Evidence from Shadow Price of Equity on "Too-Big-to-Fail" Banks

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Abstract

This paper estimates shadow price of equity for U.S. commercial banks over 2001–2018 using nonparametric estimators of the underlying cost function and tests the existence of "Too-Big-to-Fail" (TBTF) banks. Evidence on the existence of TBTF banks are found. Specifically, I find that a negative correlation exists between the shadow price of equity and the size of banks in each year, suggesting that big banks pay less in equity than small banks. In addition, in each year there are more banks with a negative shadow price of equity in the fourth quartile based on total assets than in the other three quartiles. The data also reveal that for each year, the estimated mean shadow price of equity for the top 100 largest banks is smaller than the mean price of deposits, even though equity is commonly viewed as a riskier asset than deposits. Finally, I find that the top 10 largest banks are willing to pay much more at the start of the global financial crisis and after the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 than the other periods. These results imply that these regulations are effective in reducing the implicit subsidy, at least for the top 10 largest banks. However, it is also evident that the recapitalization has imposed significant equity funding costs for the top 10 largest banks.

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1 Introduction

The global financial crisis of 2007–2012 may have started in the U.S. banking sector and was the worst U.S. economic disaster since the 1929 Great Depression. After Lehman's failure, the U.S. Congress passed the Troubled Asset Relief Program (TARP) to funnel hundreds of billions of dollars to support banks in a period of extraordinary financial turbulence. In addition, the Federal Reserve Board lent hundreds of billions of dollars to the banks through a series of newly created special lending facilities.

As a result of this recent global financial crisis, "Too-Big-To-Fail" (TBTF) is now a virtually official "policy". TBTF "policy" means that since some banks are so big and so important that their failure would be disastrous to the whole economic system, they must be protected by the government whenever they face potential failure. Access to the federal government's safety net allows TBTF banks to operate with a lower funding cost relative to non-TBTF banks since the public believe that the government would protect the TBTF banks again whenever there is another crisis, hence their uninsured creditors (e.g., the equity investors) do not charge as high a price for the use of their funds as they would in the absence of this perception. Therefore, there may exist an implicit subsidy for TBTF banks. On the other hand, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 were intended to remove TBTF "policy" by establishing a formal process for resolving failures of large financial institutions, as well as by imposing a tighter financial regulatory regime.

All in all, TBTF has become a heated topic after the recent global financial crisis. However, until now there lack enough evidence on the existence of TBTF banks. If TBTF banks do exist, then it is rational for the government to remove the implicit subsidy. Moreover, we need to know whether the implicit subsidy has decreased after the tighter regulations. In other words, we need to know whether the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 are effective in removing the implicit subsidy for TBTF.

There exists some literature providing evidence on the existence of TBTF banks. Santos and Santos (2014) use information from bonds issued to find that the largest banks have a relatively larger cost advantage over their smaller peers, compared with the largest nonbanks over their smaller peers. This difference supports investors' beliefs of TBTF banks. Brewer and Jagtiani (2013), using data from the merger boom of 1991–2004, find that banking organizations were willing to pay an added premium for mergers that would put them over the asset sizes that are commonly viewed as the thresholds for being TBTF. Ueda and Weder di Mauro (2013) use the level of government support embedded in the credit rating and its impact on the overall credit rating to provide estimates for the structural subsidy values. They found a significant funding cost advantage for Systemically Important Financial Institutions (SIFIs), about 60 basis points as of the end of 2007, before the crisis and 80 basis points by the end of 2009. Baker and Mcarthur (2009) use data from the Federal Deposit Insurance Corporation (FDIC) on the relative cost of funds for TBTF banks and other banks, before and after the crisis, to quantify the value of the government protection provided by the TBTF "policy". They find that the spread between the average cost of funds for smaller banks and the cost of funds for institutions with assets in excess of $100 billion averaged 0.29 percentage points in the period from the first quarter of 2000 through the fourth quarter of 2007, the last quarter before the collapse of Bear Steams. In the period from the fourth quarter of 2008 through the second quarter of 2009, after the government bailouts had largely established TBTF, the gap had widened to an average of 0.78 percentage points. If this gap is attributable to the TBTF "policy", it implies a substantial taxpayer subsidy for the TBTF banks. As a conclusion, previous research uses different methods to show that TBTF banks indeed do exist in U.S. banking sector and they enjoy the benefit of the implicit guarantee from government.

This paper estimates shadow price of equity for U.S. commercial banks over 2001–2018 using nonparametric estimators of the underlying cost function and then tests the existence of "Too-Big-to-Fail" (TBTF) banks. Since TBTF banks are believed to be implicitly protected by the government, they are considered safer and are willing to pay a lower price of equity than non-TBTF banks. If a bank is public, the price of equity can be derived from the bank's price of stock. However, most U.S. commercial banks are not public, and the price of equity is also not directly observed from the banks' balance sheets and income statement information. Hence the price of equity needs to be estimated for private banks. Following previous literature, the estimated price of equity using balance sheet and income statement information is called the "shadow price of equity" in this paper, to be differentiated from the price of equity measured using the price of stocks. An important advantage of this approach is that the shadow price of equity can be estimated for both listed and non-listed banks without using the market information. The shadow price of equity will equal the market price of equity when banks' cost is minimized at the current used amount of equity. Even if the current amount of equity does not minimize the cost, the shadow price of equity still provides a measure of opportunity cost of using the current amount of equity.

There exists some literature providing estimates of the shadow price of equity. Hughes (1999) explicitly derives the shadow price of equity capital, however, he does not show the estimates of shadow price of equity. Hughes et al. (2001) may be the first one to estimate the shadow price of equity capital using translog specification for the cost function. They find that there a positive relationship exists between asset size and the estimated shadow price of equity for the bank holding companies in 1994. Fethi et al. (2012) estimate the shadow price equity for 22 banks from Turkey over the period 2006–2009. They find that the shadow price on equity is negative in the post-financial crisis period, suggesting that the massive recapitalization of the banks during the recovery from the financial crisis drove them a long way from the equilibrium, and thus the involved deleveraging has imposed significant costs. Boucinha et al. (2013) estimate the shadow price of equity for Portuguese banks between 1992–2006 through the estimation of a translog cost frontier. The obtained measure of the shadow price of equity is in general higher than the short-term money market interest rate, however, it is lower than what is generally acknowledged to be a reasonable value for the actual price of equity. Restrepo et al. (2013) present new nonparametric measures of scale economies and total factor productivity growth for U.S. commercial banks over 2001–2010. Their results show that the sign of shadow price of equity depends on the models they used and also on the bank size. Duygun et al. (2015) use the same methods to estimate the shadow price of equity for 485 banks from emerging economies over period 2005–2008. They find a very consistent and statistically significant positive shadow price of equity capital of 4.1% to 4.9% on the capital constraint at the sample mean. Consequently the regulatory requirement to hold equity capital as a proportion of total assets is a strongly binding constraint at the sample mean. They also find that, at some sample points, the estimated shadow price of equity is negative, indicating that they have identified an "Excessive Capitalizer" operating in the uneconomic region of the banking production function because it is having to achieve a much higher equity capital to assets ratio. Radić (2015) estimates the shadow price of equity for the Japanese banking system over 1999–2011. Radić finds that at the sample mean, the shadow price on equity is between 2.8% and 6.1%. For the city banks, the cost of equity over time is significantly negative. Dong et al. (2016) estimate the shadow price of equity for Chinese commercial banks over the period 2002–2013. They find that there is a decreasing trend in the shadow price of equity over this period. They also find that the sign on the shadow price of equity is positive initially, but becomes negative by the end of the period. This may be because, during or after a severe recapitalization period, banks tend to deviate from their long-run equilibrium, which can cause the shadow price of equity to become negative. Fiordelisi et al. (2018) estimate the shadow price of equity using the data from commercial banks in Japan over the period 2000 to 2010. They find that at the sample mean the shadow price on equity is between 2.8 percent and 3.4 percent. They also find that for part of the period, the asset-weighted mean of the estimated shadow prices of equity capital did turn negative for both listed and unlisted banks indicating strong efforts at deleveraging and recapitalization. Hasannasab et al. (2019) use quadratic functional form of directional distance functions to obtain shadow prices of bank equity capital for listed and unlisted banks. They find that shadow prices for equity capital had reached abnormally high levels in the years leading up to the subprime crisis in the US indicative of excessive risk-taking behavior.

Instead of using the standard translog cost function approach, this paper uses nonparametric methods initially developed by Simar et al. (2017) to estimate the cost frontier and thereby derive the shadow price of equity. The translog cost function is not flexible enough in estimating the cost function for U.S. commercial banks, where the size distribution is heavily right-skewed (Wheelock and Wilson, 2018). I also control for cost inefficiency when estimating the shadow price of equity. I use an almost fully-nonparametric specification of the noise and inefficiency processes, as opposed to estimating the more typical parametric stochastic frontier model where the noise and inefficiency distributions do not vary. The approach only requires symmetry of the two-sided noise process and that inefficiency be distributed half-normal. However, I allow the inefficiency to depend on the same covariates in the response function. The method is along the line of Simar et al. (2017) and Wheelock and Wilson (2019). Specifically, in the first regression, a nonparametric local-linear estimator is used to estimate the conditional mean cost function. In the second regression, I regress the cubed residuals from the first regression on the same covariates in the first regression. Using the information in the second regression, I can adjust the original estimates of the conditional mean cost function to estimate the cost frontier as well as the estimates of derivatives by exploiting the right skewness of the estimated residuals. Consequently, the approach is almost fully nonparametric. Although nonparametric estimators face the "curse of dimensionality", I take two steps to mitigate this problem.[1] Specially, I estimate my model using a large dataset consisting of over 119,000 observations on all U.S. commercial banks over the period 2001–2018. I also use an eigensystem decomposition of the correlation matrix of the right-hand-side variables to reduce the dimensions of the empirical model. My estimation methodology follows that of Wheelock and Wilson (2018, 2019). However, Wheelock and Wilson (2018) focus exclusively on the estimation of return to scale for U.S. banks for 1986–2015, and Wheelock and Wilson (2019) focus exclusively on the estimation of Lerner indices for U.S. bank holding companies for 2001–2018. Here, I focus on the estimation of the shadow price of equity for U.S. commercial banks for 2001–2018.

The nonparametric estimates of the shadow price of equity show that there indeed exist implicit subsidies for the TBTF banks. Specifically, I find that in each year, the estimated median value of shadow prices of equity for the banks in the fourth quartile based on total assets is much smaller than the banks in the other three quartiles. Moreover, for any given year, there exists a negative correlation between the shadow prices of equity and the sizes of banks, suggesting that big banks pay less in equity than small banks. In addition, there are more banks with a negative shadow price of equity in the fourth quartile than the other three quartiles in each year. The data reveal that for any given year in the sample, the estimated mean shadow price of equity for the top 100 largest banks is smaller than the mean price of deposits, even though equity is commonly viewed as a riskier asset than deposits. Finally, I find that the top 10 largest banks are willing to pay much more in equity at the start of the global financial crisis and after 2010. Therefore, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 are effective in removing the implicit subsidy, at least for the top 10 largest banks, and the deleveraging has imposed significant costs on the top 10 largest banks.

In the next section, a microeconomic model is presented for commercial banks, and the

[1] "Curse of dimensionality" means the convergence rate of nonparametric estimators will decrease with the number of dimensions. In this paper, the number of dimensions are the number of independent variables included.

components needed to compute shadow price of equity are defined. In Section 3 the data used to define variables described in Section 2 are discussed. Section 4 presents the statistical model and gives details for estimation and inference. Empirical results are presented in Section 5. Summary and conclusions are given in Section 6.

2 The Economic Model

2.1 Deriving the Shadow Price of Equity

In this section, following Braeutigam and Daughety (1983), Duygun et al. (2015) and Weyman-Jones (2016), I employ a model of a representative bank's cost function that takes account of the requirement for the equity-asset ratio. Specifically, banks are required to hold the equity fixed in the short run, or to maintain a fixed equity-asset ratio to satisfy the government regulations. However, in the long run, the equity is allowed to be variable.

Consider a representative bank's production function to have p variable inputs $\boldsymbol{x} = (x_1, \ldots, x_p)$, q outputs $\boldsymbol{y} = (y_1, \ldots, y_q)$, input prices $\boldsymbol{w} = (w_1, \ldots, w_p)$, and an additional quasi-fixed input, equity q_1, i.e., an input which may be a fixed input in the short run but is variable in the long run. Assume the tranformation function $F(\boldsymbol{y}, \boldsymbol{x}, q_1, t) = 0$ for banks has the properties of convexity and weak disposability, where t is time. Weak disposability means $F_{x_i} = \frac{\partial F}{\partial x_i}$, $F_{y_j} = \frac{\partial F}{\partial y_j}$, $F_{q_1} = \frac{\partial F}{\partial q_1}$ are not restricted in sign. Therefore, banks are allowed to operate in the uneconomic region, and hence the shadow price of equity is not restricted in sign.

The long run cost function, with all inputs including q_1 treated as variables, takes the form

$$c^l(\boldsymbol{y}, \mathbf{w}, w_0, t) = \min_{\boldsymbol{x}, q_1} \{\mathbf{w}'\boldsymbol{x} + w_0 q_1 : F(\boldsymbol{y}, \boldsymbol{x}, q_1, t) = 0\}, \tag{2.1}$$

where $c^l(\boldsymbol{y}, \mathbf{w}, w_0, t)$ is the long run cost function and w_0 is the shadow price of equity. Following Duygun et al. (2015), the regulated short run cost function, modeled by specifying a fixed equity-asset ratio, $r_0 = q_1/q_2$, has the form

$$\begin{aligned} c^s(\boldsymbol{y}, \mathbf{w}, r_0, t) =& c(\boldsymbol{y}, \mathbf{w}, r_0, t) + w_0 q_1 \\ =& \min_{\boldsymbol{x}} \{\mathbf{w}'\boldsymbol{x} + w_0 q_1 : F(\boldsymbol{y}, \boldsymbol{x}, q_1, t) = 0, q_1 = r_0 q_2\}, \end{aligned} \tag{2.2}$$

where $c^s(\boldsymbol{y}, \mathbf{w}, r_0, t)$ is the short run cost function, q_2 is assets for the bank and $c(\boldsymbol{y}, \mathbf{w}, r_0, t)$ is the short run variable cost. The envelope theorem confirms that the long run cost function defines the envelope of the short run cost function

$$c^l(\boldsymbol{y}, \mathbf{w}, w_0, t) = \min_{r_0}\{c(\boldsymbol{y}, \mathbf{w}, r_0, t) + w_0 q_1, q_1 = r_0 q_2\}. \tag{2.3}$$

Consequently, the envelope theorem gives

$$\frac{\partial c^l(\boldsymbol{y}, \mathbf{w}, w_0, t)}{\partial r_0} = 0 = \frac{\partial c(\boldsymbol{y}, \mathbf{w}, r_0, t)}{\partial r_0} + w_0 q_2, \tag{2.4}$$

and rearranging this equation leads to

$$w_0 = -\frac{\partial c(\boldsymbol{y}, \mathbf{w}, r_0, t)}{\partial r_0}\frac{1}{q_2} = -\frac{\partial c(\boldsymbol{y}, \mathbf{w}, r_0, t)}{\partial q_1}, \tag{2.5}$$

where w_0 is the **shadow price** of equity, q_1. Rearranging equation (2.5) and expressing it in elasticity form gives

$$\frac{w_0 q_1}{c} = -\frac{\partial \log c(\boldsymbol{y}, \mathbf{w}, r_0, t)}{\partial \log r_0} = -\varepsilon_{q_1}, \tag{2.6}$$

where ε_{q_1} is the elasticity of short run variable cost with respect to equity-asset ratio. Therefore, the **shadow share** of equity expenses to total expenses could be estimated by the negative of the elasticity of short run variable cost with respect to equity-asset ratio.

2.2 Interpreting the Shadow Price of Equity

The shadow price of equity is derived in the previous subsection, and it is shown in equation (2.5). This equation is particularly relevant, since there is no explicit information on the price of equity, except that equity is an input fixed in the short run. Given fixed total outputs, when the bank has one more dollar increase in equity, some amount of deposits must be freed up since deposits and equity are substitutes. Expenses on deposits will surely decrease. Consequently, the variable cost, which is the sum of deposit expenses, labor expenses, and physical capital expenses, will also decrease. Therefore, the negative value of the derivative of the variable cost function with respect to equity is the shadow price for equity, as shown in equation (2.5). The rationale underlying the computation of the shadow price of equity is to provide a measure of how much banks are willing to pay for one more dollar increase in the level of equity, since it indicates the amount that they would save in the variable cost as a result of one more dollar increase in the level of equity. Consequently given the price of outputs, the shadow price of equity also indicates the amount that they would increase in the profit as a result of one more dollar increase in the level of equity. Even though equity is fixed, and hence "free" in the short run, there still exits a price for equity in the long run.

In this paper, I use year-end balance sheet and income statement information to estimate the cost function for banks. Therefore all dollar amounts are measured in book values rather than market values. Expenses on deposits are measured as the total deposits times the average annual interest rate on total deposits. Since all the other expenses are also measured annually, the estimated shadow price of equity could be interpreted as the "annual interest rate" on equity, if equity is treated the same as deposits. Therefore, the estimated shadow price of equity is directly comparable to the average price of deposits and the average price of loans and leases.

3 Data and Variable Specification

To obtain estimates of the shadow price of equity in equation (2.5), I must specify the variable cost function $c(\boldsymbol{y}, \mathbf{w}, r_0, t)$. My specification of right-hand-side (RHS) explanatory variables closely follows much of the banking literature. I use year-end data on U.S. commercial banks for 2001–2018 from the FFIEC (The Federal Financial Institutions Examination Council) call reports.[2] The widely used intermediation method of Sealey and Lindley (1977) is used to model a bank's technology as using deposits, labor, and physical capital (consisting of premises and fixed assets) to produce loans and leases, investments and off-balance items.

For the model, I specify three output quantities: total loans and leases (y_1), total securities (y_2), and off-balance sheet items consisting of non-interest income (y_3). Further, I specify three input prices: price of deposits (w_1), price of labor (w_2), and price of physical capital (w_3). The input price variables are measured by dividing expenditures on inputs by the corresponding quantities of inputs. Equity-asset ratio is also included to reflect that equity (q_1) is a quasi-fixed input. As an additional control for banks' differences in risk, I also include a measure of non-performing loans (npl), consisting of total loans and lease financing receivables past due 30 days or more and still accruing. As a final control variable, I index the years 2001–2018 by $t = 1, 2, \ldots, 18$. Although t is an ordered, categorical variable, it is treated as a continuous variable since its range is relatively large. Including t as

[2] See https://cdr.ffiec.gov/public/PWS/DownloadBulkData.aspx

an explanatory variable controls for changes in regulation, the global financial crisis, and all other changes by allowing the functional form of cost function to change over time.

The summary statistics for the variables over 2001–2018 are shown in Table 1. All monetary values are reported in constant 2018 U.S. dollars. Comparing differences between the first quartile and the median, and between the median and the third quartile for the input and output variables reveals that the marginal densities for both input and output variables are all skewed to the right. This implies that the translog specification for the cost function is not likely to be well specified. The translog specification for the cost function in U.S. banks is rejected in Wheelock and Wilson (2012, 2018, 2019).

Figure 1 shows the kernel density estimates of the log of total assets for U.S. commercial banks in 2001, 2009, and 2018. The estimates displayed in Figure 1 illustrate the evolution of commercial banks' sizes over the period covered by the sample. The distribution of U.S. commercial banks' sizes has shifted rightward over time, suggesting that U.S. commercial banks are expanding and some commercial banks have very large sizes. The nonparametric local estimator is more suitable than parametric estimators when the right skewness exists.

The medians and means for equity-asset ratio for each year are shown in Table 2. The mean and median values of the equity-asset ratio across years are around 10 percent, and the mean value is slightly larger than the median value for each year. The median value continuously increases from 2001 to 2007, and then continuously decreases from 2007 to 2009, after which, it continuously increases until 2012, where it maintains a much higher level than before. The pattern of the mean value of the equity-asset ratio appears to be the same. The decrease of the equity-asset ratio from 2007 to 2009 reflects the negative effect of the global financial crisis on U.S. commercial banks. In contrast, the increase of the equity-asset ratio after 2009 reflects the recapitalization process after the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010.

The medians of the equity-asset ratio for each size quartile based on total assets are reported in Table 3. In general, for each year the median value of the equity-asset ratio decreases when the size of banks increases. The correlations between the equity-asset ratio and size for each year in 2001–2018 are reported in Table 4. It is clear that there exists a negative correlation between the equity-asset ratio and the size of banks, suggesting that big banks tend to hold less equity, given total assets, compared with small banks. This indicates that small banks lack other resources, except increasing the equity-asset ratio to mitigate the potential market risk. However, big banks may get an implicit guarantee of bailout from the government when there is another crisis, and hence there is no need for them to hold too much equity than the level required by the government. Table 5 shows the weights for the assets of the top 10 largest commercial banks in the U.S. for each year. As shown in the table, the asset weight for the top 10 largest banks takes more than 50 percent after 2005, reflecting that the top 10 largest banks indeed have very large bank sizes and dominate the U.S. banking sector.

The relatively larger sizes of big banks may give them some market power in pricing the deposits and loans and leases. The results of the tests of differences in means for price of deposits between big and small banks for each year are shown in Table 6. For each year I split the sample into two subsamples based on the median value of total assets. The small banks are then defined as those with total assets smaller than the median value of total assets in each year, and the remaining are defined as big banks. Table 6 shows that the mean price of deposits for big banks is significantly smaller than that for small banks before 2003, while it is significantly larger for most cases after 2003. This reflects the demand effect since big banks usually need larger amount of deposits than small banks, and hence they are willing to pay a higher price for deposits than small banks. The results of the tests of differences in means for price of loans and leases between small and big banks for each year are shown in Table 7. Table 7 shows that the mean price of loans and leases for big banks is significantly smaller than that for small banks in each year. This reflects the supply effect since big banks usually provide a larger amount of loans and leases, and hence they will charge a lower price than small banks. As a robustness check, I also consider a different definition of small banks and big banks based on the bottom and top 25th percentile of total assets in each year. The results of the tests of the differences in means for price of deposits and price of loans and leases are shown in Tables 8 and 9, respectively. The results are quite consistent with my baseline results in Tables 6 and 7.

4 The Econometric Model

Simar et al. (2017) propose an almost fully-nonparametric framework for stochastic frontier models. This method involves less assumptions on the cost function and is more general than the translog or other parametric specifications of the cost function. A number of papers have rejected the translog specifications of the cost function.[3] Therefore, I use nonparametric least squares methods for stochastic frontier models to estimate the cost function for the U.S. commercial banks and thereby derive the shadow price of equity. The nonparametric estimation strategy avoids specification error that might be obtained when using a mis-specified model. A disadvantage of nonparametric estimators, however, is that they suffer from the "curse of dimensionality", i.e., the convergence rates fall as the number of dimensions in the model increases. However, the slow convergence of nonparametric estimators is mitigated by using a large dataset and an eigensystem decomposition of the correlation among the right-hand-side variables to reduce dimensions.

The variable cost function $c(\boldsymbol{y}, \mathbf{w}, r_0, t)$ must be homogeneous of degree one with respect to input prices $\mathbf{w}$ since the cost minimization problem implies that factor demand equations must be homogeneous of degree zero in input prices. Consequently I divide the input prices and the variable cost by the price of physical capital (w_3). Following Wheelock and Wilson (2012, 2018), I define the vector of covariates

$$z_i = [\frac{w_{i1}}{w_{i3}} \quad \frac{w_{i1}}{w_{i3}} \quad y_{i1} \quad y_{i2} \quad y_{i3} \quad r_{i0} \quad npl_i \quad \exp(t_i)]$$

for the right-hand-side variables (RHS) of the cost function. In order to estimate cost frontiers and to allow for inefficiency, I employ the moment-based method of Simar et al. (2017) and eigensystem decomposition of Wheelock and Wilson (2019) as described below.

I first take logs of each RHS variable, then standardize the logs by subtracting means and dividing by standard deviations of the logs. This will transform z_i to $\widetilde{z}_i$. The RHS variables are usually highly correlated. Following Wheelock and Wilson (2019), I use eigensystem decomposition of the correlation matrix of $\widetilde{z}_i$ to reduce dimensions. Let E denote the matrix of eigenvectors of the correlation matrix of $\widetilde{z}_i$. The eigenvectors in the columns of E are ordered so that the first column corresponds to the largest eigenvalue and the last column corresponds to the smallest eigenvalue. Then I compute the $(n \times 8)$ matrix

$$\boldsymbol{\Psi}_{full} = [\boldsymbol{\Psi} \quad \boldsymbol{\Psi}_{del}] = \widetilde{z}_i E \tag{4.7}$$

of principal components, where $\boldsymbol{\Psi}$ contains the desired principal components and $\boldsymbol{\Psi}_{del}$

[3]See Wheelock and Wilson (2012, 2018, 2019)

contains the removed components. Let e_j denote the eigenvalues, sorted in decreasing order, and let $\tilde{e_j} = \sum_{k=1}^{j} e_k / \sum_{k=1}^{8} e_k$ for $j = 1, 2, \ldots, 8$. Then $\tilde{e_j}$ gives the proportion of the independent linear transformation in $\widetilde{z}_i$ contained in the first j principal components, i.e., the first j columns of $\boldsymbol{\Psi}_{full}$. These values are 0.3986, 0.6122, 0.7610, 0.8742, 0.9341, 0.9708, 0.9870, and 1.0000. Consequently, I define the partition in equation (4.7) so that $\boldsymbol{\Psi}$ is an $(n \times 5)$ matrix, and I use these first $d = 5$ principal components to estimate the cost function. By construction, $\boldsymbol{\Psi}$ contains more than 93 percent of the independent linear information in $\widetilde{z}_i$ for the period 2001–2018, and consequently the number of dimensions are reduced from 8 to 5.

Now let $\boldsymbol{\Psi}_i = (\Psi_{i1}, \Psi_{i2}, \ldots, \Psi_{id})$ denote the ith row of $\boldsymbol{\Psi}$. I use the local-linear estimator to estimate the following cost function

$$\log(\frac{c_i}{w_{i3}}) = m(\Psi_{i1}, \Psi_{i2}, \ldots, \Psi_{id}) + V_i + U_i, \tag{4.8}$$

where $m(\boldsymbol{\Psi}_i) = m(\Psi_{i1}, \Psi_{i2}, \ldots, \Psi_{id})$ is a conditional mean function measuring the cost function frontier, and V_i is the statistical noise term, for which I assume that $E(V_i|\boldsymbol{\Psi}_i) = 0$ and $\mathrm{Var}(V_i|\boldsymbol{\Psi}_i) \in (0, \infty)$ for all i and that U_i is a nonnegative random variable, capturing the individual cost inefficiency. Moreover, U_i is assumed to be independent from V_i. Conditionally on $\boldsymbol{\Psi}_i$, $U_i|\boldsymbol{\Psi}_i$ is assumed to follow half-normal distribution $|N(0, \sigma_U^2(\boldsymbol{\Psi}_i))|$, and hence $\mu_U(\boldsymbol{\Psi}_i) = \sqrt{\frac{2}{\pi}}\sigma_U(\boldsymbol{\Psi}_i)$. In addition, I make no functional form assumptions regarding $m(\boldsymbol{\Psi}_i)$ and only make the regular assumptions to ensure the consistency of nonparametric estimators.

Following Simar et al. (2017) and Wheelock and Wilson (2019), let $\varepsilon_i = V_i + U_i - \mu_U(\boldsymbol{\Psi}_i)$, and $r_1(\boldsymbol{\Psi}_i) = m(\boldsymbol{\Psi}_i) + \mu_U(\boldsymbol{\Psi}_i)$. Using the local-linear estimator I estimate the following equation

$$\log(\frac{c_i}{w_{i3}}) = r_1(\boldsymbol{\Psi}_i) + \varepsilon_i, \tag{4.9}$$

where $r_1(\boldsymbol{\Psi}_i)$ is the estimated individual cost function. Denote $r_3(\boldsymbol{\Psi}_i) = E(\varepsilon_i^3|\boldsymbol{\Psi}_i)$. It can be easily shown that

$$E(\varepsilon_i|\boldsymbol{\Psi}_i) = 0 \tag{4.10}$$

and

$$E(\varepsilon_i^3|\mathbf{\Psi}_i) = E[(U_i - \mu_U(\mathbf{\Psi}_i))^3|\mathbf{\Psi}_i], \tag{4.11}$$

where the distribution of inefficiency $U_i|\mathbf{\Psi}_i$ has a positive skewness and therefore $r_3(\mathbf{\Psi}_i) \geq 0$.

After estimating the cost function, I now have

$$\hat{\varepsilon}_i = \log(\frac{c_i}{w_{i3}}) - \hat{r}_1(\mathbf{\Psi}_i), \tag{4.12}$$

and I can get the local linear estimate of $r_3(\mathbf{\Psi}_i)$ from the data points $\{\hat{\varepsilon}_i^3, \mathbf{\Psi}_i|i = 1, \ldots, n\}$. After some algebra, it can be shown that the variance function for U_i can be consistently estimated by

$$\hat{\sigma}_U^2(\mathbf{\Psi}_i) = \max\left\{0, \left[\sqrt{\frac{\pi}{2}}\Big(\frac{\pi}{4-\pi}\Big)\hat{r}_3(\mathbf{\Psi}_i)\right]^{\frac{2}{3}}\right\}, \tag{4.13}$$

and

$$\hat{c}_i = w_{i3}\exp(\hat{m}(\mathbf{\Psi}_i)) = w_{i3}\exp(\hat{r}_1(\mathbf{\Psi}_i) - \hat{\mu}_U(\mathbf{\Psi}_i)). \tag{4.14}$$

Therefore according to (2.5) in Section 2, the shadow price of equity is equal to

$$w_{i0} = -\frac{\partial c_i}{\partial r_{i0}}\frac{1}{q_{i2}} = -c_i(\frac{\partial r_1(\mathbf{\Psi}_i)}{\partial r_{i0}} - \frac{\partial \mu_U(\mathbf{\Psi}_i)}{\partial r_{i0}})\frac{1}{q_{i2}}, \tag{4.15}$$

where for z_{il}, the l-th element of z_i, I have

$$\frac{\partial r_1(\mathbf{\Psi}_i)}{\partial z_{il}} = s_l^{-1} z_{il}^{-1} \sum_{j=1}^{d} \hat{\beta}_{1ij} E_{lj}, \tag{4.16}$$

and

$$\frac{\partial \mu_U(\mathbf{\Psi}_i)}{\partial z_{il}} = \begin{cases} \frac{2^{1/3}}{3}(4-\pi)^{-1/3}\hat{r}_3(\mathbf{\Psi}_i)^{-2/3} s_l^{-1} z_{il}^{-1} \sum_{j=1}^{d} \hat{\beta}_{3ij} E_{lj}, & \forall \hat{r}_3(\mathbf{\Psi}_i) > 0 \\ 0 \quad \text{otherwise}, \end{cases} \tag{4.17}$$

where E_{lj} is the (l, j)-th element of the matrix E of eigenvectors, and s_l is the standard deviation of the logged l-th variable, i.e., the standard deviation of the l-th column of $\widetilde{z}$. The slope terms are $\hat{\beta}_{1ij} = \frac{\partial r_1(\mathbf{\Psi}_i)}{\partial \Psi_{ij}}$ and $\hat{\beta}_{3ij} = \frac{\partial r_3(\mathbf{\Psi}_i)}{\partial \Psi_{ij}}$, $j = 1, 2, \ldots, 5$. Moreover, the $\hat{\beta}_{1ij}$s and

$\hat{\beta}_{3ij}$s are computed at each observation i in each regression due to the local nature of the local-linear estimator. The estimation approach described here is almost fully nonparametric. Although I assume that inefficiency is distributed half-normal, the shape parameter is estimated locally and is allowed to vary continuously across observations. A fully nonparametric approach does not seem possible, as some structures are needed in order to identify expected inefficiency.

To implement the local-linear estimator a bandwidth parameter must be selected to control the smoothing over the continuous dimensions in the data. Following Wheelock and Wilson (2011, 2012, 2018, 2019), I use least-squares cross-validation to optimize an adaptive, κ-nearest-neighbor bandwidth. In addition, I employ a second-order Epanechnikov kernel function. I use the bandwidth inside the kernel function. This means that when estimating cost at any fixed point of interest in the space of the RHS variables, only the κ observations closet to that point can influence estimated cost. In addition, among these κ observations, the influence that a particular observation has on estimated cost diminishes with distance from the point at which the response is being estimated. The estimator here is thus a *local* estimator and is very different from typical, parametric, *global* estimation strategies (e.g. ordinary least squares, maximum likelihood, etc.) where all observations in the sample influence (with equal weights) estimation at any given point in the data space. Moreover, because I use adaptive nearest-neighbor bandwidths, the bandwidths automatically adapt to variation in the sparseness of data throughout the support of the RHS variables. This results in relatively larger values for the bandwidths where the data are sparse (and where more smoothing is required), and smaller values for the bandwidths where the data are relatively dense (where less smoothing is needed).

For making inference about the shadow prices of equity or differences in these across different years or groups based on the nonparametric estimates, I use the wild bootstrap introduced by Härdle (1990) and Härdle and Mammen (1993), which avoids making specific distributional assumptions. Although the estimators are asymptotically normal, the bootstrap avoids the needs to estimate those unknown parameters in an asymptotically normal distribution. I estimate confidence intervals using methods described in Wheelock and Wilson (2011, 2012, 2018, 2019).

First, I obtain bootstrap estimates $\{\hat{w}^*_{0b}\}_{b=1}^{B}$ (set $B = 1,000$), then sort the values in

$\{\hat{w}^*_{0b} - \hat{w}_0\}_{b=1}^{B}$ by algebraic value, delete $(\frac{\alpha}{2} \times 100)\%$ of the elements at either end of this sorted array, and denote the lower and upper end points of the remaining, sorted array as $-b^*_\alpha$ and $-a^*_\alpha$, respectively. Then a bootstrap estimate of a $(1-\alpha)\%$ confidence interval for $\hat{w}_0$ is

$$\hat{w}_0 + a^*_\alpha \leq w_0 \leq \hat{w}_0 + b^*_\alpha. \tag{4.18}$$

The idea underlying equation (4.18) is that the empirical distribution of the bootstrap values $(\hat{w}^*_{0b} - \hat{w}_0)$ mimics the unknown distribution of $(\hat{w}_0 - w_0)$, with the approximation improving as $n \to \infty$. As $B \to \infty$, the choices of $-b^*_\alpha$ and $-a^*_\alpha$ become increasingly accruate estimates of the percentiles of the distribution of $(\hat{w}^*_{0b} - \hat{w}_0)$. Any bias in $\hat{w}_0$ relative to w_0 is reflected in the bias of $\hat{w}^*$ relative to $\hat{w}$. The estimated confidence interval may not contain the original estimates of $\hat{w}$ if the bias is large because the estimated confidence interval corrects for the bias in $\hat{w}$.

5 Empirical Results

I use nonparametric local linear methods and some moment conditions to estimate the frontier, from which I derive the shadow price of equity for each commercial bank over 2001–2018. However, there are some unreasonable estimates of the shadow prices of equity, therefore, I first remove the outliers in the estimates before analyzing the results. If the estimated shadow price of equity is smaller than $Q1 - 3 \times IQR$ or larger than $Q3 + 3 \times IQR$, then this estimate is defined as an outlier, where $Q1$ is the first quartile, $Q3$ is the third quartile, and IQR is the interquartile range (i.e., $IQR = Q3 - Q1$). In total there are 1443 outliers out of $119,028$ observations. After removing the outliers, I do not lose much information, and the estimates, after removing the outliers, still capture the changes in the trend of quartiles of the estimates.

The summary statistics for the estimated shadow prices of equity are reported in Table 10. The mean value of the estimated shadow prices of equity is 0.0875 in 2001. This means that for a typical U.S. commercial bank in the beginning of 2001, if it borrows one more dollar of equity from an investor for just one year, then it is estimated to pay back 1.0875 dollars by the end of 2001. In other words, the "interest rate" on equity is 0.0875 in 2001. The median value of the estimated shadow prices of equity continuously decreases from 2001 to 2005, and then increases from 2005 to 2006, after which, it decreases again from 2006 to 2008. The median value increases from 2008 to 2010, and then decreases from 2010 to 2014, after which it increases from 2014 to 2016. The median value then decreases from 2016 to 2017 and increases from 2017 to 2018. The mean values of the estimated shadow prices of equity have similar trend over the period 2001–2018. I find that the median values before 2008 are, in general, higher than that after 2008, thus implying that the recapitalization process in U.S. commercial banks leads to a decrease in the shadow price of equity. The lower median values after 2008 may also reflect the relatively low funding costs, low potential market risk, and the increased competition in the U.S. banking sector. The increase in shadow price of equity from 2008 to 2010 implies that banks are willing to pay more to increase their equity capital during the global financial crisis since the market risk during this time is perceived to be very high. Specifically, the larger median value (0.0324) in 2010 may be due to the tighter regulations of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 that require banks to hold a much higher level of equity than before. Banks are willing to pay more in 2010 to raise their equity capital to satisfy the government's regulations. This result is consistent with Dong et al. (2016), who find that there is an increase in the shadow price of equity for Chinese banks from 2008 to 2009. Surprisingly, some amount of banks with negative estimates of shadow prices of equity show up across years. This suggests that for any given year, these banks actually operate in an uneconomic region of the production function. These banks may hold a much higher equity level than their efficient level, causing their shadow prices of equity to be negative.

Stated previously, the estimated shadow price of equity is directly comparable to the price of deposits and the price of loans and leases. The comparisons among the median values of these three prices are reported in Table 11. Equity is commonly considered more risky than deposits because equity holders are the last to receive any distribution of assets as a result of bankruptcy proceedings. Therefore, equity holders expect greater returns from their investment in the firm's stock than depositors. Table 11 shows that for most years, the estimated shadow price of equity is larger than the price of deposits and smaller than the price of loans. However, over the period 2006–2008, the estimated shadow price of equity is smaller than the price of deposits. Moreover, over the period 2006–2008, the price of loans and leases is very high. The potential profits for banks over 2006–2008 may lead banks to be willing to pay an unreasonable price for deposits.

Table 12 reports the summary statistics for the estimated shadow shares of equity costs to total variable expenses in each year. The median values of the estimated shadow shares of equity costs have a decreasing trend from 2001 to 2008, and then have an increasing trend from 2008 to 2018. The mean values have a similar pattern. Even though Table 10 shows that the median values of the estimated prices of equity before 2008 are in general higher than that after 2008, Table 12 shows that the median values of estimated shadow shares of equity costs increase in general after 2008, reflecting that banks use much more equity than before, and U.S. banking systems have been undergoing recapitalization since the global financial crisis.

Table 13 shows the summary statistics for the estimated cost inefficiency in each year. Even though the changes of median and mean values of the cost inefficiency over this period are mixed, it is evident that the cost inefficiency before 2008 is lower in general than that after 2008. This suggests that banks became less cost efficient after 2008, and on average they are much farther away from the cost frontier. The increase in inefficiency may be caused by the tighter regulations from the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, suggesting that the deleveraging has imposed significant costs on banks.

The difference in medians for the estimated shadow prices of equity by size quartile based on log of total assets are reported in Table 14. It is evident that the median values of estimated shadow prices of equity for the fourth quartile are much smaller than the other three quartiles for any given year. Moreover, the median values of shadow prices of equity for the fourth quartile are negative over 2005–2008 and 2015–2016. Specifically the median values for the banks in the fourth quartile have the lowest negative value in 2008, suggesting that these banks do not pay anything to equity investors at the start of the global financial crisis, and instead they get paid implicitly by the equity investors. This fact implies that big banks indeed get an implicit guarantee from the government during the upheaval global financial crisis. To further understand the relationship between the estimated shadow price of equity and the size of banks, I report their correlation in Table 15. For any given year, there is a negative correlation between the shadow price of equity and the size of banks, suggesting that big banks indeed consistently pay less in equity than small banks over the sample period. Our results are different from Hughes et al. (2001) who find that a positive relationship exists between the size and the estimated shadow price of equity for the bank holding companies in 1994. This is not surprising since I use nonparametric methods instead of translog cost function and also here I focus on commercial banks over 2001–2018 rather than bank holding companies in 1994.

The results of tests about whether the estimated shadow prices of equity are different from 0 are reported in Table 16. The table reports the number of banks for which I reject that the shadow price of equity is significantly different from 0 (at .05 significance) in favor of a positive shadow price of equity or a negative shadow price of equity, or for which I cannot reject that the shadow price of equity is equal to 0 in each quartile of total assets in each year. In each quartile, I find that a small number of banks have a negative shadow price of equity in each year, suggesting that only a small number of banks operate in an uneconomic region of production. However, among banks in the fourth quartile (the largest 25 percent of banks by assets), I find that there are more banks having negative shadow price of equity than the other three quartiles in each year. Therefore, the results suggest that more banks in the fourth quartile get paid implicitly by equity investors than the other three quartiles, providing evidence of TBTF banks.

Table 17 reports the correlations between the equity-asset ratios and the shadow prices of equity across years. Economic theory predicts that in a free market, if a bank uses more equity given fixed outputs (or assets), the price (or opportunity cost) of equity should be lower. Table 17 shows that the correlations are only negative for 2001, 2002, and 2006. This means that if a bank uses more equity given fixed assets, the shadow price of equity will be lower over these three years. However, for most years, the correlations are positive. This result is not surprising and supports the choice of treating equity capital as a quasi-fixed input rather than a variable input. In the short run, equity is not variable due to government's regulations and constraints.

Turning to differences in the means of estimated shadow price of equity between the top 100 largest banks and the other banks in Table 19, the data reveal that for any given year in the sample, the estimated mean shadow price of equity for the top 100 largest banks is smaller than the mean price of deposits, which is smaller than the mean price of loans and leases. This result thus provides evidence that, on average, the top 100 largest banks get the implicit guarantee from the government, so they are able to pay a much lower price on equity than on deposits, even though equity is commonly viewed as a much riskier asset than deposits. Also, for most years, the mean shadow price of equity for the top 100 largest banks is negative, again implying that they get paid implicitly by the equity investors. In addition, the mean shadow price of equity for the top 100 largest banks in 2007 has the largest positive value (0.0148), suggesting that on average they would like to pay more to get equity capital at the start of the global financial crisis, even though this value is still much smaller than the price of deposits. Comparing the difference in the mean shadow prices of equity between the top 100 largest banks and the other banks, I find that the mean value for the top 100 largest banks is much smaller than that for the other banks, again providing evidence that the top 100 largest banks get paid implicitly by the equity investors.

I further check differences in the means of the estimated shadow prices of equity for the top 10 largest banks and the other banks with results reported in Table 20. The data reveal that in 2001–2005, 2007, and 2009–2011, the estimated mean shadow prices of equity for the top 10 largest banks are smaller than the mean prices of deposits, which is smaller than the mean price of loans and leases. This is evidence that there exits an implicit subsidy for the top 10 largest banks. However, for the remaining periods, the estimated mean shadow price of equity for the top 10 largest banks is larger than the mean price of deposits and even larger than the mean price of loans and leases in some cases. In addition, the mean shadow price of equity for the top 10 largest banks in 2007 has a very large positive value (0.133), suggesting that on average they would like to pay much more to get equity capital to mitigate the market risk at the start of the global financial crisis. Moreover, the mean shadow price of equity for the top 10 largest banks maintains a very high level after 2010. Comparing the difference in mean shadow prices of equity between the top 10 largest banks and the other banks, I find that the mean values for the top 10 largest banks are larger than for the other banks at the start of the global financial crisis and after the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. Comparing these results with those in Table 19, I find that even though on average the top 100 largest banks pay less in equity for each year, the top 10 largest banks actually pay more for some years, especially at the start of the global financial crisis and after the Dodd-Frank Wall Street Reform and Consumer

Protection Act of 2010. These results imply that the regulations are effective in reducing the implicit subsidy at least for the top 10 largest banks. However, it is also evident that the recapitalization has imposed significant equity funding costs on the top 10 largest banks.

6 Summary and Conclusions

After the global financial crisis, TBTF has become a heated topic. However, until now there was little evidence of the existence of TBTF banks. This paper contributes to the literature on the existence of TBTF banks by providing a new piece of evidence.

By estimating the shadow price of equity, using nonparametric local-linear method for stochastic frontier models initially introduced by Simar et al. (2017), I find that there are indeed implicit subsidies for the TBTF banks. Specifically, I find that the estimated median values of shadow prices of equity for the banks in the fourth quartile based on total assets are much smaller than the banks in the other three quartiles. Moreover, for any given year there exists a negative correlation between the shadow prices of equity and the sizes of banks, suggesting that big banks pay less in equity than small banks. In addition, there are more banks with a negative shadow price of equity in the fourth quartile than the other three quartiles in each year. The data reveal that for any given year in the sample, the estimated mean shadow price of equity for the top 100 largest banks is smaller than the mean price of deposits, even though equity is commonly viewed as a riskier asset than deposit. Finally, I find that the top 10 largest banks are willing to pay much more at the start of the global financial crisis and after the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. Therefore, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 is effective in removing the implicit subsidy for the top 10 largest banks. However, it is also evident that the recapitalization has imposed significant equity funding costs on the top 10 largest banks.

My results are consistent with the evidence of the existence of TBTF banks, provided by Baker and Mcarthur (2009), Brewer and Jagtiani (2013), Ueda and Weder di Mauro (2013), and Santos and Santos (2014). Given the importance of TBTF in the U.S., the policies trying to remove the implicit subsidy on TBTF have significant impacts on the U.S. banking market. Policy makers should be cautious of the fact that the increased safety of banks may be offset by the adjustment costs (decreased efficiency and increased shadow price of equity) imposed by the recapitalization process. This is a critical question for both policy makers and banking regulators.

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Table 1: Summary Statistics for Years 2001–2018

Variable	N	Min	Q1	Median	Mean	Q3	Max
Total Deposits (x_1)	119028	$2.2470 \times 10^{+02}$	$7.3740 \times 10^{+04}$	$1.5320 \times 10^{+05}$	$1.7880 \times 10^{+06}$	$3.5260 \times 10^{+05}$	$1.9300 \times 10^{+09}$
No. of Full Time Employee (x_2)	119028	$1.0000 \times 10^{+00}$	$2.0000 \times 10^{+01}$	$4.0000 \times 10^{+01}$	$2.9210 \times 10^{+02}$	$8.7000 \times 10^{+01}$	$2.3520 \times 10^{+05}$
Physical Capital (x_3)	119028	$1.0000 \times 10^{+00}$	$9.4750 \times 10^{+02}$	$2.8440 \times 10^{+03}$	$1.8650 \times 10^{+04}$	$7.1960 \times 10^{+03}$	$1.3430 \times 10^{+07}$
Total Loans (y_1)	119028	$2.1820 \times 10^{+01}$	$4.8060 \times 10^{+04}$	$1.0840 \times 10^{+05}$	$1.1450 \times 10^{+06}$	$2.6070 \times 10^{+05}$	$9.7350 \times 10^{+08}$
Total Securities (y_2)	119028	$1.0230 \times 10^{+00}$	$1.3460 \times 10^{+04}$	$3.2700 \times 10^{+04}$	$3.9260 \times 10^{+05}$	$8.0820 \times 10^{+04}$	$4.3280 \times 10^{+08}$
Off-balance Sheet Itmes (y_3)	119028	$1.0000 \times 10^{+00}$	$3.7640 \times 10^{+02}$	$9.7780 \times 10^{+02}$	$3.6950 \times 10^{+04}$	$2.8490 \times 10^{+03}$	$4.5050 \times 10^{+07}$
Price of Deposit (w_1)	119028	1.4910×10^{-05}	6.9250×10^{-03}	1.7620×10^{-02}	2.0080×10^{-02}	2.9900×10^{-02}	$2.9720 \times 10^{+00}$
Price of Labor (w_2)	119028	2.4000×10^{-01}	$5.6740 \times 10^{+01}$	$6.6070 \times 10^{+01}$	$7.0360 \times 10^{+01}$	$7.8980 \times 10^{+01}$	$8.5300 \times 10^{+02}$
Price of Physical Capital (w_3)	119028	1.2660×10^{-04}	1.8460×10^{-01}	2.7560×10^{-01}	6.3330×10^{-01}	4.6640×10^{-01}	$4.2380 \times 10^{+03}$
Non-performing Loans (npl)	119028	$1.0000 \times 10^{+00}$	$7.4000 \times 10^{+02}$	$2.0980 \times 10^{+03}$	$3.7720 \times 10^{+04}$	$5.7650 \times 10^{+03}$	$8.5170 \times 10^{+07}$
Equity (q_1)	119028	$2.7890 \times 10^{+01}$	$8.8220 \times 10^{+03}$	$1.7850 \times 10^{+04}$	$2.1750 \times 10^{+05}$	$4.0300 \times 10^{+04}$	$2.1650 \times 10^{+08}$
Total Assets (q_2)	119028	$3.1080 \times 10^{+03}$	$8.3840 \times 10^{+04}$	$1.7300 \times 10^{+05}$	$2.0590 \times 10^{+06}$	$3.9560 \times 10^{+05}$	$2.2190 \times 10^{+09}$
Equity-asset Ratio (r_0)	119028	8.0210×10^{-05}	8.6600×10^{-02}	1.0070×10^{-01}	1.0860×10^{-01}	1.2070×10^{-01}	9.8790×10^{-01}
Time (t)	119028	$1.0000 \times 10^{+00}$	$4.0000 \times 10^{+00}$	$8.0000 \times 10^{+00}$	$8.7980 \times 10^{+00}$	$1.3000 \times 10^{+01}$	$1.8000 \times 10^{+01}$
Variable Cost (c^{ν})	119028	$2.2730 \times 10^{+01}$	$2.7050 \times 10^{+03}$	$5.6660 \times 10^{+03}$	$5.5390 \times 10^{+04}$	$1.2990 \times 10^{+04}$	$6.8930 \times 10^{+07}$
Price of Loans and Leases	119028	1.8180×10^{-04}	5.4130×10^{-02}	6.4010×10^{-02}	6.5240×10^{-02}	7.4240×10^{-02}	$3.0900 \times 10^{+00}$

Note: All dollar amounts are given in 2018 U.S. thousand dollars

Table 2: Medians and Means for Equity-Asset Ratio

Year	N	Median	Mean
2001	8111	0.0932	0.1028
2002	7905	0.0955	0.1050
2003	7782	0.0954	0.1044
2004	7550	0.0961	0.1062
2005	7371	0.0961	0.1059
2006	7168	0.0977	0.1085
2007	7065	0.1002	0.1114
2008	6878	0.0977	0.1068
2009	6578	0.0975	0.1051
2010	6293	0.0987	0.1058
2011	6109	0.1033	0.1098
2012	6468	0.1046	0.1110
2013	6301	0.1024	0.1089
2014	6025	0.1064	0.1132
2015	5724	0.1069	0.1140
2016	5491	0.1061	0.1129
2017	5234	0.1075	0.1150
2018	4975	0.1092	0.1168

Table 3: Medians of Equity-Asset Ratio by Size Quartile Based

Year	1st Quartile	2nd Quartile	3nd Quartile	4th Quartile
2001	0.1049	0.0953	0.0909	0.0863
2002	0.1069	0.0974	0.0926	0.0890
2003	0.1058	0.0971	0.0922	0.0889
2004	0.1065	0.0980	0.0925	0.0906
2005	0.1070	0.0979	0.0929	0.0898
2006	0.1090	0.0998	0.0941	0.0919
2007	0.1117	0.1022	0.0961	0.0938
2008	0.1104	0.1002	0.0932	0.0906
2009	0.1059	0.0995	0.0939	0.0931
2010	0.1041	0.0994	0.0967	0.0967
2011	0.1067	0.1046	0.1010	0.1023
2012	0.1078	0.1045	0.1024	0.1045
2013	0.1043	0.1028	0.1004	0.1036
2014	0.1075	0.1070	0.1045	0.1068
2015	0.1101	0.1071	0.1050	0.1063
2016	0.1104	0.1067	0.1034	0.1054
2017	0.1118	0.1082	0.1045	0.1068
2018	0.1138	0.1093	0.1051	0.1091

Note: The size quartiles are defined in terms of total assets for each year.

Table 4: Correlation Between Equity-Asset Ratios and Sizes of Banks

Year	Correlation
2001	-0.1960
2002	-0.1856
2003	-0.1594
2004	-0.1394
2005	-0.1455
2006	-0.1512
2007	-0.1497
2008	-0.2007
2009	-0.1423
2010	-0.0803
2011	-0.0555
2012	-0.0411
2013	-0.0131
2014	-0.0446
2015	-0.0637
2016	-0.0658
2017	-0.0645
2018	-0.0687

Table 5: The Weight of Assets for Top 10 Largest Banks

Year	Weight
2001	0.3862
2002	0.4077
2003	0.4221
2004	0.4651
2005	0.4817
2006	0.5127
2007	0.5343
2008	0.5552
2009	0.5495
2010	0.5613
2011	0.5753
2012	0.5437
2013	0.5467
2014	0.5566
2015	0.5465
2016	0.5376
2017	0.5380
2018	0.5438

Table 6: Tests of Differences in Means for Price of Deposits Between Big and Small Banks

Year	$n1$	$n2$	Mean1	Mean2	Statistic	p-value
2001	4055	4056	0.0497	0.0485	-4.5192	6.21×10^{-06}
2002	3952	3953	0.0326	0.0313	-6.2582	3.90×10^{-10}
2003	3891	3891	0.0237	0.0231	-3.5160	4.38×10^{-04}
2004	3775	3775	0.0194	0.0197	1.9707	4.88×10^{-02}
2005	3685	3686	0.0231	0.0249	11.0570	2.03×10^{-28}
2006	3584	3584	0.0313	0.0346	12.3775	3.46×10^{-35}
2007	3532	3533	0.0357	0.0393	4.5629	5.04×10^{-06}
2008	3439	3439	0.0281	0.0294	7.3395	2.14×10^{-13}
2009	3289	3289	0.0208	0.0210	0.1990	8.42×10^{-01}
2010	3146	3147	0.0148	0.0152	3.0753	2.10×10^{-03}
2011	3054	3055	0.0107	0.0109	1.6835	9.23×10^{-02}
2012	3234	3234	0.0081	0.0082	1.2454	2.13×10^{-01}
2013	3150	3151	0.0062	0.0062	0.5783	5.63×10^{-01}
2014	3012	3013	0.0052	0.0052	0.5788	5.63×10^{-01}
2015	2862	2862	0.0048	0.0048	-0.1576	8.75×10^{-01}
2016	2745	2746	0.0047	0.0048	0.5972	5.50×10^{-01}
2017	2617	2617	0.0049	0.0052	3.4847	4.93×10^{-04}
2018	2487	2488	0.0061	0.0070	9.4219	4.43×10^{-21}

Note: I split the total observations of each year into two even subsamples by the median total assets in that year. The number of small banks is $n1$, while the number of big banks is $n2$.

Table 7: Tests of Differences in Means for Price of Loans and Leases Between Big and Small Banks

Year	$n1$	$n2$	Mean1	Mean2	Statistic	p-value
2001	4055	4056	0.0887	0.0843	-11.2364	2.70×10^{-29}
2002	3952	3953	0.0788	0.0733	-13.0674	5.05×10^{-39}
2003	3891	3891	0.0730	0.0665	-18.3902	1.58×10^{-75}
2004	3775	3775	0.0681	0.0626	-6.1035	1.04×10^{-09}
2005	3685	3686	0.0710	0.0666	-14.2099	7.96×10^{-46}
2006	3584	3584	0.0771	0.0743	-9.2144	3.13×10^{-20}
2007	3532	3533	0.0796	0.0759	-9.5987	8.09×10^{-22}
2008	3439	3439	0.0716	0.0667	-14.8066	1.33×10^{-49}
2009	3289	3289	0.0673	0.0624	-10.7416	6.49×10^{-27}
2010	3146	3147	0.0666	0.0618	-12.3055	8.46×10^{-35}
2011	3054	3055	0.0643	0.0596	-14.9504	1.55×10^{-50}
2012	3234	3234	0.0612	0.0566	-11.8717	1.66×10^{-32}
2013	3150	3151	0.0576	0.0526	-15.2305	2.22×10^{-52}
2014	3012	3013	0.0549	0.0500	-15.5815	9.73×10^{-55}
2015	2862	2862	0.0538	0.0486	-15.8820	8.44×10^{-57}
2016	2745	2746	0.0535	0.0479	-18.0996	3.21×10^{-73}
2017	2617	2617	0.0531	0.0485	-11.2615	2.03×10^{-29}
2018	2487	2488	0.0546	0.0506	-12.1416	6.36×10^{-34}

Note: I split the total observations of each year into two even subsamples by the median total assets in that year. The number of small banks is $n1$, while the number of big banks is $n2$.

Table 8: Tests of Differences in Means for Price of Deposits Between Big and Small Banks

Year	$n1$	$n2$	Mean1	Mean2	Statistic	p-value
2001	2028	2028	0.0494	0.0479	-3.5437	3.95×10^{-04}
2002	1976	1977	0.0326	0.0306	-6.1715	6.76×10^{-10}
2003	1946	1946	0.0235	0.0226	-3.5992	3.19×10^{-04}
2004	1888	1888	0.0189	0.0195	2.6699	7.59×10^{-03}
2005	1843	1843	0.0222	0.0253	13.1272	2.30×10^{-39}
2006	1792	1792	0.0300	0.0353	17.9959	2.10×10^{-72}
2007	1766	1767	0.0344	0.0391	8.8235	1.11×10^{-18}
2008	1720	1720	0.0272	0.0294	8.2329	1.83×10^{-16}
2009	1645	1645	0.0208	0.0209	0.0710	9.43×10^{-01}
2010	1573	1574	0.0141	0.0150	4.2883	1.80×10^{-05}
2011	1527	1528	0.0104	0.0108	2.4803	1.31×10^{-02}
2012	1617	1617	0.0078	0.0081	2.3653	1.80×10^{-02}
2013	1575	1576	0.0060	0.0061	1.0969	2.73×10^{-01}
2014	1506	1507	0.0050	0.0051	0.7422	4.58×10^{-01}
2015	1431	1431	0.0047	0.0047	0.2447	8.07×10^{-01}
2016	1373	1373	0.0046	0.0047	0.9334	3.51×10^{-01}
2017	1309	1309	0.0048	0.0052	3.9932	6.52×10^{-05}
2018	1244	1244	0.0059	0.0072	9.2318	2.66×10^{-20}

Note: I split the total observations of each year into the top 25% quantile group and the bottom 25% quantile group in terms of total assets. The number for small banks is $n1$, while the number of big banks is $n2$.

Table 9: Tests of Differences in Means for Price of Loans and Leases Between Big and Small Banks

Year	$n1$	$n2$	Mean1	Mean2	Statistic	p-value
2001	2028	2028	0.0897	0.0831	-11.3313	9.18×10^{-30}
2002	1976	1977	0.0807	0.0718	-13.9986	1.59×10^{-44}
2003	1946	1946	0.0752	0.0646	-19.7196	1.46×10^{-86}
2004	1888	1888	0.0699	0.0598	-15.9104	5.37×10^{-57}
2005	1843	1843	0.0721	0.0656	-13.2573	4.10×10^{-40}
2006	1792	1792	0.0777	0.0734	-9.5689	1.08×10^{-21}
2007	1766	1767	0.0804	0.0750	-8.3365	7.66×10^{-17}
2008	1720	1720	0.0733	0.0656	-14.0755	5.37×10^{-45}
2009	1645	1645	0.0688	0.0616	-8.5787	9.60×10^{-18}
2010	1573	1574	0.0678	0.0609	-11.3459	7.77×10^{-30}
2011	1527	1528	0.0655	0.0585	-13.1973	9.10×10^{-40}
2012	1617	1617	0.0624	0.0555	-10.7737	4.58×10^{-27}
2013	1575	1576	0.0589	0.0513	-13.6655	1.63×10^{-42}
2014	1506	1507	0.0563	0.0485	-14.9686	1.18×10^{-50}
2015	1431	1431	0.0552	0.0469	-15.3249	5.21×10^{-53}
2016	1373	1373	0.0551	0.0465	-16.2377	2.73×10^{-59}
2017	1309	1309	0.0545	0.0476	-9.2036	3.46×10^{-20}
2018	1244	1244	0.0557	0.0498	-10.3783	3.11×10^{-25}

Note: I split the total observations of each year into the top 25% quantile group and the bottom 25% quantile group in terms of total assets. The number for small banks is $n1$, while the number of big banks is $n2$.

Table 10: Summary Statistics for Estimated Shadow Prices of Equity

Year	N	Min	Q1	Median	Mean	Q3	Max
2001	7907	-0.7965	-0.0646	0.0830***	0.0875***	0.2437	0.8760
2002	7793	-0.7991	-0.0559	0.0647***	0.0759***	0.2048	0.8757
2003	7694	-0.7863	-0.0746	0.0466***	0.0526**	0.1840	0.8726
2004	7458	-0.7973	-0.0930	0.0366***	0.0402**	0.1740	0.8747
2005	7234	-0.7989	-0.1156	0.0304***	0.0299	0.1816	0.8711
2006	6945	-0.7974	-0.1267	0.0310***	0.0368**	0.2029	0.8768
2007	6843	-0.7894	-0.1287	0.0307***	0.0345*	0.2072	0.8754
2008	6761	-0.7937	-0.1148	0.0229**	0.0232	0.1640	0.8671
2009	6526	-0.7791	-0.0846	0.0276***	0.0299*	0.1460	0.8715
2010	6255	-0.7953	-0.0739	0.0324***	0.0328**	0.1415	0.8766
2011	6087	-0.7904	-0.0622	0.0286***	0.0333**	0.1292	0.8632
2012	6452	-0.7822	-0.0565	0.0275***	0.0333**	0.1222	0.8262
2013	6281	-0.7924	-0.0681	0.0226***	0.0198	0.1148	0.8236
2014	6014	-0.7804	-0.0599	0.0223***	0.0235*	0.1086	0.8463
2015	5700	-0.7972	-0.0668	0.0237***	0.0243*	0.1164	0.8600
2016	5468	-0.7808	-0.0666	0.0255***	0.0290**	0.1261	0.8760
2017	5215	-0.7787	-0.0681	0.0245***	0.0278**	0.1278	0.8739
2018	4952	-0.7992	-0.0788	0.0267***	0.0256*	0.1311	0.8695

Note: Statistical significance (difference from 0) for the median and mean values at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively.

Table 11: Differences in Medians for Estimated Shadow Prices of Equity, Prices of Deposits and Prices of Loans and Leases

Year	Equity	Deposits	Loans
2001	0.0830	0.0496	0.0860
2002	0.0647	0.0321	0.0753
2003	0.0466	0.0234	0.0687
2004	0.0366	0.0195	0.0636
2005	0.0304	0.0242	0.0679
2006	0.0310	0.0331	0.0749
2007	0.0307	0.0374	0.0771
2008	0.0229	0.0289	0.0683
2009	0.0276	0.0204	0.0640
2010	0.0324	0.0148	0.0632
2011	0.0286	0.0106	0.0610
2012	0.0275	0.0077	0.0576
2013	0.0226	0.0057	0.0536
2014	0.0223	0.0048	0.0509
2015	0.0237	0.0044	0.0499
2016	0.0255	0.0043	0.0494
2017	0.0245	0.0046	0.0494
2018	0.0267	0.0062	0.0511

Table 12: Summary Statistics for Estimated Shadow Shares of Equity Costs to Total Expenses

Year	N	Min	Q1	Median	Mean	Q3	Max
2001	7907	-2.1198	-0.1431	0.2027	0.1955	0.5460	2.2585
2002	7793	-2.6517	-0.1762	0.2070	0.2161	0.6035	2.5181
2003	7694	-2.8934	-0.2569	0.1744	0.1816	0.6150	3.0163
2004	7458	-2.7709	-0.3392	0.1577	0.1534	0.6329	3.1989
2005	7234	-3.4110	-0.3800	0.1174	0.1142	0.6111	3.7346
2006	6945	-2.9897	-0.3886	0.1073	0.1205	0.6114	3.0056
2007	6843	-3.5348	-0.3682	0.1038	0.1085	0.5880	3.1385
2008	6761	-3.6798	-0.3398	0.0735	0.0931	0.5189	2.9500
2009	6526	-4.5818	-0.2869	0.1086	0.1252	0.5328	2.9416
2010	6255	-2.9489	-0.2910	0.1396	0.1444	0.5866	2.8939
2011	6087	-2.7813	-0.2939	0.1472	0.1617	0.6162	3.0730
2012	6452	-3.5784	-0.2961	0.1609	0.1748	0.6389	3.5406
2013	6281	-3.2565	-0.3653	0.1343	0.1357	0.6383	3.7433
2014	6014	-4.0487	-0.3614	0.1449	0.1551	0.6586	5.3166
2015	5700	-3.8380	-0.4031	0.1575	0.1678	0.7358	4.7627
2016	5468	-6.2755	-0.3878	0.1733	0.1806	0.7470	5.5381
2017	5215	-5.1794	-0.3943	0.1630	0.1797	0.7419	4.1570
2018	4952	-4.2895	-0.4272	0.1540	0.1550	0.7191	3.3417

Table 13: Summary Statistics for Estimated Mean Cost Inefficiency

Year	N	Min	Q1	Median	Mean	Q3	Max
2001	7907	1.0000	1.0603	1.1684	1.1641	1.2510	1.6734
2002	7793	1.0000	1.1194	1.1955	1.1896	1.2695	1.6526
2003	7694	1.0000	1.1346	1.2116	1.2014	1.2820	1.6786
2004	7458	1.0000	1.1444	1.2210	1.2093	1.2893	1.6842
2005	7234	1.0000	1.1451	1.2204	1.2086	1.2901	1.6692
2006	6945	1.0000	1.1400	1.2171	1.2059	1.2888	1.6837
2007	6843	1.0000	1.1404	1.2188	1.2087	1.2914	1.6498
2008	6761	1.0000	1.1493	1.2238	1.2190	1.3004	1.6558
2009	6526	1.0000	1.1488	1.2263	1.2232	1.3084	1.6851
2010	6255	1.0000	1.1499	1.2272	1.2236	1.3079	1.6553
2011	6087	1.0000	1.1495	1.2269	1.2215	1.3089	1.6497
2012	6452	1.0000	1.1474	1.2245	1.2213	1.3116	1.6582
2013	6281	1.0000	1.1505	1.2294	1.2225	1.3116	1.6361
2014	6014	1.0000	1.1539	1.2320	1.2231	1.3131	1.6637
2015	5700	1.0000	1.1498	1.2301	1.2214	1.3110	1.6538
2016	5468	1.0000	1.1456	1.2286	1.2188	1.3117	1.6451
2017	5215	1.0000	1.1411	1.2238	1.2140	1.3071	1.6169
2018	4952	1.0000	1.1250	1.2121	1.2036	1.2976	1.5906

Table 14: Difference in Medians for Shadow Prices of Equity by Size Quartile

Year	1st Quartile	2nd Quartile	3nd Quartile	4th Quartile
2001	0.0761	0.0975	0.1064	0.0498
2002	0.0673	0.0858	0.0729	0.0317
2003	0.0460	0.0640	0.0596	0.0142
2004	0.0358	0.0630	0.0425	0.0123
2005	0.0291	0.0536	0.0434	-0.0010
2006	0.0344	0.0556	0.0534	-0.0093
2007	0.0285	0.0662	0.0380	-0.0040
2008	0.0291	0.0460	0.0295	-0.0164
2009	0.0310	0.0470	0.0313	0.0006
2010	0.0319	0.0468	0.0410	0.0093
2011	0.0313	0.0444	0.0334	0.0046
2012	0.0292	0.0395	0.0326	0.0079
2013	0.0255	0.0320	0.0282	0.0044
2014	0.0231	0.0321	0.0307	0.0050
2015	0.0313	0.0382	0.0275	-0.0040
2016	0.0347	0.0478	0.0276	-0.0088
2017	0.0386	0.0323	0.0307	0.0021
2018	0.0316	0.0359	0.0376	0.0019

Table 15: Correlation Between the Estimated Shadow Prices of Equity and Sizes of Banks

Year	Correlation
2001	-0.0682
2002	-0.0856
2003	-0.0862
2004	-0.0884
2005	-0.0635
2006	-0.0738
2007	-0.0741
2008	-0.0946
2009	-0.0806
2010	-0.0630
2011	-0.0783
2012	-0.0801
2013	-0.0526
2014	-0.0643
2015	-0.1010
2016	-0.1153
2017	-0.0888
2018	-0.0817

Table 16: Counts of Banks Having Negative, 0, and Positive Shadow Prices of Equity by Size Quartile (.05 significance)

	— 1st quartile —			— 2nd quartile —			— 3rd quartile —			— 4th quartile —		
Year	Neg.	0	Pos.	Neg.	0	Pos.	Neg.	0	Pos.	Neg.	0	Pos.
2001	173	1432	372	121	1485	371	114	1469	393	229	1359	389
2002	171	1385	393	133	1406	409	123	1464	361	239	1354	355
2003	179	1391	354	164	1354	405	169	1414	340	262	1323	339
2004	203	1310	352	196	1277	391	211	1324	329	274	1279	312
2005	225	1262	322	208	1250	350	183	1322	303	280	1259	270
2006	227	1212	298	163	1247	326	161	1286	289	236	1223	277
2007	203	1241	267	153	1234	324	158	1246	306	281	1155	275
2008	166	1229	296	164	1204	322	193	1228	269	261	1188	241
2009	178	1165	289	135	1174	322	165	1193	273	228	1139	265
2010	160	1091	313	157	1104	303	165	1098	300	227	1032	305
2011	155	1085	282	143	1059	320	156	1058	307	226	1007	289
2012	179	1112	323	169	1092	351	161	1110	342	228	1100	285
2013	183	1091	297	203	1063	304	207	1058	305	247	1013	310
2014	161	1057	286	155	1066	282	175	1018	310	243	988	273
2015	166	962	297	139	972	314	159	977	289	295	866	264
2016	160	930	277	124	967	276	169	925	273	268	839	260
2017	132	864	308	146	907	251	156	871	276	236	805	263
2018	125	850	263	141	828	269	130	848	260	230	751	257

Table 17: Correlation Between the Estimated Shadow Prices of Equity and Equity-Asset Ratios

Year	Correlation
2001	-0.0206
2002	-0.0285
2003	0.0084
2004	0.0138
2005	0.0286
2006	-0.0021
2007	0.0039
2008	0.0626
2009	0.0477
2010	0.0296
2011	0.0104
2012	0.0050
2013	0.0632
2014	0.0453
2015	0.0455
2016	0.0399
2017	0.0472
2018	0.0438

Table 18: Correlation Between the Ratio of Shadow Prices of Equity over Price of Deposits and the Ratio of Equity over Deposits

Year	Correlation
2001	-0.0159
2002	-0.0191
2003	-0.0040
2004	-0.0053
2005	0.0036
2006	-0.0167
2007	-0.0015
2008	0.0467
2009	-0.0041
2010	0.0013
2011	-0.0080
2012	-0.0022
2013	0.0017
2014	0.0005
2015	-0.0003
2016	0.0274
2017	0.0026
2018	0.0027

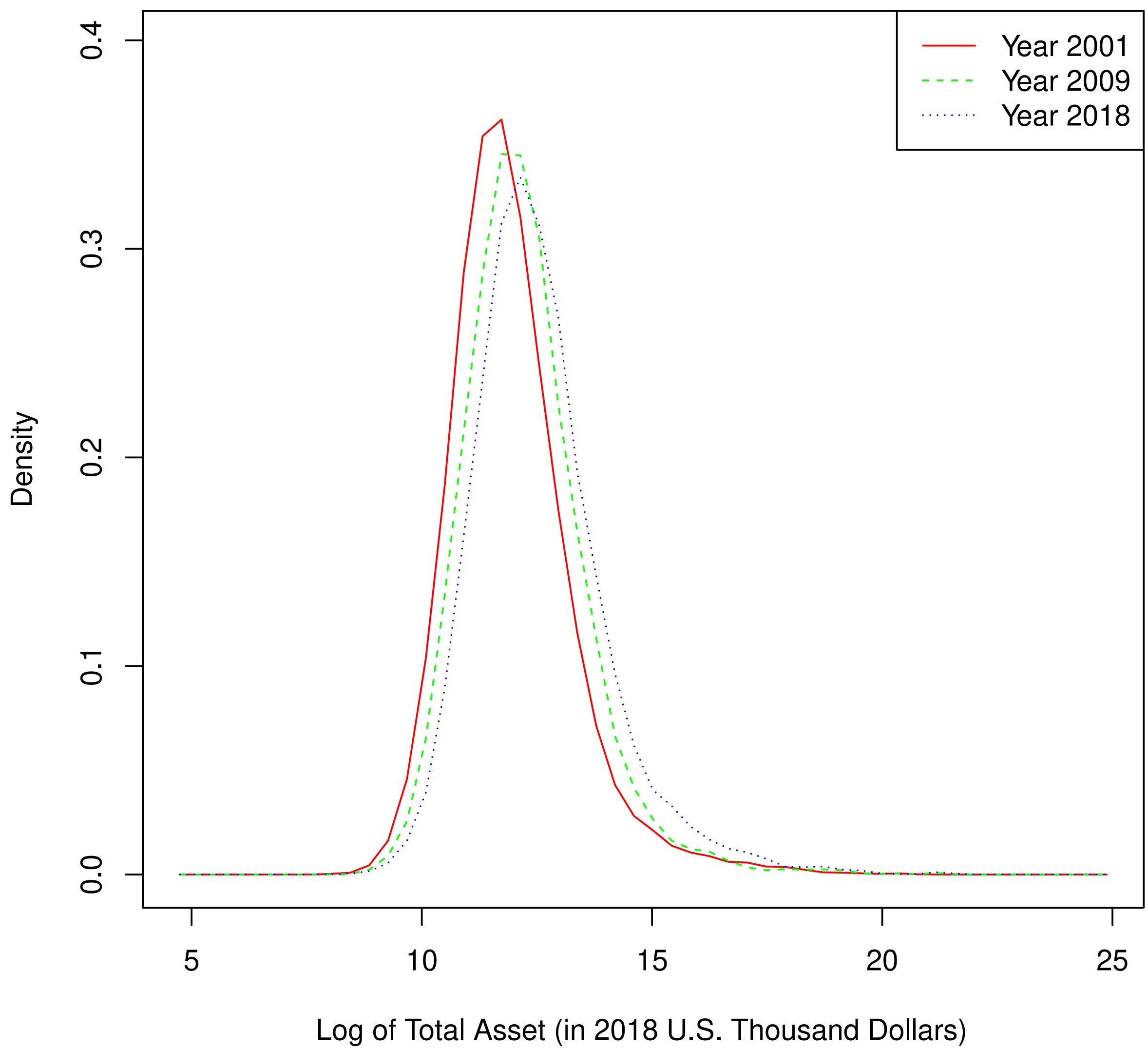
Table 19: Differences in Means for Shadow Prices of Equity, Prices of Deposits, and Prices of Loans and Leases for the Top 100 Largest Banks and the Other Banks

	— **Top 100 Largest Banks** —			— **The Other Banks** —		
Year	Equity	Deposits	Loans	Equity	Deposits	Loans
2001	-0.0126	0.0452	0.0834	0.0888	0.0490	0.0863
2002	-0.0206	0.0276	0.0693	0.0772	0.0320	0.0761
2003	-0.0117	0.0205	0.0607	0.0535	0.0234	0.0699
2004	-0.0211	0.0182	0.0555	0.0410	0.0195	0.0654
2005	-0.0127	0.0273	0.0622	0.0305	0.0239	0.0689
2006	-0.0139	0.0366	0.0692	0.0376	0.0328	0.0757
2007	0.0148	0.0386	0.0707	0.0348	0.0374	0.0778
2008	-0.0076	0.0269	0.0639	0.0237	0.0287	0.0691
2009	-0.0305	0.0162	0.0586	0.0308	0.0209	0.0649
2010	-0.0045	0.0122	0.0589	0.0334	0.0150	0.0643
2011	-0.0218	0.0087	0.0539	0.0342	0.0109	0.0621
2012	-0.0166	0.0071	0.0515	0.0341	0.0081	0.0591
2013	0.0023	0.0055	0.0484	0.0201	0.0062	0.0552
2014	-0.0222	0.0048	0.0454	0.0243	0.0052	0.0526
2015	-0.0193	0.0046	0.0461	0.0251	0.0048	0.0513
2016	-0.0077	0.0047	0.0448	0.0297	0.0047	0.0508
2017	-0.0019	0.0054	0.0456	0.0283	0.0050	0.0509
2018	0.0031	0.0082	0.0516	0.0261	0.0065	0.0526

Table 20: Differences in Means for Shadow Prices of Equity, Prices of Deposits, and Prices of Loans and Leases for the Top 10 Largest Banks and the Other Banks

	— **Top 10 Largest Banks** —			— **The Other Banks** —		
Year	Equity	Deposits	Loans	Equity	Deposits	Loans
2001	-0.0619	0.0434	0.0773	0.0877	0.0490	0.0863
2002	-0.0628	0.0236	0.0614	0.0761	0.0319	0.0760
2003	-0.0898	0.0164	0.0543	0.0528	0.0234	0.0698
2004	-0.0721	0.0148	0.0474	0.0404	0.0195	0.0653
2005	-0.1212	0.0253	0.0567	0.0301	0.0239	0.0688
2006	0.0583	0.0370	0.0738	0.0368	0.0329	0.0757
2007	0.1325	0.0393	0.0740	0.0343	0.0374	0.0777
2008	0.0327	0.0236	0.0643	0.0232	0.0287	0.0691
2009	-0.0632	0.0109	0.0533	0.0301	0.0209	0.0649
2010	-0.0242	0.0074	0.0573	0.0329	0.0150	0.0642
2011	0.0147	0.0053	0.0414	0.0333	0.0108	0.0620
2012	0.0462	0.0041	0.0419	0.0333	0.0081	0.0590
2013	0.0593	0.0033	0.0400	0.0197	0.0062	0.0551
2014	0.0383	0.0027	0.0379	0.0235	0.0052	0.0525
2015	0.0633	0.0027	0.0359	0.0242	0.0048	0.0512
2016	0.0650	0.0031	0.0374	0.0289	0.0047	0.0507
2017	0.0968	0.0043	0.0400	0.0276	0.0050	0.0508
2018	0.1546	0.0074	0.0447	0.0253	0.0066	0.0526

Figure 1: Density of (log) Total Assets of U.S. Commercial Banks in 2001, 2009, and 2018



NOTE: Solid line shows density for 2001; dashed line shows density for 2009; dotted line shows density for 2018.