The Financial Crisis and the Shadow Price of Bank Capital

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Abstract

We employ parametric forms of directional distance functions to obtain shadow prices of bank equity capital for listed and unlisted banks. We exploit cost, revenue and profit maximisation as the optimisation criteria to derive pricing rules, which allow us to find shadow prices for both inputs and outputs by explicitly accounting for the bank's capital structure choices and hence risk-taking behaviour. We show how knowledge of one input price can be used to price outputs and how knowledge of one output price can be used to price inputs along with information on input and output quantities. We also show how information on total cost or revenue can be used to shadow price inputs and outputs, respectively. We obtain some striking results highlighting the perils of overambitious balance sheet expansions supported by excessive leverage.

Key words: bank efficiency, directional distance function, risk, shadow prices, US banks

JEL: D24, G21, C61

1. Introduction

The recent financial crisis brought into the forefront once more the twin-perils of undercapitalised banks and non-performing loans both of which greatly affect the safety and soundness of financial intermediation. In this study, we set out to estimate the opportunity costs of equity capital and risky loans from the angle of bank efficiency focussing on US banks. We incorporate the capital structure in a model of banks' production technology, hence explicitly modelling how banks' production decisions influence their riskiness (see Hughes et al., 2001, Weyman-Jones, 2016). While new capital requirements have ignited considerable debate in academic circles, and are facing fierce opposition from financial institutions, empirical evidence on their alleged costs remains scant (see Kisin and Manela, 2016). Largely the controversy centres on theoretical arguments and supporting evidence for or against the premises that (1) the cost of capital is greater than the cost of debt (see the survey by Gorton and Winton, 2003); and (2) by making banks less risky increases their cost of capital, constraining lending and hence investment and growth (see Baker and Wurgler, 2013).

According to Baker and Wurgler (2013), the Modigliani-Miller capital structure irrelevance theorem breaks down since the 'low risk anomaly' in debt markets may be significantly smaller than in equity markets,[1] and hence as stricter capital requirements are phased-in the banks' weighted average cost of capital becomes inversely related to their leverage. Kashyap et al. (2010) estimate that a 10-percentage-point increase in capital ratios would raise banks' weighted average cost of capital by 25–45 basis points, while Baker and Wurgler (2013) estimate the increase to be as high as 85 basis points, which in turn could triple banks' average risk premium, from 40 to 125 basis points per year. On the other hand, proponents of higher capital requirements, such as Admati and Hellwig (2013), argue that the cost of capital is related to the risks that are inherent in the asset portfolio rather than the mix of debt and equity with little, if any, consequences on bank lending. Moreover, we would expect the cost of equity capital to vary with the bank's capital structure rather than assuming to be fixed and invariant to it (Allen et al., 2015). Hence, undercapitalised and highly leveraged banks are more likely to face higher rather than lower price of equity capital, a proposition that we subject to empirical testing.

We employ parametric forms of directional distance functions to obtain shadow prices of bank inputs and outputs, paying particular attention to the modelling of both good and bad outputs, recognising the importance of credit risk for banks (see Fukuyama and Weber, 2008). We exploit cost minimisation and revenue maximisation as the optimisation criteria to derive direct pricing rules, which allow us to find shadow prices for both inputs and outputs. We show how knowledge of bank cost can be used to price inputs and knowledge of bank revenue can be used to price outputs along with information on input and output quantities. We also obtain indirect or crossover pricing rules exploiting profit

[1] The low risk anomaly refers to an empirical pattern arising from historical returns and thus realised cost of equity being higher, rather than lower, for less risky equity. A similar albeit much weaker pattern arises in the debt markets (see Frazzini and Pedersen, 2014; Baker and Wurgler, 2014).

maximisation as the optimisation criterion, which allows us to find shadow prices for both inputs and outputs simultaneously. We show how knowledge of one input price can be used to price outputs and how knowledge of one output price can be used to price inputs along with information on input and output quantities. We parameterise the directional input distance function using a quadratic functional form. We then proceed to obtain shadow prices for inputs utilising an input directional distance function, shadow prices for outputs using an output directional distance, and price inputs and outputs simultaneously utilising a non-oriented directional distance function.

We study samples of US Federal Deposit Insurance Corporation (FDIC) member banks during the period 2002 to 2016, which allows us to evaluate the main hypotheses of interest before, during and after the global financial crisis (GFC). A big change in the banking industry in recent years, mainly in response to GFC exposing the systemic ills of thinly capitalised banks, is the introduction of far more demanding capital requirements, together with new rules for leverage and liquidity. In contrast to standard finance approaches, which calculate the cost of equity capital using asset-pricing models based on market prices, we construct a measure of the cost of equity capital by exploiting the duality between the directional distance function and the profit function, and similarly the duality between the input (output) directional distance function and the cost (revenue) function. The shadow price of equity will equal the market price when the amount of equity minimises cost, maximises revenue or maximises profit, recognising that the shadow price will still provide a measure of opportunity cost even if the level of equity does not conform to any of these optimisation objectives (Hughes et al., 2001). An important advantage of our approach is that it can be used to estimate the cost of equity capital for both publicly listed and non-listed banks without requiring information on the market price of equity.

The paper is organised as follows. Section 2 describes the methodology used to compute the efficiency measures and shadow prices for inputs and outputs. Section 3 describes the data and presents the empirical results. Section 4 concludes the paper.

2. Methodology

2.1. *Parametric method*

The parametric method uses a functional form to model empirically the associated distance function, from which the shadow prices of inputs and outputs can be calculated. Once the functional form is determined, we use the Aigner and Chu (1968) approach to estimate the parameters of the model by minimising the sum of deviations of the distance function value from the frontier of production technology subject to the underlying technology constraints. The constraint conditions cover the feasibility, monotonicity, disposability, translation properties of the distance function. While desirable inputs and outputs satisfy strong disposability, we assume that undesirable outputs (non-performing loans) and desirable outputs satisfy joint weak disposability. Equity capital is a quasi-fixed input, so it is fixed in the short-run but variable in the long-run, and its shadow price is not constrained to be positive.[2] In addition, we require that the functional form should be flexible, i.e. allow for interaction and second order terms to provide a complete characterisation of technology. Färe and Sung (1986) show that within the class of generalised quadratic functions, the quadratic function is the best choice for the directional distance function, in the sense that it provides a second order approximation to the true but unknown production relation, with parameters restrictions to satisfy the translation property.

We assume that we observe inputs, good and bad output data, $(x, y, b) \in \mathbb{R}^N_{\geq} \times \mathbb{R}^M_{\geq} \times \mathbb{R}^J_{\geq}$ and in addition, we assume that both input and output direction vectors $g^x = (g^x_1, \dots, g^x_N), g^y = (g^y_1, \dots, g^y_M), g^b = (g^b_1, \dots, g^b_J)$ have been chosen. We estimate the directional technology distance function $\vec{D}_T((x, y, b; g^x, g^y, g^b)$ using a quadratic functional form. The representation of directional technology distance function is defined as:

$$\vec{D}_T(x, y, b; g^x, g^y, g^b) = max\left\{\beta : \left(x - \beta g^x, y + \beta g^y, b - \beta g^b\right) \in T\right\}.$$

Note that this function satisfies the representation and translation properties, i.e,

$$T = \left\{(x, y, b): \vec{D}_T(x, y, b; g^x, g^y, g^b) \geq 0\right\},$$
$$\vec{D}_T\left(x - \alpha g^x, y + \alpha g^y, b - \beta g^b; g^x, g^y, g^b\right) = \vec{D}_T(x, y, b; g^x, g^y, g^b) - \alpha, \quad \alpha \in \mathbb{R}.$$

To translate the shadow pricing formulas into empirical results we need to parameterise the distance function. We choose the quadratic functional form expressed by:

$$\vec{D}_T(x, y, b; g^x, g^y, g^b) = \alpha_0 + \sum_{n=1}^{N} \alpha_n x_n + \sum_{m=1}^{M} \beta_m y_m + \sum_{j=1}^{J} \gamma_j b_j$$
$$+ \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} \alpha_{n\acute{n}} x_n x_{\acute{n}} + \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M} \beta_{mm'} y_m y_{m'} + \frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J} \gamma_{jj'} b_j b_{j'}$$
$$+ \sum_{n=1}^{N}\sum_{m=1}^{M} \delta_{nm} x_n y_m + \sum_{n=1}^{N}\sum_{j=1}^{J} \nu_{nj} x_n b_j + \sum_{m=1}^{M}\sum_{j=1}^{J} \mu_{mj} y_m b_j$$

We estimate the quadratic directional distance function by solving the following linear programming problem:

$$\min \sum_{k=1}^{n} \vec{D}_T\left(x^k, y^k, b^k; g^x, g^y, g^b\right)$$
$$s.t.$$
$$(1)\ \vec{D}_T\left(x^k, y^k, b^k; g^x, g^y, g^b\right) \geq 0, \qquad k = 1, \dots, K, \quad (feasibility)$$
$$(2)\ \partial_{y_m}\vec{D}_T\left(x^k, y^k, b^k; g^x, g^y, g^b\right) \leq 0, k = 1, \dots, K, \qquad m = 1, \dots, M, \quad (monotonicity)$$
$$(3)\ \partial_{x_n}\vec{D}_T\left(x^k, y^k, b^k; g^x, g^y, g^b\right) \geq 0, k = 1, \dots, K, \qquad n = 1, \dots, N-1, \quad (monotonicity)$$
$$(4)\ \partial_{b_j}\vec{D}_T\left(x^k, y^k, b^k; g^x, g^y, g^b\right) \geq 0, k = 1, \dots, K, \qquad j = 1, \dots, J, \quad (monotonicity)$$

[2] For example, negative shadow capital prices may result from extensive deleveraging as banks attempt to rebuild their capital above well-capitalised levels after suffering major mortgage-related losses (see Weyman-Jones, 2016).

$$(5)\ -\sum_{n=1}^{N}\alpha_n g_n^x+\sum_{m=1}^{M}\beta_m g_m^y-\sum_{j=1}^{J}\gamma_j g_j^b=-1,\quad (translation),$$
$$-\sum_{n=1}^{N}\delta_{nm}g_n^x+\sum_{\acute{m}=1}^{M}\beta_{mm'}g_m^y-\sum_{j=1}^{J}\mu_{mj}g_j^b=0,\quad \mathrm{m}=1,\dots,\mathrm{M},$$
$$-\sum_{n=1}^{N}\nu_{nj}g_n^x+\sum_{m=1}^{M}\mu_{mj}g_m^y-\sum_{\acute{j}=1}^{J}\gamma_{j\acute{j}}g_j^b=0,\quad j=1,\dots,J,$$
$$-\sum_{n'=1}^{N}\alpha_{n\acute{n}}g_n^x+\sum_{\mathrm{m}=1}^{M}\delta_{nm}g_m^y-\sum_{j=1}^{J}\nu_{nj}g_j^b=0,\quad \mathrm{n}=1,\dots,\mathrm{N},$$
$$(6)\ \alpha_{nn'}=\alpha_{n'n},n\neq\acute{n};\ \beta_{mm'}=\beta_{m'm},m\neq m';\ \gamma_{jj'}=\gamma_{j'j},j\neq j'.(Symmetry)$$

Note that

$$\partial_{x_n}D_T(x^k,y^k,b^k)=\frac{\partial D_T(x,y,b)}{\partial x_n}=\alpha_n+\sum_{n'=1}^{N}\alpha_{nn'}x_{n'}^k+\sum_{m=1}^{M}\delta_{nm}y_m^k+\sum_{j=1}^{J}\nu_{nj}b_j^k,$$
$$\partial_{y_m}D_T(x^k,y^k,b^k)=\frac{\partial D_T(x,y,b)}{\partial y_m}=\beta_m+\sum_{m'=1}^{M}\beta_{mm'}y_{m'}^k+\sum_{n=1}^{N}\delta_{nm}x_n^k+\sum_{j=1}^{J}\mu_{mj}b_j^k,$$
$$\partial_{b_j}D_T(x^k,y^k,b^k)=\frac{\partial D_T(x,y,b)}{\partial b_j}=\gamma_j+\sum_{j'=1}^{J}\gamma_{jj'}b_{j'}^k+\sum_{n=1}^{N}\nu_{nj}x_n^k+\sum_{m=1}^{M}\mu_{mj}y_m^k.$$

We use the same functional form for all banks, large and small, recognising that all banks face fundamentally the same production technology for traditional core banking activities (i.e., taking deposits and making loans). Although the largest banks may rely much more on securities trading and off-balance-sheet activities, it is not a priori clear whether this will affect significantly the empirical results, recognising that the US is characterised by a small number of large banks and a large number of smaller banks.[3]

2.2. *Pricing models and shadow prices*

We follow the approach of Färe et al. (2017) to obtain shadow prices using the estimated distance functions via the Lagrangian method. We use different pricing rules based on different, in terms of their orientation, directional distance functions associated with different economic optimisation criteria. The pricing rule based on an input directional distance function is associated with cost minimisation as the behavioural criterion and requires either total cost or one of the input prices to be observed. The pricing rule based on an output directional distance function is associated with revenue maximisation as the behavioural criterion and requires either total revenue or one of the output prices to be known. The pricing rule based on a non-oriented directional distance function is associated with profit maximisation and requires one of the input or output prices to be known. When we require one of the prices to be

[3] See Spierdijka et al. (2017) for a similar argument in relation to the US banking industry.

known, we rely on what we perceive to be the most reliable input or output price proxy to calculate shadow prices for the other inputs and outputs. For robustness purposes, we experiment with alternative choices of the 'known' price. We then compare the shadow prices with actual prices. Since we are mainly interested in pricing inputs and outputs for which we have no explicit pricing information (equity capital and non-performing loans and leases), we estimate their shadow prices and compare it with the actual and shadow price of the corresponding inputs (deposits and borrowed funds) and outputs (loans and leases), respectively.

We first show how to calculate shadow prices for inputs and outputs using a non-oriented directional distance function that simultaneously contracts inputs and expands outputs. We rely on profit maximisation as the optimisation criterion, which allows us to construct shadow prices for both inputs and outputs. Second, we construct input prices using an input directional distance function. Third, we exploit revenue maximisation as the optimisation criterion to construct shadow prices for outputs, both desirable and undesirable, using an output directional distance function.

In an environment of low interest rates coupled with important regulatory changes, we expect that bank revenue from interest-bearing activities would be under pressure, thereby directly affecting bank profitability (see Spierdijka et al., 2017). Under these conditions, cost management by banks in terms of their ability to use a more efficient input-output mix is important. To this end, we set out to calculate shadow input and output prices representing the opportunity cost of choosing the observed input or output quantity from the perspective of the next best alternative use. Unlike debt (deposits or borrowed funds), equity carries no explicit cost albeit shareholders expect to earn a return on their equity investment which is a cost to the bank. Similarly, the pricing of provisions for loans and leases losses is not straightforward recognising that monitoring of non-performing loans is costly and there is uncertainty about potential costs (distress and bankruptcy). We estimate shadow prices using observed (proxy) prices of associated inputs and outputs. Since smaller banks may have lesser ability to diversify their activities, and they may face higher capital costs, we would like to see if there any differences between large and small banks. Similarly, we would like to know how capital costs might vary in relation to a host of other bank indicators.

We set up the profit maximisation Lagrangian problem as follows

$$\max py - wx - rb - \mu \vec{D}_T(x, y, b; g^x, g^y, g^b)$$

where p, w, r are the prices for desirable outputs y , inputs (x), and undesirable outputs (b), respectively, and μ is the Lagrangian multiplier (e.g. a measure of how much profit would increase if the optimisation constraint was relaxed). The first order conditions associated with the Lagrangian profit maximization problem are as follows:

$$p - \mu \nabla_y \vec{D}_T(x, y, b; g^x, g^y, g^b) = 0,$$
$$-w - \mu \nabla_x \vec{D}_T(x, y, b; g^x, g^y, g^b) = 0$$

$$-r - \mu \nabla_b \vec{D}_T\left(x, y, b; g^x, g^y, g^b\right) = 0$$

If one output price, say p_1, is known then we have

$$\mu = \frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^x, g^y, g^b)}$$

which as shown by Färe et al. (2017) yields the estimation of all other prices, $w_1, \dots, w_m, p_2, \dots, p_s$ as:

$$(w_1, \dots, w_N) = -\frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^y, g^b)} \left(\partial_{x_1} \vec{D}_T\left(x, y, b; g^x g^y, g^b\right), \dots, \partial_{x_N} \vec{D}_T\left(x, y, b; g^x, g^y, g^b\right)\right),$$
$$(p_2, \dots, p_M) = \frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^y, g^b)} \left(\partial_{y_2} \vec{D}_T\left(x, y, b; g^x g^y, g^b\right), \dots, \partial_{y_M} \vec{D}_T\left(x, y, b; g^x g^y, g^b\right)\right),$$
$$\left(r_1, \dots, r_J\right) = \frac{p_1}{\partial_{y_1} \vec{D}_T(x, y, b; g^y, g^b)} \left(\partial_{b_1} \vec{D}_T\left(x, y, b; g^x g^y, g^b\right), \dots, \partial_{b_J} \vec{D}_T\left(x, y, b; g^x g^y, g^b\right)\right),$$

Similarly, if one of the input prices, say w_1, is known then

$$\mu = -\frac{w_1}{\partial_{x_1} \vec{D}_T(x, y, b; g^x g^y, g^b)}$$

which yields the estimation of all other prices, $w_1, \dots, w_m, p_2, \dots, p_s$ as:

$$(w_1, \dots, w_N) = \frac{w_1}{\partial_{x_1} \vec{D}_T(x, y, b; g^x g^y, g^b)} \left(\partial_{x_2} \vec{D}_T\left(x, y, b; g^x g^y, g^b\right), \dots, \partial_{x_N} \vec{D}_T\left(x, y, b; g^x g^y, g^b\right)\right),$$
$$(p_1, \dots, p_M) = -\frac{w_1}{\partial_{x_1} \vec{D}_T(x, y, b; g^x g^y, g^b)} \left(\partial_{y_1} \vec{D}_T\left(x, y, b; g^x g^y, g^b\right), \dots, \partial_{y_M} \vec{D}_T\left(x, y, b; g^x g^y, g^b\right)\right),$$
$$\left(r_1, \dots, r_J\right) = \frac{w_1}{\partial_{x_1} \vec{D}_T(x, y, b; g^x g^y, g^b)} \left(\partial_{b_1} \vec{D}_T\left(x, y, b; g^x g^y, g^b\right), \dots, \partial_{b_J} \vec{D}_T\left(x, y, b; g^x g^y, g^b\right)\right)$$

From here, by altering the optimisation criterion and rewriting the first order conditions for cost minimization in lieu of profit maximisation, as

$$-w - \mu \nabla_x D_I(x, y, b; g^x) = 0,$$

we can derive the input pricing rule as:

$$(w_1, \dots, w_N) = C \frac{\left(\partial_{x_1} D_I(x, y, b; g^x), \dots, \partial_{x_N} D_I(x, y, b; g^x)\right)}{\partial_x D_I(x, y, b; g^x) x},$$

where C is observed total cost. Similarly, applying the first order conditions for revenue maximisation,

$$p - \mu \nabla_y D_O\left(x, y, b; g^y, g^b\right) = 0 \text{ and } -r - \mu \nabla_b D_O\left(x, y, b; g^y, g^b\right) = 0,$$

we can obtain pricing rules for desirable and undesirable outputs as:

$$(p_1, \dots, p_M) = R \frac{\left(\partial_{y_1} D_O\left(x, y, b; g^y, g^b\right), \dots, \partial_{y_M} D_O\left(x, y, b; g^y, g^b\right)\right)}{\partial_y D_O(x, y, b; g^y, g^b) y},$$
$$\left(r_1, \dots, r_J\right) = R \frac{\left(\partial_{b_1} D_O\left(x, y, b; g^y, g^b\right), \dots, \partial_{b_J} D_O\left(x, y, b; g^y, g^b\right)\right)}{\partial_y D_O(x, y, b; g^y, g^b). y},$$

where R is observed total revenue.

3. Empirical application

3.1 Data

We use FDIC data for US banks for the period 2002 to 2016. We follow the intermediation approach (see Sealey and Lindley, 1977) to select the inputs and outputs of the banks' production technology. The inputs comprise labour measured by number of employees, physical capital measured by fixed assets, customer deposits, borrowed funds, Tier 1 (core) capital comprising common equity plus noncumulative perpetual preferred stock plus minority interests in consolidated subsidiaries less goodwill and other ineligible intangible assets. There are two desirable outputs, net loans and leases and total securities, and one undesirable output, provisions for loan and lease losses. We measure the price of deposits as the ratio of interest paid on deposits over total deposits, the price of borrowed funds as interest expense on demand notes issued by the US treasury and other borrowed money over borrowed funds. The price of loans is measured as interest income on loans over total loans, and the price of securities as securities gains (losses) plus interest income on securities over total securities. Table 1 presents the descriptive statistics of the data for the entire period (2002-2016). As expected, the input and output data is highly (right) skewed. Total assets is also highly right skewed (median 6.78 billion). The cost of borrowed funds is much higher on average than the cost of deposits whereas loans appear to be more profitable than other earning assets.

Table 1: Descriptive Statistics -- Bank Inputs and Outputs

2002-2016			Mean	Std. Dev.	Min	Max
Inputs-Outputs	**Inputs**	**EMP**	7.021	23.958	0.157	235.18
		FA	0.354	1.079	0.02	11.56
		DEP	31.893	124.476	0.007	1480.24
		BF	3.977	13.91	0.05	212.7
		T1	3.628	13.589	0.012	179.34
	Desired Outputs	**LN**	25.17	84.094	0.652	934.26
		SEC	8.3	33.203	0.001	407.74
	Undesired Output	**PLL**	0.284	1.39	0.0001	29.4
		TA	46.113	177.739	2.001	2082.8
Prices		**PD**	0.0132	0.0105	0.0001	0.099
		PBF	0.0309	0.0187	0.0001	0.0999
		PL	0.0552	0.0177	0.0002	0.1956
		PSEC	0.0409	0.0318	0.0003	0.5158

Notes: EMP is number of employees measured in thousands, FA is fixed assets, DEP is deposits, BF is borrowed funds, T1 is tier one (core) capital, LN is net loans, SEC is total securities, PPL is provisions for loan and lease losses, all measured in billions of US dollars. PD is price of deposits, PBF is price of other borrowed funds, PL is price of loans and PSEC is price of securities.

3.2 Empirical results

We estimate directional distance functions by setting the values of the directional vector equal to the data averages. More specifically, we set $g^x = \vec{x}, g^y = 0, g^b = 0$ for the input directional distance function, $g^x = 0, g^y = \vec{y}, g^b = \vec{b}$ for the output directional distance function, and $g^x = \vec{x}, g^y = \vec{y}, g^b = \vec{b}$ for the directional distance function with both input and output orientation. Since equity capital is a quasi-fixed input, we set its associated value on the direction vector equal to zero.

Table 2 reports average efficiency scores based on different specifications of the distance function across the three sample periods. Bank efficiency is highest in the post-crisis period, and this finding is consistent across the three different efficiency measures. As expected, efficiency scores from the non-oriented directional distance function (DDF) are greater (and less variable) than their counterparts obtained from the partial orientation models (DDF_I and DDF_O), since DDF allows banks to adjust both inputs and outputs simultaneously. Table 2 also shows that consistent with stricter regulatory requirements, the bank capitalisation ratio (CCAP) is highest in the post-crisis period. As expected, return on assets (ROA) is lowest during the financial crisis period.

Table 2: Descriptive Statistics -- Bank Performance Indicators

	2002-2006			
	Mean	**Std. Dev.**	**MIN**	**MAX**
DDF	0.957	0.066	0.244	1
DDF_I	0.928	0.097	0.127	1
DDF_O	0.916	0.105	0.168	1
CCAP (%)	8.173	2.838	4.832	43.606
ROA (%)	1.259	0.836	-4.579	11.667
	2007-2010			
DDF	0.961	0.069	0.365	1
DDF_I	0.939	0.101	0.244	1
DDF_O	0.92	0.099	0.237	1
CCAP (%)	8.567	2.522	0.4	28.159
ROA (%)	0.067	1.963	-18.169	8.104
	2011-2016			
DDF	0.98	0.044	0.626	1
DDF_I	0.966	0.067	0.339	1
DDF_O	0.96	0.077	0.425	1
CCAP (%)	9.802	1.91	2.23	27.945
ROA (%)	0.955	0.846	-12.084	9.16

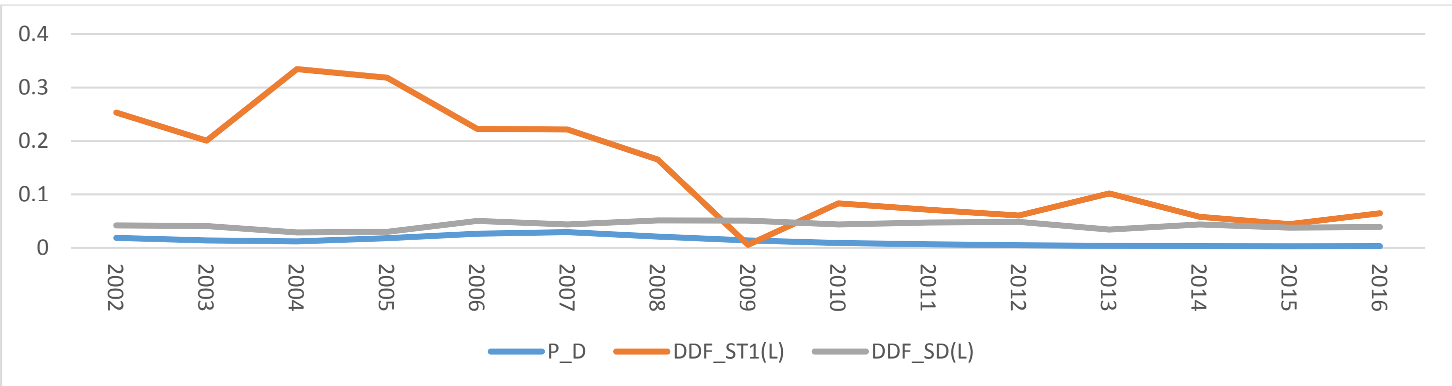
Notes: DDF_I, DDF_O and DDF are the efficiency scores based an input directional distance function, output directional distance function and non-oriented distance function, respectively. For convenience, efficiency scores are reported in the range of zero to one, by rescaling the distance function values as $1/(1+\vec{D}_T)$. CCAP is core capital (leverage) ratio. ROA is return on assets.

Figures 1 and 2 present plots of shadow prices for the two series of interest, (Tier 1) equity capital and provisions for loan losses. Figure 1 shows the actual price of deposits, the shadow price of deposits (DDF_SD(L)) and shadow price of Tier 1 capital (DDF_ST1(L)) estimated from the directional distance function (DDF) using the crossover pricing rule with information on the price of loans. We present two sets of results: average prices in figure 1(a) and individual prices for a balanced panel of 20 banks, randomly selected across size quantiles, in figure 1(b). The left side of Figure 1 is a startling display of the perils of excessively leveraged bank balance sheets during the period prior to the financial crisis, with the shadow price of equity capital rising to levels well in excess what may be a reasonable market price of capital, and well over the price of debt.[4]

The shadow price of equity will equal the market price when the amount of equity minimises cost, maximises revenue or maximises profit (see Hughes et al., 2001). What we observe here is banks underutilise capital relative to what may be perceived as prudent levels, pushing the implicit required return to equity to very high levels, a pattern consistent with excessive risk-taking behaviour. While these shadow prices may seem very high relative to the prevailing market cost of capital at the time, they convey a clear signal that the environment at the time, either in terms of mispriced safety-net protections (e.g. deposit insurance), relaxed regulatory standards or simply exuberance was conducive to excessive risk-taking.

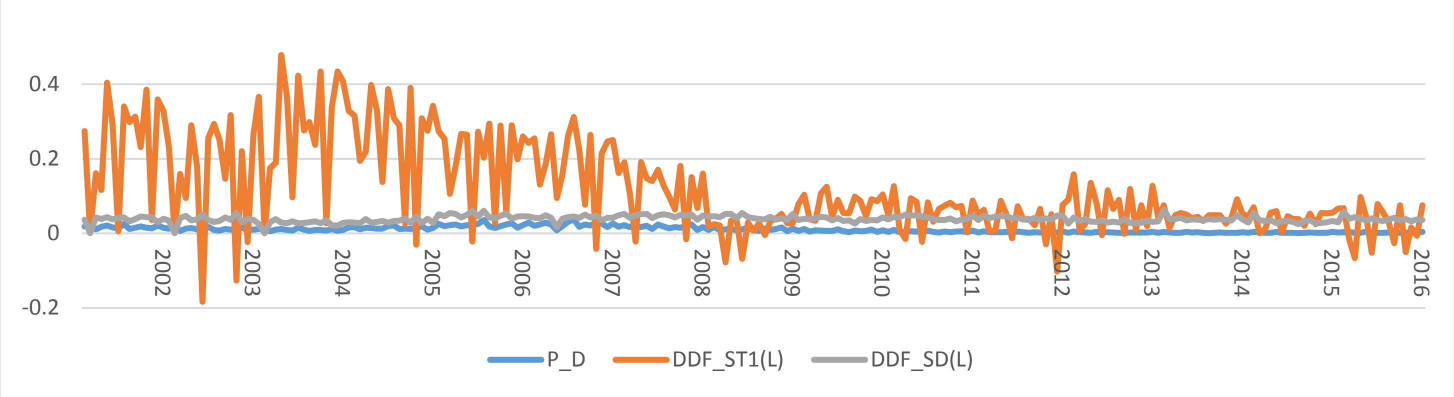
Figure 1 also shows that the shadow price (opportunity cost rate) of deposits is consistently greater than the actual interest rate paid on deposits. In a simplified situation where there is infinite supply of deposits, the shadow price would presumably be zero. Hence, a positive value is indicative of the intrinsic cost to the bank to ramp deposits up or down quickly in order to meet liquidity demands or regulatory requirements.

Figure 1(a): Deposits and Tier 1 Capital Prices (Annual Averages)



[4] Leverage amplifies shocks to the value of banks' assets, increasing the chance of distress, insolvency, and costly bailouts, thereby raising the required return on equity capital (Kisin and Manela, 2016).

Figure 1(b): Deposits and Tier 1 Capital Prices (Panel of Banks)



Notes: P_D indicates the price of deposits; DDF_SD(L) is the shadow price for deposits (D) calculated using a crossover pricing rule with known price of loans and leases (L); DDF_ST1(L) is the shadow price for Tier 1 capital (T1) calculated from a directional distance function using a crossover pricing rule with known price of loans.

Table 3 corroborates the observations from Figure 1 demonstrating (see Panel B) excessive shadow price of equity capital levels in the period leading to GFC. We estimate negative shadow prices of equity capital for some banks, especially after the onset of the financial crisis. Negative shadow prices are likely to be associated with extensive short-run deleveraging adjustments, with short-run levels of equity capital set well above their long-run equilibrium levels. For example, in late 2007 and 2008, Citigroup raised about $40 billion of new capital and cut its dividend by 30% to offset losses from mortgages and other investments, with the objective to restore its Tier 1 capital ratio above "well capitalized" levels (see Berger et al., 2008).

Panel A of Table 3 shows that the shadow price of capital is low, even lower than plausible market prices for the largest quantile of US banks. Shadow prices at all other quantiles appear to be higher than plausible market prices. To the extent that the choice of equity is consistent with profit maximisation, the inverse relationship between bank size and estimated shadow price suggests that larger banks have lower levels of market-priced risk, and hence lower required return on equity than their smaller peers. If on the other hand banks' capitalisation is not consistent with profit maximisation, our estimates imply that largest banks may be over-utilising capital whereas smaller banks may be underutilising capital. This conjecture is consistent with Berger et al. (2008) who report the largest US banking companies held capital far in excess of even the most stringent regulatory requirements during the period 1992 to 2006. However, there is no evidence that larger banks held significantly more capital than smaller banks in our data.

Table 3: Shadow price of Tier 1 equity capital

Panel A	2002-2016			
Total Assets (billion)	Mean	Std. Dev.	t-statistic	Obs.
Q1 < 2.958	0.188	0.135	34.305	611
Q2 = [2.958, 4.925)	0.182	0.129	34.973	611
Q3 = [4.925, 9.506)	0.180	0.125	35.394	611
Q4 = [9.506, 27.582)	0.163	0.127	31.516	610
Q5 >= 27.582	0.028	0.284	2.444	602
All	0.148	0.181	45.140	3045
Panel B	2002-2006			
Descriptive Statistics	Mean	Std. Dev.	MIN	MAX
DDF_ST1(L)	0.227	0.141	-0.183	0.478
DDF_I_ST1(L)	0.202	0.149	-0.16	0.448
	2007-2010			
DDF_ST1(L)	0.102	0.09	-0.077	0.312
DDF_I_ST1(L)	0.108	0.128	-0.163	0.446
	2011-2016			
DDF_ST1(L)	0.044	0.044	-0.102	0.158
DDF_I_ST1(L)	0.043	0.043	-0.091	0.14

Notes: DDF_ST1(L) and DDF_I_ST1(L) indicate the shadow prices for Tier 1 capital (T1) calculated from a non-oriented directional distance function and a directional distance function with input orientation, respectively, using a crossover pricing rule with known price of loans.

Figure 2 shows the actual (P_L) and shadow prices of loans (DDF_SL(D)) calculated from the directional distance function (DDF) using the crossover pricing rule with known price of deposits, and the shadow price of provisions for loan and lease losses using the crossover pricing rule with information on the price of deposits (DDF_SPLL(D)). As above, we present two sets of results: average prices in figure 2(a) and individual prices for a balanced panel of 20 randomly selected banks in figure 2(b). Figure 2 is also a lucid display of the dangers of overambitious balance sheet expansions, with excessive leverage coupled with low loss absorbing capacity leading to serious credit risk problems. Our estimates show that the opportunity cost rate of provisions for loan losses is much greater than the actual and shadow price of loans during 2003 to 2007. It then becomes smaller than the actual price of loans staying close to the shadow price for loans.

Figure 2(a): Loan and Provision for loan and losses Prices (Annual Averages)

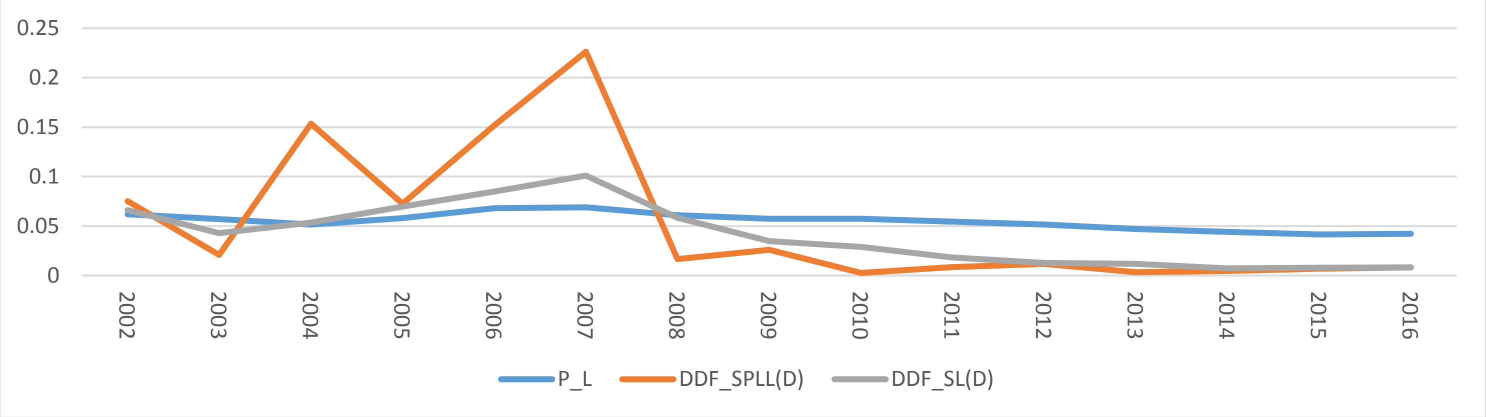
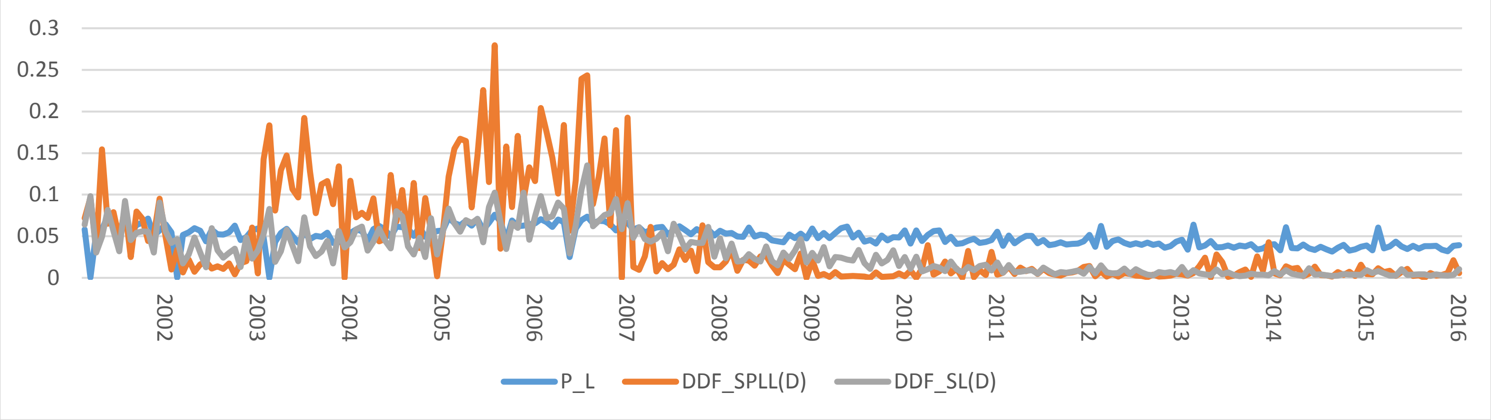


Figure 2(b): Loan and Provision for loan and losses Prices (Panel of Banks)



Notes: P_L indicates prices for loans; DDF_SPLL(D) indicates that the shadow price for provision for loan and lease losses is calculated from a directional distance function using a crossover pricing rule with known price of deposits; DDF_SL(D) indicates that the shadow price for loans is calculated from a directional distance function using a crossover pricing rule with known price of deposits.

We turn next to provide more insights on banks' debt and equity choices by relating actual or estimated price (gross return) ratios across five quantiles of various bank indicators. They include size, the core capital (leverage) ratio, loans to deposits ratio, securities to total assets ratio, provision for loan losses to total loans ratio, net interest margin, and return on assets as shown in the tables below. We report shadow prices based on the directional distance function (DDF). Results based on partially oriented distance functions, DDF_I and DDF_O, are similar. These results are available upon request from the authors.

Table 4 reports efficiency scores and price ratios across bank size quantiles measured by total assets. Column 1 displays a monotonically decreasing pattern, with smaller banks being more efficient and larger banks less efficient on average. Columns 2 and 3 exhibit a similar pattern, albeit with smaller banks facing higher and larger banks lower equity to debt shadow prices, which is consistent with the results reported in Table 3 above. Larger banks also face lower loans to deposits shadow prices (column 6). These findings suggest that larger banks may be over-utilising equity relative to its profitmaximising value, perhaps protecting charter value, whereas smaller banks may be underutilising equity, perhaps exploiting implicit deposit (safety-net) subsidies. However, columns 4 and 5 show that larger banks face higher rather than lower opportunity costs for loan loss provisions which may explain why they may choose to carry more equity in their capital structure. Based on these findings, we surmise that lower capital costs for larger banks are more likely to arise from their ability to exploit implicit too-big-to-fail subsidies rather than from lower risk (see FDIC 2013).

Table 4: Efficiency scores and relative prices across different bank sizes

TA	DDF	ST1_SD	ST1_SBF	SPLL_SL	SPLL_PL	SL_SD	SL_SSEC	SL_PL	PL_PD	SD_PD
All	0.966 (0.061)	1.103 (0.177)	1.083 (0.171)	1.011 (0.066)	0.999 (0.082)	1.000 (0.037)	1.032 (0.028)	0.987 (0.029)	1.042 (0.014)	1.029 (0.019)
Q1	0.992 (0.005)	1.140 (0.132)	1.114 (0.129)	1.001 (0.047)	0.992 (0.064)	1.004 (0.033)	1.036 (0.027)	0.990 (0.026)	1.043 (0.009)	1.028 (0.011)
Q2	0.989 (0.010)	1.136 (0.126)	1.112 (0.122)	1.003 (0.046)	0.993 (0.063)	1.004 (0.034)	1.034 (0.028)	0.990 (0.027)	1.041 (0.010)	1.027 (0.012)
Q3	0.982 (0.016)	1.135 (0.123)	1.113 (0.119)	1.008 (0.048)	0.998 (0.068)	1.004 (0.035)	1.033 (0.028)	0.990 (0.028)	1.041 (0.011)	1.026 (0.013)
Q4	0.967 (0.035)	1.116 (0.127)	1.094 (0.124)	1.012 (0.062)	1.002 (0.082)	1.002 (0.039)	1.034 (0.030)	0.989 (0.032)	1.041 (0.016)	1.028 (0.018)
Q5	0.903 (0.106)	0.988 (0.276)	0.979 (0.268)	1.030 (0.106)	1.010 (0.120)	0.984 (0.042)	1.022 (0.025)	0.978 (0.030)	1.042 (0.022)	1.036 (0.032)
Q5-Q1 t-stat	-0.089 -20.693	-0.152 -12.186	-0.134 -11.093	0.028 5.966	0.018 3.252	-0.021 -9.416	-0.014 -9.268	-0.011 -7.086	-0.001 -0.852	0.009 6.353

Notes: TA is total assets; DDF is the efficiency score; ST1, SD, SBF, SPLL, SL, SSEC are shadow prices of tier one capital, deposits, other borrowed funds, provision for loan and lease losses, loans, and securities, respectively; PL and PD as the prices for loans and deposits, respectively. Numbers in brackets are standard deviations.

Table 5 reports efficiency scores and price ratios across five Tier 1 core capital ratio quantiles.[5] Column 1 shows that better capitalised banks are also more efficient. Columns 2 and 3 show that the ratio of the shadow price of Tier 1 capital to the shadow price of deposits is inversely related to the core capital ratio, consistent with the view that better-capitalised banks should have lower equity to debt costs than less capitalised banks. Following from this, column 5 shows that better capitalised banks also face lower opportunity costs for loan losses. Hence, our findings suggest that the inverse relationship between size and cost of equity is more likely to hold for more efficient and better-capitalised banks.

[5] Tier 1 (core) capital as a percent of average total assets minus ineligible intangibles. Tier 1 (core) capital includes: common equity plus noncumulative perpetual preferred stock plus minority interests in consolidated subsidiaries less goodwill and other ineligible intangible assets. The amount of eligible intangibles (including mortgage servicing rights) included in core capital is limited in accordance with supervisory capital regulations.

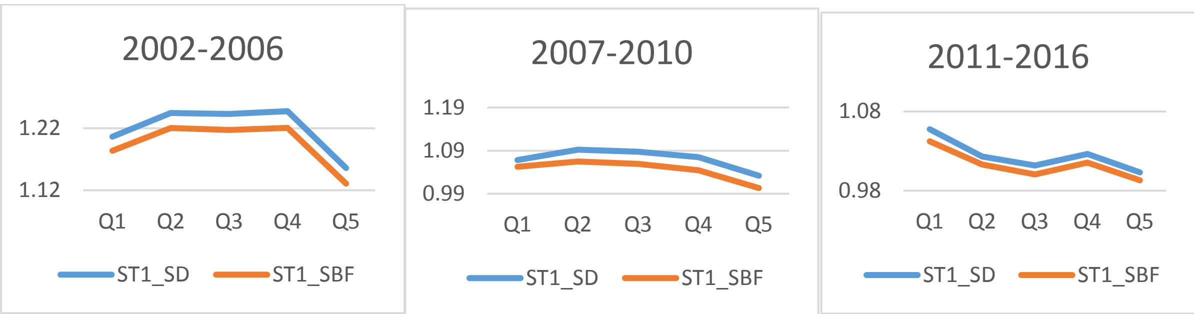
Table 5: Bank efficiency and relative prices across core capital (leverage) ratios

COR_CAP	DDF	ST1_SD	ST1_SBF	SPLL_SL	SPLL_PL	SL_SD	SL_SSEC	SL_PL	PL_PD	SD_PD
All	0.966	1.103	1.083	1.011	0.999	1.000	1.032	0.987	1.042	1.029
	(0.061)	(0.177)	(0.171)	(0.066)	(0.082)	(0.037)	(0.028)	(0.029)	(0.014)	(0.019)
Q1	0.953	1.161	1.141	1.012	1.017	1.019	1.044	1.002	1.038	1.021
	(0.087)	(0.216)	(0.202)	(0.062)	(0.091)	(0.036)	(0.027)	(0.028)	(0.011)	(0.015)
Q2	0.966	1.162	1.136	1.014	1.012	1.013	1.041	0.997	1.040	1.023
	(0.055)	(0.160)	(0.156)	(0.055)	(0.071)	(0.032)	(0.027)	(0.025)	(0.010)	(0.011)
Q3	0.972	1.106	1.085	1.008	0.996	1.000	1.032	0.988	1.041	1.028
	(0.050)	(0.141)	(0.136)	(0.050)	(0.068)	(0.034)	(0.028)	(0.026)	(0.010)	(0.013)
Q4	0.976	1.069	1.051	1.003	0.983	0.988	1.022	0.979	1.041	1.032
	(0.046)	(0.138)	(0.136)	(0.042)	(0.059)	(0.033)	(0.026)	(0.025)	(0.011)	(0.017)
Q5	0.966	1.017	1.001	1.015	0.987	0.978	1.021	0.972	1.047	1.041
	(0.054)	(0.175)	(0.173)	(0.104)	(0.108)	(0.036)	(0.025)	(0.029)	(0.023)	(0.028)
Q5-Q1	0.013	-0.144	-0.139	0.003	-0.030	-0.041	-0.024	-0.030	0.009	0.020
t-stat	3.196	-12.749	-12.897	0.614	-5.219	-19.825	-15.835	-18.422	8.779	15.523

Notes: CCAP is core capital (leverage) ratio. DDF is the efficiency score; ST1, SD, SBF, SPLL, SL, SSEC are shadow prices of tier one capital, deposits, other borrowed funds, provision for loan and lease losses, loans, and securities, respectively; PL and PD as the prices for loans and deposits, respectively. Numbers in brackets are standard deviations.

To shed more light on the relationship between capitalisation and shadow prices we break down the sample period to before, during and after the financial crisis and report plots of equity to debt shadow prices across the five quantiles of core capital ratios in figure 3. The left plot provides further evidence of unusually high equity to debt shadow prices prevailing in the period before the crisis.

Figure 3. Shadow Price Ratios



Notes: ST1_SD is the shadow price ratio of tier 1 capital to deposits; ST1_SBF is the shadow price ratio of tier 1 capital to borrowed funds.

Table 6 reports efficiency scores and price ratios across the five quantiles of provisions for loan and lease losses. Column 1 shows that efficiency is lowest for banks at the top quantile of loan losses whereas columns 2 and 3 show these banks have the lowest ratio of the shadow price of equity to debt and lowest ratio of the shadow price of loans to deposits (column 6). These findings suggest that banks are deleveraging (holding more loss absorbing capital) to protect their charter values.

Table 6: Bank efficiency and relative prices across provision for loan and lease losses to loans ratios

PLL_L	DDF	ST1_SD	ST1_SBF	SPLL_SL	SPLL_PL	SL_SD	SL_SSEC	SL_PL	PL_PD	SD_PD
All	0.966 (0.061)	1.103 (0.177)	1.083 (0.171)	1.011 (0.066)	0.999 (0.082)	1.000 (0.037)	1.032 (0.028)	0.987 (0.029)	1.042 (0.014)	1.029 (0.019)
Q1	0.970 (0.060)	1.128 (0.154)	1.114 (0.144)	1.016 (0.052)	1.008 (0.071)	1.004 (0.037)	1.030 (0.031)	0.991 (0.029)	1.036 (0.010)	1.023 (0.013)
Q2	0.976 (0.044)	1.131 (0.154)	1.114 (0.144)	1.017 (0.048)	1.008 (0.081)	1.002 (0.035)	1.030 (0.030)	0.989 (0.026)	1.039 (0.009)	1.026 (0.013)
Q3	0.968 (0.060)	1.134 (0.173)	1.112 (0.166)	1.011 (0.052)	1.001 (0.067)	1.004 (0.036)	1.033 (0.028)	0.990 (0.027)	1.041 (0.011)	1.026 (0.014)
Q4	0.964 (0.059)	1.108 (0.163)	1.082 (0.163)	1.005 (0.051)	0.993 (0.072)	1.000 (0.037)	1.033 (0.027)	0.988 (0.028)	1.043 (0.010)	1.030 (0.017)
Q5	0.954 (0.073)	1.015 (0.207)	0.992 (0.197)	1.003 (0.108)	0.982 (0.110)	0.988 (0.040)	1.033 (0.025)	0.979 (0.032)	1.049 (0.024)	1.040 (0.029)
Q5-Q1 t-stat	-0.016 -4.180	-0.113 -10.783	-0.123 -12.396	-0.013 -2.695	-0.026 -4.892	-0.016 -7.241	0.003 1.604	-0.012 -7.043	0.013 12.850	0.017 13.209

Notes: PLL_L is provision for loan losses to loans ratio. DDF is the efficiency score; ST1, SD, SBF, SPLL, SL, SSEC are shadow prices of tier one capital, deposits, other borrowed funds, provision for loan and lease losses, loans, and securities, respectively; PL and PD as the prices for loans and deposits, respectively. Numbers in brackets are standard deviations.

The loans to core deposits ratio shows how lending activity is matched to the expansion of the core deposits base with lower ratios being indicative of more stable funding source. Table 7 shows that banks with higher loans to deposits ratios face higher cost of equity to debt, higher costs for loan losses, higher shadow prices of loans to deposits, and a higher ratio of the shadow price to the actual price of loans.

Table 7: Bank efficiency and relative prices across net loans and leases to core deposits ratios

NLL_CD	DDF	ST1_SD	ST1_SBF	SPLL_SL	SPLL_PL	SL_SD	SL_SSEC	SL_PL	PL_PD	SD_PD
All	0.966 (0.061)	1.103 (0.177)	1.083 (0.171)	0.999 (0.082)	0.999 (0.082)	1.000 (0.037)	1.032 (0.028)	0.987 (0.029)	1.042 (0.014)	1.029 (0.019)
Q1	0.958 (0.078)	1.071 (0.149)	1.048 (0.145)	0.971 (0.045)	0.971 (0.045)	0.982 (0.027)	1.017 (0.020)	0.973 (0.022)	1.043 (0.013)	1.034 (0.015)
Q2	0.973 (0.046)	1.088 (0.148)	1.070 (0.130)	0.981 (0.051)	0.981 (0.051)	0.990 (0.029)	1.023 (0.023)	0.979 (0.022)	1.042 (0.009)	1.031 (0.012)
Q3	0.974 (0.056)	1.105 (0.152)	1.086 (0.145)	0.996 (0.062)	0.996 (0.062)	1.000 (0.033)	1.030 (0.027)	0.988 (0.025)	1.039 (0.009)	1.027 (0.012)
Q4	0.971 (0.050)	1.129 (0.168)	1.107 (0.162)	1.007 (0.070)	1.007 (0.070)	1.010 (0.033)	1.039 (0.026)	0.996 (0.026)	1.039 (0.011)	1.025 (0.014)
Q5	0.957 (0.065)	1.123 (0.244)	1.103 (0.242)	1.039 (0.133)	1.039 (0.133)	1.016 (0.050)	1.050 (0.032)	1.001 (0.039)	1.044 (0.024)	1.029 (0.033)
Q5-Q1 t-stat	-0.001 -0.266	0.052 4.501	0.055 4.777	0.068 11.937	0.068 11.937	0.034 14.398	0.033 22.048	0.027 15.165	0.001 0.780	-0.004 -2.983

Notes: NLL_CD is net loans and leases to core deposits ratio. DDF is the bank efficiency score; ST1, SD, SBF, SPLL, SL, SSEC are shadow prices of tier one capital, deposits, other borrowed funds, provision for loan and lease losses, loans, and securities, respectively; PL and PD as the prices for loans and deposits, respectively. Numbers in brackets are standard deviations.

The securities to total assets ratio is often used as an indicator of the bank business model, with larger, more diversified, banks associated with higher securities to assets ratios. However, our data shows that there is an inverted U-shaped relationship between bank size and the securities to assets ratio, with the value of the ratio being lowest for banks at the top quantile of the size distribution. This is consistent with US evidence that shows interest earned on investment securities is a more important source of revenue for smaller rather than larger US banks. Table 8 shows that banks with a higher ratio of securities to total assets also have a higher ratio of shadow price of Tier 1 capital to the shadow prices of deposits and borrowed funds albeit they have lower opportunity costs for loan losses.

Table 8: Bank efficiency and relative prices across securities to total assets ratios

SEC_TA	DDF	ST1_SD	ST1_SBF	SPLL_SL	SPLL_PL	SL_SD	SL_SSEC	SL_PL	PL_PD	SD_PD
All	0.966 (0.061)	1.103 (0.177)	1.083 (0.171)	1.011 (0.066)	0.999 (0.082)	1.000 (0.037)	1.032 (0.028)	0.987 (0.029)	1.042 (0.014)	1.029 (0.019)
Q1	0.966 (0.062)	1.066 (0.231)	1.047 (0.228)	1.021 (0.110)	1.011 (0.126)	0.998 (0.047)	1.035 (0.031)	0.988 (0.037)	1.044 (0.022)	1.034 (0.030)
Q2	0.970 (0.054)	1.090 (0.140)	1.071 (0.135)	1.006 (0.049)	0.991 (0.064)	0.997 (0.033)	1.029 (0.027)	0.985 (0.025)	1.041 (0.012)	1.029 (0.015)
Q3	0.967 (0.061)	1.115 (0.173)	1.095 (0.167)	1.009 (0.049)	0.998 (0.067)	1.002 (0.036)	1.033 (0.028)	0.989 (0.027)	1.041 (0.011)	1.028 (0.015)
Q4	0.961 (0.069)	1.112 (0.183)	1.092 (0.167)	1.008 (0.046)	0.993 (0.062)	0.997 (0.034)	1.029 (0.026)	0.985 (0.025)	1.042 (0.011)	1.029 (0.017)
Q5	0.969 (0.056)	1.132 (0.136)	1.108 (0.134)	1.009 (0.054)	0.999 (0.073)	1.004 (0.036)	1.033 (0.029)	0.990 (0.030)	1.040 (0.012)	1.026 (0.014)
Q5-Q1 t-stat	0.003 0.949	0.066 6.061	0.060 5.628	-0.012 -2.461	-0.012 -1.985	0.006 2.319	-0.002 -1.348	0.002 0.995	-0.004 -3.712	-0.008 -5.872

Notes: SEC_TA is securities to total assets. DDF is the efficiency score; ST1, SD, SBF, SPLL, SL, SSEC are shadow prices of tier one capital, deposits, other borrowed funds, provision for loan and lease losses, loans, and securities, respectively; PL and PD as the prices for loans and deposits, respectively. Numbers in brackets are standard deviations.

The next two tables report information on price ratios across bank profitability quantiles. The net interest margin is a proxy for profitability (the income generation capacity of the intermediation function of banks). Table 9 shows banks with higher net interest margin are more efficient. They face higher opportunity costs of equity to debt (columns 2 and 3) but lower opportunity costs for loan losses (column 5). The return on assets (ROA) shows how efficiently a bank uses its assets and equity to generate profits. Table 10 shows that banks with higher ROA also face higher opportunity costs of equity to debt (columns 2 and 3) and also have higher opportunity costs for loan losses (columns 4 and 5) suggesting they are engaging in more risky activities (e.g. exploiting safety-net subsidies).

Table 9: Bank efficiency and relative prices across net interest margins

NIM	DDF	ST1_SD	ST1_SBF	SPLL_SL	SPLL_PL	SL_SD	SL_SSEC	SL_PL	PL_PD	SD_PD
All	0.966	1.103	1.083	1.011	0.999	1.000	1.032	0.987	1.042	1.029
	(0.061)	(0.177)	(0.171)	(0.066)	(0.082)	(0.037)	(0.028)	(0.029)	(0.014)	(0.019)
Q1	0.949	1.072	1.058	1.016	1.021	1.013	1.038	1.003	1.030	1.021
	(0.087)	(0.192)	(0.177)	(0.064)	(0.084)	(0.042)	(0.034)	(0.032)	(0.009)	(0.016)
Q2	0.969	1.099	1.081	1.006	0.995	1.000	1.029	0.989	1.037	1.026
	(0.050)	(0.148)	(0.144)	(0.049)	(0.063)	(0.032)	(0.027)	(0.024)	(0.006)	(0.010)
Q3	0.975	1.108	1.088	1.005	0.992	0.999	1.030	0.987	1.040	1.028
	(0.045)	(0.148)	(0.146)	(0.043)	(0.058)	(0.034)	(0.027)	(0.024)	(0.006)	(0.015)
Q4	0.974	1.118	1.095	1.006	0.990	0.998	1.030	0.984	1.043	1.029
	(0.050)	(0.145)	(0.142)	(0.045)	(0.061)	(0.031)	(0.025)	(0.023)	(0.007)	(0.012)
Q5	0.966	1.119	1.092	1.020	0.995	0.988	1.032	0.973	1.057	1.042
	(0.057)	(0.232)	(0.227)	(0.107)	(0.123)	(0.043)	(0.027)	(0.032)	(0.021)	(0.029)
Q5-Q1	0.017	0.047	0.034	0.004	-0.025	-0.025	-0.006	-0.030	0.027	0.021
t-stat	4.027	3.824	2.898	0.730	-4.179	-10.311	-3.296	-16.249	28.270	15.463

Notes: NIM is net interest margin. DDF is the efficiency score; ST1, SD, SBF, SPLL, SL, SSEC are shadow prices of Tier 1 capital, deposits, other borrowed funds, provision for loan and lease losses, loans, and securities, respectively; PL and PD as the prices for loans and deposits, respectively. Numbers in brackets are standard deviations.

Table 10: Bank efficiency and relative prices across return on assets

ROA	DDF	ST1_SD	ST1_SBF	SPLL_SL	SPLL_PL	SL_SD	SL_SSEC	SL_PL	PL_PD	SD_PD
All	0.966	1.103	1.083	1.011	0.999	1.000	1.032	0.987	1.042	1.029
	(0.061)	(0.177)	(0.171)	(0.066)	(0.082)	(0.037)	(0.028)	(0.029)	(0.014)	(0.019)
Q1	0.961	1.068	1.045	0.996	0.989	1.003	1.035	0.993	1.039	1.028
	(0.065)	(0.128)	(0.130)	(0.052)	(0.070)	(0.035)	(0.027)	(0.029)	(0.015)	(0.016)
Q2	0.969	1.084	1.068	1.006	0.996	0.999	1.029	0.989	1.038	1.027
	(0.060)	(0.162)	(0.144)	(0.050)	(0.070)	(0.036)	(0.028)	(0.027)	(0.009)	(0.015)
Q3	0.974	1.094	1.076	1.010	0.996	0.996	1.027	0.985	1.040	1.029
	(0.057)	(0.170)	(0.166)	(0.045)	(0.063)	(0.036)	(0.028)	(0.027)	(0.009)	(0.017)
Q4	0.970	1.140	1.120	1.014	1.003	1.003	1.033	0.988	1.042	1.027
	(0.057)	(0.157)	(0.148)	(0.049)	(0.065)	(0.036)	(0.029)	(0.027)	(0.010)	(0.014)
Q5	0.958	1.129	1.105	1.027	1.011	0.997	1.035	0.982	1.050	1.035
	(0.061)	(0.240)	(0.235)	(0.109)	(0.125)	(0.044)	(0.029)	(0.033)	(0.021)	(0.029)
Q5-Q1	-0.003	0.060	0.060	0.031	0.022	-0.006	-0.001	-0.010	0.011	0.007
t-stat	-0.797	5.465	5.505	6.368	3.812	-2.697	-0.438	-5.832	10.544	4.879

Notes: ROA is return on assets. DDF is the efficiency score; ST1, SD, SBF, SPLL, SL, SSEC are shadow prices of Tier 1 capital, deposits, other borrowed funds, provision for loan and lease losses, loans, and securities, respectively; PL and PD as the prices for loans and deposits, respectively. Numbers in brackets are standard deviations.

We turn next to assess the relation between the shadow cost of capital and capitalisation using panel regressions. Table 11 shows that better capitalised banks have lower cost of capital. More specifically, we estimate that a 100 basis points increase in the Tier 1 capital to risk adjusted assets ratio is associated with a 30 to 40 points reduction in the cost of Tier 1 capital. Arguably, this is a rather conservative estimate, recognising that the risk-adjusted measure is likely to overstate the strength of banks' balance sheet, especially for larger banks, since it reduces on-balance sheet assets by a pre-assigned risk weight while excluding off-balance sheet assets, such as derivatives.[6] Using the core capital ratio in the panel regressions, we estimate that a 100 points increase in the capital ratio is associated with a reduction in the cost of capital by 96 to 103 points. These results are not reported but are available from the authors. Table 11 also shows that banks that are more efficient have lower capital costs, and the same applies for larger and more profitable banks. On the other hand, the net interest margin and the securities to assets ratio have a positive relationship with the shadow price of equity capital.

Table 11: Shadow price of capital panel regression (2002-2016)

	Estimate (t-ratio)	Estimate (t-ratio)	Estimate (t-ratio)	Estimate (t-ratio)	Estimate (t-ratio)	Estimate (t-ratio)
Constant	0.186 (17.101)	0.589 (10.708)	0.588 (10.681)	0.523 (9.374)	0.517 (9.258)	0.554 (0.981)
T1_AdjRatio	-0.309 (-3.495)	-0.334 (-3.823)	-0.301 (-3.447)	-0.406 (-4.544)	-0.374 (-4.120)	-0.397 (-4.372)
DDF		-0.414 (-7.477)	-0.424 (-7.674)	-0.438 (-7.955)	-0.437 (-7.943)	-0.459 (-8.324)
NIM			0.014 (4.155)	0.017 (4.973)	0.018 (5.228)	0.019 (5.537)
SEC_TA				0.192 (5.093)	0.195 (5.175)	0.2 (5.297)
ROA					-0.004 (-2.025)	-0.004 (-2.011)
L_EMP						-0.033 (-3.856)
R^2-adj **DW**	0.654 1.815	0.661 1.71	0.664 1.732	0.669 1.742	0.667 1.749	0.669 1.75

Notes: Panel regression with cross section and period fixed effects. The dependent variable is the shadow price of equity capital. T1_AdjRatio is the ratio of Tier 1 capital to risk adjusted assets, DDF is the bank efficiency score, NIM is net interest margin, SEC_TA is the securities to total assets ratio, ROA is return on assets, L_EMP is the (log) number of employees.

[6] According to the FDIC Vice Chairman of FDIC Thomas Hoenig "The primary measure of capital – the risk adjusted measure - is misleading and overstates the strength of these firms' balance sheets. No other industry is allowed to make these kinds of adjustments. The tangible leverage ratio provides a more accurate measure of assets and risks than the balance sheet reported under either GAAP or Basel" see https://www.fdic.gov/about/learn/board/hoenig/statement4-2-2015.html

4. Conclusion

This is the first study to present evidence on the cost of equity capital for an extensive sample of US banks utilising a shadow-pricing approach based on bank's production technology model. One advantage of our approach is that we are able to price equity for both listed and non-listed banks since we require no information on the market price of the bank. Our analysis has revealed some rather striking results highlighting the risks of overambitious balance sheet expansions. We have unveiled excessive levels of shadow prices for both equity capital and risky loans stemming from highly leveraged bank positions conducive to excessive risk-taking. These findings are important since they provide clearer signals of the potential perils of excessive leverage not often evident from market-priced risk. While we find equity to be a more expensive source of financing than deposits, our estimates suggest that better capitalised banks are more likely to face lower rather than higher costs of equity.

References

Admati, A., and M. Hellwig. (2013). *The Bankers' New Clothes*. Princeton, NJ: University Press.

Aigner, D.J. and Chu, S.F. (1968). On estimating the industry production function. *The American Economic Review*, vol. 58, pp. 826-839.

Allen, F., Carletti, E. and Marquez, R. (2015). Deposits and bank capital structure. *Journal of Financial Economics*, vol. 118, pp. 601-619.

Baker, M. and Wurgler, J. (2013). Would stricter capital requirements raise the cost of capital? Bank capital regulation and the low risk anomaly. Harvard University working paper.

Berger, A.N., DeYoung, R., Flannery, M.J., Lee, D. and Öztekin, Ö. (2008). How do large banking organizations manage their capital ratios? *Journal of Financial Services Research*, vol. 34, pp. 123-149.

Färe, R., Grosskopf, S. and Margaritis, D. (2017). Shadow pricing. In S. Ray, R. Chambers, & S. Kumbhakar (Eds.), *Handbook of Production Economics* (forthcoming).

Färe, R. and Sung, K.J. (1986). On second-order Taylor's-series approximation and linear homogeneity. *Aequationes Mathematicae*, vol. 30 (1), pp. 180-186.

FDIC. (2013). TBTF Subsidy for Large Banks—Literature Review, Prepared for Thomas Hoenig, Vice Chair, Federal Deposit Insurance Corporation.

Frazzini, A. and Pedersen, L. (2014). Betting against beta. *Journal of Financial Economics*, 111 (1), pp. 1-25.

Fukuyama, H. and Weber, W.L. (2008). Japanese banking inefficiency and shadow pricing. *Mathematical and Computer Modelling* 48, pp. 1854–1867.

Gorton, G. and Winton, A. (2003). Financial intermediation. In G. Constantinides, M. Harris, & R. Stulz (Eds.), *Handbook of Economics and Finance*, North Holland, Amsterdam, pp. 431–552.

Hughes, J. P., Mester, L. J., and Moon C.-G. (2001). Are scale economies in banking elusive or illusive? Evidence obtained by incorporating capital structure and risk-taking into models of bank production. *Journal of Banking and Finance*, vol. 25, pp. 2169–2208.

Kashyap, A. K., J. C. Stein, and S. Hanson. 2010. An analysis of the impact of 'substantially heightened' capital requirements on large financial institutions. Harvard University working paper.

Kisin, R. and Manela, A. (2016). The shadow cost of bank capital requirements. *The Review of Financial Studies*, vol. 29 (7), pp. 1780-1820.

Sealey, C.W. and Lindley, J.T. (1977). Inputs, outputs, and a theory of production and cost at depository financial institutions. *The Journal of Finance*, vol. 32 (4), pp. 1251-1266.

Spierdijk, L., Shaffer, S. and Considine, T. (2017). How do banks adjust to changing input prices? A dynamic analysis of US commercial banks before and after the crisis. *Journal of Banking & Finance,* vol. 85, pp. 1-14.

Weyman-Jones, T. (2016). Efficiency, competition and the shadow price of capital. In E. Haven, P. Molyneux, J.O.S. Wilson, S. Fedotov and M. Duygun (Eds.), *The Handbook of Post Crisis Financial Modeling*, Palgrave Macmillan, New York, pp. 147-167.