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The Evolution of Scale Economies in U.S. Banking

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Abstract

Continued consolidation of the U.S. banking industry and a general increase in the size of banks has prompted some policymakers to consider policies that discourage banks from getting larger, including explicit caps on bank size. However, limits on the size of banks could entail economic costs if they prevent banks from achieving economies of scale. This paper presents new estimates of returns to scale for U.S. banks based on nonparametric, local-linear estimation of bank cost, revenue and profit functions. We report estimates for both 2006 and 2015 to compare returns to scale some seven years after the financial crisis and five years after enactment of the Dodd-Frank Act with returns to scale before the crisis. We find that a high percentage of banks faced increasing returns to scale in cost in both years, including most of the 10 largest bank holding companies. And, while returns to scale in revenue and profit vary more across banks, we find evidence that the largest four banks operate under increasing returns to scale.

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1 Introduction

The financial crisis of 2007–08 raised new concerns about the size and complexity of the world's largest banking organizations. Many of the largest banks are now considerably bigger than they were before the crisis. For example, on December 31, 2006, the largest U.S. bank holding company (Citigroup) had total consolidated assets of $1.9 trillion, while two others (Bank of America and JPMorgan Chase) also had more than $1 trillion of assets. By contrast, on December 31, 2015, the largest holding company (JPMorgan Chase) had $2.35 trillion of assets and three others had assets in excess of $1.7 trillion.

Are banks destined to become ever larger and, if so, is that cause for concern? The answer to this question depends, in part, on why banks have been getting larger. The policy implications are likely different if banks are growing larger to exploit technologically-driven scale economies than if government policies that encourage large size or excessive risk taking are driving bank growth. Of particular concern is the perception that regulators consider very large banks "too-big-to-fail" (TBTF), which would provide an implicit funding subsidy to banks that exceed a certain size threshold. The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 was intended to eliminate TBTF by establishing a formal process for resolving failures of large financial institutions, as well as by imposing a tighter financial regulatory regime. However, some economists and policymakers argue that Dodd-Frank does not go far enough to contain TBTF, and that banks should be subject to firm caps on their size (e.g., Fisher and Rosenblum, 2012). The imposition of size limits on banks could have a downside, however, if they prevent banks from achieving economies of scale (as noted, e.g., by Stern and Feldman, 2009). Hence, the extent to which there are scale economies in banking is an important question that has attracted renewed interest among researchers and policymakers.

This paper presents new estimates of returns to scale (RTS) for U.S. bank holding companies (BHCs) and independent (i.e., not BHC owned) commercial banks. The paper makes two main contributions. First, we report estimates for both 2006 and 2015 (as well as for 1986 and 1996) to provide a comparison of RTS for the largest banks some seven years after the financial crisis and five years after the enactment of Dodd-Frank with estimates for 2006 and earlier years. Second, whereas previous studies focus exclusively on scale economies in terms of cost, we estimate RTS in terms of revenue and profit, as well as cost. Although estimates of RTS from a cost perspective indicate whether society's resources are employed efficiently in providing banking services, economies of scale in revenue or profit are of concern to bank shareholders, as well as to policymakers interested in the forces driving industry consolidation.

Conventional wisdom, based largely on studies that use data from the 1980s and 1990s to estimate returns to scale from cost functions, holds that banks exhaust scale economies at low levels of output, e.g., \$100–\$300 million of total assets. However, several recent studies find evidence of increasing returns to scale (IRS) among much larger banks, including banks with more than \$1 trillion of assets. Improved estimation methods and data could explain the difference in findings between older studies and more recent ones.[1] However, recent advances in technology are often thought to have favored larger banks, and perhaps increased the size range over which banks could experience IRS (Berger, 2003; Mester, 2005). Wheelock and Wilson (2009) find that larger banks experienced larger gains in productivity over 1985–2004 than did smaller banks. Feng and Serletis (2009) find similar evidence for 1998–2005. These studies suggest that technological advances may have also generated IRS for banks. Indeed, using a variety of methodologies and datasets, several recent studies find more evidence of substantial economies of scale in banking, with some finding that even very large banks operate under IRS (e.g., Wheelock and Wilson, 2012; Hughes and Mester, 2013; and Kovner et al., 2014 for U.S. banks, and Becalli et al., 2015 for European banks). However, other studies are less conclusive (e.g., Feng and Zhang, 2014; Restrepo-Tobón and Kumbhakar, 2015) and questions remain.

Changes in regulation, notably the Dodd-Frank Act of 2010, might also have affected returns to scale by altering the environment in which banks operate. Most studies use data on banks from before the financial crisis of 2007–08 or just shortly thereafter. However, many of the largest U.S. banks have continued to grow even larger since the crisis, perhaps to the point of exhausting potential scale economies. Research using more recent data is

[1] Studies of scale economies in banking from the 1980s and before typically relied on estimation of translog or other parametric specifications of bank cost functions. However, subsequent studies, including the present paper, find that the translog function is a misspecification of bank cost relationships and therefore can lead to erroneous estimates of returns to scale (RTS). See McAllister and McManus (1993) and Wheelock and Wilson (2001) for discussion and evidence on the bias introduced by estimating bank scale economies from a translog cost function.

thus required to determine whether earlier conclusions about the extent of scale economies in banking are still true.

In addition to providing an update to previous research on scale economies from the perspective of bank costs, we also examine scale economies in revenue and profit. Several studies have estimated revenue and profit relationships for banks to study such topics as revenue economies of scope (Berger et al., 1996), profit efficiency (e.g., Berger and Mester, 1997), and profit productivity (Berger and Mester, 2003). In addition to economies of scope, Berger et al. (1996) estimate revenue ray-scale economies for a sample of banks using data for 1978, 1984 and 1990. That study finds evidence of significant revenue scale economies in 1978 and 1984, especially for banks with less than $500 million of assets, but not in 1990. We are unaware of any other studies that examine revenue or profit scale economies for banks. Berger and Mester (2003) argue, however, that studies that ignore revenues when evaluating bank performance could be misleading. For example, Berger and Mester (2003) find that during the 1990s, banks became less productive in terms of cost (essentially that cost per unit of output rose after controlling for output quantities, input prices, and various environmental conditions), but more productive at generating profits. Berger and Mester (2003) attribute this finding to efforts by banks to increase profits by providing more or better quality services that raise their revenues by more than they increase costs. Similarly, an examination of the evolution of RTS from a revenue or profit perspective could provide a more complete picture of scale economies in banking than a focus solely on economies of scale in terms of cost.

We use a nonparametric, local-linear estimator to estimate cost, revenue and profit relationships from which we derive estimates of RTS. The nonparametric approach avoids the potential for functional-form specification error associated with parametric estimation. Although nonparametric estimators are plagued by the "curse of dimensionality," i.e., slow convergence rates (compared to parametric estimators) that become exponentially slower with more model dimensions, we take steps to mitigate this problem. Specifically, we estimate our models using a large dataset consisting of over 800,000 observations on all U.S. banks for 1986–2015, and we employ principal components techniques to reduce the dimensions of our empirical models. Our estimation methodology is similar to that of Wheelock and Wilson (2012). However, Wheelock and Wilson (2012) focus exclusively on scale economies in terms of cost and estimate RTS for U.S. banks in 2006. Here we extend the methodology to the estimation of RTS in terms of revenue and profit, report estimates for both 2006 and 2015 (as well as 1986 and 1996), and test whether changes in RTS between 2006 and 2015 are statistically significant.

We find that, despite the growth in size of many of the largest banks during and since the financial crisis, the very largest banks continued to face IRS in terms of cost in 2015. In fact, our estimates indicate that many of the largest banks experienced statistically significant increases in RTS between 2006 and 2015. Among all banks, approximately 35 percent of banks operated under IRS in 2006, while 43 percent faced IRS in 2015. Among all banks that were in existence in both 2006 and 2015, 27 percent more banks faced IRS in 2015 than in 2006, while only a few banks experienced decreasing returns to scale (DRS) in either period. Our results for revenue and profit economies are more mixed. While overall we find that fewer banks faced IRS in terms of revenue or profit than in terms of cost, we find evidence of IRS among a number of the largest banks in both 2006 and 2015, especially among the four largest U.S. banking organizations.

The next section describes the microeconomic specification of our cost, revenue, and profit functions and the statistics to measure RTS. Section 3 introduces the econometric specification, and Section 4 discusses the nonparametric methods we use for estimation and inference. Sections 5 and 6 present our empirical findings and conclusions. Additional details on data, estimation, and results are provided in separate Appendices A–E, which are available online.

2 Microeconomic Specification

To establish notation, let $\boldsymbol{x} \in \mathbb{R}^p_+$ and $\boldsymbol{y} \in \mathbb{R}^q_+$ denote column-vectors of p input quantities and q output quantities, respectively. Let $\boldsymbol{w} \in \mathbb{R}^p$ denote the column-vector of input prices corresponding to $\boldsymbol{x}$, and let $\boldsymbol{r} \in \mathbb{R}^q$ denote the column-vector of output prices corresponding to $\boldsymbol{y}$. Then variable costs are given by $C := \boldsymbol{w}'\boldsymbol{x}$, which firms (banks) seek to minimize with respect to $\boldsymbol{x}$, subject to $h(\boldsymbol{x}, \boldsymbol{y}) = 0$ where $h(\cdot, \cdot)$ represents the product-transformation function that determines the possibilities for transforming input quantities $\boldsymbol{x}$ into output quantities $\boldsymbol{y}$. Solution to the constrained minimization problem yields a mapping $\mathbb{R}^q_+ \times \mathbb{R}^p \mapsto$

$\mathbb{R}^p_+$ such that $\boldsymbol{x} = x(\boldsymbol{y}, \boldsymbol{w})$; substitution into $C = \boldsymbol{w}'\boldsymbol{x}$ yields

$$C = \boldsymbol{w}'\boldsymbol{x} = \boldsymbol{w}'x(\boldsymbol{y}, \boldsymbol{w}) = C(\boldsymbol{y}, \boldsymbol{w}) \tag{2.1}$$

where $C(\boldsymbol{y}, \boldsymbol{w})$ is the variable cost function.

The story so far is part of the standard microeconomic theory of the firm (e.g., see Varian, 1978). Under perfect competition in output markets, the same body of theory implies that banks maximize revenue $R := \boldsymbol{r}'\boldsymbol{y}$ with respect to output quantities, again subject to $h(\boldsymbol{x}, \boldsymbol{y}) = 0$, yielding the solution $\boldsymbol{y} = y(\boldsymbol{r}, \boldsymbol{x})$. Substitution then yields $R = \boldsymbol{r}'y(\boldsymbol{r}, \boldsymbol{x}) = R^s(\boldsymbol{x}, \boldsymbol{r})$, i.e., a standard revenue function that maps input quantities and output prices to revenue. Fuss and McFadden (1978) and Laitinen (1980) describe the conditions on $h(\boldsymbol{x}, \boldsymbol{y})$ required for existence of the revenue (and profit) function(s).

Banking studies, however, often estimate *alternative* revenue or profit functions, where revenue (or profit) are functions of output levels and input prices. As discussed, for example, by Berger and Mester (1997), the alternative revenue and profit functions provide a means of controlling for unmeasured differences in output quality across banks, imperfect competition in bank output markets (which gives banks some pricing power), any inability of banks to vary output quantities in the short-run, and inaccuracy in the measurement of output prices.

Estimates of economies of scale from alternative revenue and profit functions provide information about the extent to which revenue (or profit) rises for a given increase in output, holding input prices constant. Berger et al. (1996) describe the assumptions underlying standard and alternative revenue functions, and the validity of those assumptions for banks. The standard form assumes that banks are price takers. The alternative form, by contrast, assumes that banks have some pricing power, and views banks as having greater on-going flexibility in setting output prices than output levels. Based on a review of available evidence, Berger et al. (1996) conclude that some two-thirds of bank revenues are associated with services that reflect a degree of price-setting behavior, and they proceed by viewing banks as negotiating prices and fees, where feasible, to maximize revenues and profits for given levels of output. They argue that this model better represents how banks actually operate than the perfectly-competitive model which underlies standard revenue and profit functions. Berger and Mester (1997, 2003) elaborate further on the advantages of the alternative form of the revenue and profit function. For example, they note that in addition to admitting the possibility that banks have some degree of pricing power, the alternative form can be informative about bank performance when there are unmeasured differences in the quality of bank services across banks, when banks are unable to adjust their sizes quickly, or when output prices are not measured accurately. Indeed, bank input prices are, for the most part, more readily observed in bank call report data than output prices. The absence of output price information for the vast majority of banks means that standard revenue or profit functions cannot be estimated (unless outputs are aggregated to an even greater degree than they already are in our models).

Following Berger et al. (1996) and others, we assume that banks maximize revenue with respect to output prices $\boldsymbol{r}$, subject to $g(\boldsymbol{y}, \boldsymbol{w}, \boldsymbol{r}) = 0$, where $g()$ is an implicit function representing the bank's opportunities for transforming given output levels $\boldsymbol{y}$ and input prices $\boldsymbol{w}$ into output prices $\boldsymbol{r}$. Solution of this constrained optimization problem yields a mapping $\mathbb{R}^q_+ \times \mathbb{R}^p \mapsto \mathbb{R}^q$ such that $\boldsymbol{r} = r(\boldsymbol{y}, \boldsymbol{w})$; then $R = \boldsymbol{r}'\boldsymbol{y} = r(\boldsymbol{y}, \boldsymbol{w})'\boldsymbol{y} = R(\boldsymbol{y}, \boldsymbol{w})$, where $R(\boldsymbol{y}, \boldsymbol{w})$ is the *alternative* revenue function introduced by Berger et al. (1996).

Turning to profits, let $\boldsymbol{P} = \begin{bmatrix}\boldsymbol{r}' & \boldsymbol{w}'\end{bmatrix}'$ and $\boldsymbol{Q} = \begin{bmatrix}\boldsymbol{y}' & -\boldsymbol{x}'\end{bmatrix}'$. Standard theory suggests that firms operating in perfectly competitive input and output markets maximize profit $\pi := \boldsymbol{P}'\boldsymbol{Q}$ with respect to $\boldsymbol{Q}$, subject to $h(\boldsymbol{x}, \boldsymbol{y}) = 0$. Solution of the constrained optimization problem yields $\boldsymbol{Q} = Q(\boldsymbol{P})$; substituting this back into the profit function $\pi = \boldsymbol{P}'\boldsymbol{Q}$ gives $\pi = \boldsymbol{P}'Q(\boldsymbol{P}) = \pi^s(\boldsymbol{w}, \boldsymbol{r})$, i.e., the standard profit function that maps input and output prices into profit. Under imperfect competition in output markets, however, banks maximize profit with respect to input quantities $\boldsymbol{x}$ and output prices $\boldsymbol{r}$, subject to $h(\boldsymbol{x}, \boldsymbol{y}) = 0$ and $g(\boldsymbol{y}, \boldsymbol{w}, \boldsymbol{r}) = 0$. The solution results in a mapping $\mathbb{R}^q_+ \times \mathbb{R}^p \mapsto \mathbb{R}^p_+$ such that $\boldsymbol{x} = x(\boldsymbol{y}, \boldsymbol{w})$, and a mapping $\mathbb{R}^q_+ \times \mathbb{R}^p \mapsto \mathbb{R}^q$ such that $\boldsymbol{r} = r(\boldsymbol{y}, \boldsymbol{w})$. Substituting these into the profit function gives

$$\pi = \boldsymbol{P}'\boldsymbol{Q} = \begin{bmatrix}r(\boldsymbol{y}, \boldsymbol{w})' & \boldsymbol{w}'\end{bmatrix}\begin{bmatrix}\boldsymbol{y}' & -x(\boldsymbol{y}, \boldsymbol{w})'\end{bmatrix}' = \pi(\boldsymbol{y}, \boldsymbol{w}) \tag{2.2}$$

where $\pi(\boldsymbol{y}, \boldsymbol{w})$ is the *alternative* profit function that maps output quantities and input prices to profit.

Note that the cost function $C(\boldsymbol{y}, \boldsymbol{w})$ must be homogeneous of degree one with respect to input prices $\boldsymbol{w}$ since the cost minimization problem implies that factor demand equations must be homogeneous of degree zero in input prices. However, there is no such requirement for the alternative revenue and profit functions. Without additional assumptions, the alternative revenue and profit functions are neither homogeneous with respect to input prices $\boldsymbol{w}$ nor homogeneous with respect to output quantities $\boldsymbol{y}$. See Berger et al. (1996) and Restrepo-Tobón and Kumbhakar (2014) for discussion.

To measure RTS using the cost function, we define

$$\mathcal{E}_{C,i} := (\delta C(\boldsymbol{y}_i, \boldsymbol{w}_i) - C(\delta \boldsymbol{y}_i, \boldsymbol{w}_i)) (\delta C(\boldsymbol{y}_i, \boldsymbol{w}_i))^{-1} \tag{2.3}$$

where $\delta > 1$ is a constant and $\boldsymbol{y}_i$ is the observed vector of output quantities produced by the ith bank facing observed input prices $\boldsymbol{w}_i$. Clearly, $\mathcal{E}_{C,i} < 1$. The statistic $\mathcal{E}_{C,i}$ measures *expansion-path* scale economies as the difference between δ times the cost of producing output quantities $\boldsymbol{y}_i$ and the cost of producing output quantities scaled by the factor δ. The difference is normalized by dividing by $\delta C(\boldsymbol{y}_i, \boldsymbol{w}_i)$. If $\mathcal{E}_{C,i} > \ (=, <)\ 0$ then bank i faces IRS (CRS, DRS) in terms of cost.

To interpret the magnitude of $\mathcal{E}_{C,i}$, rearrange terms in (2.3) to obtain

$$\eta_{C,i} := \delta\,(1 - \mathcal{E}_{C,i}) = C(\delta \boldsymbol{y}_i, \boldsymbol{w}_i)/C(\boldsymbol{y}_i, \boldsymbol{w}_i). \tag{2.4}$$

Hence firm i increases its output by a factor $\delta > 1$, its cost increases by a factor $(1 - \mathcal{E}_{C,i})\delta$. For example, if $\delta = 1.1$ and $\mathcal{E}_{C,i} = 0.05$, then firm i incurs a 4.5-percent increase in cost when it increases its output level by 10 percent since $1.1 \times (1 - 0.05) \approx 1.045$. The measure η_C, i defined in (2.4) can be interpreted as a "pseudo elasticity." For $\delta = 1.1$ (i.e., for a 10-percent increase in output levels), costs increase by $(\eta_{C,i} \times 100)$-percent, and the firm faces IRS (CRS, DRS) if $\eta_{C,i} < \ (=, >)\ 1.1$.[2]

As in many empirical studies, the revenue measure introduced below in Section 3 consists of *net* revenues and can take negative values. Of course, profits can also be negative. Therefore, to measure RTS from the revenue and profit functions, we define

$$\mathcal{E}_{R,i} := (R(\delta \boldsymbol{y}_i, \boldsymbol{w}_i) - \delta R(\boldsymbol{y}_i, \boldsymbol{w}_i)) (\delta |R(\boldsymbol{y}_i, \boldsymbol{w}_i)|)^{-1} \tag{2.5}$$

and

$$\mathcal{E}_{\pi,i} := (\pi(\delta \boldsymbol{y}_i, \boldsymbol{w}_i) - \delta \pi(\boldsymbol{y}_i, \boldsymbol{w}_i)) (\delta |\pi(\boldsymbol{y}_i, \boldsymbol{w}_i)|)^{-1}. \tag{2.6}$$

[2] The measure defined in (2.4) has an additional interpretation. Some algebra reveals that $\mathcal{E}_{C,i}$ $(>, =, <)$ 1 iff $\mathcal{E}_{C,i}$ $(<, =, >)$ $1 - \delta^{-1}$. For $\delta = 1.1$, $(1 - \delta^{-1}) \approx 0.09091$. Hence values of $\mathcal{E}_{C,i}$ less than 0.09091 indicate that a 10 percent increase in output levels results in an increase in total (variable) cost, whereas values of $\mathcal{E}_{C,i}$ greater than 0.09091 indicate that a 10 percent increase in output reduces cost. Of course, it is probably unlikely, but perhaps not impossible, for an increase in output to reduce total cost.

In the definitions of $\mathcal{E}_{R,i}$ and $\mathcal{E}_{\pi,i}$, the constant factor δ multiplies output levels $\boldsymbol{y}$ in the first term of the numerator, in contrast to the definition of $\mathcal{E}_{C,i}$ in (2.3), where δ multiplies output levels $\boldsymbol{y}$ in the second numerator term. Similarly, δ multiplies the second term of the numerators of $\mathcal{E}_{R,i}$ and $\mathcal{E}_{\pi,i}$, rather than the first term as in (2.3). These differences reflect the fact that banks attempt to *maximize* revenue and profit but *minimize* cost. In addition, the denominators in (2.5) and (2.6) involve absolute values to account for the possibility that measured revenue or profit can be negative. Clearly, $\mathcal{E}_{R,i} >\ (=,<)\ 0$ implies IRS (CRS, DRS) and similarly for values of $\mathcal{E}_{\pi,i}$. Moreover, following the logic in footnote 2, it is easy to show that a 10 percent increase in output levels (i.e., $\delta = 1.1$) increases revenue or profit whenever $\mathcal{E}_{R,i}$ or $\mathcal{E}_{\pi,i}$ is greater than -0.09091 (although revenue or profit might increase by less than 10 percent).

To facilitate interpretation by providing a pseudo elasticity measure for revenue and profit analogous to the one given for cost in (2.4), consider the scale measure $\mathcal{E}_{\pi,i}$ defined in (2.6) (similar reasoning applies to the scale measure $\mathcal{E}_{R,i}$ defined in (2.5)). Suppose $\pi(\boldsymbol{y}_i, \boldsymbol{w}_i) > 0$ and $\pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i) > 0$, which is the most common (by far) scenario.[3] Then (2.6) can be rearranged to define

$$\eta_{\pi,i} := (1 + \mathcal{E}_{\pi,i})\delta = \pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i)/\pi(\boldsymbol{y}_i, \boldsymbol{w}_i). \tag{2.7}$$

Clearly, in this case $\mathcal{E}_{\pi,i} \geq -1$. Increasing output levels by a factor δ leads to an $(\eta_{\pi,i} \times 100)$ percent change in profits. Hence, for $\delta = 1.1$, values $\eta_{\pi,i} >\ (=,<)\ 1.1$ indicate IRS (CRS, DRS). Moreover, increasing output levels by a factor $\delta > 1$ leads to an increase in profit whenever $\eta_{\pi,i} > 1$. Using similar reasoning, we define $\eta_{R,i} := (1 + \mathcal{E}_{R,i})\delta = R(\delta\boldsymbol{y}_i, \boldsymbol{w}_i)/R(\boldsymbol{y}_i, \boldsymbol{w}_i)$, whose interpretation is analogous to $\eta_{\pi,i}$.

The next section describes the models we estimate to obtain the predicted values needed to estimate the returns-to-scale measures defined in (2.3)–(2.6). Subsequently, Section 4 explains how we estimate the models and make inferences.

3 Econometric Specification

To obtain estimates of the returns-to-scale measures $\mathcal{E}_{C,i}$, $\mathcal{E}_{R,i}$, and $\mathcal{E}_{\pi,i}$, we must specify versions of the cost function $C(\boldsymbol{y}, \boldsymbol{w})$, revenue function $R(\boldsymbol{y}, \boldsymbol{w})$, and profit function $\pi(\boldsymbol{y}, \boldsymbol{w})$

[3] See Appendix A for details about the interpretation of the returns-to-scale measures $\mathcal{E}_{R,i}$ and $\mathcal{E}_{\pi,i}$ when revenue or profit are negative.

for estimation. We define response and explanatory variables in the present section, and discuss our fully nonparametric estimation methods in Section 4.

Our specification of right-hand-side (RHS) explanatory variables closely follows Wheelock and Wilson (2012) and much of the banking literature. We define four inputs and five outputs that, with one exception (the measure of off-balance sheet output), are those used by Berger and Mester (2003). Specifically, we define the following output quantities: consumer loans (Y_1), real estate loans (Y_2), business and other loans (Y_3), securities (Y_4), and off-balance sheet items (Y_5) consisting of net non-interest income.[4]

We define three variable input quantities: purchased funds and core deposits, consisting of the sum of total time deposits, foreign deposits, federal funds purchased, demand notes, trading liabilities, other borrowed money, mortgage indebtedness and obligations under capitalized leases, and subordinated notes and debentures (X_1); labor services, measured by the number of full-time equivalent employees on payroll at the end of each quarter (X_2); and physical capital (X_3). The first input quantity, X_1, captures non-equity sources of investment funds for the bank.[5] We measure the corresponding prices ($W_1, \ldots, W_3$) by dividing total expenditure on the given input by its quantity. We include financial equity capital ($EQUITY$) as a quasi-fixed input, which controls somewhat for differences in risk across banks (see Berger and Mester (2003) for details).[6] As an additional control for differences in bank risk, we also include a measure of non-performing assets ($NPER$) consisting of (i) total loans and lease financing receivables past due 30 days or more and still accruing, (ii) total loans and lease financing receivables not accruing, (iii) other real estate owned, and (iv) charge-offs on past-due loans and leases.[7] With the exception of labor input (which is mea-

[4] Of the commonly used measures of off-balance sheet output, net non-interest income is the most consistently measurable across banks and over time. However, as a net, rather than gross measure of income, it is potentially a biased measure of off-balance sheet output because losses would appear to reduce off-balance sheet output. Data that would permit calculation of a gross measure of non-interest income are not available. See Clark and Siems (2002) for discussion of alternative measures of off-balance sheet activity.

[5] Wheelock and Wilson (2012) treat core deposits (i.e., total deposits less time deposits of $100,000 or more) and other funding liabilities as a separate inputs. Here, we combine them into a single input due to reporting differences in the FR Y-9C call reports for bank holding companies and the FFIEC call reports for commercial banks prior to 2001.

[6] We define $EQUITY$ as the sum of the book values of common and preferred stock, surplus, and retained earnings, which are items RCFD3210 and BHCK3210 from the FFIEC and FR Y-9C call reports, respectively.

[7] We thank a referee for pointing out that adding charge-offs to past-due and nonaccrual assets eliminates bias caused by differences in charge-off strategies across banks.

sured as full-time equivalent employees) and off-balance sheet output (which is measured in terms of net flow of income), our inputs and outputs are stocks measured by dollar amounts reported on bank balance sheets, consistent with the widely used intermediation model of Sealey and Lindley (1977).

In addition to the variables defined above, we index quarters 1986.Q4 through 2015.Q4 by setting $T = 1$ for 1986.Q4, $T = 2$ for 1987.Q1, $\ldots$, $T = 117$ for 2015.Q4. Although T is an ordered, categorical variable, we treat it as continuous since it can assume a wide range of possible values. The regulatory environment and the production technology of banking changed a great deal over the 30 years covered by our data; including T as an explanatory covariate allows functional forms to change over time. Two features of our estimation strategy allow a great deal of flexibility. First, because we use a fully nonparametric estimation method, we impose no constraints on how T might interact with other explanatory variables. Second, the local nature of our estimator means that when we estimate cost at a particular point in time, observations from distant time periods will have little or no effect on the estimate. Typical approaches that involve estimation of a fully parametric translog cost functions by OLS or some other estimation procedure are not local in the sense that when cost is estimated at some point in the data space, all observations contribute to the estimate with equal weight. Moreover, the typical approach requires the imposition of a specific functional form a priori for any interactions among explanatory variables.[8]

Turning to the response variables, we define our cost variable C as the sum of expenditures on purchased funds and core deposits, labor, and physical capital so that $C := W_1X_1 + W_2X_2 + W_3X_3$. We define our revenue variable, R, similarly to Berger and Mester (2003); i.e., $R :=$ total interest income + total non-interest income + realized gains (losses) on held-to-maturity securities + realized gains (losses) on available-for-sale securities − provision for loan and lease losses − provision for allocated transfer risk reserves. Finally, we measure profit (π) as the difference between revenue and cost; i.e., $\pi := R - C$.

Our cost, revenue, and profit functions include as right-hand side (RHS) variables the vector $\boldsymbol{y} := \begin{bmatrix} Y_1 & Y_2 & Y_3 & Y_4 & Y_5 \end{bmatrix}$ of output quantities defined above. When estimating the cost function, we also include $\boldsymbol{w}_1 := \begin{bmatrix} \frac{W_2}{W_1} & \frac{W_3}{W_1} & T & EQUITY & NPER \end{bmatrix}$ with the price of purchased funds (W_1) serving as the numeraire (we also divide cost on the left-hand side (LHS) by W_1

[8] The local nature of our estimator is discussed in more detail below in Section 4 and in Appendix D.

to ensure homogeneity with respect to input prices). As discussed in Section 2, we do not impose linear homogeneity when estimating the revenue and profit functions. Consequently, we include on the RHS (in addition to $\boldsymbol{y}$) $\boldsymbol{w}_2 := \begin{bmatrix} W_1 & W_2 & W_3 & T & EQUITY & NPER \end{bmatrix}$ when estimating revenue and profit functions.

Our cost, revenue and profit functions are each of the form

$$\mathcal{Y} = m(\boldsymbol{y}, \boldsymbol{w}) + \varepsilon \tag{3.1}$$

where $\mathcal{Y}$ represents one of our dependent variables (i.e., either C, R or π), $\boldsymbol{w}$ represents either $\boldsymbol{w}_1$ or $\boldsymbol{w}_2$ (depending on the LHS variable), and ε is a stochastic error term with $E(\varepsilon \mid \boldsymbol{y}, \boldsymbol{w}) = 0$ so that so that $m(\cdot, \cdot)$ is a conditional mean function. In addition, we assume that the densities of the continuous RHS variables are twice continuously differentiable at each point where the conditional mean function is estimated, but otherwise make no functional form assumptions regarding $m(\cdot, \cdot)$. Consistency of our estimator requires that the dependent variable $\mathcal{Y}$ must be continuous at $(\boldsymbol{y}, \boldsymbol{w})$ when the conditional mean function is estimated at $(\boldsymbol{y}, \boldsymbol{w})$, and that $E(|\mathcal{Y}|^{2+\nu} \mid \boldsymbol{y}, \boldsymbol{w})$ exists for some $\nu > 0$. One may view the conditional mean functions as either parametric but of unknown form, or nonparametric (i.e., infinitely parameterized). We provide details on estimation and inference below in Section 4 and in Appendix D.

Given a set of RHS variables, our minimal assumptions on the response function $m(\boldsymbol{y}, \boldsymbol{w})$ and inclusion of the time variable T allow far more flexibility than any parametric model. In banking and other industry studies, it has become fashionable in recent years to specify parametric models that allow (to some degree) technological heterogeneity across firms (examples include Orea and Kumbhakar, 2004 and Poghosyan and Kumbhakar, 2010). Although we maintain an assumption of continuity, our nonparametric specification and local estimation method means that $m(\boldsymbol{y}, \boldsymbol{w})$ can be quite different for different firms. In addition, the interaction of time T in the response function is left unspecified, allowing far more flexibility than in typical parametric specifications.

We estimate the models using a dataset comprised of consolidated balance sheet and income statement observations for all U.S. bank holding companies (BHCs) for 1986.Q3–2015.Q4. We include in our dataset observations for commercial banks that are not owned by holding companies. We use the seasonally adjusted, quarterly gross domestic product implicit price deflator to convert all dollar amounts to constant 2015 dollars.[9]

Using data at the level of holding companies (where relevant) permits more accurate tallying of inputs and outputs than is possible at the level of individual commercial banks, for example by accounting for interbank transfers among subsidiaries of a single holding company, as well as expenses incurred at the holding company level. Moreover, our primary interest is in the largest institutions in the industry, and these are typically holding companies. After pooling data across 117 quarters and deleting observations with missing or implausible values, 847,299 observations remain for estimation. Summary statistics are provided in Tables B.2–B.6 of the separate Appendix B.

4 Details on Estimation and Inference

Various approaches exist for estimating conditional mean functions such as those in the models described above in Section 3. A common approach is to specify a fully parametric translog functional form for the conditional mean function and then estimate the parameters via least-squares methods. However, our data easily reject the translog specification using specification tests similar to those used by Wheelock and Wilson (2001, 2012); see Appendix C for details.

Rejection of the translog functional form is hardly surprising. The translog function is merely a quadratic in log-space, which limits the variety of shapes the conditional mean function is permitted to take. Further, the translog is derived from a Taylor expansion of the cost (or revenue, or profit) function around the means of the data; one should not expect it to fit well data that are highly variable and highly skewed, as is the case with U.S. banking data.[10] Several studies have noted that the parameters of a translog function are unlikely

[9] BHC data are from Federal Reserve report FR Y-9C, which we downloaded from the website of the Federal Reserve Bank of Chicago. Data for independent commercial banks are from the Federal Financial Institutions Examination Council (FFIEC 031 and 041 reports). The reports record expenses and other flow variables (as opposed to stocks of deposits, etc.) from January 1 to the end of each quarter (March 31, June 30, September 30 and December 31). Hence for quarters 2, 3 or 4 of a given year, the previous quarter's call report must be used to first-difference flow variables in order to obtain expenses for a particular quarter. Although we use data from the 1986.Q3 reports for this purpose, our final data represent quarters from 1986.Q4 through 2015.Q4.

[10] The summary statistics for banks' total assets given in Tables B.2–B.6 in Appendix B reveal that the distribution of banks' sizes is heavily skewed to the right. In fact, estimates of Pearson's moment coefficient of skewness for total assets in each of 117 quarters range from 27.49 to 49.03. Moreover, skewness is increasing over time, despite the consolidation in the industry over the years covered by our data. Regressing the

to be stable when the function is fit globally across units of widely varying size; see, for example, Guilkey et al. (1983) and Chalfant and Gallant (1985) for Monte Carlo evidence, and Cooper and McLaren (1996) and Banks et al. (1997) for empirical evidence involving consumer demand, Wilson and Carey (2004) for empirical evidence involving hospitals, and McAllister and McManus (1993), Mitchell and Onvural (1996), and Wheelock and Wilson (2001, 2012) for empirical evidence involving banks. Similarly, Hughes and Mester (2013, 2015) estimate a nonstandard profit function and input demand equations that allow banks to trade profits for reduced risk. Their system reduces to the translog form when parameter restrictions are consistent with profit maximization and cost minimization, but their tests of these restrictions reject the translog function, implying that banks trade profits for lower risk.

We use fully nonparametric methods to avoid likely specification errors. Although nonparametric methods are less efficient than parametric methods in a statistical sense when the *true* functional form is known, nonparametric estimation avoids the risk of specification error when the true functional form is unknown, as in the present application. We use local-linear estimators described by Fan and Gijbels (1996) to estimate our cost, revenue and profit functions. Both the local-linear estimator as well as the Nadaraya-Watson kernel regression estimator (Nadaraya, 1964; Watson, 1964) are examples of local order-p polynomial estimators with $p = 1$ and 0, respectively. For a locally-fit polynomial of order p used to estimate a conditional mean function, going from an even value to an odd value of p results in a reduction of bias with no increase in variance (e.g., see Fan and Gijbels, 1996 for discussion). Hence, we use a local-linear estimator to estimate conditional mean functions, resulting in lower asymptotic mean square error than one would obtain with the Nadaraya-Watson estimator.

Nonparametric regression models can be viewed as infinitely parameterized; as such, any parametric regression model (such as an assumed translog functional form) is nested within a nonparametric regression model. Clearly, adding more parameters to a parametric model affords greater flexibility. Nonparametric regression models represent the limiting outcome of adding parameters, and may be viewed as the most general encompassing model that a

skewness coefficients for each quarter on the time variable T yields a positive estimate of the slope coefficient, 0.07302 that is significantly different from zero at .1 significance.

particular parametric specification might be tested against.[11]

Most nonparametric estimators suffer from the "curse of dimensionality," i.e., convergence rates fall as the number of model dimensions increases. The convergence rate of our local-linear estimator is $n^{1/(4+d)}$ where d is the number of distinct, continuous RHS variables, and there are $d = 10$ RHS variables in our cost function and $d = 11$ RHS variables in our revenue and profit functions. The slow convergence rate of our estimator means that for a given sample size, the order (in probability) of the estimation error we incur with our nonparametric estimator will be larger than the order of the estimation error one would achieve using a parametric estimator in a *correctly specified* model with the usual parametric rate $n^{1/2}$. However, our nonparametric estimation strategy avoids specification error that would likely render meaningless any results that might be obtained using a misspecified model. We adopt the view of Robinson (1988), who argues that parametric models are likely misspecified and should be viewed as root-n *in*consistent instead of root-n consistent.[12]

To mitigate the curse of dimensionality in our application, we (i) use a large sample with more than 800,000 observations and (ii) employ a simple dimension-reduction method. Multicollinearity among regressors is often viewed as an annoyance, but here we use the multicollinearity in our data to reduce dimensionality, thereby increasing the convergence rate of our estimators and reducing estimation error. We do this by transforming the continuous RHS variables in each model to principal components space. Principal components are orthogonal, and eigensystem analysis can be used to determine the information content of each principal component. In each model we estimate, we sacrifice a small amount of information by using only the six principal components of the continuous RHS variables that correspond to the six largest eigenvalues, hence reducing the number of continuous

[11] Several methods for nonparametric regression exist. Cogent descriptions of nonparametric regression and the surrounding issues are given by Fan and Gijbels (1996, chapter 1), Härdle and Linton (1999), and Henderson and Parmeter (2015). Härdle and Mammen (1993) propose a test of a parametric regression against a nonparametric alternative where the test statistic is an estimate of the integrated square difference between the two regressions. Although we do not implement the Härdle and Mammen test in order to avoid computational expense, it seems almost certain the test would reject the translog parametric model in view of the results from our simple specification tests discussed above and in the separate Appendix C.

[12] Convergence results for nonparametric estimators are often expressed in terms of order of convergence in probability. Briefly, for a sequence (in n) of estimators $\widehat{\theta}_n$ of some scalar quantity θ, we can write $\widehat{\theta} = \theta + O_p(n^{-a})$ when $\widehat{\theta}$ converges to θ at rate n^a, and we say that the estimation error is of order in probability n^{-a}. This means that the sequence of values $n^a|\widehat{\theta}_n - \theta|$ is bounded in the limit (as $n \to \infty$) in probability. See Serfling (1980) or Simar and Wilson (2008) for additional discussion.

RHS variables in our regressions from 10 or 11 to six. The six principal components account for 92.86 percent of the independent linear information among the RHS variables in our cost function, and 89.70 percent and 88.52 percent in the revenue and profit functions. The transformation to principal-components space can be inverted, and the interpretation of the estimators of the conditional mean functions in each model based on six principal components of the (continuous) RHS variables is straightforward because our estimator is fully nonparametric. Additional details about our principal components transformation and nonparametric estimation strategy are provided in Appendix D.

To implement the local-linear estimator we must select a bandwidth parameter to control the smoothing over the continuous dimensions in the data. We use least-squares cross-validation to optimize an adaptive, κ-nearest-neighbor bandwidth. In addition, we employ a spherically symmetric Epanechnikov kernel function. This means that when we estimate cost, revenue or profit at any fixed point of interest in the space of the RHS variables, only the κ observations closest to that point can influence estimated cost, revenue or profit. In addition, among these κ observations, the influence that a particular observation has on estimated cost, revenue or profit diminishes with distance from the point at which the response is being estimated. Our estimator is thus a *local* estimator, and is very different than typical, parametric, *global* estimation strategies (e.g., OLS, maximum likelihood, etc.) where all observations in the sample influence (with equal weight) estimation at any given point in the data space. Moreover, because we use nearest-neighbor bandwidths, our bandwidths automatically adapt to variation in the sparseness of data throughout the support of our RHS variables.

For statistical inference about our estimates of RTS, we use the wild bootstrap introduced by Härdle (1990) and Härdle and Mammen (1993), which allows us to avoid making specific distributional assumptions. We estimate confidence intervals using methods described in Wheelock and Wilson (2011, 2012). Although our estimators are asymptotically normal, the asymptotic distributions depend on unknown parameters; the bootstrap allows us to avoid the need to estimate these parameters, which would introduce additional noise.[13]

[13] Additional details about our inference methods are given in the separate Appendix D.

5 Empirical Results

We estimate the cost, revenue and profit specifications described in Section 3 using the methods described in Section 4 to obtain estimates of cost, revenue, and profit. We substitute these into the RTS measures defined in Section 2 to obtain for each bank i estimates $\widehat{\mathcal{E}}_{C,i}$, $\widehat{\mathcal{E}}_{R,i}$ and $\widehat{\mathcal{E}}_{\pi,i}$ as well as estimates $\widehat{\eta}_{C,i}$, $\widehat{\eta}_{R,i}$ and $\widehat{\eta}_{\pi,i}$ of the pseudo elasticities defined in Section 2. We use the bootstrap methods discussed in Section 4 and described in Appendix D to make inference about the corresponding *true* values of the RTS measures and corresponding pseudo elasticities.

Table 1 provides an overview of results from our estimation for 1986.Q4, 1996.Q4, 2006.Q4 and 2015.Q4. The table reports the number of banks for which we reject CRS (at .05 significance) in favor of IRS or DRS, or for which we cannot reject CRS for cost, revenue and profit in each quartile of total assets in each period.[14]

In each quartile, we find that a large majority of banks faced either CRS or IRS in cost in each period, even though the distribution of banks' sizes in terms of total assets shifted rightward over time.[15] Even among banks in the fourth quartile (the largest 25 percent of banks by assets), we reject CRS in favor of IRS for a substantial number of banks, and in favor of DRS for very few banks. Our results are thus similar to other recent studies finding that even many large banks operate under increasing returns to scale (e.g., Wheelock and Wilson, 2012; Hughes and Mester, 2013; Kovner et al., 2014 and Becalli et al., 2015).[16]

With regard to revenue economies, we are unable to reject CRS for a majority of banks in each quartile and period. However, we reject CRS in favor of IRS for more banks than we reject in favor of DRS.[17] Similarly, for profit economies, we also fail to reject CRS for more banks than not, but generally we reject CRS in favor of IRS for more banks than we reject in favor of DRS. The two exceptions are for banks in the largest-size quartile in 2006.Q4 and 2015.Q4, where we reject in favor of DRS for 420 and 378 banks, respectively, but in favor

[14] See Tables E.3 and E.5 in the separate Appendix E for similar counts at .1 and .01 significance levels.

[15] Figure B.1 in Appendix B shows kernel estimates of the density of total assets for 1986.Q4, 1996.Q4, 2006.Q4, and 2015.Q4, where the rightward shift is apparent.

[16] We estimated returns to scale for two alternative cost specifications, including one that treats physical capital as quasi-fixed, rather than as a variable input, and one that uses total cost, rather than the sum of expenditures on the variable inputs, as the dependent variable. Results of those models, which are reported in the separate Appendix E, are qualitatively very similar to those reported in Table 1.

[17] Results are qualitatively very similar for an alternative specification, reported in the separate Appendix E, in which we define revenue as total unadjusted revenue.

of IRS for only 235 and 206 banks.[18]

Because the distribution of bank asset sizes is quite skewed, the largest asset-size quartile represents a much larger range than the other three quartiles. Further, because much of the interest in economies of scale pertains to the very largest banks, we report estimates of returns to scale for the 10 largest banks in each period. Specifically, Tables 2–3 report estimates of the pseudo elasticities defined in Section 2 for each of the 10 largest banks in each period. For the cost model, pseudo elasticity estimates that are significantly *less* than 1.1 indicates IRS, whereas for the revenue and profit models, estimates that are significantly *greater* than 1.1 indicate IRS.

For cost economies, the results in Tables 2–3 indicate that we reject CRS in favor of IRS in nearly every case (34 estimates out of 40) among the 10 largest banks in each period. Moreover, we reject CRS in favor of IRS for each of the four largest banks in 1986.Q4, 1996.Q4, and 2015.Q4 (and two of the four largest in 2006.Q4). In no case do we reject CRS in favor of DRS. Thus, the evidence suggests strongly that even the very largest U.S. banks faced increasing returns to scale throughout the sample period.[19]

In contrast with the substantial evidence that the very largest banks face IRS in cost, the estimates shown in Tables 2–3 indicate that the largest banks mostly face DRS in revenue. We reject CRS in favor of DRS in revenue in 33 of 40 cases, and reject in favor of IRS in only two cases (Citigroup and Wells Fargo in 2015.Q4). However, all but one (Wells Fargo in 2006.Q4) of the revenue pseudo elasticity estimates are greater than 1.0, indicating that even though the largest banks face DRS in revenue, their revenues would still rise with an increase in output levels (though by a less than proportionate amount).

Finally, the estimates of returns to scale in profit reveal the relative importance of cost and revenue economies in determining profit economies for each bank in each period. For 1986.Q4, only two of the profit pseudo elasticity estimates in Table 2 are significantly different from 1.1, and in both cases CRS is rejected in favor of DRS. However, in 1996.Q4, nine

[18] As with cost and revenue economies, results are robust to alternative measures of profit, constructed from different measures of cost and revenue as described in the preceding footnotes. See the separate Appendix E for specific results.

[19] A referee suggested that there might be a break in RTS around $50 billion of assets due to regulatory and enforcement differences for banks beyond that threshold. Inspection of pseudo elasticity estimates for the largest 100 banks in each quarter, which are reported in Tables E.6–E.9 in the separate Appendix E, reveal no obvious break at $50 billion of assets.

estimates are significantly less than 1.1, indicating DRS. Nonetheless, these nine estimates are greater than 1.0, indicating that profits increase with size for these banks, albeit by a less than proportionate amount.

Whereas we find no indication that any of the 10 largest banks faced IRS in revenue or profit in either 1986.Q4 or 1996.Q4, results reported in Table 3 indicate that the three largest banks (JPMorgan Chase, Bank of America, and Citigroup) operated under IRS in profit in 2006.Q4, and all four of the very largest banks did so in 2015.Q4. Further, the results indicate that both Citigroup and Wells Fargo also faced IRS in revenue in 2015.Q4. By contrast, among the remaining banks in the top 10, we either fail to reject CRS, or reject in favor of DRS for both revenue and profit in both 2006.Q4 and 2015.Q4. Nonetheless, the pseudo elasticity estimates for 2015.Q4 are all greater than 1.0 for these banks, indicating that profit would increase with an increase in output (but by a less-than proportionate amount).

Evidence on the extent to which changes in RTS over time were statistically significant is shown in Table 4. Specifically, for the 10 largest banks in 2015.Q4 that were also in existence in 2006.Q4, we report whether the change in the bank's pseudo elasticity between those two periods was statistically significant (at the .05 level) and, if so, the direction of the change. Upward arrows indicate significant changes in the direction of greater returns to scale, whereas downward arrows indicate statistically significant decline in returns to scale, and the absence of an arrow indicates that the change in pseudo elasticity between the two periods is not statistically significant. As the table shows, we find statistically significant gains in RTS in terms of cost for seven banks, and a significant decline for only one bank. All of the banks that experienced a significant increase in RTS except Citigroup and JPMorgan Chase, for which we do not reject CRS in 2006.Q4, already faced IRS in 2006.Q4.

Among banks that experienced a significant change in RTS in revenue, as reflected by a statistically significant change in pseudo elasticity, four experienced a significant increase in RTS, while two had a significant decline. Among the banks that experienced significant gains, both Citigroup and Wells Fargo went from facing DRS in 2006.Q4 to IRS in 2015.Q4.

Finally, for profit, three banks, including two of the top four, experienced significant gains in RTS and one had a significant decline, while the change for six banks was not statistically significant. Among the largest four banks in 2015.Q4, the pseudo elasticity estimates in

Table 3 indicate that Citigroup, Bank of America, and JPMorgan Chase already faced IRS in 2006.Q4, whereas we are unable to reject CRS for Wells Fargo, which was the smallest of the four banks in that period. Both Citigroup and Wells Fargo experienced statistically significant gains in RTS between 2006.Q4 and 2015.Q4, and in the latter period we reject CRS in favor of IRS for Wells Fargo.

On the whole, our results are consistent with earlier studies finding that even the largest U.S. banks face IRS in terms of cost. Our findings indicate that this remains true some eight years after the financial crisis and after substantial changes in bank regulation. Further, our results indicate that while many banks face IRS in cost, many fewer operate under IRS in revenue or profit. However, substantial numbers of banks, including the four largest U.S. banks, do appear to face CRS or IRS in revenue and profit. Further, we find that, if anything, the very largest banks faced greater returns to scale in terms of revenue and profit in 2015 than they had in 2006, before the financial crisis and introduction of a new regulatory regime.[20]

6 Conclusions

As the number of banks has declined since 1986, many banks have grown considerably in size. Despite the growth in bank size, we find considerable evidence that the largest U.S. banks continue to operate under increasing returns to scale in terms of cost, as they did in 2006 and even earlier. It is perhaps not surprising that large banks faced increasing returns in earlier years, given that institutions grew larger, but it is interesting that even in 2015, the largest institutions had not exhausted scale economies in terms of cost.

The evidence for returns to scale in revenue and profit is more mixed. Still, our estimates suggest that relatively few banks with total assets below the largest 25 percent face decreasing returns to scale, while the rest face constant or increasing returns. We find that somewhat

[20] In the separate Appendix E, Table E.12 gives counts of firms that experienced a statistically significant change in RTS between 2006.Q4 and 2015.Q4. In addition, Tables E.16–E.24 give transition matrices showing the numbers of institutions facing IRS, CRS, or DRS in 2006.Q4 versus 2015.Q4. The number of banks appearing in our sample in both 2006.Q4 and 2015.Q4 is 4,148. For the cost model described in Section 3, at .05 significance, there are 3,064 significant changes, with 1,686 gains and 1,378 declines in RTS. For the revenue model, there are 2,194 significant changes, with 1,033 increases and 1,161 decreases in RTS. For the profit model, there are 1,210 significant changes, with 493 increases and 717 decreases in RTS. A majority of significant changes in cost RTS are gains, while the numbers of changes in revenue RTS are almost even between increases and decreases, and changes in profit RTS are more often downward.

fewer banks in the largest size quartile operate under increasing returns. Among the largest 10 banks, we find that some operated under increasing returns in revenue and, especially, profit in 2006 and 2015, but others faced constant or decreasing returns. In particular, the largest four U.S. banks—all of which are substantially larger than the next largest banks—faced increasing returns to scale in profit, as well as in cost, in 2015. Thus, it appears that the turmoil of 2007-08 and subsequent changes in regulation have not lessened returns to scale in terms of cost, revenue or profit for most U.S. banks. And, if anything, the largest four banks have seen significant increases in returns to scale since 2006, suggesting that scale economies still provide an impetus to become even larger.

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Table 1: Counts of Institutions Facing IRS, CRS, and DRS by Size Quartile (.05 signif.)

		1st quartile			2nd quartile			3rd quartile			4th quartile		
LHS	Period	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS
Cost	1986.Q4	1138	1439	5	734	1837	10	808	1761	12	1150	1408	23
	1996.Q4	669	1211	18	524	1356	18	513	1353	31	759	1067	72
	2006.Q4	630	932	9	526	1030	14	446	1106	18	607	884	80
	2015.Q4	528	662	20	481	696	32	469	704	36	610	528	72
Revenue	1986.Q4	287	2142	153	333	2170	78	398	2121	62	401	1807	373
	1996.Q4	245	1549	104	291	1572	35	299	1560	38	362	1347	189
	2006.Q4	201	1226	144	249	1253	68	263	1265	42	317	1037	217
	2015.Q4	204	822	184	229	796	184	289	795	125	235	555	420
Profit	1986.Q4	637	1914	31	463	2103	15	444	2119	18	389	2024	168
	1996.Q4	620	1252	26	444	1443	11	358	1527	12	305	1441	152
	2006.Q4	528	1024	19	416	1142	12	352	1199	19	313	1111	147
	2015.Q4	327	827	56	269	855	85	301	839	69	206	626	378

Table 2: Returns to Scale for Largest Banks by Total Assets, 1986.Q4 and 1996.Q4

Name	Assets	Cost	Revenue	Profit
—1986.Q4—				
CITIBANK	275	1.0371***	1.0147***	0.9834***
BK OF AMER	204	1.0928**	1.0558***	1.1622
CHASE MHTN BK	150	1.0618***	1.0820	1.0616
MANU. HAN	139	1.0855***	1.0686***	1.1819
MORGAN GNTY TC	130	1.0306***	1.0381***	1.0603
SECURITY PACIFIC	113	1.0982	1.0593***	1.0774
CHEMICAL NY	109	1.0923***	1.0574***	1.0995
BANKERS TR NY	100	1.0461***	1.0354***	1.0542***
FIRST INTRST BC	100	1.0883*	1.0705***	1.0586
WELLS FARGO & CO	81	1.0897	1.0488***	1.0622
—1996.Q4—				
CHASE MHTN	469	1.0557***	1.0334***	1.0401***
CITICORP	394	1.0368***	1.0376***	1.0426***
BK OF AMER	352	1.0412***	1.0469***	1.0485***
NATIONSBANK	266	1.0773***	1.0442***	1.0395***
MORGAN GNTY TC	245	1.0539***	1.0126***	0.9942***
FIRST UNION	195	1.0907**	1.0201***	0.9906***
WELLS FARGO & CO	155	1.0630***	1.0839***	1.1083
FIRST NBD	150	1.0663***	1.0392***	1.0440***
BANC ONE	143	1.0653***	1.0594***	1.0600***
FLEET FNCL GROUP	123	1.0587***	1.0817***	1.0781***

NOTE: For cost model, estimates of $(1-\mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For revenue and profit models, estimates of $(1+\mathcal{E}_{R,i})\delta$ and $(1+\mathcal{E}_{\pi,i})\delta$ are given. For cost model, values *less than* 1.1 indicate increasing returns to scale, while for revenue and profit models, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table 3: Returns to Scale for Largest Banks by Total Assets, 2006.Q4 and 2015.Q4

Name	Assets	Cost	Revenue	Profit
—2006.Q4—				
CITIGROUP	2082	1.1011	1.0808***	1.1355***
BK OF AMER	1672	1.0391***	1.0930***	1.1519***
JPMORGAN CHASE & CO	1543	1.1025	1.0982	1.2066***
WACHOVIA	726	1.0459***	1.0229***	1.0663
WELLS FARGO & CO	554	1.0193***	0.9996***	1.0134***
U S BC	250	1.0585***	1.0493***	1.0656***
COUNTRYWIDE	225	1.1009	1.0013***	0.9950***
SUNTRUST BK	210	1.0734***	1.0757***	1.0865
HSBC BK USA	191	1.0456***	1.0096***	0.9928***
NATIONAL CITY	160	1.0697***	1.0178***	0.9778***
—2015.Q4—				
JPMORGAN CHASE & CO	2378	1.0151***	1.1007	1.1249***
BK OF AMER	2145	1.0140***	1.1030	1.1592***
CITIGROUP	1765	1.0375***	1.1337***	1.1842***
WELLS FARGO & CO	1764	1.0347***	1.1170**	1.1180***
U S BC	418	0.9654***	1.0091***	1.0181***
BK OF NY MELLON	384	1.0697***	1.0451***	1.0348***
PNC FNCL SVC GROUP	359	0.9639***	1.0168***	1.0283***
STATE STREET	246	1.1568	1.0042***	1.0117***
T D BK	243	1.0527***	1.0666**	1.0717
BB&T	209	1.0483***	1.0795	1.1012

NOTE: For cost model, estimates of $(1-\mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For revenue and profit models, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For cost model, values *less than* 1.1 indicate increasing returns to scale, while for revenue and profit models, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table 4: Significant Changes in RTS from 2006.Q4 to 2015.Q4 for 10 Largest Banks in 2015.Q4 (.05 Significance)

	Model		
Bank	Cost	Revenue	Profit
JPMORGAN CHASE & CO	↑	—	—
BK OF AMER	↑	—	—
CITIGROUP	↑	↑	↑
WELLS FARGO & CO	—	↑	↑
U S BC	↑	↓	↓
PNC FNCL SVC GROUP	↑	—	—
STATE STREET	↓	↑	↑
T D BK	↑	↓	—
BB&T	↑	↑	—
SUNTRUST BK	—	—	—

NOTE: Upward arrows indicate a significant increase in RTS pseudo-elasticity from 2006.Q4 to 2015.Q4. Downward arrows indicate significant decrease in RTS pseueo-elasticity from 2006.Q4 to 2015.Q4. Horizontal dashes indicate no significant change.

The Evolution of Scale Economies in U.S. Banking: Appendices A–E

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A Interpretation of Scale Measures when (Net) Revenue or Profit is Negative

As noted in Section 2, either $\pi(\boldsymbol{y}_i, \boldsymbol{w}_i)$ or $\pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i)$—or $R(\boldsymbol{y}_i, \boldsymbol{w}_i)$ or $R(\delta\boldsymbol{y}_i, \boldsymbol{w}_i)$—might be negative, affecting how the magnitude of estimates of $\mathcal{E}_{\pi,i}$ and $\mathcal{E}_{R,i}$ are interpreted. Thus there are four cases to consider. In the discussion that follows, consider the scale measure $\mathcal{E}_{\pi,i}$ based on the profit function; similar reasoning applies to the scale measure $\mathcal{E}_{R,i}$ based on the revenue function.

In the most common scenario, $\pi(\boldsymbol{y}_i, \boldsymbol{w}_i) > 0$ and $\pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i) > 0$, and this case is discussed in Section 2. The other three cases are infrequent, and arise when $\pi(\boldsymbol{y}_i, \boldsymbol{w}_i) < 0$ or $\pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i) < 0$. We consider each of the three possible cases here.

1. $\pi(\boldsymbol{y}_i, \boldsymbol{w}_i) < 0$, $\pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i) > 0$.

   In this case, increasing output levels by a factor $\delta > 1$ increases profit. Also in this case, (2.6) can be written as $(1 - \mathcal{E}_{\pi,i})\delta\pi(\boldsymbol{y}_i, \boldsymbol{w}_i) = \pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i)$, implying $\mathcal{E}_{\pi,i} > 1$. Hence RTS are increasing in this case. If $\mathcal{E}_{\pi,i} = 1.05$ and $\delta = 1.1$, then increasing output levels by 10 percent leads to profits increasing by $100 + (1 - 1.05) \times 100 = 105$ percent from an initial negative value to a positive value. Alternatively, (2.6) can be rearranged to show the difference $\pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i) - \delta\pi(\boldsymbol{y}_i, \boldsymbol{w}_i) > 0$ equals $\mathcal{E}_{\pi,i}\delta|\pi(\boldsymbol{y}_i, \boldsymbol{w}_i|$; if $\mathcal{E}_{\pi,i} = 1.05$ and $\delta = 1.1$, then increasing output levels by 10 percent increases profit to a positive level equal to $(1 - 1.05) \times 1.1 = 0.55$ times the *magnitude* of the profits that were negative before the increase. Whether the increase is big or small in absolute terms depends on the starting point, i.e., the magnitude of $\pi(\boldsymbol{y}_i, \boldsymbol{w}_i)$.

2. $\pi(\boldsymbol{y}_i, \boldsymbol{w}_i) > 0$, $\pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i) < 0$.

   In this case, increasing output levels by a factor $\delta > 1$ decreases profit. Since $\pi(\boldsymbol{y}_i, \boldsymbol{w}_i) > 0$, (2.6) can again be rewritten as $(1 + \mathcal{E}_{\pi,i})\delta\pi(\boldsymbol{y}_i, \boldsymbol{w}_i) = \pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i)$. Clearly, $\mathcal{E}_{\pi,i} < -1$ since $\pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i) < 0$. Hence RTS are decreasing in this case. If $\mathcal{E}_{\pi,i} = -1.05$ and $\delta = 1.1$, then increasing output levels by 10 percent reduces profit by $100+(1+\mathcal{E}_{\pi,i})\delta\times 100 = 105.5$ percent. As in the previous case, whether the absolute change in profit is big or small depends on the starting point.

3. $\pi(\boldsymbol{y}_i, \boldsymbol{w}_i) < 0$, $\pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i) < 0$.

   Using reasoning similar to that in footnote 2 in the paper, profit (increases, remains unchanged, decreases) as $\mathcal{E}_{\pi,i}$ $(>,=,<) 1 - \delta^{-1} \approx 0.09091$ for $\delta = 1.1$. In this case we also have again $(1 - \mathcal{E}_{\pi,i})\delta\pi(\boldsymbol{y}_i, \boldsymbol{w}_i) = \pi(\delta\boldsymbol{y}_i, \boldsymbol{w}_i)$. Since both profit terms are negative, $\mathcal{E}_{\pi,i} < 1$ and returns to scale are either increasing, constant, or decreasing depending on whether $\mathcal{E}_{\pi,i}$ is greater than, equal to, or less than 0. Increasing output levels by a factor δ causes profits to fall by a factor $(1 - \mathcal{E}_{\pi,i})\delta$; for If $\mathcal{E}_{\pi,i} = 0.05$ and $\delta = 1.1$, a 10 percent increase in output levels results in profits that are still negative, but 4.5 percent greater than before the increase in output.

B Summary Statistics for Data Used for Estimation

As mentioned in the paper, we estimate several specifications in addition to the cost, revenue and profit models described in Section 3 of the paper. All together, we estimate 8 different models—2 cost functions, 2 revenue functions, and 4 profit functions. In subequent appendices, we number these models 1–8, with models 1, 3, and 5 corresponding to the cost, revenue and profit functions described in Section 3. In the tables that follow, we denote the dependent variables for these models as C_1, R_1, and π_1 respectively. In model 2, cost (C_2) is measured by total interest expense plus total non-interest expense. Similarly, in model 4 revenue (R_2) is measured by total interest income plus total non-interest income. In models 6–8, profit is measured by $\pi_2 = R_1 - C_2$, $\pi_3 = R_2 - C_1$ and $\pi_4 = R_2 - C_2$ (whereas in model 5 profit is measured by $\pi_1 = R_1 - C_1$). Results for estimated returns to scale given below in Appendix E are broadly qualitatively similar across the sets of specifications for cost, revenue and profit functions.

Table B.1 gives correlations for the dependent variables used in each of the 8 models described above. Table B.2–B.5 give summary statistics for left-hand and right-hand side variables used in Models 1–8 over the 4 quarters in which returns-to-scale are estimated (i.e., 1986.Q4, 1996.Q4, 2006.Q4, and 2015.Q4). Table B.6 gives similar summary statistics over the 117 quarters used for estimation (i.e., 1986.Q4–2015.Q4). All dollar amounts have been converted to constant 2015 dollars using the quarterly, seasonally adjusted, gross domestic product implicit price deflator.

Figure B.1 shows kernel density esitmates of log total assets for 1986.Q4, 1996.Q4, 2006.Q4 and 2015.Q4. The esimates displayed in Figure B.1 illustrate the evolution of bank sizes over the period covered by our sample; i.e., the distribution of bank sizes has shifted rightward over time.

Table B.1: Correlation Matrices for Dependent Variables, All Periods

	C_1/W_1	C_2/W_1	R_1	R_2	π_1	π_2	π_3	π_4
Homogeneity wrt prices not imposed on revenue, profit variables:								
C_1/W_1	1.0000							
C_2/W_1	0.9935	1.0000						
R_1	0.7106	0.6828	1.0000					
R_2	0.7031	0.6752	0.9944	1.0000				
π_1	0.7733	0.7518	0.9577	0.9399	1.0000			
π_2	0.6431	0.5990	0.7974	0.7585	0.8869	1.0000		
π_3	0.7571	0.7339	0.9678	0.9757	0.9687	0.8003	1.0000	
π_4	0.6950	0.6513	0.9092	0.9144	0.9265	0.8986	0.9481	1.0000

Table B.2: Quantiles and Means for Variables used in Estimation, 1986.Q4

	0.01	0.25	0.50	Mean	0.75	0.99
C_1/W_1	1.4285E+04	4.8580E+04	9.0857E+04	7.0159E+05	1.8405E+05	1.1684E+07
C_2/W_1	1.6762E+04	5.7208E+04	1.0817E+05	8.3290E+05	2.1925E+05	1.4208E+07
R_1	−3.2161E+03	2.6552E+03	5.3853E+03	4.7041E+04	1.1450E+04	7.2623E+05
R_2	8.2147E+02	3.3081E+03	6.3493E+03	5.1503E+04	1.2755E+04	7.8661E+05
π_1	−1.1057E+07	−1.7302E+05	−8.5864E+04	−6.5455E+05	−4.5699E+04	−1.3489E+04
π_2	−1.3692E+07	−2.0839E+05	−1.0242E+05	−7.8586E+05	−5.4381E+04	−1.5760E+04
π_3	−1.0964E+07	−1.7129E+05	−8.4585E+04	−6.5009E+05	−4.5199E+04	−1.3274E+04
π_4	−1.3650E+07	−2.0665E+05	−1.0157E+05	−7.8140E+05	−5.4012E+04	−1.5679E+04
Y_1	9.4970E+01	2.7478E+03	6.5611E+03	5.4197E+04	1.4842E+04	9.4352E+05
Y_2	6.0057E+02	5.6446E+03	1.1661E+04	1.7275E+05	2.5399E+04	2.4975E+06
Y_3	2.9062E+02	5.0820E+03	1.2893E+04	9.0136E+04	3.0702E+04	1.4840E+06
Y_4	3.8996E+03	1.5778E+04	3.1069E+04	1.9748E+05	6.4592E+04	2.8690E+06
Y_5	2.1739E+01	1.8319E+02	4.0705E+02	8.0615E+03	1.0033E+03	1.1912E+05
W_1	2.9941E−02	4.7824E−02	5.2315E−02	5.1871E−02	5.6474E−02	6.9519E−02
W_2	2.4148E+01	3.8039E+01	4.4386E+01	4.8134E+01	5.3449E+01	1.1244E+02
W_3	5.0803E−02	2.1430E−01	3.2525E−01	5.2831E−01	5.3877E−01	3.2728E+00
W_2/W_1	4.3850E+02	7.1662E+02	8.6105E+02	9.7204E+02	1.0762E+03	2.6353E+03
W_3/W_1	9.5988E−01	4.0663E+00	6.3178E+00	1.1330E+01	1.0651E+01	7.5292E+01
X_3	2.8957E+01	4.4644E+02	1.0862E+03	8.1347E+03	2.5143E+03	1.3590E+05
EQUITY	4.6844E+02	3.0110E+03	5.7012E+03	3.2222E+04	1.1211E+04	5.3531E+05
NPER	3.4032E−04	1.6663E−02	3.1966E−02	4.4983E−02	5.6878E−02	2.1259E−01
TIME	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00	1.0000E+00
ASSETS	9.3010E+03	3.4814E+04	6.7352E+04	5.1436E+05	1.3537E+05	8.0312E+06

NOTE: Dollar figures are given in thousands of constant 2015 dollars.

Table B.3: Quantiles and Means for Variables used in Estimation, 1996.Q4

	0.01	0.25	0.50	Mean	0.75	0.99
C_1/W_1	1.9638E+04	6.8268E+04	1.3051E+05	1.2362E+06	2.7415E+05	1.2393E+07
C_2/W_1	2.4015E+04	8.1068E+04	1.5610E+05	1.5254E+06	3.3136E+05	1.5835E+07
R_1	7.4775E+02	3.5114E+03	6.9199E+03	7.2351E+04	1.4604E+04	7.1875E+05
R_2	8.7486E+02	3.6294E+03	7.1503E+03	7.4768E+04	1.5053E+04	7.3635E+05
π_1	−1.1712E+07	−2.6014E+05	−1.2354E+05	−1.1639E+06	−6.4618E+04	−1.8718E+04
π_2	−1.5166E+07	−3.1588E+05	−1.4894E+05	−1.4530E+06	−7.7339E+04	−2.3150E+04
π_3	−1.1658E+07	−2.5979E+05	−1.2339E+05	−1.1614E+06	−6.4476E+04	−1.8707E+04
π_4	−1.5151E+07	−3.1585E+05	−1.4849E+05	−1.4506E+06	−7.7178E+04	−2.3115E+04
Y_1	2.6258E+02	2.6478E+03	5.8175E+03	8.8979E+04	1.3725E+04	8.9102E+05
Y_2	5.0755E+02	6.0800E+03	1.2481E+04	1.9537E+05	2.5904E+04	1.4277E+06
Y_3	7.8824E+02	1.0595E+04	2.5656E+04	2.1970E+05	6.4027E+04	2.7739E+06
Y_4	4.1874E+03	1.7792E+04	3.3857E+04	3.1128E+05	7.0037E+04	3.0415E+06
Y_5	3.3334E+01	2.4517E+02	5.6283E+02	1.6617E+04	1.4214E+03	1.4524E+05
W_1	1.9594E−02	3.2982E−02	3.7037E−02	3.6638E−02	4.0576E−02	5.0377E−02
W_2	3.0004E+01	4.4822E+01	5.2365E+01	5.6208E+01	6.2693E+01	1.2609E+02
W_3	6.3216E−02	1.9908E−01	2.9122E−01	5.2205E−01	4.6896E−01	2.8226E+00
W_2/W_1	7.5975E+02	1.1952E+03	1.4391E+03	1.5908E+03	1.8106E+03	3.9926E+03
W_3/W_1	1.6388E+00	5.3958E+00	8.1142E+00	1.5264E+01	1.3369E+01	9.0522E+01
X_3	3.2687E+01	5.1065E+02	1.3453E+03	1.3182E+04	3.3807E+03	1.3020E+05
EQUITY	1.0588E+03	4.5069E+03	8.5316E+03	6.7811E+04	1.7396E+04	6.7885E+05
NPER	0.0000E+00	7.2233E−03	1.4046E−02	1.8648E−02	2.4139E−02	8.1476E−02
TIME	4.1000E+01	4.1000E+01	4.1000E+01	4.1000E+01	4.1000E+01	4.1000E+01
ASSETS	1.0925E+04	4.4322E+04	8.5241E+04	8.1747E+05	1.7826E+05	7.7399E+06

NOTE: Dollar figures are given in thousands of constant 2015 dollars.

Table B.4: Quantiles and Means for Variables used in Estimation, 2006.Q4

	0.01	0.25	0.50	Mean	0.75	0.99
C_1/W_1	2.7372E+04	1.0834E+05	2.1287E+05	2.8111E+06	4.7847E+05	1.9688E+07
C_2/W_1	3.4790E+04	1.3144E+05	2.5476E+05	3.3825E+06	5.7645E+05	2.4183E+07
R_1	7.5553E+02	4.1226E+03	8.7530E+03	1.5337E+05	2.0892E+04	8.8074E+05
R_2	8.7438E+02	4.3025E+03	9.1663E+03	1.5918E+05	2.1518E+04	9.0536E+05
π_1	−1.8792E+07	−4.5884E+05	−2.0425E+05	−2.6578E+06	−1.0416E+05	−2.6562E+04
π_2	−2.3032E+07	−5.5530E+05	−2.4635E+05	−3.2292E+06	−1.2709E+05	−3.3546E+04
π_3	−1.8769E+07	−4.5843E+05	−2.0379E+05	−2.6520E+06	−1.0410E+05	−2.6551E+04
π_4	−2.2999E+07	−5.5446E+05	−2.4571E+05	−3.2233E+06	−1.2677E+05	−3.3524E+04
Y_1	5.4270E+01	2.0337E+03	4.5317E+03	1.3393E+05	1.0605E+04	5.0776E+05
Y_2	6.8023E+02	7.9104E+03	1.7427E+04	3.0917E+05	4.0890E+04	1.8210E+06
Y_3	1.7185E+03	2.2155E+04	5.7937E+04	6.2418E+05	1.5227E+05	5.0291E+06
Y_4	3.7717E+03	1.9683E+04	3.8899E+04	8.8022E+05	8.4208E+04	4.1177E+06
Y_5	2.5222E+01	2.9465E+02	7.6319E+02	4.7674E+04	2.0922E+03	1.7041E+05
W_1	1.2300E−02	2.5134E−02	2.9807E−02	2.9760E−02	3.4539E−02	4.7022E−02
W_2	3.3580E+01	5.1988E+01	6.0842E+01	6.5241E+01	7.3959E+01	1.3351E+02
W_3	5.7326E−02	1.5976E−01	2.4101E−01	4.3295E−01	4.0730E−01	2.6102E+00
W_2/W_1	1.0786E+03	1.7139E+03	2.0858E+03	2.3338E+03	2.6522E+03	6.0090E+03
W_3/W_1	1.6144E+00	5.3063E+00	8.4496E+00	1.6224E+01	1.4996E+01	1.0431E+02
X_3	4.0038E+01	7.9625E+02	2.3097E+03	1.9033E+04	6.0625E+03	1.9300E+05
EQUITY	1.5462E+03	7.1660E+03	1.3890E+04	1.7695E+05	2.9155E+04	1.1112E+06
NPER	0.0000E+00	5.2085E−03	1.1642E−02	1.6275E−02	2.2149E−02	7.7390E−02
TIME	8.1000E+01	8.1000E+01	8.1000E+01	8.1000E+01	8.1000E+01	8.1000E+01
ASSETS	1.3424E+04	6.3182E+04	1.2914E+05	1.9531E+06	2.9528E+05	1.2084E+07

NOTE: Dollar figures are given in thousands of constant 2015 dollars.

Table B.5: Quantiles and Means for Variables used in Estimation, 2015.Q4

	0.01	0.25	0.50	Mean	0.75	0.99
C_1/W_1	1.0626E+05	5.2067E+05	1.1119E+06	1.8666E+07	2.7318E+06	1.4240E+08
C_2/W_1	1.5534E+05	7.2978E+05	1.5695E+06	2.7335E+07	3.8389E+06	2.1414E+08
R_1	5.8014E+02	3.8511E+03	7.8937E+03	1.2840E+05	1.7659E+04	7.9773E+05
R_2	7.1519E+02	3.9455E+03	8.1673E+03	1.3408E+05	1.8168E+04	8.5243E+05
π_1	−1.4195E+08	−2.7055E+06	−1.1025E+06	−1.8538E+07	−5.1543E+05	−1.0493E+05
π_2	−2.1285E+08	−3.8207E+06	−1.5602E+06	−2.7206E+07	−7.2486E+05	−1.5328E+05
π_3	−1.4187E+08	−2.7056E+06	−1.1027E+06	−1.8532E+07	−5.1549E+05	−1.0491E+05
π_4	−2.1272E+08	−3.8207E+06	−1.5591E+06	−2.7201E+07	−7.2453E+05	−1.5328E+05
Y_1	4.9869E+00	1.4729E+03	3.4275E+03	1.9185E+05	8.1038E+03	6.7945E+05
Y_2	8.2713E+02	9.3589E+03	2.1943E+04	5.5048E+05	5.3645E+04	3.8193E+06
Y_3	2.5233E+03	3.2677E+04	8.0097E+04	7.3225E+05	1.9746E+05	7.1351E+06
Y_4	5.4605E+03	2.9490E+04	5.8854E+04	1.5083E+06	1.2884E+05	5.0939E+06
Y_5	3.5752E+01	3.5377E+02	9.8589E+02	5.0507E+04	2.8920E+03	2.2895E+05
W_1	7.0980E−04	2.6526E−03	3.9677E−03	4.3177E−03	5.6056E−03	1.1163E−02
W_2	3.9563E+01	5.9819E+01	7.0071E+01	7.4142E+01	8.4415E+01	1.3954E+02
W_3	5.9994E−02	1.5105E−01	2.2741E−01	4.4754E−01	3.9024E−01	3.7542E+00
W_2/W_1	5.9063E+03	1.2661E+04	1.8070E+04	2.4135E+04	2.7267E+04	1.1704E+05
W_3/W_1	9.7897E+00	3.5035E+01	6.2436E+01	1.4857E+02	1.2599E+02	1.5046E+03
X_3	3.5086E+01	8.9979E+02	2.7917E+03	2.2944E+04	7.0597E+03	2.4833E+05
$EQUITY$	1.8127E+03	9.7273E+03	1.9529E+04	3.4081E+05	4.1760E+04	2.0533E+06
$NPER$	0.0000E+00	5.9330E−03	1.2205E−02	1.8037E−02	2.2530E−02	1.1501E−01
$TIME$	1.1700E+02	1.1700E+02	1.1700E+02	1.1700E+02	1.1700E+02	1.1700E+02
$ASSETS$	1.8508E+04	8.8917E+04	1.7926E+05	2.9854E+06	3.9060E+05	1.8417E+07

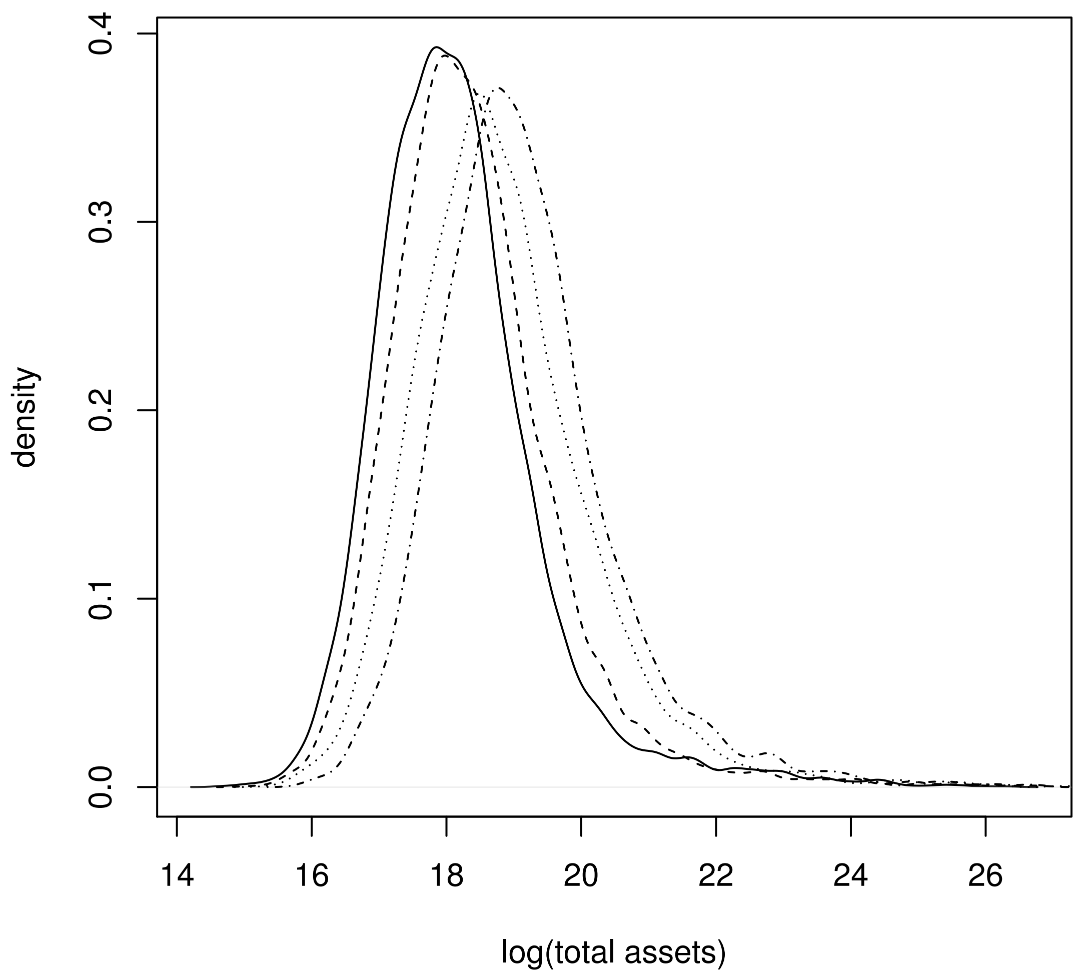
NOTE: Dollar figures are given in thousands of constant 2015 dollars.

Table B.6: Quantiles and Means for Variables used in Estimation, All Quarters

	0.01	0.25	0.50	Mean	0.75	0.99
C_1/W_1	1.7581E+04	7.7641E+04	1.7125E+05	3.4098E+06	4.4550E+05	2.3379E+07
C_2/W_1	2.0990E+04	9.3050E+04	2.0875E+05	4.8089E+06	5.6213E+05	3.0692E+07
R_1	5.5909E+02	3.4482E+03	6.9426E+03	8.5015E+04	1.5174E+04	7.2486E+05
R_2	8.0460E+02	3.6451E+03	7.2711E+03	9.1672E+04	1.5882E+04	7.7272E+05
π_1	−2.2596E+07	−4.2852E+05	−1.6297E+05	−3.3248E+06	−7.3402E+04	−1.6517E+04
π_2	−3.0026E+07	−5.4462E+05	−2.0024E+05	−4.7239E+06	−8.8673E+04	−1.9901E+04
π_3	−2.2542E+07	−4.2761E+05	−1.6260E+05	−3.3181E+06	−7.3203E+04	−1.6476E+04
π_4	−2.9967E+07	−5.4374E+05	−1.9993E+05	−4.7173E+06	−8.8490E+04	−1.9861E+04
Y_1	7.9818E+01	2.2160E+03	5.1518E+03	9.6592E+04	1.2025E+04	7.0749E+05
Y_2	5.6932E+02	6.3087E+03	1.3550E+04	2.4207E+05	3.1154E+04	1.8640E+06
Y_3	7.1851E+02	1.1362E+04	3.1410E+04	3.4505E+05	8.7623E+04	3.3477E+06
Y_4	4.1916E+03	1.8965E+04	3.7406E+04	5.6377E+05	8.0598E+04	3.6474E+06
Y_5	2.9044E+01	2.4066E+02	5.9222E+02	2.5616E+04	1.6037E+03	1.4839E+05
W_1	2.1543E−03	1.9285E−02	3.3102E−02	3.2665E−02	4.5244E−02	6.6601E−02
W_2	2.8801E+01	4.3852E+01	5.2515E+01	5.6152E+01	6.4042E+01	1.2041E+02
W_3	6.5227E−02	1.8211E−01	2.6997E−01	4.6718E−01	4.3943E−01	2.8289E+00
W_2/W_1	5.2789E+02	1.0499E+03	1.6292E+03	3.7772E+03	3.2204E+03	3.2890E+04
W_3/W_1	1.5785E+00	5.4754E+00	9.4494E+00	2.9362E+01	1.9831E+01	2.9017E+02
X_3	3.0665E+01	5.4687E+02	1.5438E+03	1.4450E+04	4.1485E+03	1.6133E+05
$EQUITY$	8.6404E+02	4.7176E+03	9.5730E+03	1.1172E+05	2.0518E+04	8.5412E+05
$NPER$	0.0000E+00	7.8813E−03	1.6633E−02	2.5232E−02	3.1354E−02	1.5069E−01
$TIME$	1.0000E+00	2.2000E+01	4.8000E+01	5.1908E+01	8.0000E+01	1.1600E+02
$ASSETS$	1.0983E+04	4.8178E+04	9.7835E+04	1.2465E+06	2.1775E+05	9.9231E+06

NOTE: Dollar figures are given in thousands of constant 2015 dollars.

Figure B.1: Density of (log) Total Assets of in 1986.Q4, 1996.Q4, 2006.Q4 and 2015.Q4



NOTE: Solid line shows density for 1986.Q4; dashed line shows density for 1996.Q4; dotted line shows density for 2006.Q4; and dash-dotted line shows density for 2015.Q4.

C Test of Translog Specifications

In order to provide a simple test of the translog specification for our cost, revenue, and profit equations, we divide our data for each of 117 quarters (1986.Q4–2015.Q4) into two mutually exclusive, collectively exhaustive subsamples containing (i) observations on banks with total assets up to the median of total assets, and (ii) observations on banks with total assets greater than the median of total assets (medians are over all banks within a given group). Thus for each quarter we have two subsamples. For each model $m \in \{1, \ldots, 8\}$, we specify a translog form for the conditional mean function after omitting the time (T) variable from the RHSs of the models. For each subsample in each quarter, we estimate via ordinary least squares (OLS) each of 8 models with translog specifications.

For a given quarter and a given model m, we obtain parameter estimates $\widehat{\boldsymbol{\beta}}_{mj}$ and corresponding covariance matrix estimates

$$\widehat{\Sigma}_{mj} = (\frac{n_{mj}}{n_{mj} - K_m})(\boldsymbol{X}'_{mj}\boldsymbol{X}_{mj})^{-1}\boldsymbol{X}'_{mj}\text{diag}(\widehat{\varepsilon}^2_{mji})\boldsymbol{X}_{mj}(\boldsymbol{X}'_{mj}\boldsymbol{X}_{mj})^{-1}, \tag{C.1}$$

where $j \in \{1, 2\}$, $\boldsymbol{X}_{mj}$ is the $(n_{mj} \times K_m)$ matrix of RHS variables (including interaction terms) used in the translog specification and the $\widehat{\varepsilon}_{mji}$ are the OLS residuals for model m, subset j. The factor $(\frac{n_{mj}}{n_{mj}-K_m})$ scales up the usual White (1980) heteroskedasticity-consistent covariance estimator as suggested by Davidson and MacKinnon (1993) to account for the fact that squared OLS-estimated residuals tend to underestimate squares of true residuals.

Finally, for a given quarter and model, we compute the Wald statistic

$$\widehat{W} = (\widehat{\boldsymbol{\beta}}_{m1} - \widehat{\boldsymbol{\beta}}_{m2})'(\widehat{\Sigma}_{m1} + \widehat{\Sigma}_{m2})^{-1}(\widehat{\boldsymbol{\beta}}_{m1} - \widehat{\boldsymbol{\beta}}_{m2}) \tag{C.2}$$

to test the null hypothesis $H_0\colon \boldsymbol{\beta}_{m1} = \boldsymbol{\beta}_{m2}$ versus the alternative hypothesis $H_1\colon \boldsymbol{\beta}_{m1} \neq \boldsymbol{\beta}_{m2}$. Rejection of the null provides evidence against the translog specification within a given group. Using the sample described in Section 3, we obtain p-values for the $117 \times 8 = 936$ Wald tests ranging from $10^{-85.456}$ to 0.0514. Only 1 out of 936 p-values are greater than 0.05, and only 4 are greater than 0.01. The median p-value is $10^{-13.723}$ (i.e., essentially zero). Splitting the data into $117 \times 2 = 234$ cells allows the translog parameters to vary across quarters as well as across bank-size. Even so, we find overwhelming evidence against the translog specification.

D Details of Non-parametric Estimation and Inference

D.1 Dimension reduction

Non-parametric regression methods typically suffer from the well-known curse of dimensionality, a phenomenon that causes rates of convergence to become slower, and estimation error to increase dramatically, as the number of continuous right-hand side variables increases (the presence of discrete dummy variables does not affect the convergence rate of our estimator). We use eigensystem analysis and principal components to help mitigate this problem. The idea is to sacrifice a relatively small amount of information in the data to permit a reduction in dimensionality that will have a large (and favorable) impact on estimation error.

We begin by applying marginal transformations to the continuous right-hand side RHS variables in each model. The marginal transformations are chosen to yield distributions that are approximately normal. For output quantities Y_1, Y_2, Y_3 and Y_5 we add 1 and then take the (natural) logarithm. For Y_4 we take the logarithm without adding 1. For the physical capital variable X_4 used in the first model, and for the normalized input price variables used in each of the cost models, we take logarithms. We similarly take logarithms of the input price variables (that are not normalized) in the revenue and profit models.

For an $(n \times 1)$ vector $\boldsymbol{V}$ define the function $\psi_1(\cdot)\colon \mathbb{R}^n \mapsto \mathbb{R}^n$ such that

$$\psi_1(\boldsymbol{V}) \equiv (\boldsymbol{V} - n^{-1}\boldsymbol{i}'\boldsymbol{V}) \left[n^{-1}\boldsymbol{V}'\boldsymbol{V} - n^{-2}\boldsymbol{V}'\boldsymbol{i}\boldsymbol{i}'\boldsymbol{V}\right]^{-1/2} \tag{D.1}$$

where $\boldsymbol{i}$ denotes an $(n \times 1)$ vector of ones. The function $\psi_1(\cdot)$ standardizes a variable by subtracting its sample mean and then dividing by its sample standard deviation. We apply this function to marginal transformations of the continuous RHS variables in each model.

For model $j \in \{1, \ldots, 8\}$, let K_j be the number of continuous RHS variables, and let $\boldsymbol{A}_j$ be the $(n \times K_j)$ matrix with columns containing the standardized, marginal transformations of the continuous RHS variables in the given model. Let $\boldsymbol{\Lambda}_j$ be the $(K_j \times K_j)$ matrix whose columns are the eigenvectors of the correlation matrix of Pearson correlation coefficients for pairs of columns of $\boldsymbol{A}_j$, and let λ_{jk} be the eigenvalue corresponding to the kth eigenvector in the kth column of $\boldsymbol{\Lambda}_j$, where the columns of $\boldsymbol{\Lambda}_j$, and their corresponding eigenvalues, have been sorted so that $\lambda_{j1} \geq \ldots \geq \lambda_{jK_j}$. Then let $\boldsymbol{P}_j = \boldsymbol{A}_j\boldsymbol{\Lambda}_j$. The matrix $\boldsymbol{P}_j$ has dimensions $(n \times K_j)$, and its columns are the principal components of $\boldsymbol{A}_j$. It is well-known that principal components are orthogonal. Moreover, for each $k \in \{1,\ 2,\ \ldots,\ K_j\}$, the quantity

$$\phi_{jk} = \frac{\sum_{\ell=1}^{k} \lambda_{j\ell}}{\sum_{i=1}^{K} \lambda_{ji}} \tag{D.2}$$

represents the proportion of the independent linear information in $\boldsymbol{A}_j$ that is contained in the first k principal components, i.e., the first k columns of $\boldsymbol{P}_j$.

Using the dataset described in Section 3, for models $j \in \{1,\ 2\}$ and $k \in \{1,\ \ldots,\ 10\}$ we find $\phi_{j,k} = 0.4004706$, 0.6409254, 0.7411243, 0.8358076, 0.8875271, 0.9285652, 0.9551966, 0.9735527, 0.9886108 and 1.0000000. For the revenue and cost models ($j \in \{3,\ \ldots,\ 8\}$) and $k \in \{1,\ \ldots,\ 11\}$ we find $\phi_{j,k} = 0.3714919$, 0.5653879, 0.6641117, 0.7547991, 0.8381867, 0.8969946, 0.9292129, 0.9531239, 0.9751464, 0.9888575 and 1.0000000. As discussed in Section 3, we use the first 6 principal components in each case, omitting the last 4 in models 1–2, and the last 5 in models 3–8. In doing so, we sacrifice a relatively small amount of information, while retaining 89.7 to 93.2 percent of the independent linear information in the sample, in order to reduce the dimensionality of our estimation problem by 6 or 7 dimensions in the space of the continuous covariates. We regard this as a worthwhile trade-off given the curse of dimensionality.

Now write model j, $j \in \{1,\ \ldots,\ 8\}$ from the list of models given in Section 3 as

$$\mathcal{Y}_{ji} = m_j(\mathcal{X}_{ji}) + \varepsilon_i \tag{D.3}$$

where $\mathcal{Y}_{ji}$ is the ith observation, $i = 1,\ \ldots,\ n$ on left-hand side (LHS) variable in model j and $\mathcal{X}_{ji}$ is the vector of ith observations on K_j continuous RHS variables in model j. Let $\boldsymbol{\mathcal{Y}}_j = \begin{bmatrix}\mathcal{Y}_{ji} & \ldots & \mathcal{Y}_{jn}\end{bmatrix}'$. Define functions $\psi_2(\cdot)\colon \mathbb{R}^n \mapsto \mathbb{R}^n$ such that

$$\psi_2(\boldsymbol{V}) := \psi_1\left(\log(\boldsymbol{V} - \min(\boldsymbol{V}) + 1)\right) \tag{D.4}$$

and $\psi_3(\cdot)\colon \mathbb{R}^n \mapsto \mathbb{R}^n$ such that

$$\psi_3(\boldsymbol{V}) := \boldsymbol{V}/\mathrm{IQR}(\boldsymbol{V}) \tag{D.5}$$

where $\mathrm{IQR}(\boldsymbol{V})$ gives the inter-quartile range of the elements of $\boldsymbol{V}$.

Instead of estimating (D.3) directly, we estimate the model

$$\mathcal{Y}_{ji}^{+} = m_j^{+}(\mathcal{X}_{ji}^{+}) + \xi_i \tag{D.6}$$

where $E(\xi_i) = 0$, $\text{VAR}(\xi_i) = \sigma^2(\mathcal{X}^+_{ji})$, $\mathcal{Y}^+_{ji}$ is the ith element of the $(n \times 1)$ vector $\boldsymbol{\mathcal{Y}}^+_j = \psi_2(\boldsymbol{\mathcal{Y}}_{ji})$ for the cost models ($j \in \{1,\ 2\}$) or $\boldsymbol{\mathcal{Y}}^+_j = \psi_3(\boldsymbol{\mathcal{Y}}_{ji})$ for the revenue and profit models ($j \in \{3,\ \ldots,\ 8\}$), $\mathcal{X}^+_{ij}$ is the row vector containing the ith observations on $\psi_4(\boldsymbol{P}_{j,\cdot 1}),\ \ldots, \psi_4(\boldsymbol{P}_{j,\cdot 6})$, with $\boldsymbol{P}_{j,\cdot k}$ denoting the kth column of the principal component matrix $\boldsymbol{P}_j$ and $\psi_4(\cdot)\colon \mathbb{R}^n \mapsto \mathbb{R}^n$ such that

$$\psi_4(\boldsymbol{P}_{j,\cdot k}) := \boldsymbol{P}_{j,\cdot k} \left[n^{-1} \boldsymbol{P}'_{j,\cdot k} \boldsymbol{P}_{j,\cdot k} - n^{-2} \boldsymbol{P}'_{j,\cdot k} \boldsymbol{i}\boldsymbol{i}' \boldsymbol{P}_{j,\cdot k} \right]^{-1/2}. \tag{D.7}$$

The transformation $\psi_4(\boldsymbol{P}_{j,\cdot k})$ of $\boldsymbol{P}_{j,\cdot k}$ has (constant) unit variance. Moreover, all of the transformations that have been introduced can be inverted. Hence, given estimated values $\widehat{\boldsymbol{M}}^+ = \left[\widehat{m}^+_j(\mathcal{X}^+_{j1}) \quad \ldots \quad \widehat{m}^+_j(\mathcal{X}^+_{jn} \right]'$, straightforward algebra yields estimated or predicted values

$$\widehat{\boldsymbol{\mathcal{Y}}}_{ji} = \left[\widehat{\mathcal{Y}}_{j1} \quad \ldots \quad \widehat{\mathcal{Y}}_{jn} \right]' = \psi_2^{-1} \left(\widehat{\boldsymbol{M}}^+ \right). \tag{D.8}$$

As discussed below, we use a local linear estimator to estimate $m^+_j(\mathcal{X}^+_{ji})$. Although this estimator is weakly consistent, it is asymptotically biased. Moreover, even if $\widehat{m}^+_j(\mathcal{X}^+_{ji})$ were *unbiased*, use of the nonlinear transformation in (D.8) means that $\widehat{\mathcal{Y}}_{ji}$ obtained from (D.8) would not, in general, be unbiased because of the linearity of the expectations operator. Furthermore, even if an unbiased estimator of $\widehat{\mathcal{Y}}_{ji}$ were available, plugging such an estimator into the returns-to-scale measures $\mathcal{E}_{C,i}$, $\mathcal{E}_{R,i}$, and $\mathcal{E}_{\pi,i}$ defined in Section 2 to obtain estimators $\widehat{\mathcal{E}}_{C,i}$, $\widehat{\mathcal{E}}_{R,i}$, and $\widehat{\mathcal{E}}_{\pi,i}$ involves additional nonlinear transformations. Fortunately, any bias in the resulting estimates $\widehat{\mathcal{E}}_{C,i}$, $\widehat{\mathcal{E}}_{R,i}$, and $\widehat{\mathcal{E}}_{\pi,i}$ can be corrected while making inference about returns to scale; as discussed below in Section D.3, we employ a bias-corrected bootstrap method when estimating confidence intervals for our returns-to-scale measures.

D.2 Non-parametric estimation of conditional mean functions

Local polynomial estimators are discussed by Fan and Gijbels (1996), and are a generalization of the Nadaraya-Watson (Nadaraya, 1964; Watson, 1964) kernel estimator which amounts to fitting locally a polynomial of order $p = 0$. The local-linear estimator that we employ has less bias, but no more variance than the Nadaraya-Watson estimator; see Fan and Gijbels for explanation.

We specify the kernel function $\mathcal{K}(\cdot)\colon \mathbb{R}^\ell \mapsto \mathbb{R}^1_+$ needed by the local linear estimator as an

ℓ-variate, spherically symmetric Epanechnikov kernel with a single, scalar bandwidth h_0; i.e.,

$$\mathcal{K}(\boldsymbol{t}) = \frac{\ell(\ell+2)}{2S_\ell}(1-\boldsymbol{t}\boldsymbol{t}')\mathbb{1}(\boldsymbol{t}\boldsymbol{t}' \leq 1) \tag{D.9}$$

where $\mathbb{1}(\cdot)$ again represents the indicator function, $S_\ell = 2\pi^{\ell/2}/\Gamma(\ell/2)$, and $\Gamma(\cdot)$ denotes the gamma function (recall that for each of the transformed models represented by (D.6), $\ell = 6$). The spherically symmetric Epanechnikov kernel is optimal in terms of asymptotic minimax risk; see Fan et al. (1997) for details and a proof.

Note that the principal components transformation pre-whitens the data; in addition, the principal components are orthogonal. These two facts allow us to work with a single bandwidth rather than a vector or matrix of bandwidths. Moreover, we use an is an adaptive, scalar-valued bandwidth $h(\mathcal{X}_0^+)$ that depends on the point $(\mathcal{X}_0^+)$ in the space of the continuous, transformed RHS variables where the conditional mean function is to be evaluated as explained below.

D.3 Practical issues for implementation

To implement our estimator, optimize the bandwidth $h(\mathcal{X}_0^+)$. All of the right-hand side variables $\mathcal{X}_0^+$ are continuous, but the sparseness of the data varies. Hence we use an adaptive, nearest-neighbor bandwidth. We define $h(\mathcal{X}_0^+)$ for any particular point $\mathcal{X}_0^+ \in \mathbb{R}^\ell$ as the maximum Euclidean distance between $\mathcal{X}_0^+$ and the κ nearest points in the observed sample $\{\mathcal{X}_{ji}^+\}_{i=1}^n$, $\kappa \in \{2,\ 3,\ 4,\ \ldots\}$. Thus, given the data and the point $\mathcal{X}_0^+$, the bandwidth $h(\mathcal{X}_0^+)$ is determined by κ, and varies depending on the density of the continuous explanatory variables locally around the point $\mathcal{X}_0^+ \in \mathbb{R}^\ell$ at which the conditional mean function is estimated. This results in a bandwidth that is increasing with decreasing density of the data around the point of interest, $\mathcal{X}_0^+$. More smoothing is required where data are sparse than where data are dense; our nearest-neighbor bandwidth adapts automatically to the density of the data.

Note that we use a nearest-neighbor *bandwidth* rather than a nearest-neighbor *estimator*. The bandwidth is used inside a kernel function, and the kernel function integrates to unity. Loftsgaarden and Quesenberry (1965) use this approach in the density estimation context to avoid nearest-neighbor density estimates (as opposed to bandwidths) that do not integrate to unity (see Pagan and Ullah, 1999, pp. 11-12 for additional discussion). Fan and Gijbels (1994; 1996, pp. 151–152) discuss nearest-neighbor bandwidths in the regression context.

As a practical matter, for models $j \in \{1, \ldots, 8\}$ we optimize κ_j by minimizing a least-squares cross-validation function; i.e., we select

$$\kappa_j = \operatorname*{argmin}_{\kappa_j} \sum_{i=1}^{n} \left[\mathcal{Y}_{ji}^{+} - \widehat{m}_{j,-i}^{+}(\mathcal{X}_{ji}^{+}) \right]^2, \tag{D.10}$$

where $\widehat{m}_{j,-i}^{+}(\mathcal{X}_{ji}^{+})$ is computed the same way as $\widehat{m}_{j}^{+} j(\mathcal{X}_{ji}^{+})$, except that the ith observation is omitted. The least-squares cross validation function approximates the part of mean integrated square error that depends on the bandwidths.[1]

Once appropriate values of the bandwidth parameters have been selected, the conditional mean function can be estimated at any point $\mathcal{X}_0^{+} \in \mathbb{R}^{\ell}$. We then estimate the returns-to-scale measures defined in the text by replacing the cost terms with estimates obtained from the relation (D.8). To make inferences about returns to scale, we use the wild bootstrap proposed by Härdle (1990) and Härdle and Mammen (1993).[2] After B replications, we obtain a set bootstrap estimates $\left\{\widehat{m}_{j,b}^{*}(\cdot)\right\}_{b=1}^{B}$, which we substitute into the definitions of the returns-to-scale measures given in the text. Letting $\mathcal{S}$ denote the relevant returns-to-scale measure, we have the original estimate $\widehat{\mathcal{S}}$ and the bootstrap estimates $\left\{\widehat{\mathcal{S}}_b\right\}_{b=1}^{B}$. to obtain bootstrap values $\widehat{\mathcal{S}}_b^{*}$ and $\widehat{\mathcal{E}}_b^{*}$ for particular values of $\mathcal{X}^{+}$, with $b = 1, \ldots, B$.

To make inference about $\mathcal{S}$, we use the bias-correction method described by Efron and Tibshirani (1993). In particular, we estimate $(1-\alpha) \times 100$-percent confidence intervals by $\left(\widehat{\mathcal{S}}^{*(\alpha_1)}, \widehat{\mathcal{S}}^{*(\alpha_2)}\right)$, where $\widehat{\mathcal{S}}^{*(\alpha)}$ denotes the α-quantile of the bootstrap values $\widehat{\mathcal{S}}_b^{*}$, $b = 1, \ldots, B$, and

$$\alpha_1 = \Phi\left(\widehat{\varphi}_0 + \frac{\widehat{\varphi}_0 + \varphi^{(\alpha/2)}}{1 - \widehat{\varphi}_0 + \varphi^{(\alpha/2)}}\right), \tag{D.11}$$

$$\alpha_2 = \Phi\left(\widehat{\varphi}_0 + \frac{\widehat{\varphi}_0 + \varphi^{(1-\alpha/2)}}{1 - \widehat{\varphi}_0 + \varphi^{(1-\alpha/2)}}\right), \tag{D.12}$$

[1] Choice of κ by cross validation has been proposed by Fan and Gijbels (1996) and has been used by Wheelock and Wilson (2001, 2001, 2011, and 2012), Wilson and Carey (2004), and others. Time required to compute the cross validation function *once* is of order $O(n^2)$, and it must be computed many times in order to find optimal values of the bandwidths. With almost one million observations, this presents a formidable computational burden. However, the problem is trivially parallel; using n_p CPUs, the computation time required for each evaluation of the cross-validation function is only slightly more than $1/n_p$ times the time that would be required on a single processor. We performed all computations on the Palmetto cluster operated by Clemson University's Cyber Infrastructure Technology Integration (CITI) group.

[2] Ordinary bootstrap methods are inconsistent in our context due to the asymptotic bias of the estimator; see Mammen (1992) for additional discussion.

$\Phi(\cdot)$ denotes the standard normal distribution function, $\varphi^{(\alpha)}$ is the $(\alpha \times 100)$-th percentile of the standard normal distribution, and

$$\widehat{\varphi}_0 = \Phi^{-1}\left(\frac{\#\{\widehat{\mathcal{S}}_b^* < \widehat{\mathcal{S}}\}}{B}\right), \tag{D.13}$$

with $\Phi^{-1}(\cdot)$ denoting the standard normal quantile function (e.g., $\Phi^{-1}(0.95) \approx 1.6449$).

E Additional Results

Tables E.1–E.24 show additional results not appearing in the paper. To facilitate comparison, Tables E.4 and E.14 are included here, even though the same tables appear as Tables 1 and 4 in the paper.

Tables E.1 gives percentiles and means for estimates of the returns to scale indices $\mathcal{E}_{C,i}$, $\mathcal{E}_{R,i}$ and $\mathcal{E}_{\pi,i}$ for quarters 1986.Q4, 1996.Q4, 2006.Q4 and 2015.Q4. Table E.2 gives counts of institutions facing IRS, CRS, or DRS in each of the four quarters examined. Results are given for .1, .05 and .01 significance; counts of institutions facing CRS include those for which CRS could not be rejected in favor of either IRS or DRS. Tables E.3–E.5 give counts at .1, .05 and .01 significance similar to those in Table E.2, but broken into quartiles of institutions' sizes as measured by their total assets.

Tables E.6–E.9 give estimates of the pseudo-elasticities given by $(1-\mathcal{E}_{C,i})\delta$, $(1+\mathcal{E}_{R,i})\delta$ and $(1+\mathcal{E}_{\pi,i})\delta$ for the 100 largest banks in each quarter 1986.Q4, 1996.Q4, 2006.Q4 and 2015.Q4 instead of only the 10 largest banks as in in Tables 2–3 of the paper.

Tables E.10–E.11 give the estimates of the RTS statistics $\mathcal{E}_{C,i}$, $\mathcal{E}_{R,i}$ and $\mathcal{E}_{\pi,i}$ or the 10 largest institutions in each of the four quarters examined. These estimates correspond to the estimates of the pseudo-elasticities given by $(1-\mathcal{E}_{C,i})\delta$, $(1+\mathcal{E}_{R,i})\delta$ and $(1+\mathcal{E}_{\pi,i})\delta$ displayed in Tables 2–3 of the paper.

Table E.12 gives, for significance levels .1, .05 and .01, counts of institutions appearing in both 2006.Q3 and 2015.Q4 and which have a statistically significant change in their estimated RTS. These counts are broken down by direction, i.e., whether institutions increased or decreased their RTS. Tables E.13–E.15 give similar information for the 10 largest institutions (in terms of total assets) for significance levels .1, .05 and .01.

Tables E.16–E.24 show transition matrices for each of the 8 models estimated and giving the numbers of institutions facing IRS, CRS, or DRS in 2006.Q4 versus 2015.Q4.

Table E.1: Quantiles and Means for Estimates of Returns to Scale Indices

Model	LHS	Period	0.01	0.25	0.50	Mean	0.75	0.99
1	C_1/W_1	1986.Q4	−0.0482	−0.0059	0.0060	0.0062	0.0180	0.0626
		1996.Q4	−0.0842	−0.0160	0.0054	0.0047	0.0262	0.0895
		2006.Q4	−0.0866	−0.0154	0.0059	0.0060	0.0273	0.0917
		2015.Q4	−0.1026	−0.0156	0.0117	0.0106	0.0388	0.1140
2	C_2/W_1	1986.Q4	−0.0505	−0.0069	0.0065	0.0066	0.0198	0.0667
		1996.Q4	−0.0945	−0.0193	0.0046	0.0036	0.0275	0.0973
		2006.Q4	−0.0960	−0.0172	0.0067	0.0059	0.0293	0.0966
		2015.Q4	−0.1089	−0.0155	0.0135	0.0120	0.0419	0.1181
3	R_1	1986.Q4	−0.1210	−0.0186	−0.0055	0.0050	0.0086	0.2587
		1996.Q4	−0.0930	−0.0152	−0.0036	0.0058	0.0080	0.0820
		2006.Q4	−0.1029	−0.0190	−0.0041	−0.0047	0.0097	0.0892
		2015.Q4	−0.0933	−0.0217	−0.0064	−0.0058	0.0088	0.0893
4	R_2	1986.Q4	−0.1023	−0.0182	−0.0049	0.0018	0.0082	0.1343
		1996.Q4	−0.1003	−0.0171	−0.0032	−0.0028	0.0108	0.0867
		2006.Q4	−0.1073	−0.0212	−0.0043	−0.0021	0.0127	0.1011
		2015.Q4	−0.1016	−0.0225	−0.0053	−0.0028	0.0114	0.1201
5	π_1	1986.Q4	−0.7191	−0.0357	−0.0011	0.0771	0.0405	1.0819
		1996.Q4	−0.1329	−0.0193	0.0009	0.0163	0.0236	0.3351
		2006.Q4	−0.1731	−0.0228	0.0028	0.0306	0.0301	0.5844
		2015.Q4	−0.1144	−0.0244	−0.0039	−0.0011	0.0170	0.1303
6	π_2	1986.Q4	−0.7718	−0.0365	0.0034	0.0456	0.0562	1.8145
		1996.Q4	−0.1862	−0.0197	0.0047	0.0407	0.0314	0.7837
		2006.Q4	−0.2652	−0.0220	0.0072	0.0764	0.0431	1.1727
		2015.Q4	−0.1420	−0.0212	0.0048	0.0158	0.0309	0.5001
7	π_3	1986.Q4	−0.1529	−0.0256	−0.0017	−0.0245	0.0246	0.3762
		1996.Q4	−0.1117	−0.0198	0.0019	0.0134	0.0254	0.2419
		2006.Q4	−0.1326	−0.0217	0.0044	0.0205	0.0324	0.3601
		2015.Q4	−0.1219	−0.0244	−0.0030	0.0002	0.0204	0.1666
8	π_4	1986.Q4	−0.2791	−0.0229	0.0026	0.0539	0.0346	1.0055
		1996.Q4	−0.1232	−0.0141	0.0059	0.0547	0.0278	0.6802
		2006.Q4	−0.1442	−0.0144	0.0089	0.0800	0.0366	0.9155
		2015.Q4	−0.1240	−0.0178	0.0056	0.0341	0.0313	0.4635

Table E.2: Counts of Institutions Facing IRS, CRS, and DRS

			.1 signif.			.05 signif.			.01 signif.		
Model	LHS	Period	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS
1	C_1/W_1	1986.Q4	4774	5477	74	3830	6445	50	2278	8019	28
		1996.Q4	3076	4313	202	2465	4987	139	1453	6053	85
		2006.Q4	2697	3432	153	2209	3952	121	1406	4794	82
		2015.Q4	2371	2275	192	2088	2590	160	1542	3183	113
2	C_2/W_1	1986.Q4	4680	5567	78	3733	6539	53	2136	8157	32
		1996.Q4	2929	4455	207	2302	5136	153	1307	6195	89
		2006.Q4	2657	3465	160	2184	3983	115	1377	4821	84
		2015.Q4	2442	2215	181	2136	2558	144	1576	3170	92
3	R_1	1986.Q4	2065	7462	798	1419	8240	666	672	9113	540
		1996.Q4	1725	5408	458	1197	6028	366	560	6757	274
		2006.Q4	1474	4231	577	1030	4781	471	517	5401	364
		2015.Q4	1195	2635	1008	957	2968	913	577	3475	786
4	R_2	1986.Q4	2120	7380	825	1466	8177	682	720	9057	548
		1996.Q4	1811	5389	391	1300	5975	316	607	6745	239
		2006.Q4	1584	4213	485	1164	4707	411	551	5404	327
		2015.Q4	1286	2688	864	1038	3026	774	653	3507	678
5	π_1	1986.Q4	2852	7198	275	1933	8160	232	817	9319	189
		1996.Q4	2354	4990	247	1727	5663	201	780	6649	162
		2006.Q4	2102	3941	239	1609	4476	197	814	5318	150
		2015.Q4	1396	2785	657	1103	3147	588	643	3703	492
6	π_2	1986.Q4	3371	6643	311	2504	7557	264	1248	8861	216
		1996.Q4	2838	4385	368	2177	5102	312	1220	6120	251
		2006.Q4	2552	3446	284	2061	3982	239	1293	4785	204
		2015.Q4	1956	2326	556	1615	2721	502	1039	3359	440
7	π_3	1986.Q4	2789	7119	417	1980	7989	356	930	9121	274
		1996.Q4	2473	4895	223	1823	5584	184	872	6568	151
		2006.Q4	2257	3790	235	1736	4346	200	878	5246	158
		2015.Q4	1524	2738	576	1230	3096	512	759	3628	451
8	π_4	1986.Q4	3452	6390	483	2609	7302	414	1429	8552	344
		1996.Q4	3076	4170	345	2422	4873	296	1402	5938	251
		2006.Q4	2834	3149	299	2352	3665	265	1498	4561	223
		2015.Q4	2110	2188	540	1803	2554	481	1216	3192	430

Table E.3: Counts of Institutions Facing IRS, CRS, and DRS by Size Quartile (.1 signif.)

			1st quartile			2nd quartile			3rd quartile			4th quartile		
Model	LHS	Period	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS
1	C_1/W_1	1986.Q4	1376	1196	10	988	1579	14	1028	1534	19	1382	1168	31
		1996.Q4	817	1054	27	695	1175	28	670	1174	53	894	910	94
		2006.Q4	759	797	15	672	876	22	573	971	26	693	788	90
		2015.Q4	616	569	25	563	607	39	537	623	49	655	476	79
2	C_2/W_1	1986.Q4	1432	1144	6	1005	1563	13	1004	1558	19	1239	1302	40
		1996.Q4	824	1048	26	689	1173	36	634	1218	45	782	1016	100
		2006.Q4	767	787	17	658	890	22	560	979	31	672	809	90
		2015.Q4	622	558	30	595	580	34	571	597	41	654	480	76
3	R_1	1986.Q4	423	1969	190	517	1970	94	582	1910	89	543	1613	425
		1996.Q4	334	1433	131	443	1403	52	460	1382	55	488	1190	220
		2006.Q4	290	1105	176	359	1115	96	389	1120	61	436	891	244
		2015.Q4	262	736	212	295	702	212	366	698	145	272	499	439
4	R_2	1986.Q4	456	1914	212	524	1942	115	563	1908	110	577	1616	388
		1996.Q4	379	1412	107	457	1387	54	465	1383	49	510	1207	181
		2006.Q4	309	1112	150	401	1103	66	435	1079	56	439	919	213
		2015.Q4	297	742	171	319	726	164	374	697	138	296	523	391
5	π_1	1986.Q4	884	1662	36	706	1854	21	702	1853	26	560	1829	192
		1996.Q4	787	1078	33	611	1275	12	540	1335	22	416	1302	180
		2006.Q4	658	890	23	569	981	20	464	1082	24	411	988	172
		2015.Q4	402	736	72	365	743	101	371	755	83	258	551	401
6	π_2	1986.Q4	1286	1274	22	989	1578	14	686	1870	25	410	1921	250
		1996.Q4	1093	779	26	839	1049	10	582	1290	25	324	1267	307
		2006.Q4	944	614	13	754	812	4	540	1008	22	314	1012	245
		2015.Q4	715	469	26	574	593	42	478	668	63	189	596	425
7	π_3	1986.Q4	822	1706	54	682	1863	36	657	1869	55	628	1681	272
		1996.Q4	757	1110	31	647	1236	15	565	1312	20	504	1237	157
		2006.Q4	642	905	24	608	940	22	549	996	25	458	949	164
		2015.Q4	436	708	66	388	733	88	405	724	80	295	573	342
8	π_4	1986.Q4	1264	1286	32	964	1593	24	704	1829	48	520	1682	379
		1996.Q4	1117	749	32	874	1010	14	674	1196	27	411	1215	272
		2006.Q4	960	593	18	866	695	9	626	927	17	382	934	255
		2015.Q4	739	449	22	618	551	40	532	616	61	221	572	417

Table E.4: Counts of Institutions Facing IRS, CRS, and DRS by Size Quartile (.05 signif.)

			1st quartile			2nd quartile			3rd quartile			4th quartile		
Model	LHS	Period	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS
1	C_1/W_1	1986.Q4	1138	1439	5	734	1837	10	808	1761	12	1150	1408	23
		1996.Q4	669	1211	18	524	1356	18	513	1353	31	759	1067	72
		2006.Q4	630	932	9	526	1030	14	446	1106	18	607	884	80
		2015.Q4	528	662	20	481	696	32	469	704	36	610	528	72
2	C_2/W_1	1986.Q4	1189	1390	3	757	1816	8	764	1805	12	1023	1528	30
		1996.Q4	644	1233	21	529	1350	19	475	1390	32	654	1163	81
		2006.Q4	637	925	9	533	1020	17	450	1105	15	564	933	74
		2015.Q4	544	645	21	509	677	23	487	691	31	596	545	69
3	R_1	1986.Q4	287	2142	153	333	2170	78	398	2121	62	401	1807	373
		1996.Q4	245	1549	104	291	1572	35	299	1560	38	362	1347	189
		2006.Q4	201	1226	144	249	1253	68	263	1265	42	317	1037	217
		2015.Q4	204	822	184	229	796	184	289	795	125	235	555	420
4	R_2	1986.Q4	318	2095	169	344	2149	88	364	2136	81	440	1797	344
		1996.Q4	270	1546	82	320	1548	30	319	1543	35	391	1338	169
		2006.Q4	227	1220	124	292	1224	54	307	1218	45	338	1045	188
		2015.Q4	235	830	145	260	810	139	299	790	120	244	596	370
5	π_1	1986.Q4	637	1914	31	463	2103	15	444	2119	18	389	2024	168
		1996.Q4	620	1252	26	444	1443	11	358	1527	12	305	1441	152
		2006.Q4	528	1024	19	416	1142	12	352	1199	19	313	1111	147
		2015.Q4	327	827	56	269	855	85	301	839	69	206	626	378
6	π_2	1986.Q4	1032	1530	20	720	1848	13	469	2093	19	283	2086	212
		1996.Q4	919	958	21	635	1255	8	387	1495	15	236	1394	268
		2006.Q4	815	745	11	620	947	3	408	1150	12	218	1140	213
		2015.Q4	609	582	19	476	701	32	379	779	51	151	659	400
7	π_3	1986.Q4	591	1947	44	474	2074	33	444	2095	42	471	1873	237
		1996.Q4	583	1285	30	469	1418	11	396	1492	9	375	1389	134
		2006.Q4	496	1053	22	473	1083	14	397	1156	17	370	1054	147
		2015.Q4	356	803	51	302	837	70	328	817	64	244	639	327
8	π_4	1986.Q4	1020	1534	28	712	1849	20	490	2060	31	387	1859	335
		1996.Q4	956	916	26	674	1216	8	486	1393	18	306	1348	244
		2006.Q4	836	719	16	728	838	4	490	1065	15	298	1043	230
		2015.Q4	655	537	18	536	640	33	443	724	42	169	653	388

Table E.5: Counts of Institutions Facing IRS, CRS, and DRS by Size Quartile (.01 signif.)

			1st quartile			2nd quartile			3rd quartile			4th quartile		
Model	LHS	Period	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS	IRS	CRS	DRS
1	C_1/W_1	1986.Q4	712	1868	2	375	2202	4	411	2164	6	780	1785	16
		1996.Q4	381	1508	9	273	1619	6	282	1599	16	517	1327	54
		2006.Q4	411	1154	6	326	1238	6	243	1319	8	426	1083	62
		2015.Q4	372	827	11	340	848	21	333	852	24	497	656	57
2	C_2/W_1	1986.Q4	754	1825	3	349	2230	2	363	2214	4	670	1888	23
		1996.Q4	364	1523	11	258	1632	8	260	1616	21	425	1424	49
		2006.Q4	424	1143	4	328	1234	8	249	1313	8	376	1131	64
		2015.Q4	387	811	12	366	829	14	342	852	15	481	678	51
3	R_1	1986.Q4	148	2314	120	145	2378	58	169	2372	40	210	2049	322
		1996.Q4	106	1721	71	129	1747	22	125	1752	20	200	1537	161
		2006.Q4	98	1367	106	112	1413	45	127	1416	27	180	1205	186
		2015.Q4	128	937	145	109	954	146	174	939	96	166	645	399
4	R_2	1986.Q4	169	2288	125	149	2368	64	173	2351	57	229	2050	302
		1996.Q4	117	1718	63	135	1746	17	143	1732	22	212	1549	137
		2006.Q4	102	1374	95	123	1409	38	140	1398	32	186	1223	162
		2015.Q4	151	938	121	140	950	119	181	936	92	181	683	346
5	π_1	1986.Q4	297	2264	21	187	2380	14	153	2417	11	180	2258	143
		1996.Q4	303	1573	22	198	1690	10	144	1746	7	135	1640	123
		2006.Q4	309	1246	16	196	1370	4	163	1395	12	146	1307	118
		2015.Q4	213	964	33	133	1021	55	163	993	53	134	725	351
6	π_2	1986.Q4	623	1945	14	324	2247	10	180	2394	7	121	2275	185
		1996.Q4	617	1264	17	343	1550	5	158	1733	6	102	1573	223
		2006.Q4	570	993	8	378	1189	3	245	1315	10	100	1288	183
		2015.Q4	429	766	15	296	888	25	224	952	33	90	753	367
7	π_3	1986.Q4	291	2259	32	196	2364	21	201	2356	24	242	2142	197
		1996.Q4	312	1561	25	191	1698	9	172	1719	6	197	1590	111
		2006.Q4	272	1282	17	231	1330	9	175	1383	12	200	1251	120
		2015.Q4	244	928	38	165	994	50	193	961	55	157	745	308
8	π_4	1986.Q4	623	1936	23	367	2197	17	236	2331	14	203	2088	290
		1996.Q4	648	1228	22	394	1497	7	209	1681	7	151	1532	215
		2006.Q4	614	948	9	461	1107	2	284	1276	10	139	1230	202
		2015.Q4	477	720	13	361	820	28	276	899	34	102	753	355

Table E.6: Returns to Scale for 100 Largest Banks by Total Assets, 1986.Q4

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
CITIBANK	275	1.0371***	1.0405***	1.0147***	1.0253***	0.9834***	0.9760***	1.0205***	0.9982***
BK OF AMER	204	1.0928**	1.0956	1.0558***	1.0481***	1.1622	1.2975(3)	1.0466***	1.0319***
CHASE MHTN BK	150	1.0618***	1.0595***	1.0820	1.0892	1.0616	1.0513	1.1124	1.0779***
MANU. HAN	139	1.0855***	1.0870**	1.0686***	1.0570***	1.1819	1.1124	1.0611***	1.0459***
MORGAN GNTY TC	130	1.0306***	1.0269***	1.0381***	1.0598***	1.0603	1.0498	1.0904	1.0347***
SECURITY PACIFIC	113	1.0982	1.1006	1.0593***	1.0542***	1.0774	1.0697	1.0376***	1.0315***
CHEMICAL NY	109	1.0923***	1.0927**	1.0574***	1.0613***	1.0995	1.1203	1.0577***	1.0587***
BANKERS TR NY	100	1.0461***	1.0422***	1.0354***	1.0409***	1.0542***	1.0433	1.0609***	1.0436***
FIRST INTRST BC	100	1.0883*	1.0904	1.0705***	1.0675***	1.0586	0.9843	1.0484***	1.0084***
WELLS FARGO & CO	81	1.0897	1.0920	1.0488***	1.0463***	1.0622	1.0662	1.0405***	1.0417***
FIRST	74	1.0796***	1.0809***	1.0415***	1.0392***	1.0946	1.0494	1.0825***	1.0619***
BK OF BOSTON	62	1.0662***	1.0716***	1.0799***	1.0870***	1.1007	0.9894	1.1076	1.0370***
CONTINENTAL IL NB&TC C	56	1.0571***	1.0505***	1.0637	1.0755	1.2408	1.0085	1.2889***	1.0601***
FIRST BK SYS	51	1.0815***	1.0892**	1.0862***	1.0963***	1.1041	1.0630	1.1129	1.0593***
NCNB	49	1.1071	1.1153	1.0742***	1.0748***	1.0461***	1.0072***	1.0422***	1.0334***
MELLON BK	46	1.0816***	1.0847***	1.0475***	1.0715***	1.0663	0.9056	1.0985	1.0517***
FIRST UNION	45	1.0827	1.0924	1.0372***	1.0409***	1.0872	1.0282*	1.1041	1.0622***
PNC FNCL	45	1.0948	1.1085	1.0401***	1.0472***	1.0750	1.0318***	1.0950***	1.0529***
IRVING BK	44	1.0803***	1.0806***	1.0604***	1.0731***	1.1016	0.9862***	1.1295	1.0295***
SUNTRUST BANKS	43	1.0743***	1.0676***	1.0309***	1.0333***	1.0701	1.0484	1.0821***	1.0644***
MCORP	41	1.0528***	1.0730**	1.0037***	1.0507***	0.7969(3)	1.0856(3)	1.0764	1.0227***
MARINE MIDLAND BANK	41	1.0776***	1.0731***	1.0908***	1.0834***	1.1785*	1.2700	1.0843***	1.0449***
REPUBLICBANK ORATION	40	1.0587***	1.0521***	1.0979	1.0943	1.2439	−1.4827(2)	1.0936	1.0142***
BK OF NEW ENGLAND	40	1.1036	1.1157	1.0779***	1.0856***	1.0540***	1.0217***	1.0707***	1.0447***
NBD BANCORP INC	39	1.1078	1.1115	1.0698***	1.0832***	1.0736***	1.0307***	1.1072	1.0675***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.6: Returns to Scale for 100 Largest Banks by Total Assets, 1986.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
NORWEST	38	1.0749***	1.0690***	1.0698***	1.0766***	1.1433	0.9912	1.1069	1.0477***
BK OF NY CO	37	1.0645***	1.0699***	1.0690***	1.0745***	1.0751	1.0300	1.0962	1.0402***
TEXAS CMRC BSHRS	36	1.0747***	1.0819***	1.0405***	1.0696***	0.8976	1.0006$^{(3)}$	1.0976	0.9913***
CITIZENS & SOUTHERN	34	1.0849***	1.0875***	1.0587***	1.0639***	1.0486***	1.0024***	1.0763*	1.0384***
BARNETT BK OF FL	34	1.1076	1.1138	0.9950***	0.9931***	0.9930***	0.9904***	0.9955***	0.9929***
INTERFIRST ORATION	34	1.0770***	1.0793***	1.0427***	1.0708***	1.1122$^{(3)}$	1.1306$^{**(3)}$	1.1232	1.0354***
FIRST WACHOVIA	34	1.0929***	1.0892***	1.0517***	1.0560***	1.0262***	0.9892***	1.0162***	1.0084***
REPUBLIC NB OF NY	31	1.0339***	1.0343***	1.0242***	1.0478***	1.0062***	0.9667***	1.0710***	0.9689***
FIRST FIDELITY BC	27	1.1232	1.1284	1.0663***	1.0623***	1.0387***	0.9965***	1.0357***	1.0112***
SOVRAN	27	1.0748***	1.0731***	1.0679***	1.0778***	1.0252***	1.0317***	1.0326**	1.0633***
BANC ONE	27	1.0919**	1.0868***	1.0417***	1.0507***	1.0789	0.9947	1.0912	1.0265***
MIDLANTIC BK	27	1.0949	1.0852***	1.0537***	1.0622***	1.0799***	1.0633	1.0860***	1.0486***
FIRST CITY BANCORPORATION OF T	26	1.0856***	1.0929*	1.0689***	1.0801***	1.2113$^{**(3)}$	1.1510$^{***(3)}$	1.0833***	1.0042***
NATIONAL CITY	25	1.0643***	1.0640***	1.0723***	1.0799***	1.0581***	0.9925***	1.0604***	1.0244***
CORESTATES FNCL	25	1.0876**	1.0875**	1.0444***	1.0487***	1.0761	1.0690	1.0817***	1.0591***
HARTFORD T	23	1.1024	1.1081	0.9883***	0.9968***	0.9855***	0.9859***	0.9824***	0.9932***
BOATMENS BSHRS	23	1.0888**	1.0857***	1.0450***	1.0464***	1.0617***	1.0567	1.0623***	1.0447***
SOUTHEAST BKG	22	1.1248	1.1283	1.0602***	1.0770***	1.0618***	0.9751***	1.0955	1.0190***
FLEET FNCL GROUP	21	1.0865***	1.0913**	1.1303***	1.1107***	1.1098	1.0303	1.0816	1.0473***
NATIONAL WESTMINSTER BANK USA	20	1.0296***	1.0321***	1.0268***	1.0564***	0.9417***	0.8855***	0.9859***	0.9714***
VALLEY T	20	1.0593***	1.0559***	1.0886	1.1051	1.0491	0.7828	1.0801	1.0355***
FIDELCOR	19	1.0455***	1.0466***	1.0195***	1.0179***	1.0079***	1.0199***	0.9941***	1.0057***
AMERITRUST	19	1.0732***	1.0764***	1.0914	1.1084	1.1137	1.0848	1.1539***	1.0756
SHAWMUT	19	1.0909**	1.0911*	1.0632***	1.0440***	1.0988	1.0603	1.0877	1.0833
ALLIED BANCSHARES	18	1.0767***	1.0679***	1.0791	1.0957	0.6345	1.0846$^{(3)}$	1.0877	0.9945***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.6: Returns to Scale for 100 Largest Banks by Total Assets, 1986.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
COMERICA INC	18	1.1068	1.1031	1.0791**	1.0926	1.0817	1.0242*	1.1204***	1.0575*
CITIBANK SOUTH DAKOTA	18	1.0483***	1.0616***	0.9883***	0.9934***	0.9216***	0.7459	0.9728***	0.9396***
SIGNET BKG	17	1.0617***	1.0561***	1.0714***	1.0693**	1.0713	1.0268	1.0962	1.0613
UNION BK	17	1.0836***	1.0961**	1.0666**	1.0855	1.0227	0.9265**	1.0967	1.0296***
U S BC	17	1.0971*	1.0944**	1.0978	1.1129***	1.0392	1.0934	1.0451***	1.0954
MARYLAND T	17	1.0848	1.0913	1.0940***	1.0925	1.1256	1.0916	1.1227**	1.0970
SOCIETY	17	1.1082	1.1086	1.0754***	1.0800	1.0937	0.9958***	1.1167**	1.0236***
UNITED VA BSHRS	17	1.0766***	1.0727***	1.0801***	1.0771***	1.0461***	0.9581***	1.0441***	0.9883***
NORTHERN TR	16	1.0464***	1.0424***	1.0452***	1.0526***	1.0593***	1.0461***	1.0799	1.0600
KEYCORP	16	1.1305	1.1304	1.0640***	1.0685***	1.0840	1.0206***	1.0724***	1.0072***
HARRIS T&SB	15	1.0396***	1.0596***	1.0319***	1.0401***	1.0281***	1.0007***	1.0407***	1.0225***
RAINIER NB	15	1.0796***	1.0854***	1.1013	1.1062	1.1474*	1.1653	1.1295***	1.1049
MICHIGAN T	15	1.0730***	1.0930*	1.1082	1.1015	1.1296*	1.0590	1.1408***	1.0646***
MANUFACTURERS TIONAL .	14	1.0356***	1.0405***	1.0674***	1.0757***	1.0707	1.0685	1.0863	1.0840
BAYBANKS	14	1.1452	1.1440**	1.0588***	1.0577***	1.0948	1.0295***	1.0974	1.0142***
HUNTINGTON BSHRS	14	1.0789***	1.0917*	1.0734***	1.0803	1.0682	1.0530	1.0783	1.0643***
UNITED JERSEY BANKS	13	1.0697***	1.0841***	1.0686***	1.0729**	1.1179	1.1069	1.1110	1.0803***
FLORIDA NB OF FL	13	1.0585***	1.0673***	1.0419***	1.0462***	1.0013***	0.3775***	1.0200***	0.9844***
EUROPEAN AMER BC	13	1.1112	1.1222	1.0487***	1.0397***	0.7176*	0.4463(3)	0.8906***	0.9517***
STATE STREET BOSTON	12	1.0399***	1.0449***	1.0602***	1.0631***	1.0539***	1.0382***	1.0407***	1.0445***
MERIDIAN BC	12	1.0936**	1.0993	1.0006***	1.0119***	1.0144***	0.9963***	1.0210***	0.9996***
MERCANTILE BANCORPORATION	12	1.0757***	1.0753***	1.0909	1.0768***	1.0513	0.9414	1.0399***	1.0354***
TEXAS AMERICAN BANCSHARES INC.	11	1.0974	1.1450	1.0612***	1.0703***	0.7144	1.0556(3)	1.0301***	0.4288(3)
RIGGS T	11	1.0830***	1.0789***	1.0438***	1.0653***	1.0490***	1.0229***	1.0809	1.0323***
BK OF TOKYO TC	11	1.0468***	1.0455***	1.0919	1.0352***	1.2171***	1.0423***	1.1024	1.0539***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.6: Returns to Scale for 100 Largest Banks by Total Assets, 1986.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
CALIFORNIA FIRST BK	11	1.1202	1.1141	1.0490***	1.0784***	0.9597*	−6.7887*(3)	1.0795	1.0463***
FIRST PENNSYLVANIA ORATION	11	1.0597***	1.0662***	1.0476***	1.0663***	1.0203***	1.0146	1.0462***	1.0379***
AMSOUTH BC	11	1.0859***	1.1002	1.0416***	1.0256***	1.0316***	1.0298***	1.0844***	1.0165***
DOMINION BSHRS	11	1.1229	1.1320	1.0849	1.0860	1.0537**	1.0646	1.0753***	1.0719
FIRST AMER	11	1.1165	1.1067	0.9547***	0.9566***	0.7152***	0.6274***	0.7540***	0.7951***
FIRST TENNESSEE T	10	1.0705***	1.0696***	1.0599***	1.0489***	1.0343	1.0820	1.0469*	1.0975
MARSHALL & ILSLEY	10	1.0454***	1.0342***	1.0505***	1.0647	1.0680	1.0599	1.0892	1.0679
OLD KENT	10	1.0589***	1.0651***	1.0484***	1.0515***	1.0481***	1.0367***	1.0580***	1.0296***
CENTERRE BANCORPORATION	10	1.0596***	1.0519***	1.0872	1.0944	1.0836	0.8734	1.1269	1.0068***
CITIBANK NY ST	10	1.0951	1.1031	1.0676***	1.0774***	1.0316***	0.6968	1.0846	1.0232***
CONTINENTAL BC	10	1.0472***	1.0222***	1.0800	1.0660***	1.2140**	17.3225	1.0814	1.1284
MELLON BK EAST	10	1.1097	1.1146	1.0315***	1.0430***	1.0513***	1.0139	1.0113***	1.0182***
COMMERCE BSHRS	10	1.1100	1.1122	1.0643***	1.0658***	0.9994***	0.8238***	1.0363***	0.9707***
BANCORP HI	9	1.0885**	1.0875***	1.1024	1.1084**	1.0684***	1.0636	1.0811***	1.0545***
FIRST SCTY	9	1.0883**	1.0961	1.0812	1.0891	0.7777**	0.9886(3)	1.0653	0.9081***
CHASE MHTN BK USA	9	1.1003	1.1202***	1.0237***	1.0199***	1.0016***	0.9696***	1.0146***	0.9975***
INB FNCL	9	1.0782***	1.0818**	1.0825***	1.0865	1.0688	1.0697	1.0663***	1.0524***
SOUTHTRUST	9	1.1294	1.1306**	1.0612***	1.0670***	1.0343***	0.9937***	1.0396***	1.0104***
FIRST KENTUCKY T	9	1.0466***	1.0505***	1.0653***	1.0563***	1.0867	1.0813	1.0438***	1.0597
SANWA BK CALIFORNIA	9	1.1011	1.1004	1.0781***	1.0882***	1.0444	0.1225(3)	1.1099	1.0470***
UNITED BK OF CO	9	1.0630***	1.0615***	1.0591***	1.0798	0.9726**	0.6716*(3)	1.0271***	1.0244***
LOUISIANA BSHRS	9	1.0958***	1.0954**	1.0315***	1.0239***	1.0839	1.1230(3)	1.0375***	1.0258
FIRST NB OF MD	9	1.0522***	1.0452***	1.0581***	1.0550***	1.0327***	1.0232***	1.0379***	1.0376***
FIRST FLORIDA BK	9	1.1070	1.1080	1.0603***	1.0652***	1.0377***	1.0218***	1.0548***	1.0234***
SOUTH CAROLINA T	9	1.0722***	1.0613***	1.0748**	1.0865	1.0418	1.1222	1.0395***	1.0766
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.7: Returns to Scale for 100 Largest Banks by Total Assets, 1996.Q4

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
CHASE MHTN	469	1.0557***	1.0480***	1.0334***	1.0328***	1.0401***	1.0521***	1.0308***	1.0448***
CITICORP	394	1.0368***	1.0364***	1.0376***	1.0309***	1.0426***	1.0698***	1.0293***	1.0496***
BK OF AMER	352	1.0412***	1.0435***	1.0469***	1.0446***	1.0485***	1.0641***	1.0379***	1.0533***
NATIONSBANK	266	1.0773***	1.0621***	1.0442***	1.0589***	1.0395***	1.0446***	1.0616***	1.0460***
MORGAN GNTY TC	245	1.0539***	1.0475***	1.0126***	1.0144***	0.9942***	0.9881***	1.0025***	0.9975***
FIRST UNION	195	1.0907**	1.0930**	1.0201***	1.0209***	0.9906***	0.9925***	0.9875***	0.9982***
WELLS FARGO & CO	155	1.0630***	1.0523***	1.0839***	1.0821***	1.1083	1.0766***	1.0910	1.0549***
FIRST NBD	150	1.0663***	1.0627***	1.0392***	1.0423***	1.0440***	1.0150***	1.0431***	1.0138***
BANC ONE	143	1.0653***	1.0725***	1.0594***	1.0593***	1.0600***	1.0476***	1.0377***	1.0454***
FLEET FNCL GROUP	123	1.0587***	1.0589**	1.0817***	1.0917***	1.0781***	1.0720***	1.0836	1.0657***
NORWEST	113	1.0324***	1.0235***	1.0782***	1.0868***	1.0637***	1.0637***	1.0838***	1.0698***
PNC BC	102	1.0965	1.1134	1.0939***	1.1092	1.0830	1.0913***	1.1039	1.1016
KEYCORP	95	1.0792***	1.0929*	1.0896***	1.0965	1.0830***	1.0623***	1.0985	1.0708***
BK OF BOSTON	88	1.0736***	1.0872***	1.0817***	1.0942	1.1079	1.0929	1.0925	1.1013***
BK OF NY CO	77	1.0763***	1.0935**	1.0378***	1.0742***	1.0461***	1.0176***	1.0993	1.0169***
SUNTRUST BK	73	1.0717***	1.0816***	1.1247***	1.1264***	1.1271**	1.0957	1.1428***	1.1054
NATIONAL CITY	72	1.0866**	1.0827**	1.1089*	1.1247***	1.0825***	1.0429***	1.1209	1.0575***
WACHOVIA	67	1.0700***	1.0713***	1.1018	1.0922	1.1066	1.0295***	1.1008	1.0531***
REPUBLIC NB OF NY	66	1.0206***	1.0236***	1.0505***	1.0440***	1.0391***	1.0347***	1.0324***	1.0355***
CORESTATES FNCL	65	1.0630***	1.0630***	1.1132***	1.1124***	1.0988	1.0579***	1.1007	1.0725***
MELLON BC	61	1.1136	1.1066	1.1049	1.1134***	1.0801***	1.0496***	1.0916	1.0657***
BARNETT BK	59	1.1191	1.1246	1.0804***	1.0802**	1.1014	1.0185***	1.0993	1.0333***
BOATMENS BSHRS	58	1.0419***	1.0410***	1.0814***	1.0835	1.0974	1.0197***	1.0991	1.0427***
FIRST BK SYSTEM	52	1.0942	1.1156	1.0775***	1.0857	1.0813	1.0447***	1.0890	1.0639***
COMERICA	49	1.0441***	1.0436***	1.0612***	1.0658***	1.0648*	1.0325***	1.0711	1.0500***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.7: Returns to Scale for 100 Largest Banks by Total Assets, 1996.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
U S BC	48	1.0608***	1.1188	1.0698***	1.0743***	1.0695	1.0331***	1.0720*	1.0496***
STATE STREET BOSTON	43	1.0901**	1.0969	1.0131***	1.0225***	1.0214***	1.0239***	1.0297***	1.0258***
UNION BK OF CA	41	1.1224	1.1501	1.0647***	1.0638***	1.0345***	1.0157***	1.0401***	1.0363***
SOUTHTRUST	36	1.1074	1.1343	1.0445***	1.0582***	1.0731	0.9546***	1.1141	0.9742***
MARINE MIDLAND BK	32	1.1156	1.1351*	1.0658***	1.0729	1.0891	1.0302***	1.0937	1.0503***
FIRST OF AMER BK	31	1.0675***	1.1199	1.0788***	1.0683***	1.1018	0.9796***	1.0503***	0.9962***
NORTHERN TR	31	1.0883**	1.0691***	1.0528***	1.1001***	1.0801***	1.0390***	1.1459**	1.0408***
SOUTHERN T	30	1.0883*	1.0790*	1.0513***	1.0370***	1.0513***	1.0299***	1.0510**	1.0341***
HUNTINGTON BSHRS	29	1.0556***	1.0624***	1.0741***	1.0785***	1.0374***	0.9915***	1.0446***	1.0070***
FIFTH THIRD BC	29	1.0380***	1.1143	1.0699***	1.0811	1.0579**	0.9947***	1.0473***	1.0070***
FIRSTAR	28	1.0672***	1.1079	1.0640***	1.0740***	1.0858	1.0405***	1.0878	1.0488***
SUMMIT BK	28	1.0782***	1.0970	1.0864***	1.0887	1.0820***	1.0679***	1.0907	1.0770***
REGIONS	27	1.0476***	1.0535***	1.0721***	1.0721***	1.0361***	0.9940***	1.0407***	1.0070***
MERCANTILE BANCORPORATION	27	1.0719***	1.0566***	1.0653***	1.0502***	1.0752	1.0037***	1.0544***	1.0133***
CRESTAR	26	1.0596***	1.0650***	1.0767***	1.0878***	1.0391***	0.9762***	1.0476***	1.0005***
AMSOUTH BC	26	1.0771***	1.1050	1.0591***	1.0810***	1.0735	1.0627***	1.0842	1.0643***
BANPONCE	24	1.0725***	1.0507***	1.0834***	1.0870***	1.0372***	0.9807***	1.0524***	1.0033***
MBNA	23	1.1125*	1.1174***	0.9745***	0.9744***	0.9454***	0.9556***	0.9474***	0.9672***
HARRIS T&SB	21	1.0964	1.1181	1.0938	1.1222*	1.1361***	1.0410***	1.1861***	1.0556***
MARSHALL & ILSLEY	21	1.0819***	1.1059	1.0738***	1.0680***	1.0916	1.0542***	1.0904***	1.0592***
FIRST SCTY	20	1.0686***	1.0705***	1.0637***	1.0629***	1.0471***	1.0174***	1.0622***	1.0270***
BANCORP HI	20	1.0862**	1.0985	1.0033***	1.0137***	0.9928***	0.9931***	1.0120***	0.9875***
UNION PLANTERS	19	1.0634***	1.0861*	1.0762***	1.0790	1.1253	1.0670	1.0848	1.0924***
FIRST TENNESSEE T	18	1.1080	1.1283	1.0816***	1.0849***	1.0956***	1.0626***	1.0980	1.0652***
LASALLE NB	18	1.0639***	1.0905***	1.0695***	1.0826	1.0662	1.0234***	1.0702	1.0424***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.7: Returns to Scale for 100 Largest Banks by Total Assets, 1996.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
FIRST EMPIRE ST	18	1.0921*	1.0856**	1.0878***	1.0794**	1.1155*	1.0841***	1.1017	1.0716***
OLD KENT	18	1.1079	1.0876*	1.0702***	1.0757***	1.0873***	1.0611***	1.0973	1.0615***
COMPASS BSHRS	17	1.0749***	1.0785***	1.0601***	1.0640***	1.0619***	1.0454***	1.0603***	1.0531***
SIGNET BKG	17	1.0920**	1.1051	1.0945***	1.1131*	1.1270***	1.0624***	1.1321***	1.0641***
CENTRAL FIDELITY BK	15	1.0562***	1.0590***	1.0518***	1.0599***	1.1233*	1.0762***	1.1643***	1.0929
FIRST AMER	15	1.0699**	1.0780*	1.0884***	1.0901	1.1117*	1.0846***	1.1090*	1.0812***
STAR BC	14	1.0844**	1.0922*	1.0753***	1.0764***	1.1025	1.0400***	1.0998	1.0510***
COMMERCE BSHRS	14	1.0692***	1.0672***	1.0658***	1.0596***	1.0574***	1.0330***	1.0622***	1.0421***
EUROPEAN AMER BK	13	1.0752***	1.1045	1.0381***	1.0458***	1.0450***	1.0310***	1.0488***	1.0458***
MICHIGAN NB	13	1.1290***	1.1345***	1.1288**	1.1644***	1.0979	1.0891	1.1250***	1.1051
FIRST CMRC	13	1.0562***	1.0561***	1.0661***	1.0695**	1.1214	1.0663***	1.1173*	1.0705***
FIRST NB OF MD	13	1.0172***	1.0303***	1.0516***	1.0419***	1.0462***	1.0508***	1.0361***	1.0630***
HIBERNIA	13	1.0763***	1.0799	1.0517***	1.0473***	1.0723*	1.0632***	1.0830	1.0758***
FIRST VA BK	12	1.0655***	1.0672***	1.0616***	1.0597***	1.0738***	1.0470***	1.0752***	1.0402***
FIRST HAWAIIAN	12	1.0324**	1.0843	0.9718***	0.9724***	0.9001***	0.9371***	0.9004***	0.9421***
FIRST CITIZENS BSHRS	11	1.1013	1.1142	1.0779***	1.0762***	1.0649**	1.0284***	1.0538***	1.0338***
SANWA BK CA	11	1.0871**	1.1072	1.0570***	1.1008	1.0736	1.0156***	1.1214*	1.0359***
PROVIDENT BC	10	1.0604***	1.0668***	1.0398***	1.0217***	1.0607***	1.0501***	1.0463***	1.0576***
FIRST T OF NE	9	1.0422***	1.0722***	1.0587***	1.0629***	1.0521***	0.9889***	1.0853	1.0486***
ZIONS BC	9	1.0888	1.0923	1.0804	1.0751	1.0539**	1.0284***	1.0546***	1.0402***
MERCANTILE BSHRS	9	1.1198	1.1355	1.1100*	1.1043	1.0781***	1.0128***	1.0669	1.0236***
DEPOSIT GUARANTY	9	1.1329	1.1329	1.0802***	1.0984	1.0601***	1.0410***	1.0849	1.0525***
UMB	9	1.0730***	1.0769***	1.1009	1.1127**	1.1092**	1.1024	1.1352***	1.1120
CENTURA BANKS	9	0.9353***	0.9620***	1.0683***	1.0921***	1.0709*	1.0432***	1.1055	1.0637***
DAUPHIN DEPOSIT	8	1.1190	1.1337*	1.0880	1.0958	1.1055*	1.0956	1.1122**	1.1150
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.7: Returns to Scale for 100 Largest Banks by Total Assets, 1996.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
WILMINGTON TR	8	1.0626***	1.0486***	1.0578***	1.0676***	1.1062	1.0344***	1.1037	1.0478***
MAGNA GROUP	8	1.0794***	1.1044	1.0956	1.0957	1.1013	1.0740**	1.1019	1.0861
FIRST COMMERCIAL	8	1.0964*	1.1197	1.0912	1.0940	1.0766	1.0382***	1.0668**	1.0430***
ONBANCORP	8	1.0492***	1.0699***	1.0705**	1.0611***	1.0870	1.0319***	1.0642**	1.0266***
FIRSTMERIT	8	1.1015	1.0942	1.0989	1.1131*	1.1081**	1.0949	1.1203***	1.1180
CCB	7	1.0628***	1.0933**	1.0749***	1.0799***	1.0505***	1.0237***	1.0592***	1.0298***
OLD T BC	7	1.0782***	1.0982*	1.0574***	1.0663**	1.0262***	1.0341***	1.0399***	1.0434***
KEYSTONE FNCL	7	1.1217	1.1351	1.0995	1.0896	1.1296***	1.0851	1.1518***	1.1139
TRUSTMARK	7	1.1264***	1.1407***	1.1340***	1.1143**	1.1414***	1.1054	1.1276***	1.1317**
INDUSTRIAL BK OF JAPAN TC	7	1.0935**	1.0851***	1.0131***	1.0161***	1.0100***	1.0064***	1.0178***	1.0126***
BK OF THE WEST	7	1.0837	1.0821	1.0634***	1.0688***	1.0373***	1.0284***	1.0404***	1.0340***
SUMITOMO BK OF CA	7	0.9845***	0.9875***	1.0722*	1.0504***	1.1051	1.0660***	1.0804	1.0685***
PEOPLES HERITAGE FNCL GROUP	7	1.0459***	1.0583***	1.0913	1.0820	1.0917	1.0606	1.0819	1.0767
RIGGS T	7	1.1231	1.1208***	1.0028***	1.0107***	0.9959***	0.9944***	1.0116***	1.0142***
NORTH FORK BC	7	1.0872***	1.0846***	0.9898***	0.9943***	0.9886***	0.9790***	0.9969***	0.9773***
COLONIAL BANCGROUP	7	1.1659	1.1826	1.0812	1.0858	1.1077*	1.1076	1.1096	1.1031
CULLEN/FROST BKR	7	1.0819**	1.1038	1.0905	1.0956	1.0836	1.0560***	1.0879	1.0661***
VALLEY NBC	7	1.1583***	1.1467***	1.0573***	1.0545***	1.0596**	1.0362***	1.0263***	1.0288***
BOK	6	1.0716**	1.0777*	1.0816***	1.0890	1.0871***	1.0181***	1.0949	1.0352***
UNITED CAROLINA BSHRS	6	1.1212***	1.1355***	1.1051	1.0998	1.1126	1.0706***	1.1106*	1.0794***
ASSOCIATED BANC-CORP	6	1.1046	1.1010	1.0786**	1.0750***	1.0584***	1.0378***	1.0460***	1.0499***
ONE VALLEY BC	6	1.0672***	1.0665***	1.0765***	1.0814***	1.0520***	1.0178***	1.0528***	1.0283***
CITIZENS BC	6	1.0303**	0.9903***	1.0220***	1.0360***	1.0130***	1.0262***	1.0318**	1.0324***
CITY T	6	1.0507***	1.0708***	1.0341***	1.0338***	1.0738	1.0425***	1.0559***	1.0381***
CNB BSHRS	6	1.1011	1.1152	1.0675***	1.0654***	1.1095	1.0405***	1.1167*	1.0503***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.8: Returns to Scale for 100 Largest Banks by Total Assets, 2006.Q4

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
CITIGROUP	2082	1.1011	1.0925*	1.0808***	1.0773***	1.1355***	1.1124	1.1105**	1.0648***
BK OF AMER	1672	1.0391***	1.0396***	1.0930***	1.1136	1.1519***	1.1721***	1.1498***	1.1089
JPMORGAN CHASE & CO	1543	1.1025	1.1001	1.0982	1.0958	1.2066***	1.1376	1.1774***	1.0789***
WACHOVIA	726	1.0459***	1.1073	1.0229***	1.0660*	1.0663	1.0825	1.1272	1.0402***
WELLS FARGO & CO	554	1.0193***	1.0256***	0.9996***	1.0377***	1.0134***	1.0480	1.0245***	1.0271***
U S BC	250	1.0585***	1.0554***	1.0493***	1.0566***	1.0656***	1.0701***	1.0707***	1.0656***
COUNTRYWIDE	225	1.1009	1.1131	1.0013***	1.0023***	0.9950***	0.9910***	1.0002***	0.9958***
SUNTRUST BK	210	1.0734***	1.0731***	1.0757***	1.0777***	1.0865	1.0560***	1.0902	1.0472***
HSBC BK USA	191	1.0456***	1.0436***	1.0096***	1.0161***	0.9928***	0.9851***	1.0234***	1.0027***
NATIONAL CITY	160	1.0697***	1.0657***	1.0178***	1.0273***	0.9778***	1.0039***	0.9907***	1.0138***
CAPITAL ONE	140	1.0599***	1.0491***	1.0958	1.0712***	1.1368**	1.0991	1.0892	1.0555***
BB&T	138	1.0653***	1.0628***	1.0384***	1.0406***	1.0414***	1.0242***	1.0668***	1.0294***
REGIONS	132	1.0712***	1.0608***	1.0212***	1.0026***	0.9968***	1.0274***	0.9693***	1.0243***
STATE STREET	126	1.1016	1.1009	1.0012***	1.0003***	0.9959***	0.9993***	0.9946***	0.9980***
BK OF NY CO	121	1.0536***	1.0496***	0.9897***	0.9956***	0.9861***	0.9735***	0.9979***	0.9926***
FIFTH THIRD BC	118	1.0883***	1.0862***	1.0400***	1.0522***	1.0266***	1.0240***	1.0490***	1.0250***
PNC FNCL SVC GROUP	115	1.0660***	1.0778***	1.0402***	1.0571***	1.0377***	1.0126***	1.0891	1.0178***
KEYCORP	108	1.0104***	1.0161***	1.0566***	1.0646***	1.0711***	1.0577***	1.0878***	1.0608***
LASALLE BK	83	1.0681***	1.0594***	1.0061***	1.0359***	1.0051***	1.0023***	1.0555***	1.0211***
COMERICA	68	1.0480***	1.0416***	1.0460***	1.0454***	1.0432***	1.0491***	1.0533***	1.0482***
NORTHERN TR	66	1.0372***	1.0323***	1.0207***	1.0024***	1.0271***	1.0377***	1.0005***	1.0453***
BK OF THE WEST	64	1.1092***	1.1023	1.0919***	1.1058	1.1235	1.0560***	1.1442***	1.0646***
MANUFACTURERS & TRADERS TC	64	1.0691***	1.0661***	1.0855***	1.0898*	1.0958	1.0900	1.1017	1.0962***
MARSHALL & ILSLEY	64	1.0586***	1.0513***	1.0483***	1.0683***	1.0543***	1.0425***	1.0965	1.0462***
UNION BK OF CA	59	0.9759***	0.9673***	1.0263***	1.0168***	1.0209***	1.0469***	1.0068***	1.0438***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.8: Returns to Scale for 100 Largest Banks by Total Assets, 2006.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
POPULAR	54	1.0894***	1.0875**	1.0795***	1.0876***	1.0801	1.0113***	1.0861	1.0321***
ZIONS BC	53	1.0919**	1.0921***	1.0545***	1.0503***	1.0653***	1.0628***	1.0682***	1.0614***
CHARTER ONE BK	53	1.1178	1.1083	1.1241***	1.1227***	1.1989***	1.1201	1.1751***	1.1376*
COMMERCE BC	51	1.0732***	1.0740***	1.0357***	1.0361***	1.0449***	1.0552***	1.0546***	1.0638***
HARRIS	47	1.1334***	1.1337***	1.0342***	1.0396***	1.0133***	1.0373***	0.9955***	1.0290***
TD BANKNORTH	46	1.1111***	1.1007	1.1715***	1.1966***	1.2452***	1.2089***	1.2963***	1.2148***
FIRST HORIZON T	45	1.0543***	1.0443***	1.0583***	1.0779	1.0618*	1.0631***	1.1190	1.0524***
HUNTINGTON BSHRS	41	1.1154**	1.1144	1.0424***	1.0473***	1.0332***	1.0475***	1.0310***	1.0532***
CITIZENS BK OF MA	41	1.0523***	1.0272***	1.1014	1.1726**	1.1086	1.0514***	1.1550	1.0582***
COMPASS BSHRS	39	1.1033	1.0938**	1.0316***	1.0256***	1.0421***	1.0378***	1.0485***	1.0449***
SYNOVUS	36	1.0882***	1.0865***	1.0951	1.1007	1.1051	1.0945	1.1165	1.0884
NEW YORK CMNTY BC	33	1.0449***	1.0463***	1.0355***	1.0201***	1.0402***	1.0574	1.0323***	1.0633
MELLON BK	31	1.1076	1.0839***	1.0441***	1.0444***	1.0730***	1.0746***	1.0739***	1.0749***
COLONIAL BANCGROUP	26	1.0923***	1.0968	1.0199***	1.0042***	1.0834	1.0457*	1.0693	1.0549***
RBC CENTURA BK	25	1.1032	1.1144**	1.0632***	1.0680***	1.1125	1.1441	1.1259	1.1120
ASSOCIATED BANC	24	1.0809***	1.0859**	1.0496***	1.0430***	1.0672*	1.0954	1.0796	1.1077
BOK	20	1.0456***	1.0532***	1.0631***	1.0405***	1.1000	1.0865	1.0765	1.0752***
MERCANTILE BSHRS	20	1.0557***	1.0356***	1.0980***	1.1373*	1.1237	1.0917	1.1513**	1.0944***
WEBSTER FNCL	20	1.0748***	1.0792***	1.0084***	0.9925***	1.0517**	1.0339***	1.0303***	1.0345***
CITIZENS BK	19	1.1007	1.1035	1.1647***	1.1917***	1.3255***	1.2915***	1.3400***	1.2613***
SKY FNCL GROUP	19	1.0631***	1.0622***	1.0967	1.0957	1.1108**	1.1074*	1.1062*	1.1010
FIRST CITIZENS BSHRS	18	1.1289***	1.1551***	1.0659***	1.0713***	1.0603***	1.0542***	1.0700***	1.0661***
COMMERCE BSHRS	17	1.1478***	1.1735***	1.0676**	1.0901	1.0888	1.0935	1.1123**	1.1058***
FULTON FNCL	17	1.0992	1.0988	1.0628**	1.0480***	1.1104*	1.0758	1.1058**	1.0880***
CITY T	17	1.2171***	1.2179***	1.1080	1.0977	1.1356**	1.0924	1.1202**	1.0885***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.8: Returns to Scale for 100 Largest Banks by Total Assets, 2006.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
TCF	17	1.0986	1.1015	1.1417*	1.1735***	1.1410**	1.1257	1.1621***	1.1172
SOUTH FNCL GROUP	16	1.1092	1.1054	1.0031***	1.0212***	1.0477***	1.0602***	1.0725	1.0504***
CITIZENS BK RI	16	1.0626***	1.0171***	1.0337***	1.0336***	1.0267***	1.0282***	1.0345***	1.0331***
FBOP	16	1.0591***	1.0642***	0.9747***	0.9718***	0.9554***	0.9700***	0.9852***	0.9999***
CULLEN/FROST BKR	14	1.0775***	1.0775***	1.0274***	1.0015***	1.0774	1.0642**	1.0478***	1.0494***
VALLEY T BC	14	1.1521***	1.1609***	1.0634***	1.0722***	1.0947	1.0720***	1.1184***	1.0780***
BANCORPSOUTH	14	1.1461***	1.1630***	1.0544***	1.0485***	1.0527***	1.0536***	1.0590***	1.0567***
FIRST HAWAIIAN BK	14	1.1066	1.1032	1.0837***	1.0771***	1.0623***	1.0167***	1.0618***	1.0374***
INVESTORS FNCL SVC	13	1.0873**	1.0866**	1.0102***	1.0051***	1.0086***	1.0062***	1.0084***	1.0060***
WILMINGTON TR	13	1.0806**	1.0800**	1.0912	1.1011	1.1523***	1.0925	1.1393***	1.0931***
CITIZENS BKG	12	1.1025	1.1056	1.1381***	1.2009***	1.1398***	1.1285	1.1796***	1.1314
EAST W BC	12	1.0456***	1.0579***	1.0271***	1.0343***	1.0253***	0.9688***	1.0210***	0.9717***
INTERNATIONAL BSHRS	12	1.1174	1.1318	1.0751***	1.0760***	1.0385***	1.0056***	1.0371***	1.0065***
BK OF HI	12	1.0758***	1.0636***	1.0612***	1.0548***	1.1015	1.0844***	1.1026	1.0837***
FIRSTMERIT	12	1.1206	1.1195	1.0825	1.0880	1.1185*	1.1436**	1.1140	1.1010
WHITNEY HC	12	1.0893	1.0770	1.0652***	1.0659***	1.0724***	1.0774***	1.0752	1.0585***
CORUS BSHRS	11	1.0535***	1.0542***	0.9804***	0.9377***	0.9794***	0.9732***	0.9598***	0.9811***
FIRST BKS	11	1.0951	1.0945	0.9958***	0.9649***	1.0182***	1.0686	0.9993***	1.0602***
WINTRUST	11	1.0813***	1.0851***	0.9872***	0.9903***	0.9841***	1.0649	1.0087***	1.0654***
STERLING	11	1.1576***	1.1652***	1.0776***	1.0788***	1.1071	1.0499***	1.1141*	1.0497***
UCBH HOLD	11	1.0609***	1.0541***	1.0229***	1.0213***	0.9872***	0.9424***	0.9863***	0.9489***
ISRAEL DISCOUNT BK OF NY	10	1.1099	1.1150	1.0525***	1.0551***	1.1083	1.0117***	1.0922	1.0335***
TRUSTMARK	10	1.1242	1.1340	1.0808***	1.0826***	1.0745	1.0809***	1.0910	1.0870***
ARVEST BK GRP	10	1.1360***	1.1371***	1.0438***	1.0542***	1.0404***	1.0533***	1.0637***	1.0635***
FIRST MIDWEST BC	10	1.1208	1.1168	1.0651***	1.0624***	1.0657	1.0637***	1.0470***	1.0622***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.8: Returns to Scale for 100 Largest Banks by Total Assets, 2006.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
UMB	10	1.1228	1.1142	1.1489***	1.2149***	1.1477***	1.1286	1.2258***	1.1335
SUSQUEHANNA BSHRS	9	1.1567***	1.1657***	1.0468***	1.0468***	1.0741	1.0874	1.0595***	1.0863***
OLD T BC	9	1.1288	1.1243	1.0670***	1.0556***	1.1009	1.0682***	1.0793	1.0561***
MB FNCL	9	1.0239***	1.0272***	1.0228***	1.0140***	1.0238***	0.9586***	1.0030***	0.9771***
CATHAY GEN BC	9	1.0437***	1.0588***	1.0750***	1.0589***	1.0428*	1.0279***	1.0148***	1.0291***
FIRSTBANK HC	9	1.0874**	1.0762***	1.0361***	1.0262***	1.0273***	1.0088***	1.0225***	1.0138***
GREATER BAY BC	8	1.1129	1.1216	1.0732***	1.0857	1.0961	1.0504***	1.1424***	1.0669***
PACIFIC CAP BC	8	1.0978	1.1091	1.0244***	1.0027***	1.0582***	1.0967	1.0436***	1.0876
UMPQUA HC	8	1.0712***	1.0774***	1.0275***	1.0359***	0.9837***	0.9746***	0.9838***	0.9783***
ALABAMA NBC	8	1.0644***	1.0677***	1.0360***	1.0243***	1.0418***	1.0128***	1.0240***	1.0030***
CENTRAL BANCOMPANY	8	1.0999	1.1123	1.0642***	1.0725*	1.0465***	1.0315***	1.0455***	1.0344***
UNITED CMNTY BK	8	1.0808***	1.0862**	1.0410***	1.0528***	1.0497***	1.0532***	1.0683***	1.0550***
UNITED BSHRS	8	1.1273	1.1202	1.0741***	1.0608***	1.0692	1.0715	1.0535	1.0839
CHITTENDEN	8	1.0248***	1.0090***	1.0457***	1.0392***	1.0498***	1.0424**	1.0566	1.0525***
PROVIDENT BSHRS	7	1.1409*	1.1530**	1.0554***	1.0505***	1.1066	1.0582***	1.0872	1.0462***
IRWIN	7	1.1007	1.1108	1.0700***	1.0766***	1.1196**	1.1185	1.1235***	1.0781
HANCOCK HC	7	1.1547***	1.1716***	1.0853***	1.0717***	1.0628**	1.0287***	1.0631***	1.0385***
FIRST COMMONWEALTH FNCL	7	1.1495***	1.1825	1.1228***	1.1231**	1.1440***	1.1030	1.1405***	1.1053
FNB	7	1.1405***	1.1641*	1.1062*	1.1043	1.1095*	1.1209*	1.0773	1.1210**
CVB	7	1.0655***	1.0788***	1.0378***	1.0506***	0.9898***	0.9552***	1.0176***	0.9407***
OCEAN BSHRS	7	1.0386***	1.0407***	1.0767	1.0967	1.0471***	0.9931***	1.0551***	1.0035***
FIRST CITIZENS BC	7	1.1342*	1.1446***	1.0345***	1.0377***	1.0242***	1.0236***	1.0315***	1.0221***
BANK LEUMI USA	7	1.0395***	1.0341***	1.0494***	1.0398***	1.0092***	0.9887***	1.0078***	1.0154***
CENTRAL PACIFIC FNCL	6	1.1350*	1.1244	1.0808***	1.1355**	1.0603***	1.0103***	1.0870	1.0022***
PARK T	6	1.0987	1.0990	1.0807	1.0703	1.0684	1.0719**	1.0501**	1.0641***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.9: Returns to Scale for 100 Largest Banks by Total Assets, 2015.Q4

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
JPMORGAN CHASE & CO	2378	1.0151***	0.9958***	1.1007	1.0938	1.1249***	1.1612***	1.1441***	1.1346
BK OF AMER	2145	1.0140***	0.9952***	1.1030	1.0911	1.1592***	1.3029***	1.1918***	1.2063**
CITIGROUP	1765	1.0375***	1.0108***	1.1337***	1.1070	1.1842***	1.3036***	1.1868***	1.1687**
WELLS FARGO & CO	1764	1.0347***	1.0256***	1.1170**	1.1055**	1.1180***	1.1174	1.1513***	1.1049
U S BC	418	0.9654***	0.9725***	1.0091***	0.9877***	1.0181***	1.0356***	1.0044***	1.0249***
BK OF NY MELLON	384	1.0697***	1.0649***	1.0451***	1.0538***	1.0348***	1.0550***	1.0507***	1.0497***
PNC FNCL SVC GROUP	359	0.9639***	0.9709***	1.0168***	0.9874***	1.0283***	1.0441***	1.0066***	1.0370***
STATE STREET	246	1.1568	1.1575	1.0042***	0.9979***	1.0117***	1.0876	1.0064***	1.0825
T D BK	243	1.0527***	1.0123***	1.0666**	1.0684***	1.0717	1.0922	1.0793***	1.0917***
BB&T	209	1.0483***	1.0123***	1.0795	1.0563***	1.1012	1.0938	1.0586***	1.0819***
SUNTRUST BK	189	1.0487***	1.1008*	1.0608***	1.0746***	1.0849***	1.0855***	1.0941	1.0791***
FIFTH THIRD BK	139	1.0880**	1.1568	1.0770***	1.1024	1.0921***	1.0756***	1.1322***	1.0971***
CITIZENS FNCL GRP	137	1.0338***	1.0987	1.0067***	0.9961***	1.0483***	1.0727	1.0184***	1.0671***
REGIONS	125	1.1139	1.1520	1.0995***	1.1151**	1.1289*	1.1166	1.1638***	1.1583
NORTHERN TR	118	1.0297***	1.0526***	1.0467***	1.0485***	1.0436***	1.0604***	1.0487***	1.0671***
M&T BK	110	1.1969***	1.1955***	1.0434***	1.0804***	1.0455***	1.0855	1.0918***	1.1145
BMO HARRIS BK	105	1.1009	1.0281	1.0630***	1.1413	1.0834***	1.0843	1.1647**	1.1316
KEYCORP	95	1.0487***	1.0359***	1.0561***	1.0534***	1.0572***	1.0611***	1.0545***	1.0763***
SANTANDER BK	90	1.1466***	1.1412***	1.0288***	1.0429***	1.0230***	1.0334***	1.0504***	1.0665***
COMPASS BK	85	1.1107	1.1030	1.1101	1.1203*	1.1244	1.1195	1.1466***	1.1485
BK OF THE WEST	75	1.0391***	1.0390***	1.1282*	1.1392***	1.1274	1.1496**	1.1392***	1.1768***
COMERICA	71	0.9915***	1.0179***	1.0318***	1.0321***	1.0328***	1.0358***	1.0383***	1.0427***
HUNTINGTON BSHRS	70	1.0837***	1.0564***	1.0438***	1.0450***	1.0398***	1.0339***	1.0427***	1.0373***
CIT BK	44	1.0211***	1.0620***	0.9483***	0.9541***	0.9416***	0.9561***	0.9573***	0.9683***
FIRST NIAGARA FNCL GROUP	40	1.1823***	1.1482	1.0592***	1.0663***	1.0646***	1.1079	1.0663***	1.1047
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.9: Returns to Scale for 100 Largest Banks by Total Assets, 2015.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
PEOPLES UNITED FNCL INC	38	1.1334***	1.1154	1.0496***	1.0493***	1.0563***	1.0343***	1.0489***	1.0297***
POPULAR	36	1.0997	1.0107	1.0478***	1.0801***	1.0232***	1.0675	1.0619***	1.0763
EAST WEST BC	32	1.0334***	1.0372***	1.0350***	1.0293***	1.0203***	1.0379***	0.9997***	1.0361***
FIRST CITIZENS BSHRS	31	1.2064***	1.2111***	1.0512***	1.0586***	1.0461***	1.0253***	1.0492***	1.0337***
BOK	31	1.1142	1.1215	1.0292***	1.0279***	1.0249***	1.0330***	1.0240***	1.0332***
CULLEN/FROST BKR	28	1.1812***	1.1352	1.0424***	1.0448***	1.0324***	1.0038***	1.0345***	1.0082***
SYNOVUS	28	1.1381	1.1565	1.0378***	1.0422***	1.0400***	1.0191***	1.0418***	1.0222***
ASSOCIATED BANC-CORP	28	1.0712***	1.0516***	1.0348***	1.0294***	1.0394***	1.0358***	1.0364***	1.0358***
FIRST HORIZON T	26	1.1276	1.1358	1.0304***	1.0290***	1.0143***	1.0441***	1.0021***	1.0413***
FIRSTMERIT	25	1.2250***	1.2220***	1.0311***	1.0307***	1.0345***	1.1115	1.0342***	1.1031
WEBSTER FNCL	24	1.1596	1.1715	1.0301***	1.0254***	1.0267***	1.0402***	1.0306***	1.0426***
COMMERCE BSHRS	24	1.1767***	1.1908***	1.0553***	1.0596***	1.0496***	1.0330***	1.0555***	1.0388***
UMPQUA HC	23	1.0683***	1.0712***	1.0263***	1.0273***	1.0291***	1.0961	1.0332***	1.0863
BANKUNITED	23	1.0605***	1.0617***	1.0451***	1.0394***	1.0319***	1.0628	1.0236***	1.0454
WINTRUST	22	1.1496***	1.1395	1.0669***	1.0694***	1.0515***	1.0123***	1.0601***	1.0247***
HANCOCK HC	22	1.1404	1.1689***	1.0629***	1.0752***	1.0590***	1.0275***	1.0757***	1.0401***
PROSPERITY BSHRS	22	1.0660***	1.0616***	1.0260***	1.0304***	1.0167***	0.9989***	1.0161***	0.9988***
VALLEY T BC	21	1.1443***	1.1336*	1.0896***	1.0863***	1.0983	1.0773***	1.1320*	1.0884***
TCF	20	1.2352***	1.2725***	1.0538***	1.0761***	1.0513***	1.0814	1.0682***	1.0846
IBERIABANK	19	1.1017	1.1342***	1.0354***	1.0327***	1.0163***	1.0024***	1.0063***	1.0020***
FIRST HAWAIIAN BK	19	1.2051***	1.2039***	1.0468***	1.0408***	1.0322***	0.9977***	1.0344***	1.0010***
PACIFIC WESTERN BK	19	1.0838	1.0521***	1.0292***	1.0237***	1.0152***	1.0407***	1.0131***	1.0278***
UMB	19	1.0690	1.0734	1.0492***	1.0416***	1.0446***	1.0584***	1.0405***	1.0494***
TEXAS CAP BK	19	1.1784***	1.1638***	1.0406***	1.0342***	1.0179***	1.0015***	1.0267***	1.0062***
FIRST NB OF OMAHA	18	1.2206***	1.2119***	1.0709***	1.0732***	1.0640***	1.0321***	1.0788***	1.0452***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.9: Returns to Scale for 100 Largest Banks by Total Assets, 2015.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
FULTON FNCL	18	1.0416***	1.0331***	1.0577***	1.0657***	1.0553***	1.0339***	1.0652***	1.0351***
FNB	17	1.1844***	1.2047***	1.0596***	1.0557***	1.0430***	1.0689	1.0352***	1.0639***
ARVEST BK GRP	16	1.1408***	1.1565***	1.0704***	1.0754***	1.0680***	1.0299***	1.0648***	1.0369***
BK OF HI	15	1.1899***	1.2479***	1.0642***	1.0662***	1.0627***	1.0468***	1.0660***	1.0499***
FIRSTBANK HC	15	0.9954***	1.0139***	1.0136***	1.0045***	1.0039***	0.9827***	1.0021***	0.9781***
RAYMOND JAMES BK	15	1.3002***	1.2036***	1.0469***	1.0170***	1.0250***	1.0389	1.0215***	1.0402
MB FNCL	15	1.0448***	1.0404***	1.0400***	1.0348***	1.0046***	1.0078***	0.9874***	1.0056***
RABOBANK	15	1.0949	1.0924	1.0548***	1.0669***	1.0821	1.1396	1.1080	1.1555
WASHINGTON FED INC	15	1.0982	1.1108	1.0144***	1.0224***	1.0158***	0.9978***	1.0323***	1.0064***
WESTERN ALLI BC	14	1.0242***	1.0006**	1.0648***	1.0085***	1.0555**	1.0634	1.0055***	1.0701
BANCORPSOUTH	14	1.0460***	1.0510***	1.0445***	1.0444***	1.0220***	0.9883***	1.0168***	0.9937***
CATHAY GEN BC	13	1.0718***	1.0875	1.0265***	1.0598***	1.0021***	0.9792	1.0525***	0.9924
UNITED BSHRS	13	1.1734***	1.1753***	1.0502***	1.0567***	1.0330***	1.0298***	1.0302***	1.0300***
TRUSTMARK	12	1.0396**	1.0198*	1.0466***	1.0457***	1.0367***	1.0193***	1.0383***	1.0267***
OLD T BC	12	1.1921***	1.2112***	1.0884***	1.1030	1.0805***	1.0548***	1.0933***	1.0673***
INTERNATIONAL BSHRS	12	1.0767***	1.0710***	1.0448***	1.0451***	1.0191***	0.9923***	1.0178***	0.9887***
CENTRAL BANCOMPANY INC	12	1.1054	1.1121	1.0706***	1.0800***	1.0528***	1.0113***	1.0537***	1.0140***
STERLING BC	12	1.1057	1.0889*	1.0564***	1.0629	1.0302***	1.0702	1.0409***	1.0733
BREMER BK	10	1.1821***	1.1706**	1.0535***	1.0506***	1.0336***	0.9664***	1.0323***	0.9635***
GREAT WESTERN BC	10	1.0876*	1.0765***	1.0566***	1.0628***	1.0287***	1.0029***	1.0255***	1.0035***
FIRST MW BC	10	1.1090	1.1100	1.0698***	1.0917***	1.0474***	0.9810***	1.0603***	0.9799***
BK OF THE OZARKS	10	1.1063	1.0945*	0.9926***	0.9808***	0.9693***	0.9626***	0.9534***	0.9680***
ISRAEL DISCOUNT BK OF NY	10	1.0679***	1.0421***	1.0981	1.0729	1.1023	1.0574***	1.0792	1.0519***
EASTERN BK	10	1.1816***	1.1334	1.0490***	1.0456***	1.0416***	1.0156***	1.0143***	1.0110***
NATIONAL PENN BSHRS	10	1.0719	1.0586**	1.0679***	1.0932***	1.0540***	1.0183***	1.0699***	1.0216***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.9: Returns to Scale for 100 Largest Banks by Total Assets, 2015.Q4 (continued)

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
UNITED CMNTY BK	9	1.1072	1.1065	1.0663***	1.0779***	1.0282***	1.0197***	1.0270***	1.0239***
CHEMICAL	9	1.0103***	1.0022***	1.0933***	1.1146	1.0621***	1.0175***	1.0685***	1.0118***
PINNACLE BC	9	1.0612***	1.0724**	1.0270***	1.0094***	0.9977***	0.9800***	0.9902***	0.9715***
GLACIER BC	9	1.0388***	1.0514***	1.0330***	1.0092***	1.0065***	0.9666***	0.9942***	0.9626***
HOME BSHRS	9	1.0770***	1.0573***	1.0204***	1.0101***	1.0012***	0.9646***	0.9887***	0.9530***
COLUMBIA BKG SYS	9	1.4461***	1.4280***	1.0280***	1.0112***	1.0270***	1.0079***	1.0171***	1.0106***
FIRST INTRST BANCSYSTEM	9	1.0354***	1.0622**	1.0876***	1.1070*	1.0498***	1.0205***	1.0439***	1.0264***
PINNACLE FNCL PTNR	9	1.0744***	1.0879**	1.0286***	1.0102***	0.9966***	0.9980***	0.9822***	1.0141***
PLAINSCAPITAL BK	9	1.1097	1.0749*	1.0534***	1.0623***	1.0484***	1.0531***	1.0555***	1.0571***
CADENCE BC LLC	9	1.0690***	1.0719**	1.0785***	1.0550***	1.0751***	1.1326	1.0267***	1.1198
SOUTH ST	9	1.1581**	1.1357	1.0442***	1.0274***	1.0199***	1.0071***	1.0081***	1.0123***
WESBANCO	8	1.1274	1.1166	1.0615***	1.0415***	1.0440***	1.0021***	1.0296***	0.9978***
COMMUNITY BK SYS	8	0.9961***	0.9918***	1.0563***	1.0592***	1.0379***	1.0082***	1.0412***	1.0062***
NBT BC	8	1.0229***	1.0133***	1.0719***	1.0679***	1.0553***	1.0406***	1.0504***	1.0355***
MERCANTIL COMMERCEBANK	8	1.0158***	0.9840***	1.0157***	0.9944***	0.9840***	0.9959	0.9445***	1.0049
FIRST FNCL BC	8	1.0441***	1.0352***	1.0624***	1.0513***	1.0649***	1.0080***	1.0602***	1.0059***
CUSTOMERS BC	8	1.0300***	1.0309***	1.0681***	1.0968	1.0335***	1.1102	1.0637	1.1112
RENASANT	8	1.0637**	1.0709*	1.0548***	1.0576***	1.0240***	0.9672***	1.0232***	0.9629***
BERKSHIRE HILLS BC	8	1.0685**	1.0756**	1.1069	1.1604***	1.1113	1.0199***	1.1484***	1.0217***
BBCN BC	8	1.1027	1.1048	1.0780	1.1245**	1.0356***	1.0595	1.0595	1.0650
BANC OF CA	8	1.0444***	1.0347***	1.0832***	1.1359	1.0683***	1.0755	1.0909	1.0870
UNION BSHRS	8	1.1024	1.0827**	1.0361***	1.0343***	1.0173***	1.0014***	1.0195***	1.0005***
CVB	8	1.3245***	1.2981***	1.0377***	1.0308***	0.9938***	0.9635***	1.0176***	0.9763***
SIMMONS FIRST T	8	1.0951**	1.1105	1.0370***	1.0266***	0.9982***	0.9556***	0.9880***	0.9656***
BANNER	8	1.1028	1.1034	1.0767	1.0191***	1.0451***	1.0573	1.0080***	1.0651
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $(1 - \mathcal{E}_{C,i})\delta$ are reported ($\delta = 1.1$). For Models 3–4 and Models 5–8, estimates of $(1 + \mathcal{E}_{R,i})\delta$ and $(1 + \mathcal{E}_{\pi,i})\delta$ are given. For Models 1–2, values *less than* 1.1 indicate increasing returns to scale, while for Models 3–8, values *greater than* 1.1 indicate increasing returns to scale. Statistical significance (difference from 1.1) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.10: Returns to Scale for Largest Banks by Total Assets, 1986.Q4 and 1996.Q4

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
—1986.Q4—									
CITIBANK	275	0.0572***	0.0541***	−0.0775***	−0.0679***	−0.1060***	−0.1128***	−0.0722***	−0.0926***
BK OF AMER	204	0.0065**	0.0040	−0.0402***	−0.0472***	0.0566	$0.1795^{(3)}$	−0.0486***	−0.0619***
CHASE MHTN BK	150	0.0348***	0.0368***	−0.0163	−0.0099	−0.0349	−0.0442	0.0112	−0.0201***
MANU. HAN	139	0.0132***	0.0118**	−0.0286***	−0.0391***	0.0744	0.0113	−0.0354***	−0.0491***
MORGAN GNTY TC	130	0.0631***	0.0664***	−0.0563***	−0.0366***	−0.0361	−0.0457	−0.0087	−0.0594***
SECURITY PACIFIC	113	0.0016	−0.0006	−0.0370***	−0.0417***	−0.0206	−0.0275	−0.0567***	−0.0623***
CHEMICAL NY	109	0.0070***	0.0067**	−0.0387***	−0.0352***	−0.0004	0.0185	−0.0385***	−0.0376***
BANKERS TR NY	100	0.0490***	0.0525***	−0.0588***	−0.0538***	−0.0416***	−0.0516	−0.0356***	−0.0513***
FIRST INTRST BC	100	0.0106*	0.0087	−0.0269***	−0.0295***	−0.0376	−0.1052	−0.0469***	−0.0832***
WELLS FARGO & CO	81	0.0093	0.0072	−0.0465***	−0.0488***	−0.0343	−0.0307	−0.0541***	−0.0530***
—1996.Q4—									
CHASE MHTN	469	0.0403***	0.0473***	−0.0605***	−0.0611***	−0.0545***	−0.0435***	−0.0629***	−0.0502***
CITICORP	394	0.0575***	0.0578***	−0.0567***	−0.0628***	−0.0522***	−0.0274***	−0.0643***	−0.0458***
BK OF AMER	352	0.0535***	0.0514***	−0.0483***	−0.0504***	−0.0468***	−0.0327***	−0.0564***	−0.0425***
NATIONSBANK	266	0.0207***	0.0344***	−0.0507***	−0.0374***	−0.0550***	−0.0503***	−0.0349***	−0.0491***
MORGAN GNTY TC	245	0.0419***	0.0477***	−0.0794***	−0.0778***	−0.0962***	−0.1018***	−0.0886***	−0.0932***
FIRST UNION	195	0.0085**	0.0064**	−0.0726***	−0.0719***	−0.0994***	−0.0977***	−0.1023***	−0.0925***
WELLS FARGO & CO	155	0.0337***	0.0434***	−0.0146***	−0.0163***	0.0075	−0.0212***	−0.0082	−0.0410***
FIRST NBD	150	0.0307***	0.0339***	−0.0553***	−0.0525***	−0.0509***	−0.0772***	−0.0517***	−0.0783***
BANC ONE	143	0.0316***	0.0250***	−0.0369***	−0.0370***	−0.0364***	−0.0477***	−0.0566***	−0.0496***
FLEET FNCL GROUP	123	0.0376***	0.0374**	−0.0166***	−0.0076***	−0.0200***	−0.0254***	−0.0149	−0.0312***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	π_1	π_2	π_3	π_4
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $\mathcal{E}_{C,i})$ are reported. For Models 3–4 and Models 5–8, estimates of $\mathcal{E}_{R,i})$ and $\mathcal{E}_{\pi,i})$ are given. In all cases, values greater than (equal to, less than) 0 indicate increasing (constant, decreasing) returns to scale. Statistical significance (difference from 0) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.11: Returns to Scale for Largest Banks by Total Assets, 2006.Q4 and 2015.Q4

Name	Assets	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
—2006.Q4—									
CITIGROUP	2082	−0.0010	0.0068*	−0.0175***	−0.0206***	0.0323***	0.0113	0.0095**	−0.0320***
BK OF AMER	1672	0.0553***	0.0549***	−0.0064***	0.0124	0.0472***	0.0656***	0.0453***	0.0081
JPMORGAN CHASE & CO	1543	−0.0023	−0.0001	−0.0016	−0.0038	0.0969***	0.0342	0.0704***	−0.0192***
WACHOVIA	726	0.0492***	−0.0066	−0.0701***	−0.0309*	−0.0306	−0.0159	0.0247	−0.0544***
WELLS FARGO & CO	554	0.0734***	0.0676***	−0.0913***	−0.0566***	−0.0787***	−0.0472	−0.0687***	−0.0663***
U S BC	250	0.0378***	0.0405***	−0.0461***	−0.0394***	−0.0313***	−0.0272***	−0.0267***	−0.0313***
COUNTRYWIDE	225	−0.0008	−0.0119	−0.0897***	−0.0888***	−0.0955***	−0.0990***	−0.0907***	−0.0948***
SUNTRUST BK	210	0.0241***	0.0245***	−0.0221***	−0.0202***	−0.0123	−0.0400***	−0.0089	−0.0480***
HSBC BK USA	191	0.0495***	0.0513***	−0.0821***	−0.0763***	−0.0975***	−0.1045***	−0.0696***	−0.0885***
NATIONAL CITY	160	0.0276***	0.0312***	−0.0748***	−0.0661***	−0.1111***	−0.0873***	−0.0994***	−0.0784***
—2015.Q4—									
JPMORGAN CHASE & CO	2378	0.0772***	0.0948***	0.0007	−0.0056	0.0226***	0.0556***	0.0401***	0.0315
BK OF AMER	2145	0.0782***	0.0953***	0.0027	−0.0081	0.0539***	0.1844***	0.0835***	0.0966**
CITIGROUP	1765	0.0568***	0.0811***	0.0306***	0.0064	0.0765***	0.1851***	0.0789***	0.0624**
WELLS FARGO & CO	1764	0.0594***	0.0677***	0.0154**	0.0050**	0.0163***	0.0158	0.0466***	0.0044
U S BC	418	0.1224***	0.1159***	−0.0827***	−0.1021***	−0.0744***	−0.0585***	−0.0869***	−0.0683***
BK OF NY MELLON	384	0.0275***	0.0319***	−0.0499***	−0.0420***	−0.0592***	−0.0409***	−0.0448***	−0.0457***
PNC FNCL SVC GROUP	359	0.1237***	0.1173***	−0.0756***	−0.1024***	−0.0652***	−0.0508***	−0.0849***	−0.0573***
STATE STREET	246	−0.0516	−0.0522	−0.0871***	−0.0928***	−0.0803***	−0.0113	−0.0851***	−0.0159
T D BK	243	0.0430***	0.0797***	−0.0304**	−0.0287***	−0.0257	−0.0071	−0.0188***	−0.0076***
BB&T	209	0.0470***	0.0797***	−0.0187	−0.0398***	0.0011	−0.0057	−0.0377***	−0.0164***
Dep. Var.		C_1/W_1	C_2/W_1	R_1	R_2	π_1	π_2	π_3	π_4
RHS Vars.		$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: For Models 1–2, estimates of $\mathcal{E}_{C,i}$) are reported. For Models 3–4 and Models 5–8, estimates of $\mathcal{E}_{R,i}$) and $\mathcal{E}_{\pi,i}$) are given. In all cases, values greater than (equal to, less than) 0 indicate increasing (constant, decreasing) returns to scale. Statistical significance (difference from 0) at the ten, five, or one percent levels is denoted by one, two, or three asterisks, respectively. Assets are given in millions of constant 2015 dollars.

Table E.12: Numbers of Significant Changes in RTS Elasticities from 2006.Q4 to 2015.Q4

	.1 signif.			.05 signif.			.01 signif.		
Model	Change	RTS↑	RTS↓	Change	RTS↑	RTS↓	Change	RTS↑	RTS↓
1	3228	1765	1463	3064	1686	1378	2791	1552	1239
2	3195	1784	1411	3031	1704	1327	2702	1538	1164
3	2444	1162	1282	2194	1033	1161	1805	841	964
4	2653	1260	1393	2448	1155	1293	2123	1001	1122
5	1427	589	838	1210	493	717	896	364	532
6	1483	702	781	1260	594	666	935	431	504
7	2260	956	1304	2004	849	1155	1593	656	937
8	2108	995	1113	1843	860	983	1485	690	795

NOTE: For each level of significance, "Change" gives the number of cases among 4148 banks in 2015.Q4 that also appear in 2006.Q4 and for which the estimated elasticities in Table 3 significantly differ between 2006.Q4 and 2015.Q4. Columns labelled "RTS↑" and "RTS↓" give counts of banks where returns to scale improve and worsen, respectively.

Table E.13: Significant Changes in RTS from 2006.Q4 to 2015.Q4 for 10 Largest Banks in 2015.Q4 (.1 Significance)

	Model							
Bank	1	2	3	4	5	6	7	8
JPMORGAN CHASE & CO	↑	↑	—	—	↓	—	—	—
BK OF AMER	↑	↑	—	↓	—	—	↑	↑
CITIGROUP	↑	↑	↑	↑	↑	↑	↑	↑
WELLS FARGO & CO	—	—	↑	↑	↑	↑	↑	↑
U S BC	↑	↑	↓	↓	↓	↓	↓	↓
PNC FNCL SVC GROUP	↑	↑	↓	↓	—	—	↓	↑
STATE STREET	↓	↓	↑	↑	↑	↑	↑	↑
T D BK	↑	↑	↓	↓	—	↓	↓	—
BB&T	↑	↑	↑	—	—	—	—	↑
SUNTRUST BK	—	↓	—	—	—	—	—	—
Dep. Var.	C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: Upward arrows indicate a significant increase in RTS pseudo-elasticity from 2006.Q4 to 2015.Q4. Downward arrows indicate significant decrease in RTS pseueo-elasticity from 2006.Q4 to 2015.Q4. Horizontal dashes indicate no significant change.

Table E.14: Significant Changes in RTS from 2006.Q4 to 2015.Q4 for 10 Largest Banks in 2015.Q4 (.05 Significance)

	Model							
Bank	1	2	3	4	5	6	7	8
JPMORGAN CHASE & CO	↑	↑	—	—	—	—	—	—
BK OF AMER	↑	↑	—	↓	—	—	↑	↑
CITIGROUP	↑	↑	↑	↑	↑	↑	↑	↑
WELLS FARGO & CO	—	—	↑	↑	↑	↑	↑	↑
U S BC	↑	↑	↓	↓	↓	—	↓	↓
PNC FNCL SVC GROUP	↑	↑	—	↓	—	—	↓	↑
STATE STREET	↓	↓	↑	↑	↑	↑	↑	↑
T D BK	↑	↑	↓	↓	—	—	↓	—
BB&T	↑	↑	↑	—	—	—	—	↑
SUNTRUST BK	—	↓	—	—	—	—	—	—
Dep. Var.	C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: Upward arrows indicate a significant increase in RTS pseudo-elasticity from 2006.Q4 to 2015.Q4. Downward arrows indicate significant decrease in RTS pseueo-elasticity from 2006.Q4 to 2015.Q4. Horizontal dashes indicate no significant change.

Table E.15: Significant Changes in RTS from 2006.Q4 to 2015.Q4 for 10 Largest Banks in 2015.Q4 (.01 Significance)

	Model							
Bank	1	2	3	4	5	6	7	8
JPMORGAN CHASE & CO	↑	↑	—	—	—	—	—	—
BK OF AMER	↑	↑	—	↓	—	—	—	↑
CITIGROUP	↑	↑	↑	↑	↑	↑	↑	↑
WELLS FARGO & CO	—	—	↑	↑	↑	↑	↑	↑
U S BC	↑	↑	↓	↓	↓	—	↓	↓
PNC FNCL SVC GROUP	↑	↑	—	↓	—	—	↓	↑
STATE STREET	↓	↓	↑	↑	↑	↑	↑	↑
T D BK	↑	↑	↓	↓	—	—	↓	—
BB&T	—	↑	↑	—	—	—	—	—
SUNTRUST BK	—	—	—	—	—	—	—	—
Dep. Var.	C_1/W_1	C_2/W_1	R_1	R_2	$R_1 - C_1$	$R_1 - C_2$	$R_2 - C_1$	$R_2 - C_2$
RHS Vars.	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_1)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$	$(\boldsymbol{y}, \boldsymbol{w}_2)$

NOTE: Upward arrows indicate a significant increase in RTS pseudo-elasticity from 2006.Q4 to 2015.Q4. Downward arrows indicate significant decrease in RTS pseueo-elasticity from 2006.Q4 to 2015.Q4. Horizontal dashes indicate no significant change.

Table E.16: Transition Matrices, 2006.Q4 to 2015.Q4, Cost Models, .1 Significance

Model 1 (dep. var. C_1):

	IRS	CRS	DRS	Total
IRS	866	803	47	1716
CRS	1085	1143	96	2324
DRS	52	45	11	108
Total	2003	1991	154	4148

Model 2 (dep. var. C_2):

	IRS	CRS	DRS	Total
IRS	883	752	49	1684
CRS	1130	1138	88	2356
DRS	51	45	12	108
Total	2064	1935	149	4148

NOTE: For each transition matrix, rows correspond to RTS in 2006.Q4 and columns correspond to RTS in 2015.Q4.

Table E.17: Transition Matrices, 2006.Q4 to 2015.Q4, Revenue Models, .1 Significance

Model 3 (dep. var. R_1):

	IRS	CRS	DRS	Total
IRS	295	536	182	1013
CRS	714	1601	485	2800
DRS	53	143	139	335
Total	1062	2280	806	4148

Model 4 (dep. var. R_2):

	IRS	CRS	DRS	Total
IRS	327	611	145	1083
CRS	761	1607	426	2794
DRS	44	114	113	271
Total	1132	2332	684	4148

NOTE: For each transition matrix, rows correspond to RTS in 2006.Q4 and columns correspond to RTS in 2015.Q4.

Table E.18: Transition Matrices, 2006.Q4 to 2015.Q4, Profit Models, .1 Significance)

Model 5 (dep. var. π_1):

	IRS	CRS	DRS	Total
IRS	441	793	145	1379
CRS	783	1566	296	2645
DRS	16	38	70	124
Total	1240	2397	511	4148

Model 6 (dep. var. π_2):

	IRS	CRS	DRS	Total
IRS	787	767	106	1660
CRS	963	1144	213	2320
DRS	15	51	102	168
Total	1765	1962	421	4148

Model 7 (dep. var. π_3):

	IRS	CRS	DRS	Total
IRS	524	877	131	1532
CRS	799	1441	252	2492
DRS	19	33	72	124
Total	1342	2351	455	4148

Model 8 (dep. var. π_4):

	IRS	CRS	DRS	Total
IRS	943	806	111	1860
CRS	927	1002	198	2127
DRS	16	43	102	161
Total	1886	1851	411	4148

NOTE: For each transition matrix, rows correspond to RTS in 2006.Q4 and columns correspond to RTS in 2015.Q4.

Table E.19: Transition Matrices, 2006.Q4 to 2015.Q4, Cost Models, .05 Significance

Model 1 (dep. var. C_1):

	IRS	CRS	DRS	Total
IRS	640	716	30	1386
CRS	1073	1514	88	2675
DRS	41	37	9	87
Total	1754	2267	127	4148

Model 2 (dep. var. C_2):

	IRS	CRS	DRS	Total
IRS	645	690	28	1363
CRS	1124	1500	82	2706
DRS	35	38	6	79
Total	1804	2228	116	4148

NOTE: For each transition matrix, rows correspond to RTS in 2006.Q4 and columns correspond to RTS in 2015.Q4.

Table E.20: Transition Matrices, 2006.Q4 to 2015.Q4, Revenue Models, .05 Significance

Model 3 (dep. var. R_1):

	IRS	CRS	DRS	Total
IRS	167	427	112	706
CRS	645	2032	494	3171
DRS	33	120	118	271
Total	845	2579	724	4148

Model 4 (dep. var. R_2):

	IRS	CRS	DRS	Total
IRS	197	509	92	798
CRS	692	2004	426	3122
DRS	30	103	95	228
Total	919	2616	613	4148

NOTE: For each transition matrix, rows correspond to RTS in 2006.Q4 and columns correspond to RTS in 2015.Q4.

Table E.21: Transition Matrices, 2006.Q4 to 2015.Q4, Profit Models, .05 Significance

Model 5 (dep. var. π_1):

	IRS	CRS	DRS	Total
IRS	266	688	93	1047
CRS	709	1994	296	2999
DRS	11	31	60	102
Total	986	2713	449	4148

Model 6 (dep. var. π_2):

	IRS	CRS	DRS	Total
IRS	531	723	72	1326
CRS	918	1545	217	2680
DRS	7	44	91	142
Total	1456	2312	380	4148

Model 7 (dep. var. π_3):

	IRS	CRS	DRS	Total
IRS	319	753	88	1160
CRS	756	1878	249	2883
DRS	10	29	66	105
Total	1085	2660	403	4148

Model 8 (dep. var. π_4):

	IRS	CRS	DRS	Total
IRS	681	798	73	1552
CRS	923	1329	198	2450
DRS	10	40	96	146
Total	1614	2167	367	4148

NOTE: For each transition matrix, rows correspond to RTS in 2006.Q4 and columns correspond to RTS in 2015.Q4.

Table E.22: Transition Matrices, 2006.Q4 to 2015.Q4, Cost Models, .01 Significance

Model 1 (dep. var. C_1):

	IRS	CRS	DRS	Total
IRS	311	526	13	850
CRS	952	2215	73	3240
DRS	22	28	8	58
Total	1285	2769	94	4148

Model 2 (dep. var. C_2):

	IRS	CRS	DRS	Total
IRS	313	507	11	831
CRS	975	2226	58	3259
DRS	19	34	5	58
Total	1307	2767	74	4148

NOTE: For each transition matrix, rows correspond to RTS in 2006.Q4 and columns correspond to RTS in 2015.Q4.

Table E.23: Transition Matrices, 2006.Q4 to 2015.Q4, Revenue Models, .01 Significance

Model 3 (dep. var. R_1):

	IRS	CRS	DRS	Total
IRS	52	234	52	338
CRS	449	2693	458	3600
DRS	7	100	103	210
Total	508	3027	613	4148

Model 4 (dep. var. R_2):

	IRS	CRS	DRS	Total
IRS	63	259	46	368
CRS	498	2697	406	3601
DRS	11	86	82	179
Total	572	3042	534	4148

NOTE: For each transition matrix, rows correspond to RTS in 2006.Q4 and columns correspond to RTS in 2015.Q4.

Table E.24: Transition Matrices, 2006.Q4 to 2015.Q4, Profit Models, .01 Significance

Model 5 (dep. var. π_1):

	IRS	CRS	DRS	Total
IRS	84	396	43	523
CRS	480	2793	276	3549
DRS	4	19	53	76
Total	568	3208	372	4148

Model 6 (dep. var. π_2):

	IRS	CRS	DRS	Total
IRS	232	546	36	814
CRS	705	2291	219	3215
DRS	1	38	80	119
Total	938	2875	335	4148

Model 7 (dep. var. π_3):

	IRS	CRS	DRS	Total
IRS	110	417	44	571
CRS	554	2692	247	3493
DRS	4	21	59	84
Total	668	3130	350	4148

Model 8 (dep. var. π_4):

	IRS	CRS	DRS	Total
IRS	318	607	40	965
CRS	777	2077	202	3056
DRS	5	36	86	127
Total	1100	2720	328	4148

NOTE: For each transition matrix, rows correspond to RTS in 2006.Q4 and columns correspond to RTS in 2015.Q4.

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