July 2005

Economies of Scale and Cost Efficiencies: A Panel-Data Stochastic-Frontier Analysis of Real Estate Investment Trusts

Stephen M. Miller
University of Nevada, Las Vegas and University of Connecticut

Terrence M. Clauretie
University of Nevada, Las Vegas

Thomas M. Springer
Clemson University

University of Connecticut

Department of Economics Working Paper Series

Economies of Scale and Cost Efficiencies: A Panel-Data Stochastic-Frontier Analysis of Real Estate Investment Trusts

Stephen M. Miller
University of Nevada, Las Vegas, and University of Connecticut

Terrence M. Clauretie
University of Nevada, Las Vegas

Thomas M. Springer
Clemson University

Working Paper 2005-21

July 2005

---

341 Mansfield Road, Unit 1063
Storrs, CT 06269–1063
Phone: (860) 486–3022
Fax: (860) 486–4463
http://www.econ.uconn.edu/

Abstract

This paper extends the existing research on real estate investment trust (REIT) operating efficiencies. We estimate a stochastic-frontier panel-data model specifying a translog cost function, covering 1995 to 2003. The results disagree with previous research in that we find little evidence of scale economies and some evidence of scale diseconomies. Moreover, we also generally find smaller inefficiencies than those shown by other REIT studies. Contrary to previous research, the results also show that self-management of a REIT associates with more inefficiency when we measure output with assets. When we use revenue to measure output, selfmanagement associates with less inefficiency. Also contrary with previous research, higher leverage associates with more efficiency. The results further suggest that inefficiency increases over time in three of our four specifications.

Journal of Economic Literature Classification: G2, L25, L85

Keywords: Real Estate Investment Trusts, X-efficiency, scale economies

Presented at the Money Macro and Finance Research Group conference "Efficiency Analysis in Macroeconomics and Finance," 3 June 2005 at the University of Essex, United Kingdom.

I. Introduction

Over the past decade, the publicly traded Real Estate Investment Trust (REIT) industry experienced extensive growth and change. The industry expanded from a total market capitalization of $8.74 billion (119 REITs) in 1990 to $305.1 billion (190 REITs) in 2004 (NAREIT.org). Based on these statistics, the size of the average publicly traded REIT has increased from $73.4 million in 1990 to $1.6 billion in 2004. Given the dramatic changes to both the industry and the size of the average REIT, considerable interest emerged on the underpinnings and the sustainability of the growth of this sector.

Two schools of thought exist regarding the long-term viability of projected growth and consolidation in the REIT industry. One opinion argues that the full potential for this sector remains untapped. Essentially, REITs can develop as low-cost producers of investment real estate through growth. The sources of the competitive advantage include economies of scale, lower capital costs, and superior sources of capital (Linneman, 1997). At the same time, a second opinion argues that the real estate industry still exhibits a cyclical pattern and that the industry cannot sustain the current growth spurt. Vogel (1997) suggests that external factors drive the rapid growth of the REIT industry and do not arise from superior operating performance. Generally, most analysts believe that scale economies and the potential for gains in operating efficiencies do exist. Considerable debate continues, however, over the sources and the magnitude of these efficiencies (see Anderson, Lewis, Springer, 2000, for a general review).

This paper extends the research on REIT operating efficiencies and scale economies. First, while previous studies, for the most part, considered a single output measure with which to measure efficiency and scale economies, we use two alternative output measures. Next, whereas previous studies generally used cross-sectional analysis, we employ a panel-data model, covering

1995 to 2003. Specifying a translog cost function, we estimate a stochastic-frontier panel-data model of REIT operating efficiencies that also identifies various influences on efficiency.

The results disagree with previous research in that we find little evidence of scale economies and some evidence of scale diseconomies. Moreover, the consideration of input prices and the analysis of the industry using a multi-year sample generally reveal smaller inefficiencies than those shown by other studies. Contrary to previous studies, the results also show that self-management of a REIT associates with more inefficiency when we measure output with assets. When we use revenue to measure output, self-management associates with less inefficiency. Also contrary with prior research, higher leverage associates with more efficiency. The results further suggest that inefficiency increases over time in three of our four specifications.

The paper unfolds as follows. The next section reviews the existing literature for both efficiency studies, in general, and of REITs, in particular. Section III discusses the stochastic-frontier, panel-data methodology used to estimate REIT operating efficiency. Section IV reports and interprets the results of our analysis. Section V concludes.

II. Literature review

Cost scale and efficiency studies, using frontier techniques, of the financial services industry remain controversial. The controversy stems from, at least, two sources -- the general debate in the empirical production analysis literature and the peculiarities of the financial firm.

Approaches to Frontier Estimation

Farrell (1957) introduces the basic framework for studying and measuring inefficiency, defined as deviations of actual from "optimum behavior." The frontier establishes the optimum benchmark against which to calculate deviations. Various methods, using statistical and mathematical programming techniques, exist for the construction-estimation of the relevant frontier. At one level, a general distinction emerges between deterministic and stochastic frontiers.[1] Both techniques bound the data, but in different ways. Deterministic frontiers by construction fix the frontier in the relevant space and encompass all sample observations. Thus, a small subset of data supports the frontier, making it more prone to sampling, outlier, and statistical noise problems, which may distort the measurement of efficiency.[2] Two different techniques exist for constructing deterministic frontiers. Mathematical programming techniques assume no statistical noise, an assumption that seems unreasonable for large economic data sets (Schmidt 1985-86), while the statistical approach to deterministic frontier estimation asserts that random shocks, statistical noise, and firm-specific effects together reflect inefficiency, a rather questionable practice (Førsund, Lovell, and Schmidt 1980).

Stochastic frontiers avoid some of the problems associated with deterministic frontiers by explicitly considering the stochastic properties of the data, and distinguishing through a composite error term between firm-specific effects, and random shocks or statistical noise. Here, the frontier can shift from one observation to the next, being random rather than exact.

Other problems still exist, however, with the parametric stochastic-frontier approach. First, implementation requires the choice of an explicit functional form for the production or cost function, the appropriateness of which raises questions. The use of a flexible functional form, such as the translog, helps to alleviate this concern to some extent.

---

[1] Deterministic frontiers fall into two categories -- either non-parametric (e.g., Farrell 1957) or parametric, and in the latter case, either non-statistical (e.g., Aigner and Chu 1968, and Timmer 1971) or statistical (e.g., Afriat 1972, and Richmond 1974). Stochastic frontiers can exhibit either parametric (e.g., Aigner, Lovell, and Schmidt 1977, and Meeusen and van den Broek 1977) or non-parametric (e.g., Banker and Maindiratta 1992) specifications. Schmidt (1985-86), Forsund, Lovell, and Schmidt (1980), and Bauer (1990) review this literature with a discussion of the technical and conceptual problems associated with the estimation of frontiers and the difficulties of measuring efficiency relative to the frontier benchmark. Schmidt's (1980) discussion includes an extensive bibliography.

[2] Van den Broek, Førsund, Hjalmarsson, and Meeusen (1980) provide much discussion and empirical evidence.

Second, the researcher imposes strong distributional assumptions on the error term. While debate continues, some evidence suggests a limited effect of distributional assumptions on the obtained estimates (e.g., Cowing, Reifschneider, and Stevenson 1983, and Greene 1990). Moreover, the relative rankings of firms based on inefficiency calculations seem unaffected. But, the absolute levels of inefficiencies differ over different distributional assumptions on the one-sided error term, with "... the single parameter models ... providing a more pessimistic impression than warranted." (Greene 1990, p. 158).

To avoid problems associated with the aforementioned "edge" frontier models, Berger and Humphrey (1991) introduce the "thick" frontier model, where a larger number of "best-practice" firms support the frontier and where the estimation of inefficiency requires weaker distributional assumptions. In the case of multiple-input, multiple-output technology, this approach proves problematic, however, as the ordering criterion implies a different model from that estimated.[3]

Frontier Studies of Real Estate Investment Trust Scale and Efficiency

Examination of economies and diseconomies of scale of REITs predates REIT efficiency studies. Bers and Springer (1997, 1998a,b) and Ambrose and Pennington-Cross (2000) employ the standard approach of estimating the cost function without allowing for the possibility of inefficient production (i.e., production above the efficient cost function). They all find evidence of economies of scale for REITs.

We know of four frontier studies of REIT operating efficiency. Two papers employ data envelopment analysis (DEA). Anderson, Springer, Fok, and Webb (2002) calculate economies of

[3] Berger and Humphrey (1991) order the firms according to the average total cost per dollar of assets. The banks in the lowest average cost quartile form the base for estimating the multiple-input, multiple-output cost function, which they then compare to that of the highest average cost quartile. A possible inconsistency arises, however, as the ordering of banks implied by the aggregate, one-dimensional measure (i.e., average total cost per dollar of assets) need not capture the same ordering based on an index consistent with the multiple-input, multiple-output nature of the cost function eventually estimated. Moreover, this ordering may reflect more biased than it appears at first glance, since costs will incorporate different, rather than identical, input prices.

scale and inefficiency for REITs, employing DEA for a sample ranging from 1992 to 1996. They find extremely large inefficiencies, ranging from about 45 to 60 percent. Anderson and Springer (2003) calculate REIT efficiency, using DEA for a sample ranging from 1995 to 1999, and then use that measure as an indicator for portfolio selection. Although not the main focus of their paper, they also report extremely large levels of inefficiency.

Unlike the first two studies that employ DEA analysis, Lewis, Springer, and Anderson (2003) employ a stochastic frontier that incorporates Bayesian statistics to calculate economies of scale and inefficiency for REITs with a sample from 1995 to 1997. They report much lower levels of inefficiency than either of the DEA studies. Using the Bayesian stochastic frontier methodology, they also determine on a case-by-case basis whether inefficiency differs between REITs because of (1) management type (i.e., self or externally managed), (2) leverage (i.e., high or low leverage), and (3) portfolio diversification (i.e., specialized and diversified).[4] They find that self-management correlates with higher efficiency in 1995 and 1996, but with lower efficiency in 1997. That 1997 finding raises some concern, since it proves inconsistent with prior work (Bers and Springer 1998b and Anderson, Springer, Fok, and Webb 2002). Higher debt-ratio REITs exhibit higher inefficiency than lower debt-ratio REITs in all three years. Finally, REIT diversification does not affect efficiency, contrary to some of the existing evidence (Bers and Springer 1998b and Anderson, Springer, Fok, and Webb 2002).

The last, and most recent, frontier study by Ambrose, Highfield, and Linneman (2005) also use a stochastic-frontier approach. Using data from 1990 to 2001, they find scale economies. They consider the stochastic-frontier specification in their penultimate section. The description of the model and its estimation proves sketchy, at best.

---

[4] A dummy variable captures whether the REIT experiences external of self-management. High debt REITs hold a debt ratio above 67 percent. Finally, a Hirschman-Herfindhal index above 8,000 of portfolio diversification identifies a non-diversified portfolio.

General agreement exists on how to measure output – total assets or dividing total assets into sub-categories. For the DEA studies, inputs reflect total cost or its sub-components – interest expense, operating expense, general and administrative expense, and management fees. For the stochastic frontier models, typically researchers include input prices. Lewis, Springer, and Anderson (2003) do not introduce any input prices, but only include output in the translog cost function.[5] Ambrose, Highfield, and Linneman (2005) appear to use input costs rather than input prices in their stochastic-frontier model.[6]

III. Methodology

Aigner, Lovell, and Schmidt (1977) and Meeusen and Van den Broeck (1977) first introduce the stochastic-frontier model, where a stochastic frontier provides an upper bound on actual production. The basic model includes a composite error term that sums a two-sided error term, measuring all effects outside the firm's control, and a one-sided, non-negative error term, measuring technical inefficiency. A firm can lie on or within the frontier, and the distance between actual output and the frontier output represents technical inefficiency. The early articles on stochastic frontiers used cross-section data. With panel data, however, later models (Cornwell, Schmidt, and Sickles, 1990; Kumbhakar, 1990; Battese and Coelli, 1992) include time-varying inefficiency.

The Framework

In the present study, we view the REIT firm as an intermediary, operating in competitive markets and using a multiple input-output technology. The concept of efficiency (and, thus, inefficiency), although well rooted in the history of economic thought, possesses a normative character, which is

[5] That translog cost function appears in Bers and Springer (1998a,b).

[6] As just noted, Ambrose, Highfield, and Linneman (2005) provide a sketchy description of the model and its estimation.

reinforced by the short list of inputs normally considered in empirical models.[7] Our interpretation accords with the widely held view of production as a systematic technical relationship of inputs and outputs, and with the observation that firms can survive in markets for extended periods, even though they appear to operate at relatively lower levels of efficiency.

Our analysis proceeds as follows. We specify and estimate a composite-error model. This model separates firm-specific effects, captured by the one-sided error term (u_{it}), from random shocks and statistical noise, reflected by the two-sided, symmetric error term (v_{it}), and permits the estimation of firm-specific deviations, using the method of Jondrow, Lovell, Materov, and Schmidt (1982). We also evaluate the role of some other firm-specific factors that may affect the level of inefficiency by specifying the one-sided error term as depending on these additional control variables (Battese and Coelli 1995; Coelli 1996).

The Model

We estimate a translog variable cost function with a composite error term (ε_{it}) that can be written as follows (we drop firm and time subscripts to simplify):

$$\begin{aligned}\ln C = {} & \alpha_0 + \sum_{i=1}^{m}\alpha_i \ln q_i + \sum_{j=1}^{n}\beta_j \ln(1+p_j) + \sum_{i=1}^{m}\sum_{r=1}^{m}\pi_{ir}\ln q_i \ln q_r \\ & + \sum_{j=1}^{n}\sum_{k=1}^{n}\delta_{jk}\ln(1+p_j)\ln(1+p_k) + \sum_{i=1}^{m}\sum_{j=1}^{n}\phi_{ij}\ln q_i \ln(1+p_j) + \varepsilon,\end{aligned} \tag{1}$$

where lnC = the natural logarithm of the cost; lnq_i = the natural logarithm of the i^{th} output ($i=1,...,m$); $ln(1+p_j)$ = the natural logarithm of one plus the j^{th} input price ($j=1,...,n$); $\varepsilon = v + u$ with $v \approx N(0, \sigma^2_v)$ and $u \approx N(m, \sigma^2_u)$, a truncated normal; $m = \theta_0 + \sum_{s=1}^{q}\theta_s x_s + w$; x_s = alternative control variables; w = a two-sided, symmetric random error $\approx N(0, \sigma^2_w)$; and $\alpha, \beta, \pi, \delta, \phi,$ and θ equal

[7] Stigler (1976) discusses these issues with some insightful observations.

coefficients. Since a few observations for p_j equal zero, we took the natural logarithm of $(1 + p_j)$ so as to not lose those observations.

The technical efficiency index for each firm in the sample is given as follows (Battese and Coelli 1995; and Coelli 1996):

$$TE = \exp(u) = \exp(\theta_0 + \sum_{s=1}^{q} \theta_s x_s + w)\,. \tag{2}$$

We adopt the translog cost function for two basic reasons. First, it imposes virtually no restrictions on the first- and second-order effects. At the same time, it also provides a second-order logarithmic approximation to an arbitrary continuous transformation surface.[8] Second, the dual approach, although not free of problems itself, allows the bypassing of the well-known problems of multicollinearity that inherently plagues the direct approach. The reliability of our results hinges, of course, on the validity of the cost-minimization assumption.

The Data

Our data include 1995 to 2003 information on publicly traded REITs listed in the *National Association of Real Estate Investment Trusts (NAREIT) Handbook* and the *SNL REIT Quarterly*. Due to missing values, the final sample consists of 212, 221, 222, 236, 233, 220, 208, 198, and 132 REITs in 1995, 1996, …, and 2003, respectively, for a total of 1851 observations.[9] Table 1 reports summary statistics.

We employ two alternative aggregate measures of output (q) as follows: total assets and total revenue. That is, the translog cost function includes only one output, but we estimate two

[8] Previous research on the cost structure of commercial banks concludes in favor of our specification. For example, Lawrence (1989) rejects both the more-restrictive Cobb-Douglas specification and the more-flexible Box-Cox transformation in favor of the translog. Also, Noulas, Ray, and Miller (1990a), using Call Report data for large banks, conclude against homotheticity, constant returns to scale, etc., while Noulas, Miller, and Ray (1993) demonstrate the instability of the findings from alternative Box-Cox transformations.

[9] In addition to missing values, we deleted all observations that exhibited a debt-to-asset ratio exceeding one.

specifications with different output definitions for each modification of the general model. Lewis, Springer, and Anderson (2003) employ total assets and market capitalization (i.e., share price times the number of shares) as alternative measures of output. Other studies typically employ assets to measure output. Lewis, Springer, and Anderson (2003) conclude that assets perform the best. Thus, we use the standard measure of output as well as a new measure.

Prior researchers (Bers and Springer 1998a,b; Lewis, Springer, and Anderson 2003) faced a major problem of no input prices.[10] While the data source puts a severe constraint on generating input prices, we construct two proxies for input prices. The inputs include interest expense and the sum of operating expense, general and administrative expense, and management fees. We calculate the input prices as follows: the average interest cost per dollar of debt (average price of debt, i) and the average other expenses per dollar of assets (average price of other inputs, r). The dependent variable equals total cost (C), which includes (1) interest expense, (2) operating expense, (3) general and administrative expense, and (4) management fees.

We also introduce several control variables. First, we employ the debt-to-asset ratio as a shift variable in the cost frontier. That is, for each REIT, the cost function's intercept shifts due to differences in leverage. A higher leveraged REIT should face higher costs, on average, since the debt-service cost will rise. Moreover, REITs do not garner any tax shield effect, since the interest expense does not receive a tax deduction. Second, we add three variables to explain changes in efficiency. One, a time variable (i.e., *time = 1, 2, …, and 9*) determines whether REITs became more or less cost efficient over the sample period. Two, we include a dummy variable (i.e., *Self_Managed*) that equals one, if the REIT is self-managed; zero otherwise. This dummy variable determines whether self-managed firms prove more cost efficient than externally managed REITs.

---

[10] Ambrose, Highfield, and Linneman (2005) appear to use input costs and not input prices in their stochastic-frontier model estimation.

Three, we also employ the debt-to-asset ratio as a continuous variable. This variable decides whether higher-debt REITs exhibit worse efficiency than lower-debt REITs.[11]

IV. Results

Tables 2 and 3 present the findings for output defined as total assets and total revenue, respectively. We consider the cost frontier without input prices to compare with Lewis, Springer, and Anderson (2003). Thus, for the simple models without input prices, all coefficients prove significant at the 1- or 5-percent levels. The debt-to-asset ratio shows that REITs face significantly higher (frontier) costs, other things constant, with higher leverage.

The estimates allow the calculation of economies or diseconomies of scale. For example, the calculation of the cost elasticity with respect to output in the more complex specification using assets as output comes from the coefficients in Table 2. The exact calculation equals the following:

$$\frac{\partial \ln Cost}{\partial \ln Assets} = 1.0166 + 2(0.0005)\ln Assets - (0.1027)\ln(1+i) + (0.0129)\ln(1+r)\,, \quad (3)$$

where we need to include values for *lnAssets*, *ln(1+i)*, and *ln(1+r)*. The bottom of Tables 2 and 3 report the cost elasticity with respect to output for the average, median, maximum, and minimum values of output. In addition, we use the average values for the other right-hand side except in the calculation of the median cost elasticity where we use the medians for all the variables. For example, the cost elasticity for the maximum value of *lnAssets* in the complex specification equals 1.0283. That is, costs rise slightly more than proportionately with assets, implying diseconomies of scale. That calculation used the maximum value for *lnAssets* (i.e., 17.0662) as well as the average values for *ln(1+i)* (i.e., 0.0653) and *ln(1+r)* (i.e., 0.1051) on the right-hand side of the cost elasticity shown above.

---

[11] Remember that we also allow total cost to adjust due to differences in leverage.

Except for the complex model for assets, the other three models imply little, if any, economies or diseconomies of scale, since the cost elasticity nearly equals one. The complex specification for assets suggests that diseconomies of scale exist at both the average and the median. Lewis, Springer, and Anderson (2003) report economies (increasing returns) to scale for 1995, 1996, and 1997, using assets as the measure of output. Bers and Springer (1997, 1998a,b) and Anderson, Springer, Fok, and Webb (2002) also report economies of scale for samples of REITs in the 1990s. The limited evidence for diseconomies of scale diminishes when we employ revenue as output or when we exclude the input price control variables.[12]

Our inefficiency estimates generally prove even smaller than those of Lewis, Springer, and Anderson (2003), who report dramatic reductions in inefficiency estimates when using the Bayesian stochastic frontier specification rather than DEA. For our model that comes closest to the Lewis, Springer, and Anderson (2003) specification, we report higher inefficiency (90 percent), on average, than they do (i.e., 10 to 30 percent). Our other measures of inefficiency fall to 13, 22, and 14 percent, on average.

Finally, we consider the effect of our control variables on the level of inefficiency across REITs and time. Consider again the simple model with output defined as assets. The constant term in the estimation of the average (mean) of the one-sided inefficiency term equals –1.6301. What does this imply? Since we estimate the mean of the truncated normal distribution function that captures the inefficiency, a negative mean implies that the normal distribution locates to the left of the origin. The distribution truncates the negative values, leaving only the right-side tail of the distribution. Now, consider the coefficient of self-management of 0.5978. Thus, for self-managed REITs, the self-management dummy variable equals 1 and the new mean of the truncated normal

---

[12] Bers and Springer (1997) do find that the number of REITs exhibiting economies of scale diminishes with the inclusion of other control variables

distribution equals –1.0323 (= –1.6301 + 0.5978). Thus, the distribution shifts to the right and the size of the truncated tail used to calculate the inefficiency becomes larger, implying that inefficiency rises. In sum, self-management generates more inefficient REITs in the specification closest to the Lewis, Springer, and Anderson (2003) model. They find that self-management reduces inefficiency in 1995 and 1996, but increases inefficiency in 1997. Our results consider the period from 1995 to 2003 and shows that for this specification self-management increases inefficiency, on average.

The debt-to-asset ratio provides consistent results across all specifications. To wit, a higher debt ratio associates with more efficient REIT operations. This finding counters the results of Lewis, Springer, and Anderson (2003) from their Bayesian stochastic frontier specification. Note, however, a key difference between our findings and those of Lewis, Springer, and Anderson. They consider the effects of self-management, the debt ratio, and portfolio diversification on a case-by-case basis. We include all control variables simultaneously.[13] Further, our specification of the frontier cost function includes the debt-to-asset ratio as a shift variable. More specifically, we find a significant effect whereby higher-leveraged REITs operate on a higher frontier cost function. But, given this finding, higher-leveraged REITs must exercise much more care in their operations, achieving higher efficiency than their lower-leveraged colleagues. Lewis, Springer, and Anderson (2003) do not use the debt-to-asset ratio to shift their cost frontier. Thus, the effect of the debt-to-asset ratio on the cost function dominates its effect on improving efficiency, probably leading to their conclusion that a high debt-to-asset ratio REIT exhibits more inefficiency (less efficiency).

Some evidence exists suggesting that REITs become more inefficient over time. Three coefficients prove significantly positive, and only one significantly negative in the complex

[13] We do not consider the portfolio diversification variable. But, Lewis, Springer, and Anderson (2003) find that this variable does not generate a consistent effect on REIT inefficiency.

specification with output measured by assets. We anticipated that REITs would become more efficient over time, since improved methods of operation should lower cost. It seems unlikely that REITs become less efficient over time without some external stimulus. Once possible explanation relates to increased regulatory control. We leave that conjecture for future research.

Finally, self-management exhibits contrary results, depending on whether we define output as assets or revenue. Self-managed REITs exhibit improved efficiency when we define output as revenue, but worsened efficiency when we define output as assets. That later finding proves consistent with the results of Bers and Springer (1998b) and Anderson, Springer, Fok, and Webb (2002) while the former, with Lewis, Springer, and Anderson (2003). In the conclusion, we speculate that REIT managers may focus much more energy on achieving revenue than assets, suggesting that revenue provides a better measure of REIT output.

V. Conclusions

The results show that the estimated returns to scale for publicly traded REITs do not support economies of scale. That is, our findings suggest either no economies or diseconomies of scale or possibly diseconomies of scale. Previous studies generally find economies of scale. Those studies use older data and cross-section analysis. Our panel-data model extends the coverage through 2003. The rapid growth in the size of REITs may suggest the exhaustion of economies of scale for all but the smaller firms in the industry. Breaking the sample into sub-periods and into size classes can provide further evidence on this issue. That is, given the dramatic growth in average REIT size over the sample period, the movement from economies of scale early in the sample period to diseconomies of scale at the end of the sample period makes intuitive sense. We leave such speculation for future research.

The initial tests of REIT efficiency using DEA report large inefficiencies (Anderson, Springer, Fok, and Webb, 2002; Anderson and Springer, 2003). Lewis, Springer, and Anderson (2003) employ a stochastic frontier and report much lower levels of inefficiency than either of the DEA studies. This study generally documents even lower inefficiencies. But, we also find that inefficiencies increase over time,

The finding that a higher debt-to-asset ratio associates with more efficiency runs counter to the findings of Lewis, Springer, and Anderson (2003). As noted in the text, we employ the debt-to-asset ratio to shift the frontier cost function as well as to explain the one-sided (inefficiency) error term. We do find that higher leverage raises the cost frontier as well as lowering inefficiency. Jensen (1986) argues that higher leverage can induce less efficiency through agency problems between managers and owners or more efficiency due to more intense external monitoring. Our results conform to that latter view.

Our results also offer some apparent contradictions to conventional wisdom as well as further insight into a better understanding the industry's rapid growth. Conventional wisdom and prior research suggest that self-managed REITs prove more efficient than the alternatives, namely affiliate- or third-party managed REITs. The results indicate different outcomes depending on our measure of output. When we measure output with assets, self-management associates with more inefficiency. This result supports an agency problem theory that managers act in their own self-interest to the detriment of the firm as a whole. When we measure output with revenue, self-management exhibits more efficiency, reversing the agency problem theory. How can we rationalize such findings? One possible explanation argues that revenue better captures the goal of managers. Thus, managers expend much effort to wring additional revenue out of their firm with much less concern about firm size, as measured by assets.

References:

Afriat, S. N., 1972. "Efficiency Estimation of Production Functions." *International Economic Review* 13, 568-98.

Aigner, D. J. and S. F. Chu, 1968. "On Estimating the Industry Production Function." *American Economic Review* 58, 826-39.

Aigner, D. J., C. A. K. Lovell, and P. Schmidt, 1977. "Formulation and Estimation of Stochastic Frontier Function Models." *Journal of Econometrics* 6, 21-37.

Ambrose, B. W., M. J. Highfield, and P. Linneman, 2005. "Real Estate and Economies of Scale: The Case of REITs." *Real Estate Economics* 33:2.

Ambrose, B. W., and A. Pennington-Cross, 2000. "Economies of Scale on Multi-Product Firms: The Case of REITs." Published Working Paper, Real Estate Research Institute, Bloomington, IN.

Anderson, R. I., D. Lewis, and T. M. Springer, 2000. "Operating Efficiencies in Real Estate: A Review of the Literature." *Journal of Real Estate Literature* 8:1, 3-20.

Anderson, R. I., and T. M. Springer, 2003. "REIT Selection and Portfolio Construction: Using Operating Efficiency as an Indicator of Performance." *Journal of Real Estate Portfolio Management* 9:1 17-28.

Anderson, R. I., T. M. Springer, R. Fok, and J. R. Webb, 2002. "Technical Efficiencies and Economies of Scale: A NonParametric Analysis of REIT Operating Efficiency." *European Journal of Operational Research*

Banker, R.. D., and A. Maindiratta, 1992. "Maximum Likelihood Estimation on Monotone and Concave Production Frontiers." *Journal of Productivity Analysis* 3, 401-15.

Battese, G. E, and T. J. Coelli, 1992. "Frontier Production Functions, Technical Efficiency, and Panel Data: With Applications to Paddy Farmers in India." *Journal of Productivity Analysis* 3: 153-169.

Battese G. E., and T. J. Coelli, 1995. "A Model of Technical Inefficiency effects in a Stochastic Frontier Production Function for Panel Data." *Empirical Economics* 20, 352-332.

Bauer, P. W., 1990. "Recent Developments in the Econometric Estimation of Frontiers." *Journal of Econometrics* 46, 39-56.

Berger, A. N., and D. B. Humphrey, 1991. "The Dominance of Inefficiencies Over Scale and Product Mix Economies in Banking." *Journal of Monetary Economics* 28, 117-48.

Bers, M., and T. M. Springer, 1997. “Economies-of-Scale for Real Estate Investment Trusts.” *Journal of Real Estate Research* 14:3, 275-290.

Bers, M., and T. M. Springer, 1998a. “Sources of Scale Economies for Real Estate Investment Trusts.” *Real Estate Finance* (Winter/Spring) 37-44.

Bers, M., and T.M. Springer, 1998b. “Differences in Scale Economies Among Real Estate Investment Trusts: More Evidence.” *Real Estate Finance* (Fall) 37-44.

Coelli, T. J., 1996. “A Guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation.” CEPA Working Paper 97/07, Center for Efficiency and Productivity Analysis, University of New England, Armidale.

Cornwell, C., P. Schmidt, and R. C. Sickles, 1990. “ Production Frontier with Cross-Sectional and Times-Series Variation in Efficiency Levels.” *Journal of Econometrics* 46: 185-200.

Cowing, T. G., D. Reifschneider, and R. E. Stevenson, 1983. "A Comparison of Alternative Frontier Cost Function Specifications." in *Developments in Econometric Analyses of Productivity*, ed. by Ali Dogramaci, Kluwer-Nijhoff, Chapter 4.

Farrell, M. J., 1957 "The Measurement of Productive Efficiency." *Journal of the Royal Statistical Society* 120 (series A), 253-81.

Førsund, F. R., C. A. K. Lovell, and P. Schmidt, 1980. "A Survey of Frontier Production Functions and of Their Relationship to Efficiency Measurement." *Journal of Econometrics* 13, 5-25.

Greene, W. H., 1990. "A Gamma-Distributed Stochastic Frontier Model." *Journal of Econometrics* 46, 141-63.

Jensen, M. C., 1986. “Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers.” *American Economic Review, Papers and Proceedings* 76, 323-329.

Jondrow, J., C. A. K. Lovell, I. S. Materov, and P. Schmidt, 1982. "On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model." *Journal of Econometrics* 19, 233-38.

Kumbhakar, S. C., 1990. “Production Frontiers, Panel Data, and Time Varying Technical Inefficiency.” *Journal of Econometrics* 27: 201-11.

Lawrence, C., 1989. "Banking Costs, Generalized Functional Forms, and Estimation of Economies of Scale and Scope." *Journal of Money, Credit and Banking* 21, 368-79.

Lewis, D., T. M. Springer, and R. Anderson, 2003. “The Cost Efficiency of Real Estate Investment Trusts: An Analysis with a Bayesian Frontier Model.” *The Journal of Real Estate Finance and Economics* 26:1, 65-80.

Linneman, P., 1997. “Forces Changing the Real Estate Industry Forever.” *Wharton Real Estate Review* (Spring) 1-12.

Meeusen, W., and J. van den Broek, 1977. "Efficiency Estimation from Cobb-Douglas Production Functions with Composite Errors." *International Economic Review* 18, 435-44.

Noulas, A. G., S. C. Ray, and S. M. Miller, 1990. "Returns to Scale and Input Substitution for Large U. S. Banks." *Journal of Money, Credit and Banking* 22, 94-108.

Noulas, A. G., S. M. Miller, and S. C. Ray, 1993. "Economies and Diseconomies of Scope in Large-Sized U. S. Banks." *Journal of Financial Services Research* 7, 235-248.

Richmond, J., 1974 "Estimating the Efficiency of Production." *International Economic Review* 15, 515-21.

Schmidt, P., 1985-86. "Frontier Production Functions." *Econometric Reviews* 4, 289-328.

Stigler, G. J., 1976. "The Xistence of X-efficiency." *American Economic Review* 66, 213-38.

Timmer, C. P., 1971. "Using a Probabilistic Frontier Function to Measure Technical Efficiency." *Journal of Political Economy* 79, 776-94.

van den Broek, J., F. R. Førsund, L. Hjalmarsson, and W. Meeusen, 1980. "On the Estimation of Deterministic and Stochastic Frontier Production Functions." *Journal of Econometrics* 13, 117-38.

Vogel, J. H., Jr., 1997. “Why the New Conventional Wisdom About REITs is Wrong.” *Real Estate Finance*, 7-12.

Table 1: Summary Statistics

Variable	Average	Median	Maximum	Minimum
lnCost	11.0783	11.2330	15.9116	2.6391
lnAsset	13.2183	13.4453	17.0662	7.2779
lnRevenue	11.3127	11.5140	15.9870	2.0794
ln(1+i)	0.0653	0.0631	1.0756	0.0000
ln(1+r)	0.1051	0.0784	1.7815	0.0012
Time	4.7942	5.0000	9.0000	1.0000
Self-Manage	0.7758	1.0000	1.0000	0.0000
Debt-Ratio	0.4941	0.4881	0.9964	0.0031

Note: The symbol ln stands for the natural logarithm. Cost includes interest expense, operating expense, general and administrative expense, and management fees interest cost on all deposits. Asset equals total assets. Revenue equals total revenue. We calculate the input prices as follows: *i* equals the average interest cost per dollar of debt and *r* equals the average other expenses per dollar of assets. Time runs from 1 to 9 capturing 1995 to 2003. Self-Manage equals one for self-managed REITs; 0 otherwise. Debt-Ratio equals the ratio of total debt to total assets.

Table 2: Translog Cost Function with Output Measured as Total Assets

Variable	Coefficient	t-ratio	Coefficient	t-ratio
Cost Frontier Estimates				
Constant1	-1.1090	-1.54	-4.0884*	-15.52
lnAss	0.6217*	5.63	1.0166*	26.88
lnAss*lnAss	0.0143*	3.33	0.0005	0.39
ln(1+i)			10.1945*	10.37
ln(1+i)*ln(1+i)			-5.3714*	-17.22
ln(1+r)			7.5172*	19.29
ln(1+r)*ln(1+r)			-2.9532*	-42.84
lnAss*ln(1+i)			-0.1027*	-2.62
lnAss*ln(1+r)			0.0129	0.88
ln(1+i)*ln(1+r)			-4.6010*	-13.30
Debt-Ratio	2.0825*	29.41	0.9097*	32.54
One-Sided Error (Inefficiency) Estimates				
Constant2	-1.6301*	-5.27	0.0148	0.56
Time	0.2886*	13.47	-0.0055*	-5.70
Self-Manage	0.5978*	3.59	0.1068*	2.68
Debt-Ratio	-11.5772*	-34.08	-0.0716*	-4.41
Average Efficiency	1.9018		1.1349	
Sigma-Squared	2.4366*	16.49	0.0509*	30.10
Gamma	0.9368*	173.46	0.0019**	1.80
Economies of Scale				
Average	0.9997		1.0245	
Median	1.0062		1.0246	
Maximum	1.1098		1.0283	
Minimum	0.8298		1.0185	

Note: See Table 1. We specify the cost frontier as a translog function where the debt-to-asset ratio shifts the intercept. Ass equals total assets. Sigma-squared (σ^2) equals $\sigma_v^2 + \sigma_u^2$ and gamma equals σ_u^2/σ^2.

* means significantly different from zero at the 1-percent level.
** means significantly different from zero at the 5-percent level.

Table 3: Translog Cost Function with Output Measured as Total Revenue

Variable	Coefficient	t-ratio	Coefficient	t-ratio
Cost Frontier Estimates				
Constant1	0.7428*	5.39	0.4493*	2.94
lnRev	0.6981*	28.89	0.7469*	27.26
lnRev*lnRev	0.0136*	12.31	0.0113*	8.95
ln(1+i)			-0.3388	-0.37
ln(1+i)*ln(1+i)			-0.9255*	-2.97
ln(1+r)			3.9068*	12.29
ln(1+r)*ln(1+r)			-0.7522*	-8.17
lnRev*ln(1+I)			0.0615	1.39
lnRev*ln(1+r)			-0.0893*	-6.43
ln(1+i)*ln(1+r)			0.0374	0.10
Debt-Ratio	0.9819*	30.13	0.7020*	23.68
One-Sided Error (Inefficiency) Estimates				
Constant2	-2.3940*	-4.49	-6.2220*	-3.58
Time	0.1490*	5.07	0.1971*	10.70
Self-Manage	-0.7536*	-10.19	-1.0972**	-2.46
Debt-Ratio	-4.9426*	-20.58	0.0034	0.00
Average Efficiency	1.2211		1.1404	
Sigma-Squared	0.8796*	8.02	0.7813*	3.84
Gamma	0.9621*	197.33	0.9620*	80.79
Economies of Scale				
Average	1.0058		0.9972	
Median	1.0113		1.0071	
Maximum	1.1329		1.1028	
Minimum	0.7547		0.7885	

Note: See Tables 1 and 2. Rev equal total revenue.

* means significantly different from zero at the 1-percent level.
** means significantly different from zero at the 5-percent level.