.84 percent of consumer loans held by banks and 2.17 percent of LendingClub's consumer loans are nonperforming.[2] In 2016 banks' nonperforming rate declined to 3.00 percent while LendingClub's rate rose to 4.16 percent. Does LendingClub's higher rate of nonperformance in 2016 result from lending to riskier borrowers (who default more often) or from less proficient credit analysis and risk management? And is the lower rate of nonperformance of banks in 2016 the result of taking less credit risk or getting better at credit risk management?

To explore these questions, we estimate, for each type of lender the best-practice proportion of consumer loans that are nonperforming. This is the minimum ratio of nonperforming consumer loans observed among all lenders in the sample given their total volume of consumer loans and their total loans, the average contractual interest rate they charge on their consumer loans, and the economic conditions in their lending markets measured by the average GDP growth rate and the local banking market concentration. *The best-practice ratio indicates the ratio of*

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

[2] 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.

nonperforming consumer loans to total consumer lending 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 bank's achieved nonperforming consumer loan ratio, adjusted for statistical noise, and the conditional minimum ratio – the best-observed-practice ratio – gauges the lender's relative proficiency at credit analysis and loan management.

LendingClub's volume of unsecured consumer lending in 2016 makes it comparable to large lenders with volumes in the range $1 billion to $10 billion. LendingClub's rate of observed nonperformance, 4.16, is similar to the median rate of this group of large bank lenders as well as the median rate of the largest bank lenders (with unsecured consumer loans greater than $10 billion). Does the similarity in the nonperforming loan rates imply these two groups of large bank lenders and LendingClub obtain similar exposures to credit risk? Or could one lend to riskier borrowers but be more efficient at credit risk analysis – thus, obtaining essentially the same observed rate of nonperformance? In fact, the median best-practice rates of nonperformance for the largest bank lenders (more than $10 billion) and for LendingClub are similar, but they are much higher than the median best-practice rate of the group of large bank lenders (between $1 billion and $10 billion). Therefore, the largest bank lenders and LendingClub exhibit higher lending efficiency than other bank lenders.

In 2013, LendingClub's rate of nonperformance is smaller than in 2016 and, unlike 2016, resembles the medians of groups of smaller bank lenders with less than $1 billion in unsecured consumer loans. Moreover, the best-practice ratio is relatively low and similar among these groups of smaller bank lenders and LendingClub. Thus, most of the observed nonperformance for these lenders results from inefficient lending rather than inherent credit risk. As in 2016, the two groups of the largest bank lenders exhibit the highest median observed rates of nonperformance, but the group of the largest lenders assumes a much higher best-practice rate and, hence, achieves higher lending efficiency.

2. Caveats

First, our conclusions are based on LendingClub's loan performance and, thus, may not generally apply to the overall fintech lending segment of the financial sector. Second, while the efficiency metric is well-accepted, widely used, and conceptually sound, it may be subject to some data limitations. There may be factors not observed in our data 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 if the economic downturn has different impacts on delinquency rates across bank and fintech lenders. Third, we evaluate lending efficiency in terms of the ratio of nonperforming unsecured consumer loans. We do not consider other aspects of efficiency such as the management of profit or cost associated with lending.

3. 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 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 index 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.

The sample is then 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 nonperforming consumer loans plus gross charge-offs to total consumer loans (plus charge-offs) is less than 0.001. The remaining 2016 sample consisting of 453 BHCs is then further reduced to 398 BHCs whose bank subsidiaries 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, of which 755 have data needed to calculate the average contractual loan rate.[3] LendingClub is not a bank and it does not file a Call Report, but its financial statements and additional data are publicly available in its website and the SEC website.[4]

For 2016 and 2013 data, **Figure 1** and **Figure 3**, 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, from $1.03 million to $179.28 billion.[5]

Figure 2 and **Figure 4** narrow the range of values of the volume of consumer loans 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

[3] The minimum asset threshold for mandatory quarterly reporting on the Y9-C form was raised from $0.5 billion to $1 billion in 2015. Thus, the 2016 sample contains fewer banks with less than $1 billion in consolidated assets than the 2013 sample.

[4] LendingClub loans are originated by the WebBank, which sells the loans back to LendingClub after 3 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 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 loans it sells are absorbed by the investors.

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

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 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 loans while the difference between the observed ratio adjusted for statistical noise and the minimum ratio gauges an institution's lending inefficiency since the influence of luck as well as local market conditions and the contractual interest rate have been taken into account in estimating best practice. **Figure 2** and **Figure 4** point to these values for LendingClub.

4. Estimating the Best-Practice Nonperforming Consumer Loan 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 (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 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 we capture 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 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 where the lender operates. The state concentration index is weighted by the proportion 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 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.[6] Moreover, a higher rate puts more financial pressure on a borrower and increases the probability of delinquency.[7] 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 convenience include a geographically convenient local bank with a relationship to the borrower, a

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

[7] Jagtiani and Lemieux (2018) show that the default rate on LendingClub loans increases with the contractual rate charged on its loans.

lender that offers an easy 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 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, 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.[8]

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 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

$$NP_{\mathrm{i}} = \boldsymbol{X\beta} + \varepsilon_{\mathrm{i}}, \tag{1}$$

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 = $Total\ consumer\ loans_{\mathrm{i}}$ (100 billions),

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[8] 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. 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.

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, μ_i (> 0) $\sim \theta\exp(-\theta u)$, that measures the systematic excess nonperforming loan ratio.[9] The deterministic kernel of the frontier defines the minimum (best-practice) ratio:

$$\textbf{\textit{best-practice NP}}_{\boldsymbol{i}} = \boldsymbol{X\beta}. \tag{2}$$

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, 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 v_i conditional on ε_i:

[9] 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 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.

$$\boldsymbol{noise_i} = E(v_i|\varepsilon_i) = \varepsilon_i - E(\mu_i|\varepsilon_i). \tag{4}$$

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

$$\boldsymbol{noise\text{-}adjusted\ NP_i} = NP_i - E(v_i|\varepsilon_i). \tag{5}$$

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:

$$\begin{aligned} NP_i &= \boldsymbol{best\text{-}practice\ NP_i} + \boldsymbol{excess\ NP_i} + \boldsymbol{statistical\ noise_i} \\ &= \boldsymbol{inherent\ credit\ risk_i} + \boldsymbol{inefficiency_i} + \boldsymbol{statistical\ noise_i} \\ &= \boldsymbol{X\beta} + E(\mu_i|\varepsilon_i) + E(v_i|\varepsilon_i). \end{aligned} \tag{6}$$

Figures 2 and 4 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:

$$\boldsymbol{inefficiency_i} = \boldsymbol{noise\text{-}adjusted\ NP_i} - \boldsymbol{best\text{-}practice\ NP_i}$$

$$E(\mu_i|\varepsilon_i) = [NP_i - E(v_i|\varepsilon_i)] - \boldsymbol{X\beta}. \tag{7}$$

The estimated equation (1) is described in **Table 1** for 2016 and in **Table 5** for 2013.

5. Evidence of Inherent Credit Risk and Lending Inefficiency

Figure 1 and **Figure 3** 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 2** and **Figure 4** 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 6**, 0.0384 in 2013.

Table 4 and **Table 8** 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. In 2016, the median noise-adjusted nonperforming consumer loan ratio increases from 0.0181 in the group of the smallest lenders to 0.0496 in the group of the largest lenders. In 2013, this range is 0.0244 among the smallest lenders to 0.0639 among the largest lenders.

How much of these nonperforming loan ratios reflect the inherent credit risk 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 to 4 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) 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 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 – 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, 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 which 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 8** (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 banks in the three size groups with less than $1 billion of unsecured consumer loans. Larger lenders in the range $1 billion to $10 billion exhibit a higher median best-practice ratio, 0.0024. However, in 2016 LendingClub, whose volume of consumer lending places it in the range $1 billion to $10 billion, obtains a much higher best-practice ratio – 0.0408. This ratio is similar to the median best-practice ratio, 0.0428, for lenders with more than $10 billion in consumer loans.

In 2013, **Table 8**, **Panel A**, shows that the range of median best-practice rates for smaller institutions is 0.0024 to 0.0025. For lenders with consumer loans totaling $1 billion to $10 billion, the median best-practice ratio is 0.0037. LendingClub, whose loan volume falls in the range $1 billion to $10 billion, obtains a similar ratio of 0.0061. For the largest lenders with consumer loans exceeding $10 billion, the median best-practice ratio equals 0.0479.

Thus, in 2016 and 2013 inherent credit risk tends to be substantially higher among the largest bank lenders. Notably, LendingClub's best practice ratio is considerably higher in 2016 than in 2013. For all lenders, the median best-practice ratio in 2016 is 0.0016 (**Table 2**) and 0.0025 in 2013 (**Table 6**).

As noted previously, **Tables 2** and **6** 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. The noise-adjusted ratio, represented by the red points, shows a pattern in 2016 which 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 in 2016, this difference, the median excess nonperforming loan ratio, is 0.0192, and in 2013, 0.0233. The medians broken down by the consumer lending size groups shows the pattern evident in the four plots: in 2016, the median excess nonperforming loan ratio ranges from 0.0165 for lenders with less than $10 million in consumer loans, to 0.0200 for lenders between $10 million and $100 million, to 0.0212 for lenders between $100 million and $1 billion. For bank lenders in the range, $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, much smaller than the median of its size group peers ($1 billion to $10 billion). In contrast to median excess ratio, 0.0389, of the group of large bank lenders, 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 groups. In summary, the largest bank lenders and LendingClub, appear to be more proficient at consumer lending than banks in smaller size groups (those with unsecured consumer loans less than $10 billion).

Notably, these largest lenders also assume the highest inherent credit risk measured by the median, 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 2,** 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), have hypothesized that 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.

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 3** and **4** 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. Shown in **Table 8**, **Panel B**, their median noise-adjusted nonperforming loan ratios fall in the narrow range 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 these 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 4** shows that 5 of the 6 largest bank lenders obtain a very small degree of lending inefficiency.

6. Conclusions

We apply a novel technique developed by Hughes and Moon (2017) to compare the performance of consumer 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 with assets exceeding $250 billion experience the highest median rate of nonperforming unsecured consumer loans and that this high median nonperforming rate seems to be associated with risker loans – in fact, the highest inherent credit risk among the five size groups. Moreover, we find that these largest bank lenders have the smallest inefficiency – the smallest difference between the observed ratio adjusted for statistical noise and the best-practice (minimum) ratio. Consequently, among the five size groups, these largest bank lenders are, on average, the most efficient at consumer lending even though they experience the highest observed rate of nonperformance.

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), there are notable differences between these traditional lenders and LendingClub. In 2016, the median ratio of noise-adjusted, observed nonperforming loans is similar between LendingClub and these banks in the second largest group. However the difference between the noise-adjusted, observed nonperformance ratio and the best-practice ratio is higher for these bank lenders than for LendingClub, which indicates that these bank lenders are less efficient than LendingClub. LendingClub's small degree of inefficiency more closely resembles that of the group of the largest bank lenders.

It is important to recall the caveats listed in Section 2. While our data on fintech lending is taken from the largest fintech lender, it is nevertheless data from a single fintech lender. Thus, our findings may not be generally applicable to other fintech lending platforms. There may also be factors not observed in our data or not taken into account that, if they could be observed and taken into account, might change the measured efficiencies. For example, the data do not include a period of economic downturn, which might create different effects on the lending performance of LendingClub and banks. Moreover, we do not measure the cost and profit efficiency of lending.

With these caveats in mind, 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 traditional bank lenders – that is, higher credit risk-taking and greater lending efficiency. 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 small traditional lenders.

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.

Bibliography

Hughes, Joseph P., Julapa Jagtiani, Loretta J. Mester, and Choon-Geol Moon (2018). "Does Scale Matter in Community Bank Performance? Evidence Obtained by Applying Several New Measures of Performance," Department of Economics, Rutgers University Working Paper 201803 (supersedes Working Paper 201604).

Hughes, Joseph P., and Loretta J. Mester (2015). "Measuring the Performance of Banks: Theory, Practice, Evidence, and Some Policy Implications," in *The Oxford Handbook of Banking*, second edition, edited by Allen N. Berger, Philip Molyneux, and John Wilson, Oxford University Press, 247-270.

Hughes, Joseph P., and Choon-Geol Moon (2017). "How Bad Is a Bad Loan? Distinguishing Inherent Credit Risk from Inefficient Lending (Does the Capital Market Price This Difference?)," Department of Economics, Rutgers University Working Paper 201802 (supercedes Working Paper 201709).

Jagtiani, Julapa, and Catherine Lemieux (2018). "The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the LendingClub Consumer Platform," Federal Reserve Bank of Phildelphia, Working Paper WP 18-15.

Jondrow, James, C. A. Knox Lovell, Ivan S. Materov, and Peter Schmidt (1982). "On the Estimation of Technical Efficiency in the Stochastic Frontier Production Function Model," *Journal of Econometrics* 19, 233–238.

Morgan, Donald P., and Adam B. Ashcraft (2003), "Using Loan Rates to Measure and Regulate Bank Risk: Findings and an Immodest Proposal," *Journal of Financial Services Research* 24:2/3, 181–200.

Petersen, Mitchell A., and Raghuram G. Rajan (1995). "The Effect of Credit Market Competition on Lending Relationships," *Quarterly Journal of Economics* 110 (2), 407–443.

Vuong, Q. H. (1989). "Likelihood Ratio Test for Model Selection and Non-Nested Hypotheses," *Econometrica* 57, 307-333.

Figure 1

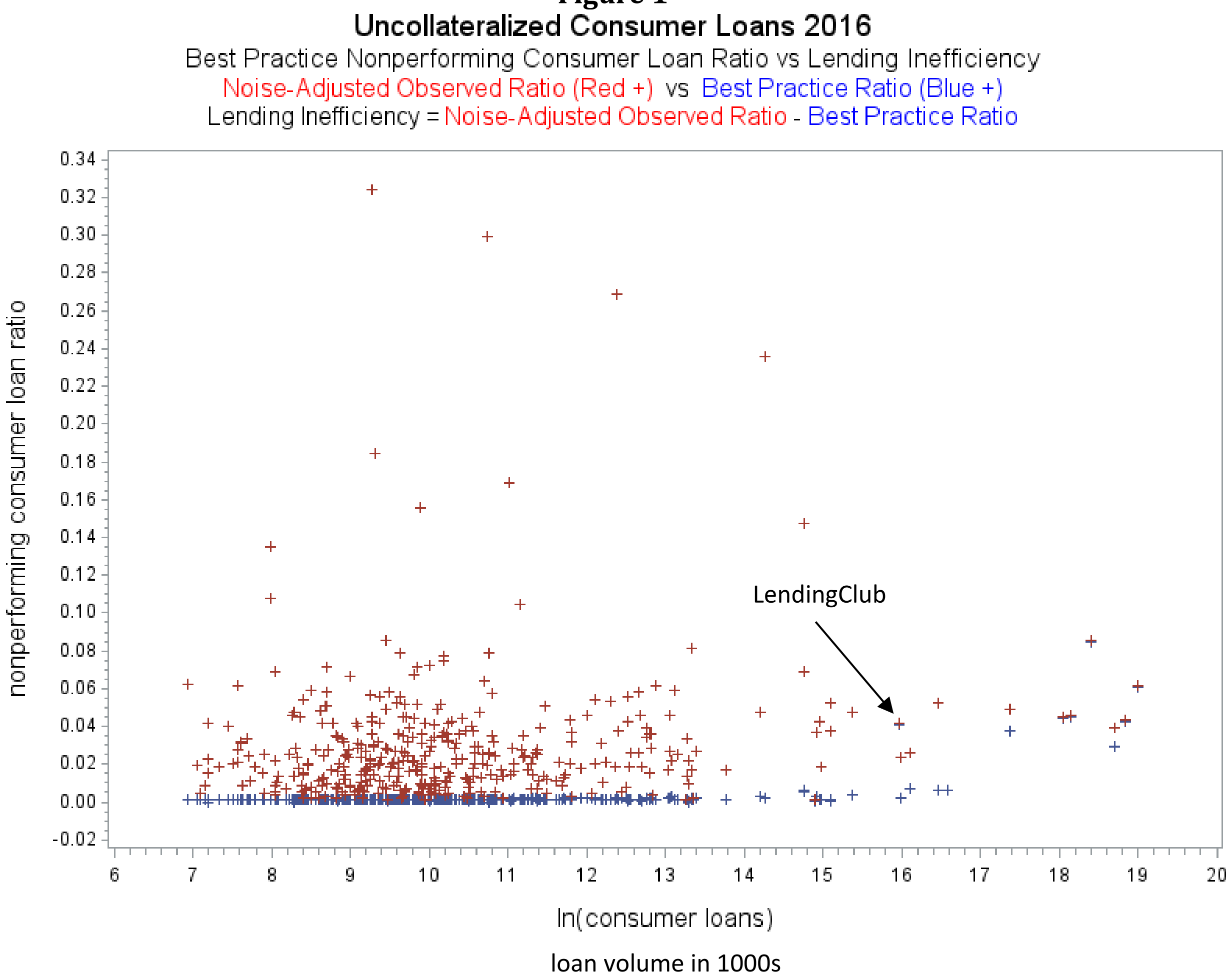

Uncollateralized Consumer Loans 2016
Best Practice Nonperforming Consumer Loan Ratio vs Lending Inefficiency
Noise-Adjusted Observed Ratio (Red +) vs Best Practice Ratio (Blue +)
Lending Inefficiency = Noise-Adjusted Observed Ratio - Best Practice Ratio
nonperforming consumer loan ratio
0.34
0.32
0.30
0.28
0.26
0.24
0.22
0.20
0.18
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
-0.02
LendingClub
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
ln(consumer loans)
loan volume in 1000s

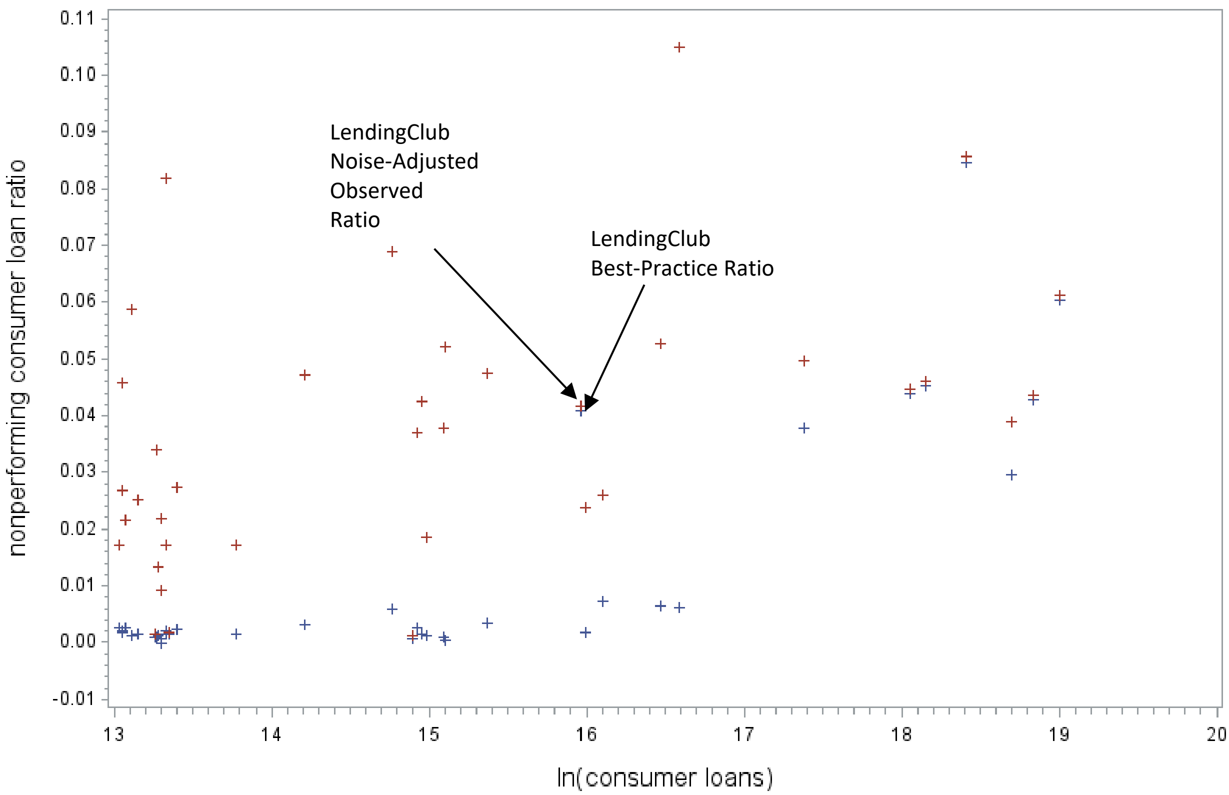
Figure 2

Uncollateralized Consumer Loans 2016

Best Practice Nonperforming Consumer Loan Ratio vs Lending Inefficiency

Noise-Adjusted Observed Ratio (Red +) vs Best Practice Ratio (Blue +)

Lending Inefficiency = Noise-Adjusted Observed Ratio - Best Practice Ratio

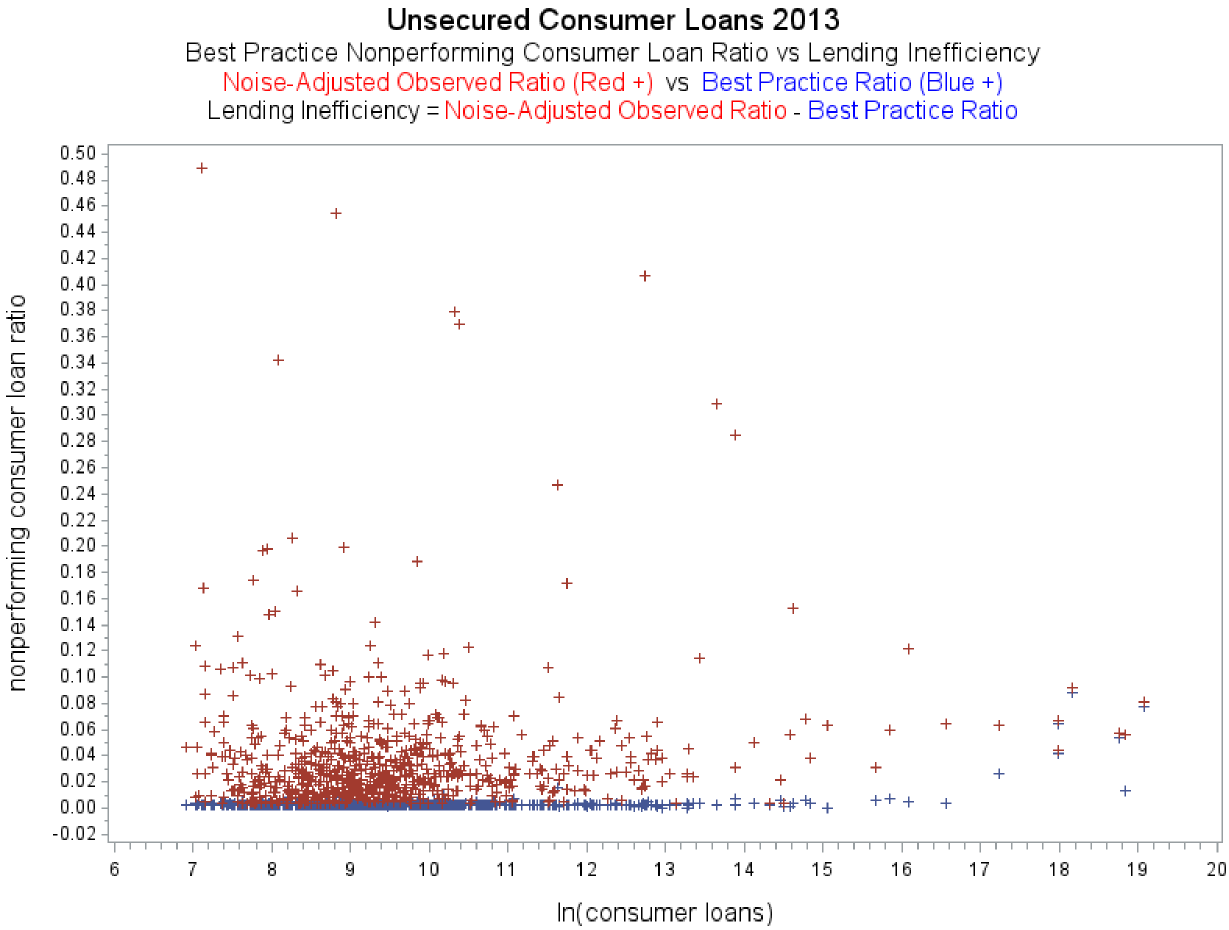


loan volume in 1000s

	Name	Book-Value of Assets	ln (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
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

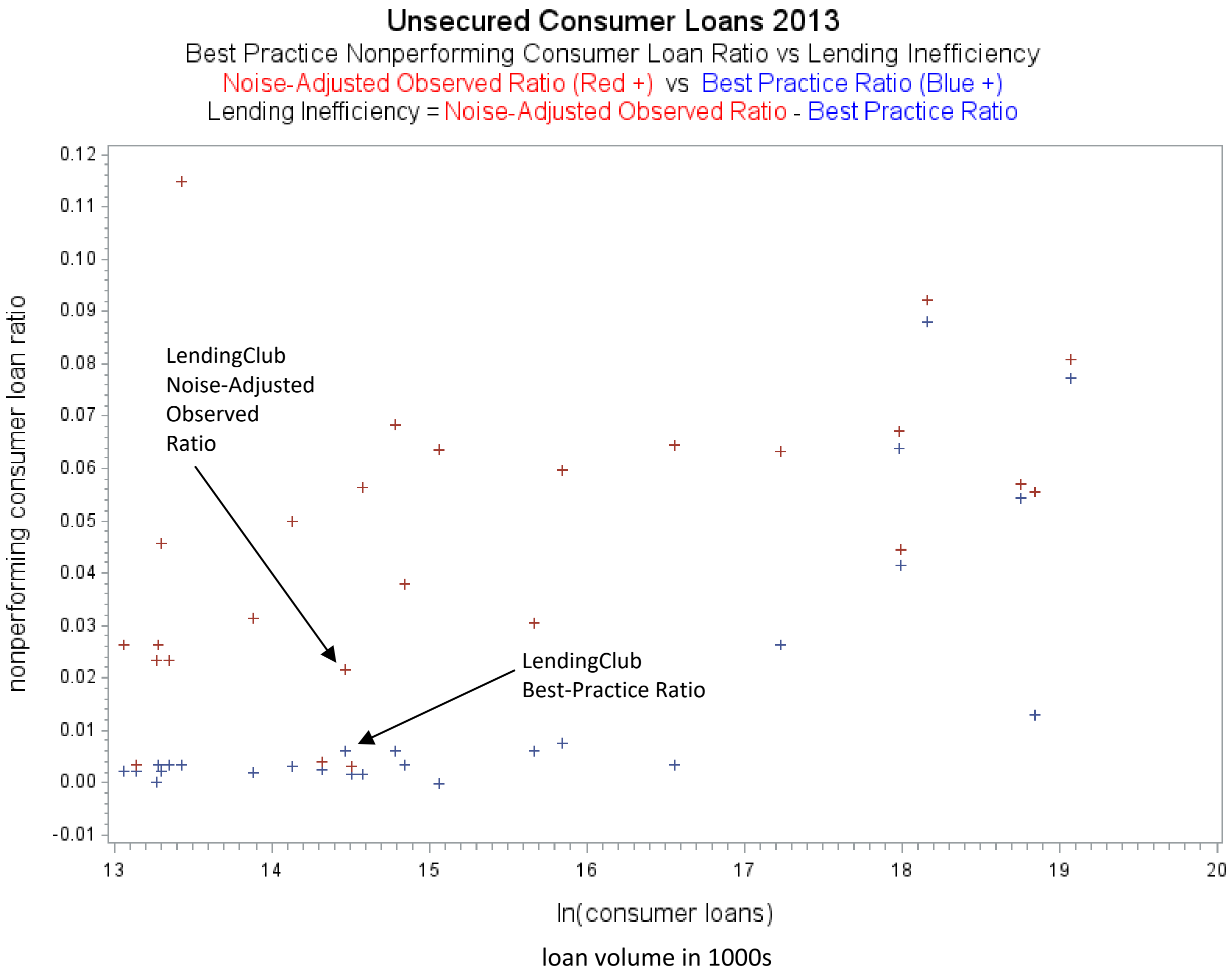
	Name	Book-Value of Assets	ln (Consumer Loans 1000s)	Noise-Adjusted Observed Ratio	Best Practice Ratio	Excess Over Best Practice	Average Contractual Interest Rate
17	REGIONS FC	126,193,957	14.956	0.0425	0.0015	0.0409	0.0565
18	GOLDMAN SACHS	860,185,000	14.923	0.0370	0.0027	0.0343	0.0238
19	BANK OF NY 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 3



loan volume in 1000s

Figure 4



bs	Name	Book-Value of Assets	ln (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 Corporat	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
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 Corpor	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

bs	Name	Book-Value of Assets	ln (Consumer Loans 1000s)	Noise-Adjusted Observed Ratio	Best Practice Ratio	Excess Over Best Practice	Average Contractual Interest Rate
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

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
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 1000s**

Table 5

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_ν		**0.035223**	0.0000

Table 6

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 7

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 8
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	Lend. 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 8

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**