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Using a panel data set on the local telecommunications companies reporting to the FCC for 1988-95, this paper investigates the subadditivity of the cost function, as well as technical and allocative inefficiency of the U.S. local telephone industry. The subadditivity test on the estimated translog cost function indicates that certain subdivisions of the monopolized regional markets between two hypothetical firms might lower total cost. However, the evidence is not as clear cut as in an earlier study by Shin and Ying (1992, RAND), with savings from a two-firm industry being negative on average over all possible two-firm output vector combinations. The results of the subadditivity test suggest that companies with a relatively high share of residential customers experience higher degrees of scale inefficiency. Specification of technical inefficiency as fixed company-specific effects results in a different efficiency ranking than the specification with random effects. The estimation results for the generalized (non-minimum) cost model suggest that capital is being under-employed relative to residual inputs. This finding does not support the theoretical prediction that an industry under rate of return regulation tends to over-employ

capital relative to other inputs. The subadditivity test for the generalized cost function that accounts for technical and allocative inefficiency generated a much more favorable estimates of cost reductions from the subdivision of the monopolized markets than the test on the conventional specification of the cost function. The estimated losses from technical, allocative and scale inefficiency reflect potential gains from competition.

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by

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COST STRUCTURE OF THE LOCAL TELECOMMUNICATIONS INDUSTRY

1. INTRODUCTION

The objective of this paper is to study cost structure of the U.S. local telecommunications industry and answer the following two questions. Is local telecommunications service a natural monopoly? Is local service provided efficiently? The answer to the first question is crucial in determining the optimal market structure of the industry – competition or regulated monopoly. The second issue is important as it gives an estimate of the degree of productive inefficiency in this industry that has been regulated as a natural monopoly until the issuance of the Telecommunications Act of 1996. Government regulation of a monopoly can induce inefficiency, and therefore, monetary measure of inefficiency reflects potential benefits of competition in this industry.

The 1982 court decree[1] that ended the antitrust case against AT&T separated telecommunications services in the USA into two distinctive parts, long distance and local markets. The decree created special geographic areas (called Local Access and Transport Areas or *LATAs*) around population centers and defined local markets as any telephone service within these areas. As a result of this decree, long distance markets became open to competition, while local markets remained under government regulation as natural monopolies. The decree assigned a single local service provider to each local area and prohibited local companies from entering long-distance markets. Long distance

[1] U.S. vs. AT&T. Modification of Final Judgment. January 6, 1982.

companies, which carry calls between local access and transport areas, were not allowed to enter local markets.

In the late 80's state governments, which regulate the intrastate intraLATA jurisdictions, began to open the intraLATA toll markets to competition. Today intraLATA toll competition is permitted in most states. The local telecommunications industry remained under rate of return regulation at the federal level until 1990, and some states continued to impose rate of return regulation after 1990.

Local telephone companies own local telecommunications networks – wires, poles, switching facilities – that constitute an essential input for telephone service providers. These local telephone networks present an economic barrier to entry into local telephone markets. Until recently, regulatory authorities in the U.S. believed that it would be wasteful to allow more than one company in a local telephone market because a new entrant would have to build its own local telephone network, thus, duplicating the existing facilities. The Telecommunications Act of 1996 reversed the traditional policy that local telephone markets should be regulated monopolies. The Act not only removed legal barriers to entry into local telephone markets, but also created guidelines designed to eliminate economic barriers to entry. In particular, the Act obliged the incumbent local telephone companies to provide access to their network facilities to new entrants at a just and nondiscriminatory price[2].

The provisions of the Act indicate that regulatory authorities do not consider local telecommunications industry to be a natural monopoly. Despite this important change in

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[2] Telecommunications Act of 1996, section 252(c).

the regulatory attitude, little evidence exists regarding the production structure of the industry. Apart from technological arguments of the feasibility of bypass of the local telephone networks, the only empirical evidence against the natural monopoly status of the local telecommunications industry is a study by Shin and Ying (1992). This paper rejected the natural monopoly hypothesis by conducting a subadditivity test on the estimated cost function of the U.S. local telecommunications industry.

A new study of the cost function of local telecommunications can shed light over the future market structure and explain the current developments in the industry – the lack of competitive entry and a series of mergers between local telecommunications companies.

The first purpose of this paper is to conduct a subadditivity test on the U.S. local telecommunications industry. The subadditivity test, which is based on Shin and Ying (1992), improves on their work in the following aspects: 1. While their results were based on the old, pre-divestiture data, I use recent data, which are more relevant to the current production structure of this industry that has been experiencing rapid technological changes. 2. Strong multicollinearity in the data set of Shin and Ying could have affected their findings. I reduce multicollinearity by changing the definitions of the output variables. 3. Instead of the traditional iterative SUR technique, I apply an asymptotically efficient estimator of Mandy and Martins-Filho (1993). This estimator is designed to correct for heteroscedasticity that naturally emerges in a system of cost and share equations and has been first pointed out by Chavas and Segerson (1987). 4. I use a different set of independent variables that, as explained below, better account for the cost variations in the local telephone industry.

The second purpose of this paper is to estimate the degree of technical and allocative inefficiency of the telecommunications firms. The issue of production efficiency has been given little attention in the empirical literature, despite the existence of technological and institutional factors that might cause inefficiency, such as rate of return regulation, unionized labor and large investment cycles. Regulatory authorities have been using econometric cost studies of telecommunications in support of major institutional changes. Such well-known studies as Evans and Heckman (1984), Shin and Ying (1992) were based on the theoretical assumptions of the cost minimization that might not hold in reality. If telecommunications firms are productively inefficient, then the estimated parameters of a cost model that ignores inefficiency lack the desirable statistical properties, and therefore, the subadditivity measures are distorted.

To my knowledge, this study presents the first attempt to estimate technical inefficiency and the second attempt after Oum and Zhang (1995) to estimate allocative inefficiency in telecommunications. I adopt the same generalized cost function approach as Oum and Zhang, but improve upon their work in the following directions: 1. I use disaggregated panel data on the local telephone companies instead of aggregating long-distance and local markets into one observation. 2. I estimate allocative inefficiency on the level of holding companies, while Oum and Zhang estimated it only on the industry level. 3. As opposed to Oum and Zhang , I use non-monetary measures of the output, thus, isolating fluctuations in the output prices from the cost model. 4. I estimate relative technical inefficiency of the holding companies simultaneously with allocative inefficiency.

The major findings of my paper are as follows. First, comparison of the costs of the monopoly provision of the local telecommunications service to the costs of different two-firm industry configurations resulted in numerous violations of the subadditivity condition, indicating that the local telecommunications industry is not a natural monopoly. In general, my subadditivity results present a weaker evidence against natural monopoly than Shin and Ying's (1992). Though the point estimates of maximum savings from a two-firm industry compared to a monopolized industry are positive, average savings are negative for most observations and as a total.

Second, I found no substantial qualitative difference between the subadditivity results generated by the SUR technique, which ignores heteroscedasticity inherent to a system of cost and share equations, and the estimator of Mandy and Martins-Filho (1993), which corrects for heteroscedasticity.

Third, my estimates indicate that telecommunications firms exhibit different levels of relative technical inefficiency. The two alternative assumptions about the nature of technical inefficiency – deterministic versus stochastic effects – produce different rankings of the firms in terms of relative technical efficiency.

Fourth, contrary to the theoretical predictions about the effects of rate of return regulation, my allocative inefficiency estimates indicate that capital was under-employed relative to materials.

Fifth, the subadditivity test on the generalized cost function that accounts for technical and allocative inefficiency provides a much stronger evidence of potential savings from the division of the monopolized markets than the traditional cost function.

2. METHODOLOGY AND LITERATURE REVIEW

2.1. Subadditivity of the Cost Function

2.1.1. Natural Monopoly in the Multiproduct Context

An industry is a *natural monopoly* if its cost function is subadditive. An industry cost function is *subadditive* if one firm can produce any given output vector Q at a cost $C\,(Q)$ that is lower than the costs of producing the same output by any combination of two or more firms. Formally,

$$C\,(Q) < \sum_{i=1}^{n} C(q^i) \text{ for all } n = 2,3,\ldots, \text{ and any vectors } Q,\ q^i \text{ such that } \sum_{i=1}^{n} q^i = Q \qquad (2.1)$$

Despite the simplicity of the definition, it is often impossible to determine whether a particular multiproduct cost function is subadditive by examining its mathematical expression. Instead, empirical studies often test for the presence of various necessary or sufficient conditions for subadditivity. The rejection of the necessary conditions presents evidence against subadditivity, while failure to reject sufficient conditions is interpreted as evidence in support of subadditivity.

Baumol, Panzar and Willig (1988) developed the most comprehensive list of necessary and sufficient conditions for subadditivity. They name two necessary conditions: economies of scope and ray subadditivity.

A cost function exhibits *economies of scope* if the following condition is satisfied: $C(Q) < \sum_{i=1}^{n} C(q_{Ti})$ for any partition $\{q_{T1}, q_{T2}, \ldots q_{Tn}\}$ of the m-dimensional vector Q such that $q_{Ti} \cap q_{Tj} = \emptyset$ for $i \neq j$ and $\bigcup_{i=1}^{n} q_{T_i} = Q$.

A cost function is *ray subadditive* at Q if $C(Q) < \sum_{i=1}^{n} C(v_i Q)$ for any set of two or more $v_i > 0$ such that $\sum_{i=1}^{n} v_i = 1$.

While economies of scope indicate economies in joint production, the concept of ray subadditivity captures single-dimensional economies of scale – decreasing average cost along the ray.

A sufficient condition for subadditivity combines two requirements: 1) economies of scope; and 2) decreasing average incremental costs of each product. The *average incremental cost* of product j is defined as $AIC_j(Q) = (C(Q) - C(Q_{m-j})) / Q_j$, where $Q_{m-j} = (Q_1, Q_2, ..Q_{j-1}, 0, Q_{j+1}, \ldots Q_m)$.

2.1.2. Empirical Tests of Subadditivity

Empirical tests for subadditivity are complicated by the fact that subadditivity is a global property. These tests may require information on the values of the cost function for output levels that lie outside the range of the observed output levels. For example, calculating economies of scope requires knowledge of the stand-alone costs of each product, which are often not observed in a multiproduct industry. The global nature of subadditivity also creates asymmetry in informational requirements necessary to prove or reject subadditivity. On the one hand, in order to establish subadditivity, the researcher needs information on the costs of all potential levels of output. On the other hand, a local violation of subadditivity is sufficient to reject global subadditivity.

Most empirical studies on the subject use estimates of the industry cost function to check for the satisfaction of certain necessary or sufficient conditions for subadditivity. Sing (1987) used cross-sectional data on U.S. firms to estimate the hybrid translog cost function of the combination of gas and electric utilities. The data set contained information on joint, as well as separate production of gas and electricity, which allowed the author to examine economies of scope. Sing found that the estimated cost function had regions of both economies and diseconomies of scope, with no economies of scope present at the mean. Thus, one of the necessary conditions for subadditivity was violated.

Kim (1987) evaluated product-specific economies of scale for U.S. water utilities by estimating average incremental costs and ray average cost curves. Although the data set did not contain observations on stand-alone costs, the author used arbitrary small levels of one output (instead of zero) to evaluate the incremental cost of producing the other output. This method generated decreasing average incremental cost of nonresidential water, and increasing average incremental cost of residential water. The result was insufficient to establish cost subadditivity. Ray average cost functions appeared to be U-shaped, thus, violating necessary condition for subadditivity.

Pulley and Braunstein (1992) used the same "quasi-scope" measure as Kim (1987) to avoid extrapolation problem. Instead of stand-alone cost, their scope measure included cost of specialized production with non-specialized outputs produced in small quantities. The authors found that the estimates of scope economies in banking varied with respect to the choice of the functional form for the cost model.

Some studies estimate economies of scope by evaluating the sign of the derivative of the marginal cost of one output with respect to another output. Keeler and Fromby (1994) calculated the values of the second cross derivative of an estimated cost function of the U.S. airline industry. They found that the sign was consistently negative for each observation in their data set, implying economies of scope between passenger and freight services.

Hunt and Lynk (1990) and Seabra (1993) conducted empirical tests of another sufficient condition for subadditivity – the simultaneous existence of ray subadditivity and transray convexity of the cost function. *Transray convexity* at a given output point implies that the cost function is convex alone a hyperplane that connects the given output point to the output axes. In other words, transray convexity indicates that the weighted average cost of specialized production is higher than the cost of producing a weighted average of the specialized vectors jointly. In order to verify transray convexity, both studies evaluated the minors of the bordered Hessian defined in Baumol, Panzar and Willig (1988, p.456).

Hunt and Lynk (1990) used cointegration analysis to estimate the long-run cost function of the British telecommunications using a time series data set for 1951-81. Because of the simple functional form of the cointegrating regression, both the transray convexity and ray subadditivity followed directly from the negative sign on the interaction term between the two outputs. The authors concluded that the British telecommunications industry was a natural monopoly.

The study by Seabra (1993) used time-series data for 1950-79 on the Portuguese telecommunications industry. The estimated hybrid translog cost function exhibited strong overall economies of scale. Transray convexity followed from the signs of the estimated coefficients. The presence of the sufficient conditions for subadditivity allowed Seabra to conclude that the Portuguese telecommunications industry was a natural monopoly. However, the study seems to be incomplete because the author limited the subadditivity analysis to the year of normalization, instead of checking the sufficient condition for each year of observation in the sample..

Guldmann (1990) used the estimated cost function for a cross section of small local exchange carriers to evaluate potential cost savings from competition. The author used two measures of the output in the model – the number of telephone lines and the service territory. He found that the level of economies of scale and density declined with size, and larger firms in the sample experienced diseconomies of scale. Guldmann calculated the costs of the competitive provision of the telephone services using several alternative configurations of the market. The author found that the costs of competitive market organization tend to be lower than the costs of monopoly in larger markets. Territorial division of the markets turned out to be cost effective for most markets, while *side-by-side competition* (division of customers within the same territory between two or more firms) was cost effective only in several markets. The author concluded that the optimal size of a telecommunications firm is small, but emphasized two limitations of the study. First, his results applied primarily to small companies serving low density telephone markets. Second, calculation of total costs of a competitive market using the estimated cost function of a monopoly does not account for the cost of interconnection necessary when the market is divided.

Gabel and Kennet (1994) used an engineering model of local telecommunications to test for the presence of scope economies – one of the necessary conditions for subadditivity. Using the simulation model, they evaluated costs necessary to provide different combinations of the four outputs – local and toll switched services, local and toll private lines. Gabel and Kennet found diseconomies of scope between the switched and non-switched services (private lines) in densely populated markets, and strong economies of scope between switched services in all markets. Although the necessary condition for subadditivity was violated, the authors decided that the presence of diseconomies of scope in densely populated markets was not a sufficient evidence to prove *superadditivity* of the cost function.

Evans and Heckman (1983, 1984) were the first to propose and implement a local test for natural monopoly based on the definition of subadditivity itself rather than its necessary or sufficient conditions. The test was based on the idea that if subadditivity is rejected over one region, then global subadditivity is also rejected, and the industry is not a natural monopoly. Evans and Heckman estimated a two-output cost function of a regulated monopoly and used the parameter estimates to calculate cost of a hypothetical two-firm industry. They compared the cost of a monopoly to the cost of all possible two-firm industry configurations for all output levels in an admissible region R. In other words, they checked the following reduced version of the definition of the subadditive cost function (2.1):

$$C(Q) < C(q^1) + C(q^2) \text{ for any observed } Q \text{ and } q^1, q^2 \in R : q^1 + q^2 = Q \quad (2.2)$$

The authors restricted the admissible region R to the values of the output vectors that satisfy the following two requirements: a) no hypothetical firm produces less than the observed level of each product; b) the output structures of both hypothetical firms lie within the range of the observed ratios of the two products.

In order to empirically implement the test, Evans and Heckman evaluated the cost function for the finite number of two-firm output combinations constructed using a grid. They measured the degree of subadditivity as a percentage difference between the cost of a monopoly and the cost of a two-firm industry. Evans and Heckman used the maximum values of the percentage difference in cost for each data point as an indicator of subadditivity. Negative values of the maximum percentage difference supported the subadditivity hypothesis, while positive values indicated violation of subadditivity.

Evans and Heckman applied their subadditivity test to the U.S. telephone industry. They estimated an autoregressive translog cost and share system using aggregated time-series data on the Bell system for 1947-77. Their specification included three inputs – capital, labor and materials, and two outputs – toll and local calls. The authors controlled for technological change by including an index of lagged R&D expenditures by Bell Laboratories. They found that the calculated maximum percentage differences between the costs of monopoly and the two-firm industry were positive for 1959-77, and no two-firm output combinations in the admissible region existed for 1947-58. The results suggested that the cost function of the Bell System was not subadditive for the period of study.

Roller (1990a, 1990b) noted that the translog cost function estimated by Evans and Heckman violated monotonicity as one of the outputs was approaching zero. In Roller's interpretation, the calculated savings from a two-firm configuration actually stemmed from negative marginal costs. Roller (1990a) modified the subadditivity test of Evans and Heckman by restricting the admissible region further to output combinations with positive marginal cost. The results of his modified test did not contradict the natural monopoly hypothesis. Roller (1990b) estimated an alternative functional form that imposes regularity conditions prior to estimation – generalized CES quadratic function – using the same data. He found no violations of local subadditivity – his maximum percentage differences between the costs of a monopoly and a two-firm industry were negative for all years.

Shin and Ying (1992) applied the subadditivity test of Evans and Heckman using an estimated translog cost function of the U.S. local telephone industry. Their data set contained a much broader and detailed sample of 58 local exchange carriers during 1976-83. The output vector included three components – toll and local calls, and the number of telephone lines. Shin and Ying widened the admissible region by allowing the outputs of the two hypothetical firms to vary from 10 to 90 % of each monopoly observation. They also modified the subadditivity test of Evans and Heckman by concentrating not on the maximum percentage savings from a two-firm industry, but on the average percentage savings and their distribution.

Shin and Ying found that the average percentage savings from a two-firm industry configuration aggregated annually were positive for all years and varied from 1.6 % to 3.8 % of the monopoly cost in each year. Monopoly costs were lower than the costs of the two-firm industry in the minority of cases, ranging from 20 % of all possible output configurations in 1976 to 40 % in 1982. Their findings suggested that the cost function of local telephone industry was not subadditive. Following Roller's criticism, Shin and Ying repeated the subadditivity test with the restriction that narrowed the admissible region to the output combinations with positive marginal cost. Imposition of this restriction only re-enforced the conclusion that the industry was not a natural monopoly during the period of study.

Gentzoglanis (1993) applied the subadditivity test of Evans and Heckman to a time series data set on a small Canadian publicly owned telecommunications firm. The author found no evidence against the natural monopoly hypothesis. However, the robustness of the results is questionable due to the small size of the data set, which contained only 18 observations.

A study by Gilsdorf (1995) presents a rare application of the subadditivity test to an industry other than telecommunications. The purpose of the study was to examine whether a vertically integrated electric utility exhibits natural monopoly properties. Thus, the two outputs measured the two stages of production – electric generation and distribution. Gilsdorf adopted the test procedure of Evans and Heckman (1983) with Roller's (1990a) restriction on marginal cost. The resulting values of the maximum percentage difference between the costs of the two alternative industry configurations turned out to be positive for 37 out of 53 companies, and at the sample mean; however, none of the signs for the maximum difference were statistically significant. The author rejected the hypothesis that integrated electric utilities were multistage natural monopolies.

2.2. Measurement of Production Performance

2.2.1. Introduction to Technical and Allocative Inefficiency

The estimation of a cost function assumes that the observed costs are generated from the solution to the following minimization problem:

$$C(W,Q) \;=\; min_L\; W*L\;\; s.t.\, f(L) \geq Q \tag{2.3}$$

where L = input vector;
Q = exogenous output vector;
W = exogenous input price vector;
C = cost of producing output Q given input prices W;
$f(L)$ = exogenous production function.

Cost minimization, as described above, might not occur for a number of reasons, including government regulation, unionized labor and the incentive systems that exist inside the firms. Government regulation and unionization might distort input prices. Internal incentive systems can create a discrepancy between the goals of the employees and the goals of the firm. For example, a bonus system that is tied to the performance of the company stock might induce managers of the company to avoid major capital investments, because these investments can lower the stock price. The violation of cost minimization results in cost inefficiency, defined as production of the observed level of the output at cost higher that the minimum possible cost.

Farrell (1957) decomposed cost inefficiency into technical and allocative inefficiency. *Technical inefficiency* occurs if a proportionally reduced input vector can still produce the observed level of the output. In other words, a technically efficient firm uses the smallest input vector to produce a given output. *Allocative inefficiency* occurs if the observed combination of input quantities deviates from the cost minimizing combination of inputs. Allocative inefficiency means that the marginal rate of substitution between some pairs of inputs is not equal to the ratio of the corresponding input prices.

Technical inefficiency indicates reduced productivity of all inputs, which can be caused by exogenous shocks such as adverse weather conditions or by endogenous factors such as internal incentive systems.

Allocative inefficiency might be caused by firms' inability to adjust certain inputs in a short period of time. A firm whose operations require substantial levels of fixed capital structures might not be able to quickly change its capital stock in response to changing relative prices of capital. Because of the lengths of investment projects, a firm that experiences an unexpected growth in demand might need to temporarily substitute other inputs for capital. If demand drops, a firm might not be able to reduce capital stock because of the negative salvage value of the embedded stock.

Allocative inefficiency can be treated as a situation in which firms base their decisions on a set of shadow prices that are not observed by econometricians. Government regulation or legal contracts may impose additional constraints on the minimization problem and create systematic deviations of the shadow prices from the observed prices. If systematic discrepancy between the shadow and the observed input prices exists, then the ratios of the observed input prices are not equal to the corresponding ratios of marginal products. A well-known example of this approach is the Averch-Johnson (1962) effect, which suggests that a firm subject to rate of return regulation may use more than the cost-minimizing share of capital.

2.2.2. Technical Inefficiency

Technical inefficiency is modeled by estimating the production or cost *frontier* rather than the "average" production or cost functions. Schmidt and Lovell (1979) were the first to estimate a stochastic production frontier system using Aigner's *et al.* (1977) specification of technical inefficiency as a factor that reduces productivity of all inputs. In this specification the technical inefficiency factor shifts the cost function C away from the cost frontier C^F. The natural logarithm of the cost function derived using this specification of technical inefficiency is a sum of the natural logarithm of the cost frontier ($ln\ C^F$) and the error term that includes not only the white noise disturbance ε, but also a nonnegative disturbance μ that accounts for technical inefficiency:

$$ln\ C = ln\ C^F + \varepsilon + \mu \qquad (2.4)$$

If the technical inefficiency term is assumed to vary over firms but not over time, then firm-specific technical inefficiency can be identified in a panel data framework. The technical inefficiency measure for firm i is defined as the difference between the firm-specific estimate for μ_i (m_i) and the estimate m_j for the most efficient firm in the sample:

$$technical\ efficiency_i = m_i - min\{m_j\} \qquad (2.5)$$

If the inefficiency term μ_i is assumed to be fixed (nonstochastic), then the frontier cost model in logarithmic representation reduces to a traditional cost model, but with firm-specific intercepts. This model is estimated using the *within* estimator or, equivalently, the Dummy Variable model with $intercept = \Sigma_i\ \mu_i\ D_i$, where D_i is a binary variable that corresponds to firm i. The least-squares estimates for μ_i are then used to measure technical efficiency as defined in equation 2.5.

If the inefficiency term μ_i is treated as random with firm-specific variance and the expected value that is constant over firms, then the model is estimated using methods that take into account the structure of the composite error term $\varepsilon_{it} + \mu_i$. The Feasible Generalized Least Squares (FGLS) methods present a two-step estimation that uses residuals from the within model to estimate the unknown variance of the composite error (see, for example, Greene, 1990, pp. 474-476, Kumbhakar, 1997a[3] for details). The estimates for the firm-specific disturbances μ_i are then obtained from the residuals of the estimated model. The FGLS assumes that firm-specific random effects μ_i are independent of the explanatory variables in the model. If this assumption does not hold, then the FGLS estimates are biased and inconsistent (see Judge *et al.*, 1985, pp. 527-529, for the discussion of fixed versus random effects). The Maximum Likelihood method is an alternative to the FGLS, though it requires additional distributional assumption for ε, μ and the explanatory variables.

Seale (1990) compared four stochastic frontier estimation methods – OLS, within, FGLS and Maximum Likelihood – applied to an unbalanced panel data of Egyptian floor tileries. Using Hausman specification test, he concluded that the within estimator that treats firm-specific effects as fixed, was the best estimator for the sample, with the Maximum Likelihood estimator being the second best. Seale interpreted the results of the test as evidence that the technical inefficiency terms are correlated with the explanatory variables in his production frontier system.

Färe and Lovell (1978) distinguished two measures of technical inefficiency – *input technical inefficiency*, defined as over-employment of inputs to produce a given level of the output, and *output technical inefficiency*, defined as failure to produce the maximum possible output with the given inputs. Input technical efficiency is measured as a factor that scales **inputs** from the production frontier, while output technical efficiency is a factor

[3] See section 3.2 for the description of Kumbhakar's (1997a) method.

that scales **output** down from the production frontier. Färe and Lovell showed that the two measures are equivalent only under constant returns to scale.

Atkinson and Cornwell (1993) derived dual measures of input and output efficiency as fixed parameters of a cost frontier. They defined input technical efficiency similar to Aigner *et al.* (1977), as a firm-specific parameter $a_i \geq 1$ that scales the cost frontier down: $C_i = \frac{1}{a_i} C(Q_i, W_i)$. Thus, input inefficiency parameter a_i represented the potential reduction in cost that firm *i* could achieve without decreasing the output level. Output technical efficiency was introduced as a parameter $b_i \leq 1$ that scales output up, to reflect the potential increase in the output possible without reducing inputs:

$$C_i = C(\frac{Q_i}{b_i}, W_i).$$

While the input efficiency parameter in a translog version of the cost model is absorbed in the firm-specific intercept and can be estimated using the above mentioned within estimator, the output technical efficiency specification makes the translog system nonlinear in parameters. This system can be estimated by either nonlinear least squares or maximum likelihood methods. Atkinson and Cornwell estimated both measures of technical efficiency for a panel sample of airline carries using the translog specification of the cost function and found that the two measures gave substantially different efficiency rankings.

2.2.3. Generalized Cost Functions

A generalized cost function relaxes the assumption that the observed input prices are equal to the *shadow prices* – prices that firms use in cost optimization. The shadow input prices, which are considered known to the firm but not to the econometrician, are assumed to depend on the observed input prices, as well as on some inefficiency parameters.

Lau and Yotopoulos (1971) introduced the shadow price specification that is now common in parametric studies of allocative inefficiency. They defined the shadow price of input j ($W^{sh\,j}$) as a product of the observed input price (w^j) and the unobserved inefficiency parameter (ξ^j) in their estimation of the profit function with Cobb-Douglas technology: $W^{sh\,j} = \xi^j \; w^j$. If the inefficiency parameter ξ^j is greater than one, then the shadow price of the input is greater than the observed price, and therefore, the quantity of the input employed by the firm is less than the amount derived from minimization of the cost function using actual input prices. If the inefficiency parameter is less than one, then the firm over-employs the input. If the inefficiency parameter is equal to one, then the shadow input price equals to the actual price, and no allocative inefficiency is present.

Toda (1976) adopted the same specification of the shadow input prices in order to estimate a cost function. Prior to estimation, Toda derived the observed cost function from the conditions of minimization of the shadow cost function for the Generalized Leontief functional form. Atkinson and Halvorsen (1980, 1984) extended the above approach to the translog forms of the cost and profit functions. Eakin and Kniesner (1988) used an additive specification of allocative inefficiency by modeling the inefficiency parameter as the difference, rather than the ratio, between the shadow and the observed input prices: $W^{sh\,j} = \xi^{\,j} + w^{\,j}$.

The derivation of a generalized translog cost function includes four steps.

Step 1. Formulation of the shadow translog cost function:

$$\ln C^{sh} = \alpha_0 + \sum_{i=1}^{M} \alpha_i \ln q_i + \sum_{j=1}^{N} \beta_j \ln W^{sh}{}_j + \sum_{k=1}^{K} \gamma_k \ln a_k + .5(\sum\sum \alpha_{ij} \ln q_i \ln q_j$$

$$+ \sum\sum \beta_{ij} \ln W^{sh}{}_i \ln W^{sh}{}_j + \sum\sum \gamma_{ij} \ln a_i \ln a_j) + \sum\sum \delta_{ij} \ln W^{sh}{}_i \ln q_j \qquad (2.6)$$

$$+ \sum\sum \mu_{ij} \ln q_i \ln a_j + \sum\sum \tau_{ij} \ln W^{sh}{}_i \ln a_j,$$

$\ln W^{sh}{}_j = \ln w_j + \ln \xi_j$,

where C^{sh} = shadow cost;
$W^{sh}{}_j$ = shadow price of input j;
w_j = observed price of input j;
ξ_j = inefficiency parameter for input j;
q_i = level of output i;
a_k = level of control variable k;
$\alpha_0, \alpha_i, \alpha_{ij}, \beta_j, \beta_{ij}, \gamma_k, \gamma_{ij}, \delta_{ij}, \mu_{ij}, \tau_{ij}$ = parameters of the translog function.

Step 2. Derivation of the input demand functions from the shadow cost function by applying Shephard's Lemma to the shadow cost function:

$$L_i = \frac{\partial C^{sh}}{\partial W_i^{sh}} = S_i^{sh} \frac{C^{sh}}{W_i^{sh}} \qquad (2.7)$$

$$S_i^{sh} = \beta_i + \sum \beta_{ij} \ln W_j^{sh} + \sum \delta_{ij} \ln q_j + \sum \tau_{ij} \ln a_j \qquad (2.8)$$

Step 3. Formulation of the observed cost function (C) as a sum of the factor inputs weighted by actual input prices; derivation of the observed cost as a function of the observed input prices and inefficiency parameters:

$$C=\sum_i w_i\ L_i = C^{sh}\sum_i \frac{w_i}{W_i^{sh}} S_i^{sh} = C^{sh}\sum_i \frac{S_i^{sh}}{\xi_i} \tag{2.9}$$

$$\ln C = \ln C^{sh} + \ln(\sum_i \frac{S_i^{sh}}{\xi_i}) \tag{2.10}$$

Step 4. Derivation of the observed input shares as functions of the observed prices and inefficiency parameters:

$$S_i = \frac{w_i\ L_i}{C} = \frac{S_i^{sh}\ /\ \xi_i}{\sum_k S_k^{sh}\ /\ \xi_k} \tag{2.11}$$

The above exercise gives rise to a system of the actual cost and share equations that does not include unobserved shadow variables and thus, can be estimated:

$$\begin{aligned}\ln C = {} & \alpha_0 + \sum_{i=1}^{M}\alpha_i \ln q_i + \sum_{j=1}^{N}\beta_j(\ln w_j + \ln\ \xi_j) + \sum_{k=1}^{K}\gamma_k \ln a_k \\ & +.5\{\sum\sum\alpha_{ij}\ln q_i \ln q_j + \sum\sum\beta_{ij}(\ln w_i + \ln\xi_i)(\ln w_j + \ln\xi_j) + \sum\sum\gamma_{ij}\ln a_i \ln a_j\} \\ & +\sum\sum\delta_{ij}(\ln w_i + \ln\xi_i)\ln q_j + \sum\sum\mu_{ij}\ln q_i \ln a_j + \sum\sum\tau_{ij}(\ln w_i + \ln\xi_i)\ln a_j \\ & +\ln\left(\sum_i\{\beta_i + \sum\beta_{ij}(\ln w_j + \ln\xi_j) + \sum\delta_{ij}\ln q_j + \sum\tau_{ij}\ln a_j\}/\xi_i\right)\end{aligned} \tag{2.12}$$

$$S_i = \frac{\left\{\beta_i + \Sigma\beta_{ij}(\ln w_j + \ln\xi_j) + \Sigma\delta_{ij}\ln q_j + \Sigma\tau_{ij}\ln a_j\right\}/\xi_i}{\sum_k\left\{\beta_k + \Sigma\beta_{kj}(\ln w_j + \ln\xi_j) + \Sigma\delta_{kj}\ln q_j + \Sigma\tau_{kj}\ln a_j\right\}/\xi_k} \tag{2.13}$$

Aside from the inefficiency parameters, the actual cost function includes the same parameters as the shadow cost function. These parameters must satisfy certain restrictions to ensure that the properties of the theoretical cost function hold for the shadow cost function. As in the traditional translog cost function estimation, continuity in input prices follows from the choice of the functional form. Linear homogeneity in input prices and symmetry of the matrix of the second order derivatives are imposed as linear restrictions on the parameter estimates. Concavity in input prices, as well as monotonicity in outputs and input prices, cannot be imposed as linear restrictions, but are checked after the estimation.

Linear homogeneity of the cost function in input prices implies that the vector of inefficiency parameters ξ is under-identified. The first order conditions for minimization can be written in terms of the ratios of marginal products:

$$\frac{\partial f / \partial X_i}{\partial f / \partial X_j} = \frac{w_i \, \xi_i}{w_j \, \xi_j}, \quad i, j = 1....N, \tag{2.14}$$

This system of the first order conditions includes N unknown inefficiency parameters for N inputs, but only N - 1 distinct equations. Therefore, one of the inefficiency parameters has to be normalized, so that only relative allocative inefficiency can be estimated.

The normalization of one of the inefficiency parameters to one is common in generalized cost function studies because it permits convenient interpretation of the inefficiency estimates. If an estimate of the inefficiency parameter is greater than one, the input is under-utilized relative to the input chosen as the norm. If the estimate of the inefficiency parameter is less than one, the input is relatively over-utilized. If the estimate is equal to one, the input is used in efficient proportions relative to the normalized input. Atkinson and Halvorsen (1986) showed that the estimates of allocative inefficiency are invariant to the choice of the normalized input.

The addition of the inefficiency parameters to the model reduces the number of degrees of freedom. The choice of the specification for the inefficiency parameters is often dictated by the limitations of the degrees of freedom. For example, a cross-sectional data set does not provide enough degrees of freedom to specify the inefficiency parameters as individual to each firm. Therefore, allocative inefficiency in a cross-sectional study can only be estimated on the industry level. Because of the degrees of freedom, most empirical studies that involve generalized cost estimation utilize restrictive specifications of the inefficiency parameters (see, for example, Eakin and Kniesner, 1988). Firm level allocative inefficiency can be estimated using panel data. To my knowledge, Atkinson and Cornwell (1994) is the only study that uses panel data and estimates firm-specific allocative inefficiency parameters.

The majority of studies treats the inefficiency parameters as fixed coefficients (see Atkinson and Halvorsen, 1984, Lau and Yotopoulos, 1971, Farber, 1989, Parker, 1994, Atkinson and Cornwell, 1994). Some authors assume that the inefficiency parameters depend on other variables (Farber, 1989, Atkinson and Halvorsen, 1990, Oum and Zhang, 1995). In a study of parametric efficiency for a sample of new electric utility plants built during 1953-81 Farber (1989) assumed that the inefficiency parameters varied over inputs but not observations, which implied that all new plants in the sample were equally inefficient. The author also tried a specification with the fuel inefficiency parameter being a linear function of a time-dependent dummy in order to account for an institutional change.

Atkinson and Halvorsen (1990) modeled allocative inefficiency as a function of exogenous variables that vary over firms. In order to test the hypothesis that competition in the U.S. long-distance telephone market had positive effect on allocative efficiency of the U.S. telecommunication industry as a whole, Oum and Zhang (1995) specified the inefficiency parameters as an exponential function of three alternative competition measures, which allowed the inefficiency parameters to change over time.

The shadow price divergence parameter ξ, though usually referred to as the allocative inefficiency parameter, captures not only any systematic over- and under-valuation of the inputs by the firm and sluggish adjustment to price changes, but also systematic measurement errors made by the observer.

The generalized cost models are nonlinear with respect to their parameters and are usually estimated by means of iterative nonlinear methods of optimization. Unfortunately, the small sample properties of these estimators and their tests statistics are unknown. In general, consistency and asymptotic distribution of the nonlinear estimators can be established under certain assumptions (see Judge *et al.*, 1985, pp. 198-201). Some of these assumptions are often violated in practice, such as the assumption that none of the explanatory variables exhibit a time trend. In addition, Judge *et al.* (1985, pp. 203-5) showed that, if an iterative algorithm is applied, the distribution of the estimator depends on the consistency of the initial estimator that was used to compute the starting values.

2.2.4. Stochastic Versus Nonstochastic Modeling of Inefficiency

The violation of cost-minimizing behavior has been modeled in two different ways. First, through introduction of inefficiency parameters directly in the model. Second, by developing special error-component structures that reflect inefficiency. The first approach assumes that systematic inefficiency is nonstochastic, while the second approach assumes that inefficiency is purely random.

Both approaches model technical efficiency in a similar way, by estimating a production or cost frontier, often through introduction of firm-specific intercepts in a model with panel data. The parametric approach treats these intercepts as fixed coefficients (*fixed effects*), while the error-component approach treats them as stochastic one-sided disturbances (*random effects*). The choice between the two models depends largely on whether the inefficiency terms are correlated with the explanatory variables in the model (Judge *et al.*, 1985, p. 527).

The two approaches differ in the treatment of allocative inefficiency. Schmidt and Lovell (1979) were the first to incorporate allocative inefficiency as the departure from the first order conditions for optimization in a stochastic frontier framework. They derived the structure of the error term as a function of allocative inefficiency for a Cobb-Douglas production function. Greene (1980) defined allocative inefficiency as error terms in the share equations for the translog cost function, though he assumed independence of the error terms in shares from the error term in cost equation – a rather strong assumption. Several studies adopted an approximate specification of the relationship between the allocative inefficiency error terms in cost and shares. Kumbhakar (1997b) derived the exact formulas for the allocative error disturbances in a system of translog cost and share equations.

The main drawback of the error component approach to modeling allocative inefficiency is that it requires distributional assumptions for the error terms. Allocative inefficiency terms might be correlated with the explanatory variables in the model, which would result in inconsistent estimates. In addition, the estimation method for Kumbhakar's (1997b) analytical model is yet to be developed. Atkinson and Cornwell (1994) argue that the error component approach concentrates on random nonsystematic deviations from allocative efficiency, while the primary interest of researchers and regulators lies in a study of the systematic deviations.

In this paper I adopt the parametric approach to modeling allocative inefficiency, though I estimate technical efficiency using both approaches in order to see whether the two methods give significantly different measures of inefficiency.

2.2.5. Studies of Productive Performance of the Telecommunications Industry

The majority of efficiency studies in telecommunications focuses on the effects of the 1984 divestiture of AT&T on the industry performance. Ying and Shin (1993) estimated the translog cost function of the local telephone industry using panel data on the U.S. local exchange carriers for 1976-87. They used a post-divestiture dummy variable in order to evaluate changes in productivity due to the AT&T breakup. The authors measured productivity changes as the percentage difference between fitted costs for the pre-divestiture and the post-divestiture periods. The estimation results suggested that local exchange carriers experienced cost savings after the divestiture. Ying and Shin attributed decreased costs to the competitive pressures from the long-distance market, though their specification does not separate competitive pressures from other factors that might have affected costs after the divestiture, such as technological change and falling labor prices.

Oum and Zhang (1995) estimated the generalized translog cost function of the U.S. telephone industry using aggregated data on all carriers reporting to the FCC during the period of 1972-90. The main goal of the study was to test the hypothesis that allocative inefficiency due to the Averch-Johnson (1962) effect reduces as the industry under the rate of return regulation becomes more competitive. The theoretical model behind their hypothesis assumed that the same incumbent firms operated in both long-distance and local markets, and the long-distance market was being opened to competition during the period of study. It can be argued that the model is inconsistent with the institutional setting of the U.S. telecommunications industry. This assumption also raises questions about the validity of aggregating data on local and long-distance firms in the study.

Oum and Zhang (1995) modeled the allocative inefficiency parameters as exponents of the linear functions of some time-dependent competition measure – the authors used three alternative measures. The labor inefficiency parameter was normalized to one. The estimates of allocative inefficiency for capital and materials turned out to be less than one, suggesting that both capital and materials were over-employed relative to labor. The inefficiency estimates for capital were substantially smaller than for materials, and the values changed significantly depending on the choice of the competition measure. For example, the inefficiency measure for capital ranged from 0.301 to 0.657 in 1972, depending on the competition variable used, while the inefficiency measure for materials ranged from 0.648 to 0.925 in the same year. The inefficiency estimates for capital exhibited a positive time trend. This result provided evidence in support of the authors' hypothesis that increased competition reduces Averch-Johnson effect. However, Oum and Zhang admitted that the positive time trend in the capital inefficiency estimates could be due to other factors, such as technological change. The relative inefficiency estimates for materials were decreasing slightly over time. Oum and Zhang attributed this reduction in efficiency to the substitution of capital for materials.

Using nonparametric data envelopment analysis, Majumdar and Chang (1996) evaluated scale efficiency of a set of local telephone companies for six different years during 1975-90. In order to derive the scale efficiency scores, the authors used the observed input and output quantities to construct the production possibility set for each year. The observed inefficiency was decomposed into pure technical and scale inefficiencies.

The calculated scale efficiency measures suggested that the scale efficiency of the U.S. local telephone industry was improving over the studied period. In order to explain the observed changes, the authors regressed the obtained scale efficiency scores on a set of institutional and firm-specific factors. According to the regression results, neither Bell Operating company dummy, nor the variables included to account for different types of regulatory setting had any significant impact on the scale efficiency. The scope of operations – the number of states in which the firm operated – was significant for most years and had a negative effect on scale efficiency. Technology, measured as average percent of digital switches, turned out to be the only variable to be significant for all years, though of unexpected negative sign. The authors explained this counterintuitive result by the adjustment process that could have been accompanying digitalization. It should be noted that Majumdar and Chang used the number of telephone access lines as one of the inputs for the two outputs, local and toll calls, while recent studies in local telecommunications such as Ying and Shin (1993), and Wilson and Zhou (1997) treat telephone access lines as an output. It is possible that their unexpected results were driven by this choice of inputs and outputs.

3. MODEL SPECIFICATION AND ESTIMATION TECHNIQUES

3.1. Model with No Inefficiency

3.1.1. General Specification

Traditionally, production behavior of the regulated U.S. telecommunications industry is modeled using the neoclassical cost function (see, for example, Evans and Heckman, 1984, Shin and Ying, 1992). Each firm is assumed to minimize production cost given the output level, input prices and technology:

$$C\,(W,Q) = \min_L W * L \;\; s.t. \;\; f\,(L) \geq Q\,, \tag{3.1}$$

where W, $f(L)$ and Q are considered exogenous.

The institutional setting of the industry – one firm is assigned to each market and is required to meet customer demand in this market, with prices being set by regulators – validates the treatment of the output as exogenous. Each telecommunications firm is assumed to have access to the same technology, which is probably appropriate given the regulatory provisions for the developers of the telecommunications equipment (such as the former Bell Laboratories).

Most studies utilize the translog functional form in the empirical estimation of the cost function because of its flexibility. Roller (1990a, 1990b) criticized the translog functional form for its poor global behavior. However, as the observed range of variables increases, this shortcoming becomes less pronounced.

Following the traditional approach, I adopt the translog functional form for the cost function and add share equations to the system:

$$\ln C = \alpha_0 + \sum_{i=1}^{m} \alpha_i \ln q_i + \sum_{j=1}^{n} \beta_j \ln w_j + \sum_{k=1}^{K} \gamma_k \ln a_k + 0.5\,(\sum_{i=1}^{m}\sum_{j=1}^{m} \alpha_{ij} \ln q_i \ln q_j$$

$$+ \sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij} \ln w_i \ln w_j + \sum_{i=1}^{K}\sum_{j=1}^{K} \gamma_{ij} \ln a_i \ln a_j) + \sum_{i=1}^{n}\sum_{j=1}^{m} \delta_{ij} \ln w_i \ln q_j \qquad (3.2)$$

$$+ \sum_{i=1}^{m}\sum_{j=1}^{K} \mu_{ij} \ln q_i \ln a_j + \sum_{i=1}^{n}\sum_{j=1}^{K} \tau_{ij} \ln w_i \ln a_j$$

where q_i = output $i = 1,...m$;
w_j = price of input $j = 1,...n$;
a_k = control variable $k = 1,...K$;
C = cost;
$\alpha_0, \alpha_i, \alpha_{ij}, \beta_j, \beta_{ij}, \gamma_k, \gamma_{ij}, \delta_{ij}, \mu_{ij}, \tau_{ij}$ = parameters of the translog function.

Application of Shephard's Lemma yields input share equations:

$$S_i = \beta_i + \sum_{j=1}^{n} \beta_{ij} \ln w_j + \sum_{i=1}^{m} \delta_{ij} \ln q_j + \sum_{k=1}^{K} \tau_{ij} \ln a_j \qquad (3.3)$$

where S_i = share of input i.

Two properties of the theoretical cost function can be expressed as linear restrictions on the parameters of the system – linear homogeneity in input prices and symmetry:

<u>Homogeneity restrictions</u>: $\sum_{j=1}^{n} \beta_i = 1 \quad \sum_{j=1}^{n} \beta_{ij} = 0 \quad \sum_{i=1}^{n} \beta_{ij} = 0 \quad \sum_{j=1}^{n} \delta_{ij} = 0 \quad \sum_{j=1}^{n} \tau_{ij} = 0$

<u>Symmetry restrictions</u>: $\alpha_{ij} = \alpha_{ji} \quad \beta_{ij} = \beta_{ji} \quad \gamma_{ij} = \gamma_{ji}$

The continuity of the theoretical cost function follows from the choice of the functional form. Other properties of the theoretical cost function – monotonicity in the outputs and concavity in input prices – cannot be imposed as linear restrictions, and are usually verified after the estimation.

The addition of random error disturbances to the cost and share equations (3.2) and (3.3) generates the empirical model:

$$\ln C = \alpha_0 + \sum_{i=1}^{m} \alpha_i \ln q_i + \sum_{j=1}^{n} \beta_j \ln w_j + \sum_{k=1}^{K} \gamma_k \ln a_k + 0.5\,(\sum_{i=1}^{m}\sum_{j=1}^{m} \alpha_{ij} \ln q_i \ln q_j$$

$$+ \sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij} \ln w_i \ln w_j + \sum_{i=1}^{K}\sum_{j=1}^{K} \gamma_{ij} \ln a_i \ln a_j) + \sum_{i=1}^{n}\sum_{j=1}^{m} \delta_{ij} \ln w_i \ln q_j$$

$$+ \sum_{i=1}^{m}\sum_{j=1}^{K} \mu_{ij} \ln q_i \ln a_j + \sum_{i=1}^{n}\sum_{j=1}^{K} \tau_{ij} \ln w_i \ln a_j + \varepsilon^0$$

$$S_i = \beta_i + \sum_{j=1}^{n} \beta_{ij} \ln w_j + \sum_{i=1}^{m} \delta_{ij} \ln q_j + \sum_{k=1}^{K} \tau_{ij} \ln a_j + \varepsilon^i \tag{3.4}$$

$$\sum_{j=1}^{n} \beta_i = 1 \quad \sum_{j=1}^{n} \beta_{ij} = 0 \quad \sum_{i=1}^{n} \beta_{ij} = 0 \quad \sum_{j=1}^{n} \delta_{ij} = 0 \quad \sum_{j=1}^{n} \tau_{ij} = 0$$

$$\alpha_{ij} = \alpha_{ji} \qquad \beta_{ij} = \beta_{ji} \qquad \gamma_{ij} = \gamma_{ji}$$

This system can be rewritten in the general matrix form:

$$Y = X\beta + \varepsilon \tag{3.5}$$

$$R\beta = r,$$

where Y = the vector of dependent variables (cost and shares);
X = the matrix of explanatory variables;
β = the vector of unknown parameters;
R = the restriction matrix of full row rank;
r = the restriction vector;
ε = the vector of error disturbances for cost and share equations.

3.1.2. SUR Estimator

The error structure in the model is usually assumed to exhibit contemporaneous correlation, which is described by the following assumptions on the error term $\varepsilon' = (\varepsilon^0, \varepsilon^1, \ldots \varepsilon^n)'$:

$$1)\ cov\,(\varepsilon^{i}_{t},\ \varepsilon^{j}_{t}) = \sigma^{2}_{ij}, \qquad i = 0, 1, \ldots n,\ t = 1, \ldots T.$$
$$2)\ cov\,(\varepsilon^{i}_{t},\ \varepsilon^{j}_{\tau}) = 0, \qquad t \neq \tau \tag{3.6}$$
$$3)\ E(\varepsilon) = 0 \quad E(\varepsilon\,'X) = 0$$
$$\varepsilon \sim (0,\ \Sigma \otimes I_T), \qquad \Sigma = [\sigma^{2}_{ij}]_{i,j=0,\ldots n}$$

where n = number of inputs; T = number of observations.

Conventional Zellner's SUR method uses Ordinary Least Squares (OLS) residuals of the original system of $n + 1$ equations to estimate the parameters of Σ. The covariance matrix of this system $\Sigma \otimes I_T$ is singular because the shares add to one. In order to eliminate singularity, Zellner's SUR method suggests dropping one of the share equations and correcting for contemporaneous correlation in the system of n equations. Zellner's method results in non-unique estimates because they depend on the choice of the share dropped. Applied researchers usually use the iterative version of Zellner's SUR method, which asymptotically eliminates non-uniqueness.

Mandy and Martins-Filho (1993) noted that if the OLS method is applied to the entire system, including the restrictions, then the estimated matrix of contemporaneous correlation is unique and invariant to the equation dropped on the second stage of the SUR method. I follow the recommendation of Mandy and Martins-Filho (1993) and calculate the SUR estimates using the following three step procedure:

1) Application of the restricted OLS to the entire system of $n + 1$ equations:

$$b^{ROLS} = (X\,'X)^{-1}X\,'Y + (X\,'X)^{-1}R\,[R\,'(X\,'X)^{-1}R\,]\,(r - R\,'(X\,'X)^{-1}X\,'Y) \tag{3.7}$$

2) Estimation of Σ by $S = [s^{ij}]$ using the residuals from the restricted OLS:

$$e = Y - X\,b^{ROLS} = \{e^{0}, e^{1}, \ldots e^{n}\}\,' \tag{3.8}$$

$$s_{ij} = (e^{i\,\prime}\,e^{j})\,/\,T;\ \ i, j = 0, \ldots n \tag{3.9}$$

3) Application of the restricted SUR estimator to the system of n equations:

$$b^{RSUR} = (X_{-1}\text{'}S_{-1}^{-1}X_{-1})^{-1}X_{-1}\text{'}S_{-1}Y_{-1} \tag{3.10}$$

$$+ (X_{-1}\text{'}S_{-1}^{-1}X_{-1})^{-1}R_{-1}[R_{-1}\text{'}(X_{-1}\text{'}S_{-1}^{-1}X_{-1})^{-1}R_{-1}](r_{-1} - R_{-1}\text{'}(X_{-1}\text{'}S_{-1}^{-1}X_{-1})^{-1}X_{-1}\text{'}S_{-1}^{-1}Y_{-1}),$$

where superscript '-1' denotes the inverse, and subscript '*-1*' indicates that one share is eliminated.

3.1.3. Consistent Error Structure

Chavas and Segerson (1987) noted the following corollary of Shephard's Lemma: the error terms in share equations are the derivatives of the error term in cost because share equations are generated as derivatives of the logarithm of cost with respect to the logarithms of input prices:

$$\varepsilon^{i} = \frac{\partial \varepsilon^{0}}{\partial \ln w_i}, \; i = 1, \ldots n \tag{3.11}$$

In order for the statistical disturbance to be present in the shares, the error term in the cost equation has to depend on the input prices. Therefore, the random error component in the cost equation is necessarily heteroscedastic. In other words, the components of the covariance matrix of the SUR model vary across observations $t=1,\ldots T$: $\Sigma^{t} = [\, \sigma^{2}{}_{ij}{}^{t}\,]$.

I assume that heteroscedasticity takes additive form and apply the consistent estimator for a system with additive heteroscedastic contemporaneous correlation derived by Mandy and Martins-Filho (1993). Following Mandy and Martins-Filho, I adopt the simplest linear specification for the error term in cost that generates the consistent error structure. For a case of three inputs this specification takes the form:

$$\varepsilon^{o} = a_{0}\, \theta_{0} + a_{1}\, \theta_{1}\, (\ln w_{1} - \ln w_{2}) + a_{2}\, \theta_{2}\, (\ln w_{3} - \ln w_{2}) \tag{3.12}$$

where θ_0, θ_1, θ_2 are random error components of θ_t;
$\theta_t \sim (0, [\, \gamma^2_{ij}]_{i,j=0,1,2})$;
a_0, a_1, a_2 are unknown parameters.

Application of Shephard's Lemma generates specification for the error terms in shares:

$$\begin{aligned} \varepsilon^{1} &= a_{1}\, \theta_{1} \\ \varepsilon^{2} &= -\, a_{1}\, \theta_{1} - a_{2}\, \theta_{2} \\ \varepsilon^{3} &= a_{2}\, \theta_{2} \end{aligned} \tag{3.13}$$

Clearly, this error structure is heteroscedastic because the covariance between errors in different equations depends on input prices. For example, the covariance between the error term in the cost equation and the first share takes the following functional form:

$$\sigma^{2}_{01} = a_{0}\, a_{1}\, \gamma^{2}_{01} + a_{1}^{2}\, \gamma^{2}_{11}\, (\ln w_{1} - \ln w_{2}) + a_{1}\, a_{2}\, \gamma^{2}_{12}\, (\ln w_{3} - \ln w_{2}) \tag{3.14}$$

In general, the covariance parameters $\sigma^{2}{}_{ij}{}^{t}$ can be expressed as a linear function of the a set of the observed variables $z^{t}{}_{ij}$ and unknown parameters d:

$$\sigma^{2}{}_{ij}{}^{t} = E(\varepsilon_{t}{}^{i}\, \varepsilon_{t}{}^{j}) = z^{t}{}_{ij}\, d \tag{3.15}$$

For example, the set of the observed variables $z^{t}{}_{01}$ that corresponds to (3.14) includes the following three vectors $T\times 1$: the identity vector, $(\ln w_{1}{}^{t} - \ln w_{2}{}^{t})$ and $(\ln w_{3}{}^{t} - \ln w_{2}{}^{t})$.

In order to estimate the system with the specified error structure, I utilize the three-step Feasible Generalized Least Squares (FGLS) method developed by Mandy and Martins-Filho (1993):

1) Use OLS residuals of the cost and share system of equations to generate the preliminary estimates of $\sigma^{2}{}_{ij}{}^{t}$:

$$e = Y - X\, b^{\,ROLS} = \{\mathrm{e}^{0}, \mathrm{e}^{1}, \ldots\, \mathrm{e}^{3}\}' \tag{3.16}$$

$$s_{ij}{}^{t} = (e^{i}{}_{t}\; e^{j}{}_{t}) \,/\, T;\;\; i, j = 0, \ldots 3 \tag{3.17}$$

2) Use OLS method to estimate the stochastic version of (3.15) using $s_{ij}^{\ t}$ as a proxy for the dependent variable. The error term in this system violates two assumptions of the Gauss-Markov theorem – its mean is not zero, and its covariance matrix is not scalar identity. In order to improve the efficiency of the estimates, Mandy and Martins-Filho (1993) apply the FGLS method to the system (3.15) after deriving the structure of the covariance matrix. The authors show that the effects of nonzero mean are negligible asymptotically.

3) Use the FGLS estimates of d to calculate the fitted values of $\sigma^2{}_{ij}^{\ t}$ in the system (3.15). These fitted values are then used as components of the estimated heteroscedastic contemporaneous correlation matrix S of the original system (3.5):

$$b^{RHSUR} = (X_{-1}\,'S_{-1}^{\ -1}X_{-1})^{-1}X_{-1}\,'S_{-1}^{\ -1}Y_{-1} \tag{3.18}$$
$$+ (X_{-1}\,'S_{-1}^{\ -1}X_{-1})^{-1}R_{-1}[R_{-1}\,'(X_{-1}\,'S_{-1}^{\ -1}X_{-1})^{-1}R_{-1}](r_{-1} - R_{-1}\,'(X_{-1}\,'S_{-1}^{\ -1}X_{-1})^{-1}X_{-1}\,'S_{-1}^{\ -1}Y_{-1}).$$

3.2. Specification and Estimation of Technical Inefficiency

I model input technical inefficiency as a firm-specific additive term in the translog cost function. I estimate it using two alternative assumptions about the nature of systematic technical inefficiency. First, I assume fixed effects and formulate the model with firm-specific intercepts – the Dummy Variable Least Squares (DVLS) model. The intercept term in the original model is substituted by the sum of the products of the firm-specific dummy variables (D_i) and firm-specific intercept coefficients ($\alpha^0{}_i$):

$$\alpha_0 = \Sigma_i\ \alpha^0{}_i\ D_i \tag{3.19}$$

I measure relative technical inefficiency of firm i as the difference between the estimate for the firm's intercept (a^{0}_{i}) and the smallest intercept:

$$a^{0}_{i} - min_{i}\{a^{0}_{i}\} \tag{3.20}$$

Second, I assume random effects, and follow Kumbhakar's (1997a) FGLS estimation method for a one-way Error Component Model (ECM) of a system of cost and share equations with unbalanced panel data. The method assumes that the random error term of the cost equation is composed of the white noise disturbance $\varepsilon_{it} \sim i.i.d.\ (0, \sigma^{2}_{e})$ and of the firm-specific effect $\mu_{i} \sim (\mu, \sigma^{2}_{i})$. The expected value of the firm-specific effects is assumed to be constant across the firms, and therefore, can be aggregated with the intercept. As a result of this aggregation, the expected value of the composite error term $v_{it} = \varepsilon_{it} + \mu_{i} - \mu$ is zero. The two components are assumed to be independent of each other and of the explanatory variables in the model.

Since the variance of the firm-specific effect changes across firms, the covariance matrix of the composite error $V = [\, v_{it}\,]_{i=1..F,\, t=1..T}$ is heteroscedastic:

$$\mathrm{cov}(V) = \begin{bmatrix} \Omega_1 & 0 & 0 \\ & \cdots & \\ 0 & 0 & \Omega_F \end{bmatrix}, \qquad \text{where } \Omega_i = E(v_i' v_i) = \begin{bmatrix} \sigma_e^2 + \sigma_i^2 & \sigma_i^2 & \cdots \\ \sigma_i^2 & \sigma_e^2 + \sigma_i^2 & \cdots \\ \cdots & \cdots & \cdots \end{bmatrix},$$

$v_{i} = (v_{i1}, \ldots v_{iT_i})$, $i = 1, \ldots F$ and T_i is the number of observations on firm i.

Residuals of the DVLS model provide a consistent estimate for σ^{2}_{e}. Following Kumbhakar (1997a), I use the residuals from the original model that ignores heteroscedasticity (e_{it}) to estimate $\eta_{i} = \sigma^{2}_{e} + \sigma^{2}_{i}$: $\hat{\eta}_i = \sum_t \frac{e_{it}^2}{T_i}$, where '^' denotes an estimate. The estimate for σ^{2}_{i} is calculated as the difference between the estimate for η_{i}

and the estimate for σ^2_e. Once the covariance matrix of the composite error *cov (V)* is estimated, both sides of the cost equation are multiplied by $\hat{\operatorname{cov}}(V)^{-1/2}$ in order to remove heteroscedasticity. Finally, the SUR method is applied to the system that includes the transformed cost equation and the original share equations.

Kumbhakar's (1997a) model presents an extension of the Generalized EC model of Baltagi and Griffin (1988) to a case of a multiple equation system with an unbalanced panel. As noted in section 2.2.2, consistency of this estimator depends on whether the firm-specific effects are correlated with the explanatory variables. Asymptotic efficiency of this family of estimators follows from the consistency of the estimator for σ^2_e and the positive definiteness of the probability limit for the matrix of estimates for σ^2_i (see Baltagi, 1994, p.104).

I estimate technical efficiency μ_i as in Schmidt and Sickles (1984) using residuals from the cost equation of the estimated system (res_{it}) averaged for each firm over time. The relative technical inefficiency of firm i is measured as:

$$\bar{res}_i - \min_j\{\bar{res}_j\}, \text{ where } \bar{res}_i = \sum_t res_{it} \tag{3.21}$$

3.3. Specification and Estimation of Allocative Inefficiency

I model allocative inefficiency by using the generalized cost function approach and specifying allocative inefficiency ξ^j for input j as a ratio between the shadow and the observed input prices: $W^{sh\,j} = \xi^j w^j$. My cost function includes three inputs – capital, labor and materials ("residual" or "other cost"). I normalize the allocative inefficiency parameters for materials to one, and allow the capital and the labor inefficiency parameters to vary across holding companies and time: $\xi^j = tr^j\ trend + \Sigma_i\, d^j{}_i\ D_i$, where $j = K, L$ (input index), *trend* is a time trend variable, D_i is a holding company dummy variable, tr^j and $d^j{}_i$ are parameters to be estimated.

I allow the intercepts of the generalized cost function to vary across companies and time in order to account for technical inefficiency. I estimate the system of cost and two share equations using the iterative nonlinear SUR method. After the estimation I calculate the allocative inefficiency of input j $(\xi^j{}_{it})$ for each holding company i and year of observation t using the estimates for tr^j and $d^j{}_i$. The values of the allocative inefficiency term that are greater than one imply that the input is being under-employed relative to materials, while the inefficiency terms that are less than one indicate that the input is over-employed compared to materials.

4. MODEL VARIABLES AND DATA

4.1. Model Variables

4.1.1. Output Vector

A telephone firm supplies two types of the output – a) a telephone call (toll or local) and b) the ability to make a call at any time (determined by the presence of telephone lines). The number of telephone lines, as well as calling patterns of customers, affect the required capacity of the telephone plant. The type of a call, local or toll, influences switching cost – cost incurred to connect calling parties. The type of a telephone line – residential, business, special access, private – affects telephone loop cost (cost necessary to establish and maintain connection between a customer and the telephone network), as well as switching cost. For example, business customers tend to reside in areas with dense customer locations, thus, requiring relatively short cable lengths per line. Special access lines present dedicated high capacity lines that bypass local switching facilities and require special electronic equipment. The capacity of a special access line also determines the type of cable necessary – fiber optic or metallic. Business customers are more likely to make calls during business peak hours, while residential customers make relatively more calls during off peak periods.

The choice of the output vector is particularly important in cost subadditivity studies because the parameter estimates for the output variables determine the outcome of the subadditivity test. Subadditivity studies use the estimated parameters of the cost function to forecast the cost at different levels of the output. As noted by Judge *et al.* (1985, p. 901), the precision of the forecast – forecast variance – depends on the degree of collinearity between the regressors. Suppose that the components of the output vector exhibit strong multicollinearity in the original data set – the data set used in the estimation of the cost function. The forecast variance is relatively small if in the forecast year the proportions between the levels of different outputs follow the same near collinear relationship as the variables in the original data set. However, as the structure of the output vector used to calculate the forecast moves further away from the near collinear dependence between the components of the observed output vector, the forecast variance increases. The later situation is typical for the subadditivity studies, which use the observed costs of a diversified monopoly to forecast cost of an alternative market structure, with the output combinations that diverge significantly from the observed proportions. Therefore, in the presence of strong multicollinearity the forecast for the cost of a hypothetical competitive industry might be rather imprecise if, for example, the hypothetical firms engage in specialization.

Traditional measures of the output include the number of telephone lines (Shin and Ying, 1992, Wilson and Zhou, 1997, Guldmann, 1990), and the number of local and toll calls (Evans and Heckman, 1984, Shin and Ying, 1992, Gabel and Kennett, 1994). Different physical measures of the output of the monopolized telecommunications industry tend to be highly correlated: the bigger the market as measured by the number of telephone lines, the more calls it generates. Correlation between the physical output measures creates serious multicollinearity problems in the panel data sets such as Shin and Ying's (1992). For example, correlation between the natural logarithm of the number of telephone lines and the natural logarithm of the number of local calls in my panel data set – the data set on the local exchange carriers reporting to FCC for 1988-95 – is 0.9865. Correlation between the natural logarithm of the number of telephone lines and the natural logarithm of the number of toll calls is 0.9684.

In order to reduce severe multicollinearity, Wilson and Zhou (1997) used the total number of calls instead of local and toll calls in their attempt to replicate Shin and Ying's (1992) estimation for a newer data set. The elimination of the distinction between local and toll calls is not desirable because local calls require less switching than toll calls, and thus, the two have different effects on cost. In addition, the total number of calls is also highly correlated with the number of telephone lines (the correlation coefficient between the logarithms of these two variables is 0.9913 in my data set). Therefore, inclusion of the total number of calls along with telephone lines does not add much information to the model.

In order to capture cost differences associated with different types of calls and avoid serious multicollinearity, I include, along with telephone lines, the variable 'percent of local calls in the total number of telephone calls.' Similarly, 'the percent of nonresidential lines' (business, special access and private) accounts for cost differences associated with the different types of customers. Thus, the output vector Q in my model is composed of a single physical measure – the number of telephone lines, and two measures of the output attributes – the percent of nonresidential lines and the percent of local calls:

$Q = (TL, BL, LC)$,

where TL = the number of telephone lines;
BL = the percent of nonresidential lines in the total number of lines;
LC = the percent of local calls in the total number of calls.

4.1.2. Inputs

I adopt the traditional classification of inputs into labor, capital and residual expenses (see, for example, Shin and Ying, 1992). Capital expenses include interest and depreciation costs, while residual expenses present operating expenses with the exclusion of wages, depreciation and amortization. Thus, residual expenses cover such inputs as materials, fuel, electricity, software and advertisement.

4.1.3. Control Variables

Telecommunications firms serve different types of markets, and the differences between these markets affect their costs. Customers in rural areas are generally more dispersed than customers in urban areas. Therefore, a rural telephone company is likely to have longer cable distances than a company that serves urban markets. Customer dispersion also determines engineering decisions, such as the choice between copper and fiber cables.

In order to account for cost differences that stem from customer density, I follow Shin and Ying (1992) to include in the model variable 'length of wire per line.' This variable measures average loop length and is defined as kilometers of wire in cable (as opposed to sheath cable length) per telephone line.

In a panel of companies that have different size and age, technological differences are likely to exist. Many parts of the telecommunications plant have long lives, and, therefore, technological differences could be persistent. Therefore, a proxy variable for technology is necessary to capture cost variations that stem from differences in technology.

Early studies on the Bell system prior to its divestiture used the index of lagged research and development expenditures for the Bell Laboratories (Vinod, 1976, Evans and Heckman, 1984). Time series studies often include time trend as a proxy for technological change – see, for example, Hunt and Lynk (1990) and Gentzoglanis (1993). Unfortunately, time trend is often highly correlated with the output variables, as noted by Shin and Ying (1992) and Seabra (1993). In addition, time trend does not capture cross-sectional technological differences and adversely affects the asymptotic properties of the estimator. Detailed cross-sectional data on engineering parameters, such as the age of the telecommunications plant and the system design used in Dalton and Mann (1988), are usually not available.

Often technological proxies used in the past studies become outdated due to the fast advances in technology. Among them – the percentage of automatic local telephone stations (Seabra, 1993, Gentzoglanis, 1993, Oum and Zhang, 1995) and the share of electronic switches (Guldmann, 1990, Shin and Ying, 1992, Gentzoglanis, 1993). Monetary measures of technology in panel data sets such as the percentage of electronic switching equipment assets used by Wilson and Zhou (1997) are not desirable because they reflect changes in the equipment prices along with the technological change.

As a proxy for technological differences between companies and across time during 1988-95, I include variable 'percent of fiber optic cable in the total cable length.' The deployment of fiber optic cable became a significant technological change as fiber prices fell in late 80's and early 90's. As noted above, the placement of fiber optic cable is often dependent on the customer types and their location. I was unable to account for another technological development – introduction of remote switches, because the data on the number of switches were unreliable for a group of companies.

In addition, I considered four other variables that might have strong effect on cost or were used in the previous studies – the dummy variable for the Bell Operating Company, the number of central office switches, the time trend and the average sheath cable length per line. Inclusion of any of the four variables resulted in strong multicollinearity, with the condition number of the design matrix being above 30. Both the Bell dummy and the number of central office switches are highly correlated with the output vector. The time trend exhibits strong correlation with the input prices, while the average sheath cable length is correlated with a number of variables.

4.2. Data Construction

The primary source of my data is the *Statistics of Communications Common Carriers* published annually by the Federal Communications Commission (FCC). The telecommunications companies reporting to the FCC – companies with annual revenues of $ 100 million or more – serve more than 90 % of the U.S. telephone market according to the FCC estimates. My unbalanced panel data set consists of 379 observations on 66 companies during 1988-95, which constitute the majority of companies reporting to the FCC. I had to exclude several small companies because of the missing data.

The majority of the firms belong to one of the 14 holding companies such as Ameritech or GTE, several companies are independent. Tables 4.1 and 4.2 contain information on the names of the holding companies and firms, the structure of the panel

Table 4.1. Firms: Codes, Names and Ownership by Year

Firm Code	Firm Name	number of observations	Ownership by Holding Company* 88	89	90	91	92	93	94	95
1	NEVADA BELL	8	P	P	P	P	P	P	P	P
2	THE BELL TELEPHONE COMPANY OF PENNSYLVANIA	8	BA	BA	BA	BA	BA	BA	BA	BA
3	CHESAPEAKE POTOMAC TELEPHONE CO.	8	BA	BA	BA	BA	BA	BA	BA	BA
4	CHESAPEAKE AND POTOMAC TELEPHONE CO. OF MARYLAND	8	BA	BA	BA	BA	BA	BA	BA	BA
5	CHESAPEAKE AND POTOMAC TELEPHONE CO. OF VIRGINIA	8	BA	BA	BA	BA	BA	BA	BA	BA
6	CHESAPEAK AND POTOMAC TELEPHONE CO. OF WEST VIRGINIA	8	BA	BA	BA	BA	BA	BA	BA	BA
7	CINCINNATI BELL TELEPHONE CO.	4	O	O	O	O				
8	THE DIAMOND STATE TELEPHONE CO.	8	BA	BA	BA	BA	BA	BA	BA	BA
9	ILLINOIS BELL TELEPHONE CO.	8	AM	AM	AM	AM	AM	AM	AM	AM
10	INDIANIA BELL TELEPHONE CO. INC.	8	AM	AM	AM	AM	AM	AM	AM	AM
11	MICHIGAN BELL TELEPHONE CO.	8	AM	AM	AM	AM	AM	AM	AM	AM
12	THE MOUNTAIN STATES TELEPHONE AND TELEGRAPH CO.	3	W	W	W					
13	NEW ENGLAND TELEPHONE AND TELEGRAPH CO.	8	N	N	N	N	N	N	N	N
14	NEW JERSEY BELL TELEPHONE CO.	8	BA	BA	BA	BA	BA	BA	BA	BA
15	NEW YORK TELEPHONE CO.	8	N	N	N	N	N	N	N	N
16	NORTHWESTERN BELL TELEPHONE CO.	3	W	W	W					
17	THE OHIO BELL TELEPHONE CO.	8	AM	AM	AM	AM	AM	AM	AM	AM
18	PACIFIC NORTHWEST BELL TELEPHONE CO.	3	W	W	W					
19	PACIFIC BELL	8	P	P	P	P	P	P	P	P
20	SOUTH CENTRAL BELL TELEPHONE CO.	4	BS	BS	BS	BS				
21	SOUTHERN BELL TELEPHONE AND TELEGRAPH CO.	4	BS	BS	BS	BS				
22	THE SOUTHERN NEW ENGLAND TELEPHONE CO.	8	IND	IND	O	O	O	O	O	O
23	SOUTHWESTERN BELL TELEPHONE CO.	8	SW	SW	SW	SW	SW	SW	SW	SW
24	WISCONSIN BELL INC.	8	AM	AM	AM	AM	AM	AM	AM	AM
25	CONTEL OF CALIFORNIA	8	C	C	C	G	G	G	G	G
26	CONTEL OF VIRGINIA d/b/a GTE VIRGINIA	5	C	C	C		G	G		
27	GTE FLORIDA INC.	8	G	G	G	G	G	G	G	G
28	GTE NORTHWEST INC.	8	G	G	G	G	G	G	G	G
29	GTE SOUTH INC.	7	G		G	G	G	G	G	G
30	GTE SOUTHWEST INC.	8	G	G	G	G	G	G	G	G
31	GTE HAWAIIN TELEPHONE CO. INC.	8	G	G	G	G	G	G	G	G
32	UNITED INTER-MOUNTAIN TELEPHONE CO.	4	UT	UT	UT	UT				
33	UNITED TELEPHONE CO. OF INDIANA	8	UT	UT	UT	UT	S	S	S	S
34	UNITED TELEPHONE CO. OF OHIO	8	UT	UT	UT	UT	S	S	S	S
35	CAROLINA TELEPHONE AND TELEGRAPH CO.	8	UT	UT	UT	UT	S	S	S	S
36	CENTRAL TELEPHONE CO. (NEVADA)	2	CT	CT						
37	GTE CALIFORNIA INC.	8	G	G	G	G	G	G	G	G
38	LINCOLN TELEPHONE AND TELEGRAPH CO.	5	O	O	O				O	O
39	PUERTO RICO TELEPHONE CO.	4		IND	IND				PR	PR
40	ROCHESTER TELEPHONE CORPORATION	2		IND	IND					
41	UNITED TELEPHONE CO. OF FLORIDA	8	UT	UT	UT	UT	S	S	S	S
42	UNITED TELEPHONE CO. OF PENNSYLVANIA	8	UT	UT	UT	UT	S	S	S	S
43	UNITED TELEPHONE CO. MISSOURI	7		UT	UT	UT	S	S	S	S
44	CENTRAL TELEPHONE CO. OF ILLINOIS	5		CT	CT			S	S	S
45	CONTEL OF NEW YORK d/b/a GTE NEW YORK	5	C	C	C		G	G		
46	ANCORAGE TELEPHOBE UTILITY	1	O							
47	CENTRAL TELEPHONE CO. OF FLORIDA	5		CT	CT			S	S	S
48	CENTRAL TELEPHONE CO. OF VIRGINIA	6	CT	CT	CT			S	S	S
49	CONTEL OF ILLINOIS	5	C	C	C	G	G			
50	CONTEL OF TEXAS INC. d/b/a GTE TEXAS	7	C	C	C	G	G	G	G	
51	GTE NORTH INC.	8	G	G	G	G	G	G	G	G
52	CONTEL OF MISSOURI	5	C	C	C	G	G			
53	US WEST COMMUNICATIONS INC.	5				W	W	W	W	W
54	COMMONWEALTH TELEPHONE CO.	3						O	O	O
55	CONTEL OF INDIANA INC. d/b/a GTE INDIANA	2				G	G			
56	UNITED TELEPHONE CO. OF NEW JERSEY INC.	5				S	S	S	S	S
57	BELLSOUTH TELECOMMUNICATIONS INC.	4					BS	BS	BS	BS
58	CITIZENS UTILITIES CO. OF CALIFORNIA	3					O	O	O	
59	CONTEL OF THE WEST INC. d/b/a GTE WEST	1					G			
60	UNITED TELEPHONE-SOUTHEAST INC.	4					S	S	S	S
61	UNITED TELEPHONE CO. OF TEXAS	4					S	S	S	S
62	CONTEL OF THE SOUTH INC. d/b/a GTE SYSTEMS	3						G	G	G
63	GTE MIDWEST INC.	3						G	G	G
64	UNITED OF THE NORTHWEST	2							S	S
65	CENTRAL TELEPHONE CO. (NEVADA AND NORTH CAROLINA)	1			CT					
66	CENTRAL TELEPHONE CO. (NORTH CAROLINA)	3						S	S	S
	TOTAL	379								

** -- empty cells correspond to years in which the firm was not in the sample* data set, as well as firm codes and abbreviations for holding companies that I use in the presentation of my results in chapter 6.

Out of the total of 379 observations, 162 observations correspond to one of the seven Regional Bell Operating Companies (RBOCs). RBOCs are listed first in Table 4.2, and their company abbreviations are marked in bold font throughout the paper. They serve more than 80 % of the telephone lines in the sample. Table 4.3 presents the distribution of telephone lines among the holding companies.

Table 4.2. Holding Companies: Codes, Names and Observations by Year

Holding Company		number of	observations in each year							
Code	Name	observations	88	89	90	91	92	93	94	95
AM	Ameritech Corporation	40	5	5	5	5	5	5	5	5
BA	Bell Atlantic Corporation	56	7	7	7	7	7	7	7	7
BS	BellSouth Corporation	12	2	2	2	2	1	1	1	1
N	Nynex Corporation	16	2	2	2	2	2	2	2	2
P	Pacific Telesis Group	16	2	2	2	2	2	2	2	2
SW	Southwestern Bell Corporation	8	1	1	1	1	1	1	1	1
W	US WEST, Inc.	14	3	3	3	1	1	1	1	1
C	Contel Corporation	18	6	6	6	0	0	0	0	0
CT	Centel Corporation	10	2	4	4	0	0	0	0	0
G	GTE Corporation	81	7	6	7	12	15	13	11	10
O	Other holding companies	22	3	2	3	2	2	3	4	3
PR	Puerto Rico Telephone Authority	2	0	0	0	0	0	0	1	1
S	Sprint Corporation	51	0	0	0	1	9	13	14	14
UT	United Telecommunications, Inc.	27	6	7	7	7	0	0	0	0
IND	Not a part of a holding company	6	1	3	2	0	0	0	0	0
total		379	47	50	51	42	45	48	49	47

Table 4.3. Telephone Access Lines by Holding Company and Year

	Year							
Holding Co.	88	89	90	91	92	93	94	95
AM	13%	13%	13%	13%	13%	13%	13%	13%
BA	14%	14%	13%	14%	14%	13%	13%	13%
BS	14%	14%	14%	14%	14%	14%	14%	14%
N	13%	12%	12%	12%	12%	11%	11%	11%
P	11%	11%	11%	12%	12%	12%	11%	11%
SW	9%	9%	9%	9%	9%	9%	10%	10%
W	10%	10%	11%	11%	11%	11%	11%	11%
C	1%	1%	1%	0%	0%	0%	0%	0%
CT	1%	1%	1%	0%	0%	0%	0%	0%
G	10%	9%	10%	10%	11%	11%	11%	11%
O	1%	1%	2%	2%	1%	2%	2%	2%
PR	0%	0%	0%	0%	0%	0%	1%	1%
S	0%	0%	0%	0%	3%	4%	4%	4%
UT	2%	3%	3%	3%	0%	0%	0%	0%
IND	2%	3%	1%	0%	0%	0%	0%	0%
total RBOCs	84%	83%	82%	85%	85%	84%	83%	83%
Telephone Lines	120,846,727	124,734,004	130,424,258	132,806,444	135,975,498	146,233,395	155,486,188	163,624,827

In addition to the *Statistics of Communications Common Carriers*, I used *The Economic Report of the President* and the databases of the Bureau of Labor Statistics as the data sources on interest rates and price deflators. *Moody's Public Utility Manual* was the source of information on the interest rates and prices of telecommunications stocks and bonds.

I obtained information on the output and control variables directly from the outside plant statistics of the telephone firms. I calculated nonresidential lines as the difference between the total number of telephone lines and residential lines. 'Length of wire per line' is the ratio of total cable (kilometers of copper wire and fiber) to the number of telephone lines. I define the percent of fiber in cable as kilometers of deployed fiber divided by kilometers of cable (copper wire and fiber).

I construct economic cost from the accounting data on local exchange carriers. Total cost is the sum of capital cost, operating taxes and total operating expenses excluding depreciation and amortization. Capital cost is the sum of cost of capital stock and interest on cash in vaults (current assets minus current liabilities). Following Shin and Ying (1992), costs of capital stock C_{KS} are calculated using the annuity form of interest and depreciation expenses: $C_{KS} = r\ KS / (1 - e^{-rT})$, where KS is real capital stock, T is the life of capital, and r is the interest rate. Since the information on the age of capital and historical investments is not available, I adopt the same simplifying assumptions as Shin and Ying (1992): I assume that capital has an average life of 20 years, and its age distribution is uniform. I use a series of 20-year average deflators on telecommunications equipment to convert book values of capital stock into net real capital stock. Labor cost is given by total compensation. Residual cost is equal to operating expenses plus operating taxes minus labor cost.

In order to calculate the price of capital, I adopt the simple version of the rental price of capital (Jorgenson, 1963). This measure is used in many empirical studies, including Kim (1987), Oum and Zhang (1995) and Krautman and Solow (1988), and is appropriate if capital stock is measured in real dollars as opposed to physical units. Rental price of capital is equal to the average of dividend and interest rates weighed by the debt structure, plus annual depreciation rate, and minus the annual rate of capital gains. The price of labor is equal to total compensation divided by the number of employees. The price of 'residual inputs' is the ratio of residual cost to the length of sheath cable, which I considered to be the best available measure of the quantity of residual inputs.

Finally, I follow the conventional practice (see, for example Friedlaender *et al.*, 1993) and use the producer price indices to convert all monetary variables into real 1987 dollars. In general, I use the same methods of data construction as Shin and Ying (1992), with three major exception: Shin and Ying calculated the price of capital as capital expenditures per line, they also used the number of lines as a proxy for the quantity of residual inputs and did not adjust for inflation.

Table 4.4 contains descriptive statistics for the variables in the data set.

Table 4.4. Descriptive Statistics for the Data Set

Variable	Mean over All Observations	Standard Deviation	Minimum	Maximum
Number of Telephone Lines	2,929,106	4,213,132	76,235	22,595,391
Percent of Nonresidential Lines	30.32%	9.41%	5.63%	71.49%
Percent of Local Calls	83.51%	7.48%	45.87%	96.65%
Total Cost	1,657,319,742	2,260,750,743	80,765,010	11,929,732,65
Share of Capital	38.29%	3.74%	28.60%	50.37%
Share of Labor	22.75%	5.31%	5.57%	55.77%
Rental Price of Capital	0.12	0.01	0.09	0.14
Price of Labor	35,385	5,106	25,404	60,134
Price of Other Inputs	5,652	5,409	178	40,930
Average Loop Length	16.99	3.05	8.43	26.69
Percent of Fiber in Cable	0.36%	0.27%	0.00%	1.95%

Since the translog functional form represents approximation to an arbitrary twice differentiable function around one, I mean-center all variables in the model to increase the precision of the estimation. Mean-centering of the explanatory variables also permits interpretation of the first-order coefficients of the translog function as elasticities at the sample mean.

5. SUBADDITIVITY TEST: THE PROCEDURE

5.1. Modified Admissible Region

I adopt the general procedure of the subadditivity test developed by Evans and Heckman (1983) and calculate the combined costs of the different combinations of the outputs produced by the two hypothetical firms. I use the grid search to construct different output vectors of the two hypothetical firms and limit the grid search to certain admissible region. The unusual structure of my output vector requires special formulation of the admissible region. Following Shin and Ying (1992), I allow the number of telephone lines for the two hypothetical firms to vary from 10 to 90 percent of the observed monopoly number of telephone lines:

$$TL^{A} = k\,TL, \quad TL^{B} = (1 - k)\,TL, \quad 0.1 \leq k \leq 0.9, \tag{5.1}$$

where TL = the observed monopoly number of telephone lines;
TL^{A} = the number of telephone lines of hypothetical firm A;
TL^{B} = the number of telephone lines of hypothetical firm B;
k = the fraction of the monopoly lines assigned to firm A.

Nonresidential lines appear in the output vector as a fraction of total lines. Therefore, in order for the two hypothetical firms to meet the market demand, the following condition should hold: the average percent of nonresidential lines of the two firms weighed by total lines should be equal to the observed percent of the nonresidential lines:

$$(BL^{A}\ TL^{A} + BL^{B}\ TL^{B})/(TL^{A} + TL^{B}) = BL, \tag{5.2}$$

where BL = the observed monopoly percent of nonresidential lines;
BL^{A} = the percent of nonresidential lines of hypothetical firm A;
BL^{B} = the percent of nonresidential lines of hypothetical firm B.

Define v^A as BL^A / BL – the ratio of the percent of nonresidential lines of firm A to the percent of nonresidential lines of the monopoly. Also, let $v^B = BL^B / BL$. Using (5.1), equation (5.2) reduces to the following:

$$v^A k + v^B (1 - k) = 1 \tag{5.3}$$

which is equivalent to $v^B = (1 - v^A k) / (1 - k)$, or $v^A = (1 - v^B (1 - k)) / k$.

In order for BL^A to be positive, v^A has to be positive. In order for BL^B and v^B to be positive, v^A has to be less than $1 / k$. For BL^A to be less than 100 percent, v^A has to be less than $1 / BL$. Similarly, v^B has to be less than $1 / BL$, which can be expressed as the following restriction on v^A: $v^A > (1 - (1 - k) / BL) / k$. Therefore, the admissible region for v^A lies within the following interval:

$$max [0, (1 - (1 - k) / BL) / k] < v^A < min [1 / k, 1 / BL] \tag{5.4}$$

In the empirical implementation of the grid search, I follow Evans and Heckman (1984), as well as Ying and Shin (1992) to add 0.1 to the lower boundary, and subtract 0.1 from the upper boundary.

I construct the admissible region for the third component of the output vector, *LC*, in a similar fashion. Variable *LC* is defined as a fraction of local calls in the total number of calls. Therefore, total calls carried by each hypothetical firm represent the appropriate weights for calculating the average proportion of local calls. Since total number of calls is excluded from the model, restriction such as (5.2) is not necessary. However, given that total calls are closely correlated with telephone lines, and in order to construct a conservative admissible region that does not contain implausible output combinations, I require the average fraction of local calls for the two firms weighed by telephone lines to be equal to the observed fraction of local calls.

I define w^A as a multiplier on the monopoly fraction of local calls that generates the fraction of local calls for firm A: $LC^A = w^A LC$. The fractions of local calls for both firms have to lie between 0 and 100 percent, which imposes the following boundaries on w^A:

$$max\,[\,0,\,(1 - (1 - k) / LC) / k\,] < w^A < min\,[\,1 / k,\,1 / LC\,] \tag{5.5}$$

5.2. Grid Search

Using the grid search described in Shin and Ying (1992), for each observation t I construct different output configurations for the two-firm industry using a grid step of 0.1 in the following output space:

$$\begin{array}{ll} Q^A{}_t = (TL^A{}_t,\, BL^A{}_t,\, LC^A{}_t) & Q^B{}_t = (TL^B{}_t,\, BL^B{}_t,\, LC^B{}_t) \\ TL^A{}_t = k\, TL_t & TL^B{}_t = (1 - k)\, TL_t \\ BL^A{}_t = v^A\, BL_t & BL^B{}_t = [\,(1 - v^A\, k) / (1 - k)\,]\, BL_t \\ LC^A{}_t = w^A\, LC_t & LC^B{}_t = [\,(1 - w^A\, k) / (1 - k)\,]\, LC_t \end{array} \tag{5.6}$$

$$0.1 \leq k \leq 0.9$$

$$0.1 + max\,[\,0,\,(1 - (1 - k) / BL_t) / k\,] \leq v^A \leq min\,[\,1 / k,\,1 / BL_t\,] - 0.1$$

$$0.1 + max\,[\,0,\,(1 - (1 - k) / LC_t) / k\,] \leq w^A \leq min\,[\,1 / k,\,1 / LC_t\,] - 0.1$$

The number of admissible output combinations varies from observation to observation because the admissible region depends on the values of BL_t and LC_t.

Following Roller's (1990a, 1990b) criticism of the subadditivity test of Evans and Heckman (1984), I impose an additional restriction on the admissible region: I calculate marginal cost for each Q_t, Q^A_t and Q^B_t and exclude from consideration any output vector with negative marginal cost[4] .

I use the parameter estimates of the translog cost function and the constructed output vectors to calculate the cost estimates. Since none of my other explanatory variables – the input prices, the average loop length and the percent of fiber in cable – are tied to the units of the output, I keep them at the observed level when calculating the cost.

5.3. Interpretation of the Subadditivity Test

For each observation I calculate the costs of different two-firm industry combinations $C(Q^A_t) + C(Q^B_t)$ using the estimated cost function. I then compare the cost of the two-firm industry to the fitted cost of the monopoly provision of the output, $C(Q_t)$.

Theoretically, if there exist k, v^A and w^A such that $C(Q_t) - C(Q^A_t) - C(Q^B_t) > 0$, then the subadditivity condition is violated at Q_t. Empirically, the calculated difference between the monopoly cost and the cost of a two-firm industry presents merely a point estimate. The distribution of this estimate depends on a number of factors, including the forecast variance in the model, as well as on the likelihood of each two-firm market configuration. Evans and Heckman (1984) chose the **maximum** value of the percentage difference between the monopoly and the two-firm industry cost as their test indicator for subadditivity. Their choice implies an assumption that a two-firm industry would operate in a competitive equilibrium – at minimum cost.

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[4] In the empirical implementation of the test reported in chapter 6, marginal costs turned out to be positive for all Q_t. Approximately 0.4 % of the output combinations were excluded from the admissible region because of the negative marginal costs for Q^A or Q^B.

Shin and Ying (1992) used the average percentage cost difference for all possible output configurations, the sample distribution of this average, as well as the fraction of the output combinations that make monopoly effective, as indicators of subadditivity. Their approach presents a more conservative test against subadditivity since it implies that all alternative two-firm industry configurations are equally probable.

6. ESTIMATION RESULTS

6.1. Subadditivity Test under the Assumption of No Inefficiency

6.1.1. Translog Estimation

Table 6.1. presents the estimation results for the translog parameters of the cost equation for the two estimation techniques, SUR and Heteroscedastic SUR (HSUR) estimators. Notations for the variables in the table are as follows:

TL = the number of telephone access lines (natural logarithm);
BL = the percent of nonresidential lines (natural logarithm)
LC = the percent of local calls (natural logarithm);
PK = the price of capital (natural logarithm);
PL = the price of labor (natural logarithm);
PO = the price of other inputs (natural logarithm);
WI = the average loop length (natural logarithm);
FI = the percent of fiber in cable (natural logarithm).

The coefficients of determination are similar to the ones obtained by Shin and Ying (1992). The cost equation has a much better fit than the shares equations, with the coefficient of determination in the cost equation being 0.987 in both SUR and heteroscedastic SUR models, 0.40 in the capital share and 0.32 in the labor share (the coefficients of determination reported by Shin and Ying are 0.998, 0.51 and 0.27 correspondingly).

In order to check whether the estimated parameters correspond to a valid cost function, I calculate the fitted shares, marginal cost and the Hessian for each observation

Table 6.1. Translog Estimates for the SUR and Heteroscedastic SUR Methods

variable	SUR		Heteroscedastic SUR	
	coefficient	t-statistics	coefficient	t-statistics
INTERCEPT	0.08	6.01 *	0.09	6.52 *
TL	0.98	82.20 *	0.97	83.11 *
BL	-1.07	-15.66 *	-1.07	-15.91 *
LC	0.10	0.68	-0.01	-0.05
WI	0.19	2.48 *	0.24	3.22 *
TLBL	-0.07	-1.95 **	-0.04	-1.12
TLTL/2	0.07	5.92 *	0.06	5.08 *
BLBL/2	-1.23	-10.87 *	-1.18	-10.68 *
LCWI	-0.71	-1.40	-1.22	-2.45 *
LCLC/2	-2.83	-2.74 *	-3.90	-3.85 *
WIWI/2	0.62	1.59	0.76	1.98 *
TLLC	0.19	1.86 **	0.26	2.66 *
TLWI	0.05	1.10	0.08	1.73 **
BLLC	0.15	0.32	-0.16	-0.37
BLWI	-0.49	-2.77 *	-0.54	-3.13 *
PK	0.39	183.80 *	0.38	181.94 *
PL	0.23	77.77 *	0.22	76.00 *
PO	0.39	106.17 *	0.39	112.64 *
TLPK	0.01	6.02 *	0.01	5.77 *
TLPL	0.01	6.33 *	0.01	6.16 *
TLPO	-0.02	-8.43 *	-0.02	-8.56 *
BLPK	0.00	-0.53	-0.01	-0.79
BLPL	0.04	3.46 *	0.04	3.40 *
BLPO	-0.03	-2.42 *	-0.03	-2.34 *
LCPK	0.06	3.06 *	0.05	2.96 *
LCPL	0.04	1.42	0.03	1.32
LCPO	-0.09	-2.93 *	-0.09	-2.93 *
WIPK	0.01	1.24	0.02	1.49
WIPL	-0.08	-5.48 *	-0.08	-5.28 *
WIPO	0.06	3.59 *	0.06	3.48 *
PKPK/2	0.04	5.14 *	0.04	4.60 *
PKPL	-0.02	-1.97 *	-0.02	-1.81 **
PKPO	-0.03	-7.55 *	-0.02	-7.07 *
PLPL/2	0.05	5.70 *	0.05	5.33 *
PLPO	-0.04	-7.43 *	-0.04	-7.33 *
POPO/2	0.06	10.13 *	0.06	10.32 *
FIPK	0.00	-2.24 *	-0.01	-2.53 *
FIPL	-0.03	-11.44 *	-0.03	-11.47 *
FIPO	0.04	10.80 *	0.04	11.59 *
TLFI	0.00	0.53	0.01	0.74
BLFI	-0.08	-1.53	-0.13	-2.52 *
LCFI	0.15	1.49	0.07	0.75
WIFI	0.08	1.09	0.08	1.25
FIFI/2	0.00	-0.04	0.00	-0.05
FI	0.02	1.16	0.02	1.55
R-squared in C	0.987		0.987	
R-squared in SK	0.396		0.400	
R-squared in SL	0.317		0.322	

* – significant at 95 % level; ** – significant at 90 % level.

in the sample. All fitted shares are positive. Positive marginal cost of the physical output 'telephone lines' for all observations indicate that the estimated cost function is non-decreasing in the output. The Hessian matrix of the second-order derivatives of the cost function with respect to the input prices is negative semi-definite for all but two observations. The components of the Hessian are determined by the values of the second-order coefficients on the input prices, as well as the input shares. The shares of capital and labor for these two observations are very high relative to the sample average, which explains why the concavity condition is violated. The Hessian matrix is also negative semi-definite at the sample mean, indicating concavity in the input prices.

Parameter estimates for both SUR and Heteroscedastic SUR models are relatively close, with only a few noticeable changes in the magnitude and the significance level: the parameter values and the levels of significance increases substantially in the Heteroscedastic SUR model for two terms – *LCWI* and *BLFI*. Two other coefficient estimates change sign, but their t-statistics are all less than 0.7 in absolute value. The Heteroscedastic SUR estimator gives a slightly better fit, with more parameters being statistically significant. The relative stability of the parameter estimates between the two models indicate that the degree of heteroscedasticity in the system might not be very strong.

The first-order coefficient on the number of telephone lines *TL*, which represents elasticity of the cost function with respect to the telephone lines at the sample mean, is slightly less than one, indicating that at the sample mean the cost function is inelastic with respect to the number of telephone lines. The 95 % confidence interval for the estimate obtained using the SUR method includes one, while the estimate for the heteroscedastic model is strictly less than one at the 95 % level of confidence. The cost elasticity with respect to total lines calculated for the individual data points ranges from 0.6 to 1.3 for both estimators, with the sample average being 0.9. The individual coefficient on the number of telephone lines is much higher then the estimate obtained by Shin and Ying (1992). However, the variable 'total lines' is the only physical measure of the output in my model, and therefore, it is more appropriate to compare this coefficient with the measure of overall scale elasticity of Shin and Ying (0.958 at the sample mean).

As expected, the first-order coefficient on the percent of nonresidential lines *BL* is significant and negative, indicating that it is cheaper to serve business customers compared to residential customers. The cost elasticity with respect to nonresidential lines is negative and less than one in absolute value for most observations, as well as for the sample average. Significant negative coefficient on the squared percent of nonresidential lines indicates that costs decrease rapidly as the percent of nonresidential lines increases.

The first-order coefficient on the percent of local calls *LC* is statistically insignificant even at the 90 % level of confidence. This result suggests that the distribution of calls between local and toll has no effect on cost at the sample mean, which is not totally unexpected given that modern digital switches are not sensitive to usage. Elasticities calculated for individual observations vary widely, from -1.1 to + 1.5 in the SUR model, with the sample averages being slightly below zero in both models.

Average loop length (*WI*) has small but statistically significant positive impact on cost, supporting the conventional wisdom that lower customer density is associated with higher cost. Input prices (*PK*, *PL* and *PO)* have positive and highly significant first order coefficients, while the proxy for technology *FI* – the percent of fiber in cable – has only indirect impact on cost through interaction with other variables. The estimates for the interaction terms between fiber and the input prices suggest that, as the percent of fiber increase, capital and labor shares decrease, while the share of other inputs increases. This result might be explained by several factors. On the one hand, during the sample period the price of capital was falling, while the percent of fiber was rising steadily. One the other hand, fiber optic cable is probably associated with higher network support expenses, and therefore, higher levels of residual inputs, because it requires conduit placement and complex electronic equipment.

6.1.2. Subadditivity Test

Tables 6.2 - 6.7 summarize the results of the subadditivity test. Tables 6.2 and 6.3 present details on the subadditivity calculations for the observations in 1988[5]. For each data point I use the estimated parameters of the translog cost function to compare the fitted monopoly cost to the cost of producing the monopoly output vector by a two-firm industry. Columns three in tables 6.2 and 6.3 contain the number of cases – two-firm industry configurations – for which the combined costs of the two hypothetical firms were higher than the fitted cost of a monopoly. Column four measures this number as a fraction of all possible two-firm configurations on the grid of the admissible region.

Columns five through eight report the difference between the costs of a two-firm industry configuration and a monopoly measured as a percent of the monopoly cost:

[5] Tables 6.2 and 6.3 provide the full output of the subadditivity procedure for the data points in 1988. Year 1988 is chosen at random to illustrate the details of the test.

Table 6.2. Detailed Subadditivity Results for the Data Points in 1988: SUR Model

Observation	Firm Code	Monopoly Cost is Lower than Two-Firm Cost		Savings From a Two-Firm Industry (Percent of Fitted Monopoly Cost)			
		Number of Cases	Percent of Cases	Minimum	Maximum	Average	Standard Error
1	1	824	86%	-35.6%	60.0%	-8.9%	13%
2	2	1229	67%	-34.5%	70.9%	-0.2%	16%
3	3	295	89%	-86.4%	14.0%	-15.0%	17%
4	4	578	78%	-32.6%	60.5%	-2.4%	9%
5	5	569	79%	-43.4%	49.0%	-4.3%	11%
6	6	835	70%	-13.6%	88.6%	1.0%	13%
7	7	361	84%	-13.6%	28.9%	-3.1%	4%
8	8	992	80%	-35.2%	62.5%	-6.5%	13%
9	9	981	71%	-37.1%	61.7%	-2.2%	14%
10	10	1033	70%	-17.6%	90.2%	1.1%	14%
11	11	950	69%	-33.2%	87.7%	-0.4%	15%
12	12	839	64%	-33.3%	87.5%	0.0%	14%
13	13	773	47%	-10.9%	93.7%	7.1%	16%
14	14	1101	56%	-17.4%	82.0%	5.2%	16%
15	15	629	66%	-37.6%	57.6%	-2.3%	12%
16	16	929	63%	-21.8%	90.1%	1.6%	14%
17	17	892	65%	-15.5%	90.3%	2.3%	13%
18	18	1017	70%	-25.2%	89.6%	0.2%	15%
19	19	620	62%	-51.0%	46.0%	-2.4%	13%
20	20	392	60%	-16.2%	89.6%	0.3%	8%
21	21	378	61%	-35.1%	84.8%	-1.6%	10%
22	22	807	58%	-9.7%	89.7%	4.2%	16%
23	23	494	56%	-29.6%	86.6%	-0.1%	12%
24	24	953	72%	-16.9%	89.6%	0.5%	13%
25	25	983	58%	-14.9%	87.8%	5.3%	19%
26	26	773	47%	-11.0%	97.3%	8.4%	21%
27	27	689	73%	-12.7%	89.0%	0.6%	10%
28	28	539	65%	-6.9%	88.1%	2.6%	13%
29	29	723	61%	-8.2%	89.1%	3.4%	13%
30	30	602	56%	-4.0%	96.0%	4.8%	15%
31	31	271	79%	-11.3%	14.1%	-2.8%	3%
32	32	510	62%	-11.6%	93.9%	2.8%	15%
33	33	706	46%	-13.5%	91.2%	9.9%	21%
34	34	780	41%	-11.1%	98.5%	11.4%	22%
35	35	638	42%	-5.7%	96.4%	9.2%	19%
36	36	441	46%	-4.7%	87.2%	5.4%	13%
37	37	484	59%	-5.7%	89.1%	2.8%	11%
38	38	697	62%	-13.2%	87.2%	2.0%	14%
39	41	753	53%	-6.8%	89.3%	6.3%	17%
40	42	700	40%	-12.2%	96.1%	12.3%	22%
41	45	716	37%	-12.8%	96.5%	14.1%	24%
42	46	294	89%	-17.2%	26.2%	-5.3%	6%
43	48	702	52%	-12.9%	94.5%	6.5%	19%
44	49	875	43%	-14.3%	98.1%	11.8%	23%
45	50	855	43%	-13.6%	97.7%	11.7%	22%
46	51	364	30%	-1.0%	96.4%	8.5%	17%
47	52	1109	41%	-15.3%	99.8%	13.8%	24%

Table 6.3. Detailed Subadditivity Results for the Data Points in 1988: HSUR Model

Observation	Firm Code	Monopoly Cost is Lower than Two-Firm Cost		Savings From a Two-Firm Industry (Percent of Fitted Monopoly Cost)			
		Number of Cases	Percent of Cases	Minimum	Maximum	Average	Standard Error
1	1	787	83%	-37.7%	53.1%	-7.9%	13%
2	2	1207	66%	-31.7%	67.7%	0.7%	16%
3	3	275	86%	-82.8%	24.9%	-13.0%	17%
4	4	536	72%	-31.8%	56.7%	-1.6%	10%
5	5	536	75%	-47.7%	41.0%	-3.7%	12%
6	6	826	69%	-15.3%	87.6%	0.9%	12%
7	7	350	82%	-14.8%	28.5%	-2.9%	4%
8	8	960	79%	-37.3%	55.0%	-5.8%	14%
9	9	938	68%	-32.6%	59.3%	-0.9%	14%
10	10	994	67%	-16.8%	87.9%	1.6%	14%
11	11	914	66%	-29.6%	85.4%	0.5%	14%
12	12	806	62%	-26.9%	85.8%	1.2%	14%
13	13	624	38%	-4.2%	94.2%	9.3%	17%
14	14	896	45%	-8.0%	85.6%	8.6%	17%
15	15	614	65%	-34.1%	55.2%	-1.6%	12%
16	16	908	61%	-20.3%	88.0%	2.3%	14%
17	17	843	61%	-12.7%	88.8%	3.1%	13%
18	18	985	68%	-22.5%	87.4%	1.0%	15%
19	19	601	60%	-39.3%	48.2%	-0.6%	13%
20	20	376	57%	-15.2%	88.4%	0.5%	8%
21	21	367	60%	-36.1%	82.2%	-1.4%	10%
22	22	653	47%	-8.2%	88.5%	6.9%	16%
23	23	479	54%	-28.0%	84.7%	0.5%	11%
24	24	913	69%	-15.7%	87.5%	1.1%	13%
25	25	921	55%	-13.7%	87.5%	6.4%	18%
26	26	802	50%	-10.0%	96.7%	8.0%	20%
27	27	659	70%	-13.1%	88.0%	0.6%	10%
28	28	555	67%	-6.4%	87.5%	2.1%	12%
29	29	715	60%	-9.3%	88.3%	3.2%	13%
30	30	603	56%	-3.8%	95.6%	4.6%	15%
31	31	262	83%	-10.2%	14.1%	-2.6%	3%
32	32	495	63%	-10.4%	94.1%	2.8%	15%
33	33	677	45%	-12.5%	91.7%	10.1%	20%
34	34	755	41%	-11.3%	98.6%	11.4%	22%
35	35	595	39%	-5.3%	95.5%	9.0%	19%
36	36	392	41%	-4.3%	86.2%	6.0%	13%
37	37	393	48%	-4.5%	87.3%	4.3%	12%
38	38	700	64%	-11.6%	87.3%	2.2%	13%
39	41	750	53%	-6.6%	88.5%	6.1%	17%
40	42	684	40%	-12.1%	96.1%	12.3%	22%
41	45	708	37%	-12.6%	96.7%	13.7%	23%
42	46	272	86%	-20.9%	25.8%	-5.1%	5%
43	48	686	52%	-11.4%	94.8%	6.7%	19%
44	49	886	44%	-13.4%	98.1%	11.0%	21%
45	50	852	43%	-12.6%	97.7%	11.4%	21%
46	51	382	31%	-1.5%	95.7%	8.2%	17%
47	52	1107	41%	-14.9%	99.5%	13.6%	24%

$[C(Q_t) - C(Q^A_t) - C(Q^B_t)] / C(Q_t)$. If the combined costs of the two firms are higher than the cost of a monopoly, then the entry is a negative number. If the combined costs of the two firms are lower than the monopoly cost, than the entry is a positive number (saving from a two-firm industry). Column six – maximum saving from a two-firm industry – corresponds to the measure of subadditivity used by Evans and Heckman (1984). Column seven – average savings from a two-firm industry – is the measure of subadditivity used by Shin and Ying (1992). Column eight is calculated, following Shin and Ying (1992), as the empirical standard deviation of the savings for all possible output combinations.

The maximum savings from a two-firm industry are positive for each observation in 1988, and, in fact, for all 379 data points in the sample. In other words, for each observation in the sample, there exists a two-firm combination such that the combined cost of the two firms is lower than the cost of one firm producing the observed output vector. Therefore, the condition for subadditivity is violated.

The average savings from a two-firm combination are of mixed signs. The average savings are positive for approximately 40 % of the data points in the sample (42 % in the SUR model, and 43 % in the Heteroscedastic SUR model). Interestingly, the sign of the average savings tends to correlate with the customer composition of the markets: in a subsample of observations with lower than average percent of nonresidential lines only 20 % of average savings are negative, and the total is positive. However, the average savings are negative for almost all (98 %) data points with higher than average percentages of nonresidential lines. The maximum savings exhibit similar correlation with the percent of nonresidential lines: the level of maximum savings expressed as the percent of the monopoly cost is almost 1.5 times higher in 'residential' markets compared to 'business' markets. This result suggests that while efficiency gains from subdividing the markets exist in predominantly residential markets, they might be small, if nonexistent, in business markets.

Tables 6.4 and 6.5 summarize the subadditivity calculations by each firm in the sample, which represents each regional monopolized market. Each entry in columns two through four measures annual dollar savings from a two-firm industry calculated as a simple average for observations on each monopoly firm over time. The average savings from a two-firm industry are negative for the 59 % of the regional markets in both models. Total average annual savings summed over all markets are also negative, indicating that total average losses from a two-firm industry exceed gains on the national level.

Tables 6.6 and 6.7 aggregate savings from a two-firm industry by year. Each entry represents combined savings from all firms that existed in a given year. Interestingly, average savings aggregated annually are negative for all years except for 1988 – the first year in the sample. The percent of observations with negative savings is also very low in 1988: 34 % in the SUR model and 26 % in the Heteroscedastic SUR model (see tables 6.2 and 6.3). However, this gain in efficiency is compensated by negative savings in the following years, resulting in a point estimate of $ 1.6 billion (SUR model) in annual losses averaged for 1988-95.

Table 6.4. Average Annual Savings from a Two-Firm Industry in Each Market: SUR

Firm Code (Market)	Minimum Saving *(dollars)*	Maximum Saving *(dollars)*	Average Saving *(dollars)*
1	-67,260,457	94,784,271	-15,189,750
2	-1,265,770,081	1,999,357,495	-89,973,610
3	-385,152,200	31,858,761	-69,475,051
4	-756,289,069	840,094,632	-71,837,974
5	-878,787,579	507,357,157	-80,597,324
6	-86,776,019	458,935,599	-6,859,025
7	-119,329,922	482,232,190	-23,201,648
8	-103,282,716	156,063,088	-19,419,437
9	-1,383,611,109	1,360,292,226	-95,352,648
10	-371,289,964	481,200,799	-35,006,902
11	-1,175,597,593	1,310,036,201	-88,990,612
12	-1,119,084,716	2,551,336,516	-11,464,896
13	-1,383,858,464	2,719,941,992	-51,763,523
14	-1,873,468,420	2,017,268,688	-178,098,128
15	-3,441,505,033	3,880,572,911	-267,270,569
16	-588,007,101	1,512,328,186	744,523
17	-663,836,108	1,645,973,939	34,638,169
18	-568,792,136	1,559,864,812	-15,144,864
19	-4,257,264,535	3,164,905,101	-273,076,367
20	-1,027,458,275	4,271,803,704	-17,514,638
21	-2,707,656,903	4,896,843,946	-127,959,586
22	-417,923,212	1,156,139,313	-16,942,200
23	-3,206,601,505	4,611,804,900	-126,775,431
24	-359,575,613	762,088,673	-26,860,617
25	-40,010,599	255,883,290	9,349,521
26	-30,491,369	235,491,844	12,965,312
27	-220,983,493	1,058,068,287	-40,749
28	-77,607,104	578,057,133	9,037,427
29	-134,088,295	577,972,267	-1,705,335
30	-152,130,973	696,250,900	11,130,622
31	-80,418,747	161,360,793	-18,415,101
32	-18,596,785	154,475,376	4,885,489
33	-22,260,912	133,652,085	11,103,711
34	-38,492,287	284,064,252	19,515,334
35	-44,245,880	458,498,936	26,575,619
36	-87,591,834	274,266,060	-8,932,760
37	-598,652,687	1,897,640,179	-14,887,165
38	-21,481,516	81,940,672	-2,538,682
39	-122,136,178	707,903,495	3,855,340
40	-43,412,662	89,556,836	-12,584,029
41	-125,224,594	676,183,762	15,077,943
42	-29,317,779	188,055,015	17,508,237
43	-26,137,826	111,829,449	-991,243
44	-33,694,968	97,734,797	-8,163,957
45	-25,347,048	187,814,931	22,507,629
46	-9,166,635	13,958,113	-2,843,961
47	-61,181,947	78,776,617	-10,146,111
48	-20,059,093	136,513,842	5,355,380
49	-16,641,479	112,553,688	11,852,322
50	-16,397,048	121,220,557	14,097,872
51	-103,278,366	1,780,069,896	146,097,024
52	-19,949,821	133,586,998	15,760,614
53	-4,298,270,023	2,137,444,278	-223,528,017
54	-19,403,900	135,337,835	8,999,357
55	-15,263,915	101,969,663	7,816,169
56	-35,384,771	92,081,547	-1,478,130
57	-5,771,396,410	6,682,525,382	-260,461,470
58	-21,610,345	86,443,312	3,034,055
59	-16,251,677	85,669,343	4,529,123
60	-25,895,621	169,951,842	-1,115,293
61	-19,513,283	100,577,349	9,812,907
62	-15,850,054	116,331,858	15,351,919
63	-37,035,019	322,833,069	23,685,198
64	-20,326,198	87,646,526	231,693
65	-36,091,452	96,917,407	-9,778,186
66	-63,527,276	60,705,081	-15,879,885
Total Annual Saving	-40,822,996,596	64,032,899,662	-1,836,746,369

Table 6.5. Average Annual Savings from a Two-Firm Industry in Each Market: HSUR

Firm Code (Market)	Minimum Saving (dollars)	Maximum Saving *(dollars)*	Average Saving *(dollars)*
1	-73,170,045	86,869,637	-13,399,016
2	-1,348,993,014	1,772,576,801	-93,930,088
3	-407,955,055	60,492,896	-67,448,770
4	-868,477,807	672,456,781	-70,883,151
5	-1,028,400,668	445,696,721	-82,017,232
6	-119,969,026	443,732,010	-12,492,607
7	-142,794,255	460,466,071	-22,469,527
8	-120,138,901	127,581,738	-18,856,570
9	-1,386,523,227	1,308,456,796	-71,975,946
10	-394,855,807	424,523,882	-30,149,484
11	-1,250,243,689	1,252,498,804	-81,177,883
12	-984,072,268	2,479,126,045	19,806,242
13	-1,444,247,259	2,644,856,686	-49,684,726
14	-1,962,972,801	2,162,000,474	-154,395,203
15	-3,429,854,697	3,568,987,062	-251,025,106
16	-595,977,704	1,460,491,810	13,309,935
17	-698,969,630	1,576,861,386	38,228,379
18	-535,504,869	1,513,147,013	-1,524,403
19	-3,810,235,681	3,497,326,338	-169,739,166
20	-1,035,504,562	4,145,757,784	-12,926,638
21	-2,796,564,235	4,598,530,370	-122,374,832
22	-444,928,201	1,130,591,107	-11,235,551
23	-3,331,140,590	4,444,629,173	-114,605,670
24	-366,358,194	715,504,315	-21,417,999
25	-40,608,270	253,143,327	9,231,934
26	-35,027,784	235,149,508	11,261,819
27	-237,830,355	1,027,363,062	-1,350,985
28	-87,588,313	565,007,335	6,885,501
29	-163,869,147	555,912,039	-6,047,536
30	-169,112,285	669,579,488	9,333,445
31	-91,111,567	153,085,195	-18,969,889
32	-16,830,082	150,894,819	4,125,525
33	-21,297,387	133,058,848	10,983,224
34	-41,012,449	279,103,334	18,583,878
35	-56,592,290	454,979,763	22,495,671
36	-89,629,233	255,898,731	-6,907,902
37	-563,730,060	1,824,865,156	-1,497,741
38	-24,031,468	74,889,804	-2,615,085
39	-148,200,846	697,701,366	-4,354,483
40	-46,129,838	87,448,642	-11,686,590
41	-145,736,412	669,015,833	13,173,537
42	-30,649,021	189,453,275	16,343,866
43	-26,852,368	107,402,724	-730,262
44	-28,330,224	97,390,074	-4,705,131
45	-25,056,686	190,885,083	21,996,246
46	-10,051,644	12,416,640	-2,429,631
47	-62,198,216	77,888,990	-8,107,608
48	-21,734,091	134,127,053	4,549,205
49	-15,860,550	115,575,811	11,108,749
50	-15,812,014	125,731,378	13,496,786
51	-129,561,592	1,727,232,347	126,837,932
52	-19,329,320	136,612,303	15,780,667
53	-4,538,167,719	2,021,365,968	-232,796,412
54	-17,899,053	136,657,006	7,270,772
55	-13,697,748	104,089,375	6,750,263
56	-40,046,480	89,095,587	-542,275
57	-5,972,692,809	5,847,163,558	-277,491,260
58	-18,916,648	82,882,892	2,809,323
59	-14,541,323	84,827,757	3,301,878
60	-32,688,146	165,137,494	-2,426,938
61	-19,034,732	101,863,760	9,780,672
62	-15,292,642	121,192,003	15,043,657
63	-46,372,359	327,158,895	21,037,078
64	-19,351,694	86,372,959	371,074
65	-31,169,212	93,870,259	-6,395,597
66	-60,059,058	68,555,418	-12,094,015
Total Annual Saving	-41,781,555,316	61,325,206,557	-1,620,981,650

Table 6.6. Total Saving from a Two-Firm Industry by Year: SUR Model

Year	Minimum Saving *(dollars)*	Maximum Saving *(dollars)*	Average Saving *(dollars)*
88	-21,333,175,519	60,768,292,682	430,706,244
89	-25,719,414,748	59,001,683,806	-750,982,621
90	-28,227,529,525	58,389,124,673	-1,061,377,901
91	-30,580,960,021	49,580,865,344	-1,700,624,016
92	-32,873,532,079	50,729,168,000	-1,228,284,741
93	-36,940,881,444	41,188,810,214	-2,272,696,485
94	-42,625,516,337	40,962,853,727	-2,932,623,308
95	-41,809,858,139	35,504,592,801	-2,917,335,030
Average for 1988 - 95	-32,513,858,477	49,515,673,906	-1,554,152,232

Table 6.7. Total Saving from a Two-Firm Industry by Year: Heteroscedastic SUR Model

Year	Minimum Saving *(dollars)*	Maximum Saving *(dollars)*	Average Saving *(dollars)*
88	-18,853,946,168	59,239,216,506	1,094,513,349
89	-24,598,544,546	57,680,299,957	-345,522,163
90	-27,820,251,485	56,473,772,510	-765,356,389
91	-31,111,855,884	47,258,892,766	-1,483,421,491
92	-34,821,017,020	48,513,583,582	-1,200,804,059
93	-38,979,507,370	38,652,391,897	-2,257,864,468
94	-44,809,568,755	39,204,038,894	-2,983,032,345
95	-45,457,902,295	33,882,854,221	-2,993,377,666
Average for 1988 - 95	-33,306,574,190	47,613,131,292	-1,366,858,154

The savings estimates of the model with the consistent error structure are slightly more favorable for a two-firm industry – the Heteroscedastic SUR cost function generates higher point estimates of averages savings from a two-firm industry than the conventional SUR model.

In general, my subadditivity test produces weaker evidence for **superadditivity** than the test conducted by Shin and Ying (1992). Though the authors reported their results only on the aggregate yearly basis, several distinctions are noticeable. First, the percent of the output combinations for which monopoly was efficient is much lower in Shin and Ying's model. Second, their average savings from a two-firm industry were positive for each year of observation. Third, unlike in Shin and Ying's study, the average savings summed for the period of observation are negative. Fourth, the magnitude of the average savings or losses expressed as the percent of the monopoly cost is lower in my model compared to Shin and Ying's, though the magnitude of the maximum and minimum savings is higher in my model. Similar to Shin and Ying's findings, the maximum savings from a two-firm industry exceed the minimum savings (losses) in absolute value for most observation and as a total.

Clearly, the two measures of subadditivity – the maximum savings of Evans and Heckman and the average savings of Shin and Ying – produce qualitatively different evidence on the subject. The measure of Evans and Heckman is appropriate only under certain ideal conditions: the feasibility of all output combinations and the existence of incentives necessary to ensure that the two firms share the market in the cost-minimizing proportions. An actual two-firm industry might not choose the cost-minimizing output vector due to economic or technological reasons. As table 6.8 demonstrates, the division of the market that results in the maximum savings is asymmetric, with one firm serving more than 50 % of the market. It is unclear whether the incentives exist to achieve this asymmetric equilibrium. The cost-minimizing output vector of the two-firm industry might be technologically implausible. Legal limitation – such as state laws requiring provision of residential service by all telecommunications companies that serve business customers – impose additional restrictions on the set of feasible output vectors.

Table 6.8. Optimal Division of the Markets: Data Points for 1988, SUR model

observation	Total Telephone Lines	Percent of Nonresidential Lines			Percent of Local Calls		
	Firm A	Monopoly	Firm A	Firm B	Monopoly	Firm A	Firm B
1	41%	35%	81%	3%	85%	72%	94%
2	31%	32%	95%	3%	72%	15%	97%
3	11%	66%	93%	63%	91%	90%	91%
4	41%	34%	78%	3%	89%	83%	94%
5	11%	36%	57%	33%	89%	13%	99%
6	31%	25%	77%	1%	87%	85%	88%
7	1%	29%	96%	28%	95%	86%	95%
8	41%	34%	79%	3%	81%	63%	94%
9	21%	34%	3%	43%	78%	8%	97%
10	31%	28%	86%	2%	82%	50%	96%
11	31%	30%	93%	2%	82%	50%	96%
12	31%	31%	97%	2%	82%	52%	96%
13	31%	29%	90%	2%	77%	34%	97%
14	41%	33%	77%	3%	68%	29%	95%
15	41%	34%	79%	3%	86%	75%	94%
16	31%	28%	86%	2%	81%	48%	96%
17	31%	27%	85%	2%	83%	54%	96%
18	31%	29%	89%	2%	81%	46%	96%
19	11%	39%	23%	41%	83%	8%	92%
20	31%	25%	76%	1%	93%	87%	96%
21	31%	29%	91%	2%	92%	84%	96%
22	31%	31%	95%	2%	81%	86%	78%
23	31%	28%	87%	2%	89%	75%	96%
24	31%	28%	87%	2%	83%	54%	96%
25	31%	23%	73%	1%	81%	86%	78%
26	21%	19%	90%	1%	84%	84%	84%
27	31%	26%	79%	1%	90%	87%	92%
28	31%	23%	70%	1%	92%	84%	96%
29	31%	24%	74%	1%	87%	86%	88%
30	21%	21%	96%	1%	91%	83%	93%
31	1%	30%	94%	30%	96%	87%	96%
32	21%	19%	89%	1%	93%	87%	95%
33	21%	17%	79%	1%	88%	85%	88%
34	21%	19%	88%	1%	82%	25%	98%
35	21%	19%	89%	1%	86%	87%	86%
36	31%	25%	77%	1%	90%	87%	92%
37	31%	31%	95%	2%	90%	85%	92%
38	31%	25%	78%	1%	88%	88%	88%
39	31%	22%	68%	1%	86%	89%	85%
40	21%	17%	79%	1%	84%	84%	84%
41	21%	15%	70%	1%	83%	88%	82%
42	1%	37%	95%	36%	95%	86%	95%
43	21%	20%	93%	1%	88%	88%	88%
44	21%	17%	76%	1%	83%	25%	98%
45	21%	17%	76%	1%	83%	84%	82%
46	21%	20%	92%	1%	90%	87%	90%
47	21%	17%	76%	1%	72%	7%	89%

Another factor that affects interpretation of the calculated maximum savings from a two-firm industry is the statistical significance of the forecast. Although the exact forecast variance does not have a limiting distribution and, therefore, cannot be calculated, it is possible to estimate the component of the forecast error that stems from the statistical error in estimating the parameters of the cost function. Obviously, the estimated statistical error of the calculated savings understates the forecast variance because it ignores its other component – random disturbance associated with the realization of the forecasted state.

Strictly speaking, the estimated forecast errors of the fitted costs cannot be directly translated into the forecast errors for the savings because the calculated savings present a nonlinear transformation of the fitted variable – the natural logarithm of cost: $Savings = exp[\, ln\, C\,(Q)] - exp\,[\, ln\, C\,(Q^{A})\,] - exp\,[\, ln\, C\,(Q^{B})\,]$. To get an approximate lower boundary for the maximum savings, I use the estimated forecast variances for the fitted costs and the associated normal 95 % confidence intervals. I calculate the approximate lower boundary for the maximum savings using the values for the lower boundary of the monopoly cost $ln\, C\,(Q)$ and the upper boundaries of the costs of the 'competitive' firms $ln\, C\,(Q^{A})$ and $ln\, C\,(Q^{B})$.

Table 6.9 contains the estimates for the forecast errors and the approximate lower boundaries of the maximum savings for the data points in 1988. As the last column indicates, only three estimates for the maximum savings are insignificant in 1988. In fact, out of 379 observations in the data set, only 14 % of the estimates for the lower boundary of the maximum savings are negative. In other words, the estimated forecast errors of the

Table 6.9. Forecast Errors for the Fitted Costs at Maximum Savings: Data Points in 1988, SUR Model

Observation	Firm Code	*ln C (Q)*		*ln C (Q^A)*		*ln C (Q^B)*		Maximum Savings*	Lower Boundary for Maximum Savings*
		value	standard error	value	standard error	value	standard error		
1	1	-2.351	0.047	-4.231	0.173	-3.749	0.290	0.057	0.025
2	2	0.690	0.037	-2.355	0.351	-0.721	0.272	1.413	0.836
3	3	-1.313	0.051	-3.329	1.128	-1.633	0.080	0.038	-0.312
4	4	-0.007	0.022	-2.172	0.100	-1.280	0.246	0.601	0.361
5	5	-0.145	0.027	-2.446	0.122	-1.036	0.227	0.423	0.158
6	6	-1.204	0.021	-3.766	0.121	-4.500	0.459	0.266	0.231
7	7	-0.945	0.027	-3.681	0.317	-1.381	0.040	0.112	0.050
8	8	-1.793	0.022	-3.787	0.172	-3.222	0.286	0.104	0.058
9	9	0.620	0.022	-1.851	0.215	-0.590	0.250	1.147	0.635
10	10	-0.419	0.018	-3.439	0.296	-3.429	0.441	0.593	0.500
11	11	0.463	0.027	-2.915	0.344	-1.961	0.398	1.393	1.094
12	12	0.710	0.028	-2.688	0.331	-1.677	0.405	1.778	1.381
13	13	0.755	0.066	-2.711	0.667	-2.696	0.684	1.994	1.365
14	14	0.676	0.108	-2.232	0.792	-1.401	0.555	1.613	0.354
15	15	1.432	0.025	-0.922	0.121	0.320	0.257	2.412	1.199
16	16	0.185	0.027	-3.143	0.345	-2.572	0.418	1.083	0.884
17	17	0.380	0.022	-2.572	0.264	-2.731	0.467	1.321	1.109
18	18	0.213	0.020	-3.090	0.346	-2.485	0.418	1.108	0.910
19	19	1.481	0.041	-1.069	0.204	0.708	0.266	2.026	0.134
20	20	1.077	0.045	-1.851	0.149	-1.909	0.463	2.630	2.111
21	21	1.365	0.032	-1.895	0.165	-0.808	0.400	3.318	2.495
22	22	-0.314	0.082	-2.871	0.540	-3.982	0.756	0.656	0.377
23	23	1.488	0.040	-1.755	0.200	-0.868	0.421	3.837	2.878
24	24	-0.317	0.018	-3.228	0.260	-3.323	0.444	0.653	0.551
25	25	-1.827	0.037	-4.058	0.354	-6.070	0.590	0.141	0.108
26	26	-1.904	0.020	-5.702	0.538	-7.221	0.713	0.145	0.131
27	27	-0.242	0.021	-2.869	0.096	-3.516	0.466	0.699	0.612
28	28	-1.036	0.023	-3.320	0.067	-5.076	0.566	0.313	0.279
29	29	-0.941	0.017	-3.415	0.130	-4.646	0.508	0.348	0.309
30	30	-0.672	0.029	-4.121	0.214	-5.454	0.631	0.490	0.443
31	31	-1.240	0.069	-4.957	0.496	-1.421	0.069	0.041	-0.042
32	32	-2.327	0.052	-5.188	0.203	-7.889	0.731	0.092	0.078
33	33	-2.603	0.046	-5.048	0.303	-9.138	0.857	0.068	0.055
34	34	-1.632	0.038	-6.026	0.690	-7.621	0.802	0.193	0.170
35	35	-1.316	0.031	-4.777	0.399	-6.640	0.681	0.258	0.229
36	36	-1.908	0.057	-4.050	0.182	-6.441	0.652	0.129	0.102
37	37	0.270	0.102	-2.203	0.310	-3.421	0.818	1.167	0.706
38	38	-2.757	0.024	-4.963	0.139	-6.765	0.547	0.055	0.048
39	41	-0.869	0.019	-4.640	0.416	-3.342	0.383	0.374	0.307
40	42	-2.171	0.045	-5.445	0.449	-8.704	0.869	0.110	0.093
41	45	-2.189	0.037	-5.582	0.495	-8.900	0.883	0.108	0.094
42	46	-3.439	0.072	-5.991	0.338	-3.855	0.106	0.008	-0.003
43	48	-2.500	0.038	-5.490	0.213	-7.852	0.688	0.078	0.068
44	49	-2.666	0.031	-6.746	0.611	-8.959	0.876	0.068	0.061
45	50	-2.692	0.027	-6.536	0.643	-9.028	0.835	0.066	0.058
46	51	0.100	0.049	-3.376	0.202	-5.229	0.714	1.065	0.932
47	52	-2.584	0.040	-12.419	2.401	-8.600	0.772	0.075	0.069

* – costs are measured in deviations from the sample mean

maximum savings fail to reject the hypothesis that the maximum savings are positive for the majority of the data points.

The subadditivity measure of Shin and Ying (1992) – the average savings from a two-firm industry – implies that each of the two-firm output combination can occur. In this case,. the more useful measure of subadditivity will be an interval, rather than a point estimate. The distributional characteristics of this estimate would depend on the unknown distribution of the feasible two-firm output combinations, as well as on the distribution of the forecast. However, in order to get a rough interval estimate, I assumed that savings from each two-firm industry configuration are independent and identically distributed, and constructed confidence intervals for each estimate of the average savings using the sample variance in savings for each observation. As table 6.2 illustrates, the standard deviations of each estimate for average savings are rather high, and therefore, the 90 and 95 % confidence intervals constructed using normal approximation contain positive and negative values. In other words, given the stochastic nature of the estimates of the average savings, it is unclear whether a two-firm industry configuration can produce at lower cost than a monopoly on average.

In the above described subadditivity test I follow the previous studies and keep all the control variables constant in the calculations of the cost of the two hypothetical firms. Therefore, the test assumes a very particular partitioning of the monopolized telecommunications markets between the two firms – geographical division or the purchase of the network elements from the incumbent rather than side by side competition that requires facilities entry. In order to test whether side by side competition is economically feasible, I conduct a modified subadditivity test. I assume that side by side competition in each market will require complete duplication of the cable facilities, and recalculate the average loop length *WI*, which is defined as length of cable wire per line, on each step of the grid search to adjust for the decrease in the number of telephone lines of each hypothetical competitive firm.

Table 6.10 summarizes the results by year. The average savings are negative for all observations, but the maximum savings are positive for 92 %, and significant for 62 % of observations. The maximum savings under side by side competition are only slightly lower than the maximum savings under geographical division of the markets. However, the average and the minimum savings differ by a factor of 10^5. These results provide evidence that side by side competition is possible, but can also produce substantial increase in costs.

Table 6.10. Side by Side Competition: Total Saving from a Two-Firm Industry by Year, SUR Model

Year	Minimum Saving *(dollars)*	Maximum Saving *(dollars)*	Average Saving *(dollars)*
88	-1,647,609,452,859,890	48,407,539,153	-15,057,930,476,134
89	-1,895,899,176,527,000	44,147,410,445	-16,519,680,117,004
90	-1,848,700,994,034,940	41,544,646,263	-16,813,236,825,864
91	-1,562,333,830,864,370	30,254,408,091	-14,543,495,817,649
92	-1,553,786,770,596,360	33,374,606,663	-14,408,631,297,612
93	-1,308,857,412,695,470	16,905,575,580	-11,906,485,719,079
94	-1,243,834,721,730,200	16,730,049,146	-10,912,849,321,092
95	-965,817,618,036,022	10,515,985,601	-10,275,013,176,878
Average for 1988 - 95	-1,503,354,997,168,030	30,235,027,618	-13,804,665,343,914

6.2. Estimation of Production Inefficiency

6.2.1. Technical Inefficiency of the Local Telephone Industry

6.2.1.1. Firm-Specific Input Technical Inefficiency

I estimate relative technical inefficiency in the panel data set by assuming that technical inefficiency varies across companies but not time. I adopt both specifications of the inefficiency effects, fixed and random. Introduction of company-specific intercepts in the SUR model (the DVLS model) permits estimation of technical inefficiency under the assumption of fixed effects. The error component model (ECM) generates the inefficiency estimates under the assumption of random effects. In each model, the company with the smallest inefficiency estimate is considered the most efficient company in the sample. The difference between the inefficiency estimate for each company and the smallest inefficiency estimate among all companies produces the relative inefficiency ranking.

First, I assume that technical inefficiency varies over firms and estimate firm-specific effects using both the fixed (DVLS) and random (ECM) effects models. Table 6.11 presents the estimates of the DVLS intercepts, ECM residuals averaged for each firm. The table also contains relative technical inefficiency and firms' efficiency rankings for both methods. Twenty eight out of the 66 DVLS intercepts have t-statistics that are lower than the critical values at the 95 % level of significance. Despite the high variance, the 95 % confidence intervals for the intercepts of these companies lie above the intercept of the most efficient firm. In fact, the 95 % confidence intervals for the intercepts of only

Table 6.11. Relative Input Technical Efficiency and Efficiency Ranking of Firms

Firm Code	DVLS model				ECM model		
	intercept	t-statistics	relative efficiency	efficiency rank	average residual	relative efficiency	efficiency rank
36	-0.446	-8.28	0.00	1	-0.0023	0.00000	1
8	-0.431	-6.04	0.02	2	-0.0003	0.00204	20
3	-0.412	-4.60	0.03	3	-0.0003	0.00202	17
40	-0.392	-5.92	0.05	4	-0.0002	0.00220	38
7	-0.375	-7.33	0.07	5	-0.0001	0.00222	45
56	-0.283	-2.51	0.16	6	-0.0006	0.00178	6
1	-0.241	-2.71	0.21	7	-0.0006	0.00174	5
24	-0.227	-8.53	0.22	8	-0.0002	0.00216	33
44	-0.207	-2.02	0.24	9	0.0000	0.00231	60
60	-0.185	-2.47	0.26	10	-0.0002	0.00219	37
65	-0.155	-1.49	0.29	11	0.0000	0.00232	61
32	-0.144	-1.90	0.30	12	-0.0001	0.00220	40
27	-0.144	-6.29	0.30	13	-0.0003	0.00204	22
14	-0.140	-3.92	0.31	14	-0.0002	0.00218	35
66	-0.138	-1.31	0.31	15	-0.0001	0.00224	47
4	-0.123	-8.43	0.32	16	-0.0005	0.00187	7
10	-0.116	-3.94	0.33	17	-0.0002	0.00213	30
17	-0.107	-6.61	0.34	18	-0.0001	0.00221	44
54	-0.106	-1.23	0.34	19	0.0000	0.00231	59
55	-0.086	-0.89	0.36	20	-0.0001	0.00228	53
6	-0.064	-1.16	0.38	21	-0.0003	0.00202	18
41	-0.060	-1.56	0.39	22	-0.0006	0.00171	4
39	-0.058	-1.25	0.39	23	-0.0004	0.00197	11
47	-0.054	-0.67	0.39	24	-0.0003	0.00210	26
9	-0.041	-1.06	0.41	25	-0.0004	0.00191	10
22	-0.027	-1.15	0.42	26	-0.0001	0.00226	49
42	-0.022	-0.29	0.42	27	-0.0004	0.00190	9
5	-0.017	-0.81	0.43	28	-0.0001	0.00220	41
2	-0.014	-0.37	0.43	29	-0.0003	0.00201	15
45	-0.010	-0.13	0.44	30	-0.0001	0.00229	55
37	0.018	1.08	0.46	31	-0.0003	0.00202	16
31	0.025	0.39	0.47	32	-0.0003	0.00209	25
62	0.030	0.31	0.48	33	-0.0001	0.00229	54
33	0.052	0.60	0.50	34	-0.0001	0.00228	52
48	0.053	0.66	0.50	35	-0.0001	0.00225	48
35	0.063	1.33	0.51	36	-0.0005	0.00189	8
18	0.064	3.25	0.51	37	-0.0001	0.00227	51
34	0.075	1.22	0.52	38	-0.0004	0.00198	13
28	0.107	2.46	0.55	39	-0.0004	0.00198	12
11	0.110	3.46	0.56	40	-0.0002	0.00217	34
25	0.111	1.56	0.56	41	-0.0003	0.00204	21
26	0.125	1.80	0.57	42	-0.0001	0.00220	39
43	0.130	1.42	0.58	43	-0.0003	0.00207	24
61	0.146	1.36	0.59	44	0.0000	0.00232	62
64	0.168	1.47	0.61	45	0.0000	0.00232	63
49	0.187	1.98	0.63	46	-0.0003	0.00210	27
58	0.195	1.47	0.64	47	-0.0002	0.00219	36
38	0.231	2.71	0.68	48	-0.0007	0.00168	2
13	0.238	4.90	0.68	49	-0.0003	0.00205	23
15	0.262	3.03	0.71	50	-0.0002	0.00214	32
59	0.264	2.04	0.71	51	0.0000	0.00232	66
29	0.318	8.22	0.76	52	-0.0001	0.00220	43
16	0.333	11.37	0.78	53	-0.0001	0.00224	46
30	0.333	11.24	0.78	54	-0.0003	0.00201	14
12	0.347	5.96	0.79	55	0.0000	0.00232	65
19	0.367	3.00	0.81	56	-0.0002	0.00213	29
52	0.379	4.15	0.83	57	-0.0003	0.00204	19
63	0.398	6.85	0.84	58	-0.0002	0.00213	31
50	0.412	4.52	0.86	59	-0.0006	0.00170	3
20	0.424	4.93	0.87	60	0.0000	0.00231	58
21	0.477	4.55	0.92	61	0.0000	0.00230	57
51	0.511	17.99	0.96	62	-0.0001	0.00220	42
46	0.528	4.04	0.97	63	0.0000	0.00232	64
23	0.598	4.75	1.04	64	-0.0002	0.00212	28
53	0.670	5.21	1.12	65	-0.0001	0.00227	50
57	0.746	4.31	1.19	66	0.0000	0.00230	56

five firms (ranked two through six) include the value of the intercept of the most efficient firm.

The relative inefficiency measures correspond to the logarithmic form of the cost function. Therefore, the inverse of the exponent of the relative inefficiency is a factor that reflects potential reductions in cost. For example, the relative technical inefficiency measure for firm 8 using the DVLS methods is 0.02, which implies that firm 8 could reduce its cost by a factor of 0.984 (= $e^{-0.02}$), or by 1.6 %, without decreasing output.

It can be easily seen from table 6.11 that the DVLS method produces higher relative inefficiency estimates than the ECM method. On average, the relative inefficiency is 0.52 for the DVLS method, and only 0.002 for the ECM method. Therefore, the DVLS model estimates the losses from technical inefficiency to be 41 % (= 1 - $e^{-.52}$) of cost on average, while according to the ECM method these losses are only 0.2 % (= 1 - $e^{-.002}$).

The two methods produce different efficiency ranking. Firm 8 – The Diamond State Telephone Company – ranked as second most efficient in the sample by the DVLS method, is only 20th according to the ECM. The top ranked firm on the ECM list, firm 36 – Central Telephone Company (Nevada and North Carolina), is also the most efficient firm according to the DVLS method. The least efficient firm of the DVLS method, firm 57 – BellSouth, is ranked 56th by the ECM method, while the least efficient firm of the ECM, firm 59 – Contel of the West, is 51st according to the DVLS method. In order to compare the efficiency rankings of both methods formally, I divided the DVLS ranking list into three groups of equal size and calculated the corresponding average ECM ranking for each group. The twenty two firms from the most efficient group on the DVLS list have an average rank of 31 on the ECM list, the middle group has a rank of 30.7, and the least efficient DVLS group is classified by the ECM as 39th on average. The above exercise provides no evidence of any consistency in the rankings by the two methods.

Table 6.12 compares the translog estimates of all other parameters of the two models, DVLS and ECM, with the estimates of the original specification – the SUR. Estimates of the terms that involve input prices are barely different from the original estimates. The most significant changes happened to the output parameters. The first order coefficient on the number of access telephone lines (variable *TL*) in the DVLS model dropped to 0.75 compared to 0.98 in the SUR model, indicating strong economies of scale at the sample means. The second order coefficient on telephone lines changed its sign to positive and remained statistically significant.

Although the elasticity of cost with respect to the number of telephone lines averaged for all observations also decreased from 0.92 in the SUR model to 0.83 in the DVLS model, its sample variance increased. The elasticity of cost with respect to access lines in the EC model decreased slightly (to 0.94 at the sample means and 0.91 on average). The number of telephone access lines turn out to be positively correlated with the technical inefficiency measure (the correlation coefficient is 0.56 in the DVLS model and 0.15 in the EC model), which explains the decreased average output elasticity. More access lines means higher total cost because firms need more inputs to produce the increased level of the output; large firms also tend to be less efficient; the SUR model does not separate the direct effect of the increased number of access lines on cost from the indirect effect of reduced efficiency.

Table 6.12. Translog Estimates for the Model with Firm-Specific Technical Inefficiency

variable	SUR model		DVLS Model		ECM model	
	coefficient	t-statistics	coefficient	t-statistics	coefficient	t-statistics
INTERCEPT	0.08	6.01	see Table 6.9	see Table 6.9	0.11	10.50
TL	0.98	82.20	0.75	13.44	0.93	107.44
BL	-1.07	-15.66	-0.36	-8.31	-0.57	-14.21
LC	0.10	0.68	0.18	2.94	0.32	5.05
WI	0.19	2.48	0.14	2.99	0.20	4.31
TLBL	-0.07	-1.95	0.05	2.25	0.04	1.84
TLTL/2	0.07	5.92	-0.08	-2.12	0.04	4.37
BLBL/2	-1.23	-10.87	-0.45	-7.14	-0.75	-12.90
LCWI	-0.71	-1.40	0.35	2.05	0.14	0.77
LCLC/2	-2.83	-2.74	1.33	2.64	0.36	0.66
WIWI/2	0.62	1.59	-0.41	-3.32	-0.22	-1.48
TLLC	0.19	1.86	-0.03	-0.81	0.08	2.04
TLWI	0.05	1.10	-0.01	-0.28	0.03	1.17
BLLC	0.15	0.32	-0.09	-0.59	-0.41	-2.27
BLWI	-0.49	-2.77	0.00	-0.02	-0.03	-0.37
PK	0.39	183.80	0.38	203.14	0.38	203.17
PL	0.23	77.77	0.22	81.25	0.23	80.56
PO	0.39	106.17	0.39	120.56	0.39	117.87
TLPK	0.01	6.02	0.01	6.60	0.01	6.75
TLPL	0.01	6.33	0.01	6.26	0.01	6.11
TLPO	-0.02	-8.43	-0.02	-9.12	-0.02	-9.02
BLPK	0.00	-0.53	0.00	0.14	0.00	0.17
BLPL	0.04	3.46	0.03	3.34	0.04	3.40
BLPO	-0.03	-2.42	-0.04	-2.92	-0.04	-2.99
LCPK	0.06	3.06	0.05	3.23	0.05	3.05
LCPL	0.04	1.42	0.04	1.83	0.03	1.38
LCPO	-0.09	-2.93	-0.09	-3.54	-0.08	-3.01
WIPK	0.01	1.24	0.00	0.51	0.01	0.87
WIPL	-0.08	-5.48	-0.08	-6.38	-0.08	-5.70
WIPO	0.06	3.59	0.08	5.15	0.07	4.35
PKPK/2	0.04	5.14	0.05	6.39	0.05	6.29
PKPL	-0.02	-1.97	-0.02	-2.82	-0.02	-2.73
PKPO	-0.03	-7.55	-0.03	-9.46	-0.03	-9.35
PLPL/2	0.05	5.70	0.05	6.15	0.05	5.93
PLPO	-0.04	-7.43	-0.03	-7.47	-0.03	-7.03
POPO/2	0.06	10.13	0.06	12.51	0.06	11.77
FIPK	0.00	-2.24	0.00	-2.31	0.00	-2.08
FIPL	-0.03	-11.44	-0.03	-13.65	-0.03	-12.74
FIPO	0.04	10.80	0.04	14.59	0.04	13.26
TLFI	0.00	0.53	0.00	-0.29	-0.01	-2.31
BLFI	-0.08	-1.53	-0.08	-4.39	-0.06	-3.08
LCFI	0.15	1.49	-0.01	-0.52	0.03	0.92
WIFI	0.08	1.09	-0.04	-2.11	-0.02	-0.70
FIFI/2	0.00	-0.04	0.00	0.06	0.00	0.13
FI	0.02	1.16	-0.02	-3.52	-0.02	-2.52
R-squared in C	0.987		0.999		0.999	
R-squared in SK	0.396		0.4		0.4	
R-squared in SL	0.317		0.317		0.316	

The correlation between the firm-specific intercepts and the number of telephone access lines provides some indication that technical efficiency is not independent from the explanatory variables in the model. This suggests that the ECM specification might result in inconsistent estimates because its distributional assumptions are violated[6].

Accounting for variations in technical efficiency also affected some other output coefficients. The absolute value of the first- and second-order coefficients on the percent of nonresidential telephone lines (variable *BL*) decreased in both models. The absolute value of the cost elasticity with respect to nonresidential lines also decreased on average, indicating that serving business (nonresidential) lines is not as cheap – compared to residential lines – as the SUR model estimates. The first order coefficient on the share of local calls in the total number of calls (variable *LC*), insignificant in the SUR model, becomes significant in both specifications. The second order coefficient on *LC*, as well as the parameter estimate of the interaction term between the share of local calls and the average loop length (*WI*) change sign in the DVLS model to positive, and become insignificant in the EC model. Average cost elasticity with respect to local calls is negative in the SUR model, and positive in both DVLS and ECM. This implies that, if technical inefficiency is accounted for, the increase in the fraction of local calls has a positive impact on cost – contrary to the evidence from the SUR model.

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[6] I was unable to test the ECM specification against DVLS formally because the calculated empirical covariance matrix used in the Hausman specification test turned out to be non-positive definite.

6.2.1.2. Input Technical Inefficiency for Holding Companies

It is reasonable to expect that many factors that affect inefficiency are common for firms that belong to the same holding company. Evaluation of technical efficiency on the level of holding companies might be also useful for regulatory authorities. In order to compare holding companies in terms of technical efficiency, I estimated the DVLS and EC models assuming that technical inefficiency varies over holding companies rather than firms.

Table 6.13 compares the relative technical efficiency estimates from the two models. As in the model with firm-specific effects, the DVLS method gives on average higher estimates of inefficiency, though the difference between the two methods is smaller – the relative technical inefficiency obtained from the DVLS model averaged over holding companies is 0.18, while the average inefficiency from the ECM is 0.09. Seven out of 15 intercepts in the DVLS model have insignificant estimates even at the 90 % level of confidence.

The two models give inconsistent efficiency rankings. Bell Atlantic, ranked as most efficient by the DVLS method, is the 3d worst company in the ECM ranking. The second most efficient ECM company, "Other Holding Companies", is ranked 11th by DVLS. The top five DVLS companies have an average rank of 9.4 in the ECM specification, the middle five – 8.2, and the bottom five – 6.4. According to the DVLS method, nonRBOCs are approximately two times less efficient that the RBOCs, while ECM gives RBOCs just a slightly better averaged efficiency estimate.

Table 6.14 compares the translog estimates of the SUR model to the parameters of the DVLS and the EC models with technical efficiency varying over holding companies.

Table 6.13. Relative Input Technical Efficiency of Holding Companies

Holding Company	DVLS model				EC model		
	intercept	t-statistics	relative efficiency	efficiency rank	average residual	relative efficiency	efficiency rank
BA	-0.113	-4.91	0.00	1	0.0560	0.142879	13
AM	-0.037	-1.57	0.08	2	-0.0868	0.000000	1
BS	-0.012	-0.19	0.10	3	-0.0004	0.086468	11
PR	-0.008	-0.09	0.10	4	-0.0002	0.086651	12
N	0.001	0.03	0.11	5	-0.0012	0.085649	10
SW	0.022	0.32	0.14	6	-0.0014	0.085456	9
P	0.024	0.52	0.14	7	-0.0066	0.080279	6
CT	0.032	0.65	0.15	8	-0.0105	0.076336	4
S	0.080	3.07	0.19	9	0.1249	0.211781	15
IND	0.090	1.66	0.20	10	-0.0034	0.083475	7
O	0.100	3.16	0.21	11	-0.0378	0.049042	2
UT	0.141	4.21	0.25	12	-0.0095	0.077385	5
W	0.147	3.52	0.26	13	-0.0033	0.083583	8
G	0.247	12.89	0.36	14	0.0656	0.152408	14
C	0.305	7.87	0.42	15	-0.0150	0.071808	3

As table 6.14 demonstrates, the changes to the translog estimates due to the introduction of the inefficiency on the level of holding companies are similar to the changes observed for the model with firm-specific inefficiency, though not as pronounced. The main difference is in the stability of the first-order coefficient on the number of telephone lines. Compared to the model with firm-specific inefficiency, the model with inefficiency on the level of holding companies has an opposite effect on the estimate of the first-order coefficient for the technology proxy – variable 'percent of fiber in cable' (*FI*). On the one hand, this parameter, insignificant in the SUR model, is negative and significant in both models with firm-specific effects. On the other hand, it is positive and significant in the models with inefficiency for holding companies. Thus, the two specifications of

Table 6.14.Translog Estimates: the Model with Input Technical Inefficiency for Holding Companies

variable	SUR model coefficient	SUR model t-statistics	DVLS Model coefficient	DVLS Model t-statistics	ECM model coefficient	ECM model t-statistics
INTERCEPT	0.08	6.01	see Table 6.11	see Table 6.11	0.03	2.06
TL	0.98	82.20	0.98	63.86	0.97	90.92
BL	-1.07	-15.66	-0.75	-10.84	-0.82	-12.77
LC	0.10	0.68	0.17	1.15	0.09	0.71
WI	0.19	2.48	0.46	5.42	0.40	5.74
TLBL	-0.07	-1.95	-0.08	-2.72	-0.08	-2.63
TLTL/2	0.07	5.92	0.08	5.53	0.08	7.03
BLBL/2	-1.23	-10.87	-0.81	-7.66	-0.92	-8.96
LCWI	-0.71	-1.40	0.72	1.62	0.84	1.85
LCLC/2	-2.83	-2.74	-0.81	-0.90	-1.00	-1.08
WIWI/2	0.62	1.59	0.37	1.08	0.43	1.26
TLLC	0.19	1.86	-0.03	-0.30	-0.04	-0.47
TLWI	0.05	1.10	0.09	1.90	0.09	2.23
BLLC	0.15	0.32	1.02	2.59	0.97	2.40
BLWI	-0.49	-2.77	-0.25	-1.55	-0.31	-2.01
PK	0.39	183.80	0.38	190.46	0.38	187.80
PL	0.23	77.77	0.22	78.75	0.22	78.87
PO	0.39	106.17	0.39	110.91	0.39	109.98
TLPK	0.01	6.02	0.01	6.23	0.01	6.18
TLPL	0.01	6.33	0.01	6.06	0.01	6.14
TLPO	-0.02	-8.43	-0.02	-8.50	-0.02	-8.52
BLPK	0.00	-0.53	0.00	-0.26	0.00	-0.37
BLPL	0.04	3.46	0.03	3.12	0.03	2.99
BLPO	-0.03	-2.42	-0.03	-2.38	-0.03	-2.19
LCPK	0.06	3.06	0.05	3.11	0.05	3.06
LCPL	0.04	1.42	0.03	1.38	0.03	1.35
LCPO	-0.09	-2.93	-0.09	-2.97	-0.09	-2.91
WIPK	0.01	1.24	0.01	1.01	0.01	1.04
WIPL	-0.08	-5.48	-0.08	-5.60	-0.08	-5.52
WIPO	0.06	3.59	0.07	3.95	0.07	3.82
PKPK/2	0.04	5.14	0.05	5.65	0.05	5.55
PKPL	-0.02	-1.97	-0.02	-2.26	-0.02	-2.21
PKPO	-0.03	-7.55	-0.03	-8.35	-0.03	-8.15
PLPL/2	0.05	5.70	0.05	5.66	0.05	5.55
PLPO	-0.04	-7.43	-0.03	-6.95	-0.03	-6.83
POPO/2	0.06	10.13	0.06	10.42	0.06	10.19
FIPK	0.00	-2.24	0.00	-2.46	0.00	-2.41
FIPL	-0.03	-11.44	-0.03	-11.97	-0.03	-11.89
FIPO	0.04	10.80	0.04	11.69	0.04	11.52
TLFI	0.00	0.53	0.00	-0.16	0.00	0.39
BLFI	-0.08	-1.53	0.00	0.05	0.02	0.39
LCFI	0.15	1.49	0.30	3.43	0.30	3.35
WIFI	0.08	1.09	0.10	1.64	0.12	1.90
FIFI/2	0.00	-0.04	0.01	1.72	0.01	1.45
FI	0.02	1.16	0.05	3.23	0.04	2.90
R-squared in C	0.987		0.992		0.991	
R-squared in SK	0.396		0.398		0.398	
R-squared in SL	0.317		0.318		0.318	

inefficiency – firm-specific versus holding company-specific – provide mixed evidence on the cost elasticity with respect to the percent of fiber in cable.

6.2.1.3. Output Technical Inefficiency

I introduce output technical efficiency in the model as a coefficient that scales down the output vector. My output vector consists of three components – the number of telephone lines (*TL*), the percent of nonresidential lines (*BL*) and the share of local calls in the number of total calls (*LC*). Only the first component measures the absolute, quantitative levels of the output, while the last two components control for heterogeneity of the output vector. Therefore, only the first variable (*TL*) is relevant to the evaluation of the output technical inefficiency.

I include the output inefficiency into the model by dividing variable 'telephone lines' (*TL*) by the output inefficiency parameter b (TL / b) in both the translog cost function and the share equations. I allow the output inefficiency parameter to vary over holding companies: $b = \Sigma_i b_i D_i$, where D_i is a holding company dummy variable, b_i is an output inefficiency parameter specific to holding company i, and $i = 1,...15$. The output parameters in this specification are perfectly collinear with the intercept of the translog function α_0. Therefore, in order to be able to estimate the model using the least squares method, I drop the intercept. The model is nonlinear in the output inefficiency parameters. I estimate the system using nonlinear iterative SUR method (SAS procedure PROC MODEL).

Table 6.15 compares the output inefficiency estimates for holding companies to the input inefficiency estimates obtained from the DVLS model. Note that the DVLS intercepts represent the natural logarithm of the inefficiency factor that scales the cost frontier up to the observed cost, while the output inefficiency parameters scale the observed cost down to the frontier. Therefore, the appropriate relative output inefficiency measure that permits comparison to the input technical efficiency estimates is $\ln [\, max_i \{ b_i \} / b_i \,]$, where index i corresponds to company i. Alternatively, the inverse of the exponent of the DVLS intercepts (column 4 of table 6.15) can be directly compared to the output inefficiency parameters.

Table 6.15. Relative Input and Output Technical Efficiency of Holding Companies: Comparison

	DVLS model (Input Inefficiency)					**Model with Output Inefficiency**			
holding company	intercept	t-statistics	inverse of exp (intercept)	relative efficiency	efficiency rank	efficiency parameter	t-statistics	relative efficiency	efficiency rank
BA	-0.113	-4.91	1.120	0.00	1	1.129	38.15	0.00	1
AM	-0.037	-1.57	1.037	0.08	2	1.047	39.06	0.08	2
BS	-0.012	-0.19	1.012	0.10	3	1.017	16.55	0.10	3
PR	-0.008	-0.09	1.008	0.10	4	0.960	9.68	0.16	7
N	0.001	0.03	0.999	0.11	5	0.992	26.82	0.13	4
SW	0.022	0.32	0.978	0.14	6	0.984	14.90	0.14	5
P	0.024	0.52	0.977	0.14	7	0.951	18.63	0.17	8
CT	0.032	0.65	0.969	0.15	8	0.974	16.02	0.15	6
S	0.080	3.07	0.923	0.19	9	0.927	32.41	0.20	9
IND	0.090	1.66	0.914	0.20	10	0.877	15.67	0.25	11
O	0.100	3.16	0.905	0.21	11	0.891	26.93	0.24	10
UT	0.141	4.21	0.869	0.25	12	0.855	25.79	0.28	13
W	0.147	3.52	0.864	0.26	13	0.876	22.52	0.25	12
G	0.247	12.89	0.781	0.36	14	0.771	48.48	0.38	14
C	0.305	7.87	0.737	0.42	15	0.722	22.38	0.45	15

The model with output inefficiency results in a slightly higher variance of inefficiency across holding companies. According to the model with output inefficiency, the least efficient holding company can decrease its cost by 36 % (= $1 - e^{-0.45}$), while the DVLS model estimates the potential cost reduction as 34 % (= $1 - e^{-0.42}$). Ordinal differences in relative inefficiency are also small – four out of the five firms ranked as most efficient by the DVLS method are in the top five in the relative output efficiency. A total of six changes of rank occur, with correlation between the two rankings being 0.96.

The translog estimates for the slope coefficients of the model with output technical efficiency (table 6.16) are close to the estimates of the model with input technical efficiency. The only noticeable changes include the parameters on the interaction terms with variable "share of local calls" – three of them reduced in absolute value, and the interaction term between the number of telephone lines *TL* and the average loop length *WI*, which became insignificant at the 95 % level.

As a result of the model specification, the output cost elasticities depend on the inefficiency parameters. The second order coefficient on the number of telephone lines is positive and significant. This suggests that costs increase faster for relatively more efficient companies as the number of telephone lines increases. Negative and significant estimate for the coefficient on the interaction term between the number of telephone lines *TL* and the percent of nonresidential lines *BL* indicates that the costs of the relatively more efficient companies are less sensitive to the changes in the composition of customers. The point estimate for the coefficient on the interaction term *TLLC* is small and insignificant, indicating that relative output inefficiency does not affect the cost elasticity with respect to the share of local calls.

Table 6.16. Translog Estimates: Models with Input and Output Technical Inefficiency (Holding Companies)

	DVLS Model (Input Inefficiency)		Model with Output Inefficiency	
variable	coefficient	t-statistics	coefficient	t-statistics
TL	0.98	63.86	0.98	61.34
BL	-0.75	-10.84	-0.76	-10.44
LC	0.17	1.15	0.15	1.00
WI	0.46	5.42	0.48	5.44
TLBL	-0.08	-2.72	-0.07	-2.33
TLTL/2	0.08	5.53	0.07	5.05
BLBL/2	-0.81	-7.66	-0.83	-7.32
LCWI	0.72	1.62	0.58	1.24
LCLC/2	-0.81	-0.90	-0.33	-0.34
WIWI/2	0.37	1.08	0.48	1.37
TLLC	-0.03	-0.30	-0.06	-0.57
TLWI	0.09	1.90	0.12	2.30
BLLC	1.02	2.59	0.97	2.43
BLWI	-0.25	-1.55	-0.21	-1.28
PK	0.38	190.46	0.38	204.49
PL	0.22	78.75	0.22	77.86
PO	0.39	110.91	0.39	na *
TLPK	0.01	6.23	0.01	6.84
TLPL	0.01	6.06	0.01	5.94
TLPO	-0.02	-8.50	-0.02	na *
BLPK	0.00	-0.26	0.00	0.11
BLPL	0.03	3.12	0.04	3.78
BLPO	-0.03	-2.38	-0.04	na *
LCPK	0.05	3.11	0.05	3.26
LCPL	0.03	1.38	0.04	1.51
LCPO	-0.09	-2.97	-0.09	na *
WIPK	0.01	1.01	0.01	1.24
WIPL	-0.08	-5.60	-0.08	-5.41
WIPO	0.07	3.95	0.06	na *
PKPK/2	0.05	5.65	0.05	5.92
PKPL	-0.02	-2.26	-0.02	-2.41
PKPO	-0.03	-8.35	-0.03	na *
PLPL/2	0.05	5.66	0.05	6.02
PLPO	-0.03	-6.95	-0.04	na *
POPO/2	0.06	10.42	0.06	na *
FIPK	0.00	-2.46	0.00	-2.51
FIPL	-0.03	-11.97	-0.03	-11.87
FIPO	0.04	11.69	0.04	na *
TLFI	0.00	-0.16	0.00	0.13
BLFI	0.00	0.05	0.00	-0.09
LCFI	0.30	3.43	0.30	3.22
WIFI	0.10	1.64	0.10	1.66
FIFI/2	0.01	1.72	0.01	1.41
FI	0.05	3.23	0.05	3.22
R-squared in C	0.992		0.991	
R-squared in SK	0.398		0.405	
R-squared in SL	0.318		0.314	

* -- coefficients were calculated after the estimation from the homogeneity conditions

6.2.2. Allocative Inefficiency of Local Telecommunications

6.2.2.1. Allocative Inefficiency Estimates

I assume that allocative inefficiency varies across holding companies and time, and estimate the generalized cost model using the nonlinear iterative SUR method (SAS procedure PROC MODEL).

Tables 6.17 and 6.18 present the estimates for the components of inefficiency coefficients – the trend coefficient tr^j and the company-specific parameter d^j_i, as well as their t-statistics. In addition, the tables contain the annual, as well as average, allocative inefficiency estimates for each holding company calculated from tr^j and d^j_i. If an allocative inefficiency estimate is greater than one, then the corresponding input is under-employed. If the allocative inefficiency estimate is less than one, then the input is over-employed. The companies in both tables are sorted in ascending order by average allocative inefficiency.

The trend variable is positive for both capital and labor, and statistically significant for capital. All coefficients on the holding company dummy variables for capital are statistically significant, while none of the coefficients for the labor inefficiency term are significant.

The allocative inefficiency estimates for capital are all greater than one, indicating that capital was under-employed compared to materials. This result does not support the theoretical prediction that an industry under rate of return regulation tends to employ more capital relative to other inputs. The positive time trend also contradicts the theory

Table 6.17. Allocative Inefficiency for Capital

	estimate		allocative inefficiency*								
variable	coefficient	t-statistics	88	89	90	91	92	93	94	95	average
time trend	0.290	3.51									
PR	2.578	2.62							4.61	4.90	4.75
IND	4.353	4.30	4.64	4.93	5.22						4.93
UT	5.352	4.69	5.64	5.93	6.22	6.51					6.08
O	5.034	4.61	5.32	5.61	5.90	6.19	6.48	6.77	7.06	7.35	6.34
CT	6.256	4.47	6.55	6.84	7.13						6.84
G	5.690	4.75	5.98	6.27	6.56	6.85	7.14	7.43	7.72	8.01	6.99
P	6.074	4.58	6.36	6.65	6.94	7.23	7.52	7.81	8.10	8.39	7.38
SW	6.447	4.13	6.74	7.03	7.32	7.61	7.90	8.19	8.48	8.76	7.75
BA	6.528	4.80	6.82	7.11	7.40	7.69	7.98	8.27	8.56	8.85	7.83
S	6.303	4.66				7.46	7.75	8.04	8.33	8.62	8.04
N	7.100	4.63	7.39	7.68	7.97	8.26	8.55	8.84	9.13	9.42	8.40
C	7.980	4.70	8.27	8.56	8.85						8.56
BS	7.332	4.34	7.62	7.91	8.20	8.49	8.78	9.07	9.36	9.65	8.64
W	7.712	4.47	8.00	8.29	8.58	8.87	9.16	9.45	9.74	10.03	9.02
AM	8.165	4.76	8.45	8.74	9.03	9.32	9.61	9.90	10.19	10.48	9.47
INDUSTRY **	6.260	4.42	6.59	6.92	7.25	7.57	7.90	8.23	8.56	8.89	7.74

* -- empty cells correspond to years in which the holding company did not exist

** -- estimated from the restricted model; time trend coefficient is not listed

that suggests that capital over-utilization should decrease after the rate of return regulation was replaced with incentive regulation. However, the allocative inefficiency estimates should be interpreted with caution, because factors other than rate of return regulation could have attributed to the estimated systematic discrepancy between the observed and the shadow prices of capital. These factors include the possibility of the divergence of the theoretical model from the actual institutional setting, as well as measurement errors.

Although the federal authorities substituted the rate of return regulation with price cap regulation in 1991 for most companies, the states continued to pursue different

Table 6.18. Allocative Inefficiency for Labor

variable	estimate		allocative inefficiency*								
	coefficient	t-statistics	88	89	90	91	92	93	94	95	average
time trend	0.091	0.89									
PR	-0.583	-0.88							0.06	0.15	0.10
IND	0.212	0.92	0.30	0.39	0.49						0.39
CT	0.320	0.94	0.41	0.50	0.59						0.50
UT	0.289	0.94	0.38	0.47	0.56	0.65					0.52
O	0.196	0.93	0.29	0.38	0.47	0.56	0.65	0.75	0.84	0.93	0.61
C	0.551	0.91	0.64	0.73	0.83						0.73
S	0.245	0.93				0.61	0.70	0.79	0.88	0.98	0.79
G	0.597	0.93	0.69	0.78	0.87	0.96	1.05	1.15	1.24	1.33	1.01
P	0.650	0.91	0.74	0.83	0.92	1.02	1.11	1.20	1.29	1.38	1.06
N	0.725	0.92	0.82	0.91	1.00	1.09	1.18	1.27	1.37	1.46	1.14
SW	0.846	0.90	0.94	1.03	1.12	1.21	1.30	1.39	1.49	1.58	1.26
BA	0.857	0.92	0.95	1.04	1.13	1.22	1.31	1.41	1.50	1.59	1.27
AM	0.932	0.92	1.02	1.11	1.21	1.30	1.39	1.48	1.57	1.66	1.34
BS	1.054	0.90	1.15	1.24	1.33	1.42	1.51	1.60	1.69	1.79	1.47
W	1.069	0.91	1.16	1.25	1.34	1.43	1.53	1.62	1.71	1.80	1.48
INDUSTRY **	1.904	1.84	2.17	2.44	2.71	2.98	3.25	3.52	3.79	4.05	3.11

* -- empty cells correspond to years in which the holding company did not exist

** -- estimated from the restricted model; time trend coefficient is not listed

regulative schemes. In addition, companies were allowed to switch back to the old, rate of return system if the price cap made them unprofitable.

Other federal and state regulatory mechanisms might have been affecting the incentive system. The theory assumes free adjustment of capital stock, while in reality new investment projects require regulatory approval. The companies might not be able to react quickly to capital price changes – which have being falling during the period of observation – because of the lengths of investment projects, or the uncertainty associated with technological change and regulatory environment. Capital investments can adversely affect stock market valuation of the company, while the company executives who make investment decisions are often evaluated according to the performance of the company's stocks and bonds.

Finally, the allocative inefficiency revealed by the data might stem from measurement errors, particularly in the input prices and input shares. For example, I calculated real capital stock from the accounting values assuming that capital has uniform age across firms. If this assumption is violated, then in the presence of inflation the real capital stock of older companies is undervalued relative to the capital stock of newer companies. This under-valuation of real capital stock can manifest itself as the estimated under-employment of capital input by older companies. Similarly, the assumption that all types of capital assets have the same depreciation rates might distort the allocative inefficiency measures.

Labor inefficiency point estimates are much closer to one than capital inefficiency estimates, being less than one for seven holding companies, and greater than one for eight companies, among them are all the RBOCs. None of the estimates are statistically significant even at the 90 % level, and nine of the company-specific coefficients are statistically insignificant from one. In fact, the hypothesis that labor has been employed efficiently at least during one year of the sample cannot be rejected for any of the companies.

The estimates imply that labor has been employed in relatively more efficient proportions compared to materials than capital, and that large companies, such as RBOCs and GTE, tend to under-use labor. Interestingly, the same group of companies also tends to under-employ capital most. This result might be explained by the fact that category "other inputs" measures all residual expenses (operating expenses other than wages, depreciation and amortization), including administrative and marketing expenses. These overhead expenses might be higher for large companies, causing relative over-use of materials input compared to capital and labor inputs. Alternatively, the differences in labor utilization between large and small companies might be due to technological, as well as regional factors. For example, RBOCs serve bigger, more urbanized markets and tend to have higher proportions of automated operations, ranging from switching equipment to bill collecting. Therefore, the technology adopted by large telecommunications firms might be less labor intensive than the technology of smaller, rural firms.

The restricted model that allows the allocative inefficiency terms to vary only over time but not companies ($d^j{}_i = d^j$) generates similar results (the last rows of tables 6.17 and 6.18). The industry level allocative inefficiency exhibits a positive time trend, with both capital and labor being consistently under-employed over time. The intercept coefficient for labor (d^l) is still insignificant, while the time trend coefficient for labor inefficiency term becomes significant at the 90 % level of confidence.

6.2.2.2. Technical Inefficiency in the Generalized Cost Model

Table 6.19 compares the input technical inefficiency ranking of the generalized cost model to the estimates obtained from the model with only input technical inefficiency (the DVLS model). The generalized cost model gives slightly lower relative inefficiency estimates than the DVLS model. This result suggests that firms that are relatively technically efficient are also more allocatively efficient, because the intercept terms in the DVLS

Table 6.19. Input Technical Inefficiency in the Generalized Cost Model

variable	Generalized Cost Model					DVLS Model		
	coefficient	t-statatistics	intercept averaged for 88-95	average relative inefficiency	efficiency rank	intercept	relative inefficiency	efficiency rank in DVLS
time trend	-0.021	-2.84	na*	na*	na*	na*	na*	na*
CT	-0.391	-2.31	-0.43	0.000	1	0.032	0.145	8
AM	-0.332	-2.35	-0.43	0.022	2	-0.037	0.077	2
BA	-0.307	-2.27	-0.40	0.047	3	-0.113	0.000	1
BS	-0.252	-1.74	-0.35	0.102	4	-0.012	0.101	3
SW	-0.243	-1.58	-0.34	0.112	5	0.022	0.135	6
S	-0.212	-1.32	-0.34	0.119	6	0.080	0.193	9
P	-0.224	-1.52	-0.32	0.130	7	0.024	0.137	7
W	-0.216	-1.54	-0.31	0.138	8	0.147	0.260	13
UT	-0.238	-1.52	-0.29	0.138	9	0.141	0.254	12
N	-0.202	-1.41	-0.30	0.152	10	0.001	0.114	5
O	-0.154	-0.96	-0.25	0.200	11	0.100	0.213	11
IND	-0.162	-1	-0.20	0.229	12	0.090	0.204	10
C	-0.131	-0.87	-0.17	0.260	13	0.305	0.418	15
PR	-0.015	-0.08	-0.17	0.316	14	-0.008	0.105	4
G	0.008	0.06	-0.09	0.362	15	0.247	0.361	14

* -- not applicable

model accumulate not only technical inefficiency, but also differences in cost that are due to allocative inefficiency. However, the two models are not directly comparable because of the difference in the methods of estimation. Significant ordinal differences are apparent, but certain consistency between the two rankings is present. The top five companies, as classified by the generalized cost model, have an average ranking of 4 on the DVLS list, the middle five are ranked 9.2, and the bottom five have an average rank of 10.8 in the DVLS model.

A comparison of the estimates for technical and allocative efficiency in the generalized cost model reveals no consistency between the two rankings. Therefore, the estimates from the generalized cost model do not provide evidence that most technically efficient companies are also most allocatively efficient, as Atkinson and Cornwell (1994) found in the airline industry.

6.2.2.3. Translog Parameter Estimates

The most obvious change in the translog estimates of other parameters (table 6.20) happened to the first order coefficients on the input prices. The estimate for capital price (0.75) almost doubled compared to the SUR value of 0.39, while the coefficients for both labor and materials dropped. These changes imply that not only the shadow price of capital is higher than the observed price, but the shadow share of capital – shadow cost elasticity with respect to capital price – is higher than the observed share at the sample mean. The shadow cost elasticity with respect to the price of labor decreased, despite the fact that the shadow price of labor was higher than the observed price for more than half of the companies, as well as at the industry level.

Cost elasticity with respect to the number of telephone lines increased at the sample mean (from 0.98 in the SUR model to 1.00). Small and statistically insignificant parameter estimates on the interaction terms between the input prices and the output vector – *TLPK*, *BLPK*, *LCPK*, *TLPL*, *BLPL* and *LCPL* – indicate that output cost elasticities do not depend on the allocative inefficiency parameters.

Several other parameter estimates changed their significance level in the generalized cost model compared to the SUR model. The coefficient on the interaction term between *WI* and *PL* became insignificant, indicating that the share of labor is not

Table 6.20.Translog Estimates for the Generalized Cost Model

	SUR model		DVLS Model		Generalized Cost Model	
variable	coefficinent	t-statistics	coefficinent	t-statistics	coefficinent	t-statistics
TL	0.98	82.20	0.98	63.86	1.00	65.61
BL	-1.07	-15.66	-0.75	-10.84	-0.46	-7.17
LC	0.10	0.68	0.17	1.15	0.00	-0.01
WI	0.19	2.48	0.46	5.42	0.26	3.38
TLBL	-0.07	-1.95	-0.08	-2.72	-0.07	-2.94
TLTL/2	0.07	5.92	0.08	5.53	0.06	5.17
BLBL/2	-1.23	-10.87	-0.81	-7.66	-0.55	-6.23
LCWI	-0.71	-1.40	0.72	1.62	-0.11	-0.29
LCLC/2	-2.83	-2.74	-0.81	-0.90	-1.50	-1.92
WIWI/2	0.62	1.59	0.37	1.08	0.68	2.45
TLLC	0.19	1.86	-0.03	-0.30	0.03	0.43
TLWI	0.05	1.10	0.09	1.90	0.05	1.28
BLLC	0.15	0.32	1.02	2.59	0.58	1.81
BLWI	-0.49	-2.77	-0.25	-1.55	-0.33	-2.54
PK	0.39	183.80	0.38	190.46	0.75	10.25
PL	0.23	77.77	0.22	78.75	0.10	1.27
PO	0.39	106.17	0.39	110.91	0.15	na *
TLPK	0.01	6.02	0.01	6.23	0.00	0.84
TLPL	0.01	6.33	0.01	6.06	0.01	1.03
TLPO	-0.02	-8.43	-0.02	-8.50	-0.01	na *
BLPK	0.00	-0.53	0.00	-0.26	0.01	0.44
BLPL	0.04	3.46	0.03	3.12	0.01	1.00
BLPO	-0.03	-2.42	-0.03	-2.38	-0.02	na *
LCPK	0.06	3.06	0.05	3.11	0.01	0.68
LCPL	0.04	1.42	0.03	1.38	0.01	0.90
LCPO	-0.09	-2.93	-0.09	-2.97	-0.02	na *
WIPK	0.01	1.24	0.01	1.01	0.01	0.51
WIPL	-0.08	-5.48	-0.08	-5.60	-0.02	-1.04
WIPO	0.06	3.59	0.07	3.95	0.01	na *
PKPK/2	0.04	5.14	0.05	5.65	0.04	2.58
PKPL	-0.02	-1.97	-0.02	-2.26	-0.02	-1.00
PKPO	-0.03	-7.55	-0.03	-8.35	-0.02	na *
PLPL/2	0.05	5.70	0.05	5.66	0.02	1.00
PLPO	-0.04	-7.43	-0.03	-6.95	0.00	na *
POPO/2	0.06	10.13	0.06	10.42	0.02	na *
FIPK	0.00	-2.24	0.00	-2.46	0.00	-0.73
FIPL	-0.03	-11.44	-0.03	-11.97	0.00	-1.01
FIPO	0.04	10.80	0.04	11.69	0.01	na *
TLFI	0.00	0.53	0.00	-0.16	0.01	1.95
BLFI	-0.08	-1.53	0.00	0.05	0.01	0.29
LCFI	0.15	1.49	0.30	3.43	0.22	3.09
WIFI	0.08	1.09	0.10	1.64	0.06	1.26
FIFI/2	0.00	-0.04	0.01	1.72	0.03	3.32
FI	0.02	1.16	0.05	3.23	0.09	4.67
R-squared in C	0.987		0.992		0.995	
R-squared in SK	0.396		0.398		0.574	
R-squared in SL	0.317		0.318		0.620	

* -- coefficients were calculated after the estimation from the homogeneity conditions

affected by the customer density if allocative inefficiency is accounted for. In other words, higher share of labor in urban areas, as revealed by the SUR estimates, might stem from allocative inefficiency. Similarly, insignificant parameter estimates on the interaction term between input prices and the percent of fiber in the generalized cost model suggest that the relation between the input shares and the percent of fiber observed in the SUR model can be explained by allocative inefficiency. The generalized cost parameter estimates on the terms involving fiber are similar to those obtained in the DVLS model. Both first- and second-order coefficients on *FI* are positive and statistically significant, indicating that, if inefficiency is being controlled for, cost elasticity with respect to fiber is positive.

6.2.2.4. Efficient Input Structure and Losses from Allocative Inefficiency

The allocative inefficiency parameters suggest that capital is under-employed relative to other inputs, and labor is under-employed for some observations and over-employed for others. In order to calculate the optimal input mix, I set the inefficiency parameters to one and compute the fitted shares. As expected, the optimal capital share increased, and the share of residual inputs decreased for all observations. The share of labor also decreased for all data points.

The estimates of allocative inefficiency do not permit comparison of different companies in terms of the degree of allocative inefficiency. In order to make this comparison, I use the estimated parameters of the generalized translog cost function to calculate the monetary measure of allocative inefficiency. In other words, I set the inefficiency parameters ξ^j equal to one and evaluate the cost function for each observation using the estimated translog parameters. I compare these estimates to the fitted values of the generalized cost function. The difference between the two monetary estimates of cost presents a measure of potential savings from increased allocative efficiency.

I calculate the fitted cost and the cost of an allocatively efficient firm for each observation in the sample. The calculated cost of an allocatively efficient firm are lower than the fitted cost in the presence of allocative inefficiency for all but one observation. The allocatively efficient costs are slightly higher than the fitted cost for firm 58 in 1993 (Citizens Utilities of California owned by 'other' holding companies), but the actual cost is significantly higher than the fitted allocatively efficient cost. Savings for other individual observations range from 0.1 to 69 % of the fitted cost. On aggregate, the potential savings from allocative efficiency constitute 24 % of the total fitted cost, or $ 21 billion annually.

Table 6.21 summarizes the results by holding company and year, with potential savings measured as a percent of the fitted cost of an allocatively inefficient firm. The holding companies in the table are sorted from the most allocatively efficient to the least efficient. The degree of allocative inefficiency, as measured by the potential percent reduction in cost, exhibits an upward time trend. Centel Corporation, which ceased to exist in 1991, seems to be most efficient; however, two other holding companies – Southwestern Bell and Pacific Telesis have lower average potential reductions in cost for the same period. Puerto Rico Telephone Authority, Ameritech and Bell Atlantic appear to be least allocatively efficient.

Table 6.21. Allocative Inefficiency: Potential Cost Savings by Holding Company and Year

holding	potential cost reductions as a fraction of fitted cost*								
company	88	89	90	91	92	93	94	95	average
CT	12%	12%	15%						13%
SW	4%	7%	11%	15%	18%	23%	26%	30%	17%
P	10%	15%	13%	18%	19%	21%	22%	22%	17%
BS	10%	14%	18%	21%	18%	20%	23%	26%	19%
UT	19%	19%	20%	21%					20%
IND	24%	20%	16%						21%
C	20%	21%	21%						21%
G	16%	18%	20%	20%	22%	25%	26%	28%	22%
S				34%	22%	26%	24%	27%	25%
O	18%	21%	25%	25%	27%	26%	26%	29%	25%
W	17%	21%	22%	20%	29%	33%	35%	31%	26%
N	20%	24%	25%	28%	31%	32%	33%	35%	28%
BA	23%	22%	24%	28%	32%	34%	36%	38%	30%
AM	22%	27%	27%	27%	39%	33%	35%	36%	31%
PR							33%	40%	37%
Total	16%	19%	21%	23%	26%	28%	29%	31%	24%

* -- empty cells correspond to years in which the holding company did not exist

6.3. Subadditivity Test on a Non-Minimum Cost Function

The estimation results of the previous section indicate that the hypothesis of technical and allocative inefficiency of the telecommunications firms cannot be rejected. Thus, the benefits of competitive entry into the telecommunications markets are not limited to the potential cost savings from increased scale efficiency, as the subadditivity test indicates, but are likely to include the reduction in costs due to increased technical and allocative efficiency. In other words, even if the potential savings from the division of the monopolized markers are negative on average (as reflected in Tables 6.6 and 6.7), they might be fully compensated by the savings from increased production performance.

Since the inclusion of the inefficiency parameters affected the parameter estimates of the cost functions, the results of the subadditivity test of section 6.1 do not hold. In order to test whether a cost function of the telecommunications industry is indeed superadditive and evaluate the level of potential saving, I repeat the subadditivity test using the estimated cost functions that control for technical and allocative inefficiency.

The primary question of interest is whether a productively efficient telecommunications firm exhibits the properties of a natural monopoly. I start with a cost function that permits inefficiency and use this cost function to predict the cost of the industry in which inefficiency is eliminated. I consider three models – the DVLS and EC models with intercepts varying over holding companies, and the generalized cost model. I remove technical inefficiency by setting the intercept terms in both parametric models to the minimum estimated intercept and assuming that the random error terms in the error component model have the same variance. In addition, I assume that allocative efficiency is eliminated and set the allocative inefficiency parameters in the generalized cost model to one.

Tables 6.22, 6.23 and 6.24 summarize the results of the subadditivity test for the DVLS, EC and the generalized cost models. The estimates of potential savings obtained using the DVLS model are similar to the estimates of the SUR model. According to the subadditivity test on the DVLS cost model, the subdivision of the monopolized markets between two firms would result in losses equal to 2 % of the fitted cost on the national level. The average savings are positive for only 40 % of observations, and negative for two thirds of the holding companies. The average savings tend to be higher for companies with lower than average percentage of business lines. Although the levels of average savings of the DVLS model on the national level are close to the estimates of the SUR model, the DVLS model predicts wider variation in savings from a two-firm industry then the SUR model. The DVLS estimates for the maximum savings are lower for all holding companies, and, in contrast to the SUR model, are less than the minimum savings in absolute value for most companies and as a total.

Table 6.22. Savings from a Two-Firm Technically Efficient Industry: DVLS Model

Holding Company	Minimum Saving		Maximum Saving		Average Saving	
	dollars	percent of fitted cost	dollars	percent of fitted cost	dollars	percent of fitted cost
AM	-89,926,873,612	-135%	34,230,191,647	51%	-1,965,396,755	-3%
BA	-424,949,482,129	-528%	38,624,788,905	48%	-4,995,046,521	-6%
BS	-17,286,386,862	-21%	49,846,812,129	60%	197,876,519	0%
C	-4,623,507,753	-95%	4,560,936,143	94%	227,073,687	5%
CT	-4,915,572,239	-131%	2,328,088,088	62%	-192,744,629	-5%
G	-78,361,551,188	-151%	39,672,362,152	76%	74,027,004	0%
IND	-118,427,097	-23%	84,480,217	16%	-20,156,323	-4%
N	-189,152,121,412	-249%	40,749,912,999	54%	-2,366,642,980	-3%
O	-42,818,887,433	-359%	9,484,368,221	79%	-441,562,185	-4%
P	-147,621,747,045	-299%	14,299,121,723	29%	-3,507,974,120	-7%
PR	-1,500,928,423	-60%	2,109,071,461	84%	16,768,430	1%
S	-1,727,764,119	-116%	1,297,411,381	87%	-57,637,437	-4%
SW	-19,432,521,462	-38%	29,828,821,751	59%	-46,620,570	0%
UT	-13,569,638,517	-106%	11,362,128,892	88%	294,322,253	2%
W	-41,354,146,587	-84%	23,047,572,857	47%	-662,252,539	-1%
Total	-1,075,858,627,454	-198%	299,416,997,105	55%	-13,462,734,598	-2%

The subadditivity test on the cost function estimated using the ECM approach (table 6.23) produces results that are qualitatively similar to the results of the subadditivity test on the DVLS model. The EC model predicts smaller variation in the possible savings from a two-firm industry than the DVLS model. The average savings

Table 6.23. Savings from a Two-Firm Technically Efficient Industry: EC Model

Holding Company	Minimum Saving		Maximum Saving		Average Saving	
	dollars	percent of fitted cost	dollars	percent of fitted cost	dollars	percent of fitted cost
AM	-48,889,482,262	-65%	41,684,035,916	55%	-2,391,075,520	-3%
BA	-243,758,181,747	-266%	47,904,617,850	52%	-5,396,578,468	-6%
BS	-19,252,437,099	-21%	60,088,333,338	65%	-101,280,135	0%
C	-1,717,147,328	-29%	5,631,481,997	95%	311,541,805	5%
CT	-3,073,525,980	-69%	2,871,642,725	64%	-247,799,299	-6%
G	-43,480,545,823	-71%	48,285,298,229	79%	206,011,971	0%
IND	-99,165,727	-16%	112,882,202	18%	-25,912,194	-4%
N	-100,813,235,228	-117%	50,482,951,441	59%	-2,550,162,305	-3%
O	-24,307,434,676	-175%	11,421,274,490	82%	-506,275,052	-4%
P	-90,204,600,626	-164%	17,663,952,474	32%	-4,076,721,509	-7%
PR	-620,454,107	-21%	2,559,376,671	87%	27,805,019	1%
S	-695,379,875	-39%	1,608,221,314	90%	-45,981,839	-3%
SW	-14,637,461,228	-26%	35,558,164,833	63%	-283,619,779	-1%
UT	-5,279,191,505	-34%	13,953,537,576	90%	418,685,538	3%
W	-24,189,113,648	-44%	28,604,055,666	52%	-838,398,448	-2%
Total	-621,017,356,859	-101%	368,429,826,721	60%	-15,499,760,216	-3%

from a two-firm industry in the ECM are also positive for approximately 40 % of observations and as a total.

The results of the subadditivity test on the generalized cost function (Table 6.24) present a much stronger evidence of the benefits of competition. Average savings are positive for all but two holding companies (Ameritech and GTE), for each year and for 77 % of observations. On aggregate, not only the average savings are positive, but the maximum savings significantly exceed the minimum savings, as well as the SUR estimates for the maximum savings.

In reality it is likely that the two companies that share the formerly monopolized market will not be able to eliminate inefficiency for a period of time, for example, due to investment lags. The above results can be generalized for a case with the two hypothetical

Table 6.24. Savings from a Two-Firm Allocatively and Technically Efficient Industry: Generalized Cost Model

Holding Company	Minimum Saving		Maximum Saving		Average Saving	
	dollars	percent of fitted cost	dollars	percent of fitted cost	dollars	percent of fitted cost
AM	-5,008,715,266	-11%	20,984,051,834	45%	492,374,283	1%
BA	-7,864,723,002	-15%	22,303,262,605	42%	150,334,811	0%
BS	-5,101,341,209	-9%	27,929,613,043	48%	1,015,950,427	2%
C	-340,730,023	-10%	3,101,210,181	87%	217,284,894	6%
CT	-356,817,626	-13%	1,461,494,654	53%	-36,581,853	-1%
G	-2,369,730,236	-7%	24,635,017,016	68%	1,213,939,644	3%
IND	-33,012,152	-9%	47,567,894	13%	-8,735,732	-2%
N	-6,137,583,693	-13%	22,692,958,969	47%	949,317,058	2%
O	-1,383,212,316	-18%	5,378,295,911	69%	77,688,023	1%
P	-8,698,325,001	-24%	10,414,889,616	29%	250,756,620	1%
PR	-74,958,915	-5%	1,061,406,067	72%	43,178,483	3%
S	-129,302,429	-13%	788,232,540	80%	19,905,736	2%
SW	-3,924,022,697	-10%	17,475,432,519	47%	677,952,826	2%
UT	-721,212,518	-8%	7,601,848,060	80%	434,435,876	5%
W	-4,402,187,617	-11%	15,914,769,652	40%	763,073,431	2%
Total	-46,545,874,700	-12%	181,790,050,561	48%	6,260,874,526	2%

companies preserving certain levels of technical or allocatively efficiency. All the three models specify technical inefficiency through an intercept term – either deterministic or stochastic – as a factor that shifts cost up. Therefore, the higher the level of technical inefficiency, the higher the 'fixed' multiplier – a multiplier on cost that does not depend on the output, and thus, the higher the combined costs of the two hypothetical firms. In other words, if the degree of inefficiency for a two-firm industry is the same as for the monopoly, inefficiency affects only the magnitude, but not the percentage of savings from a two-firm industry. However, two technically efficient firms are more likely to find the output vector combinations that would lower the cost of the inefficient monopoly than two technically inefficient firms, *ceteris paribus*.

Allocative inefficiency in the generalized cost model affects the costs through the translog terms that involve input prices. Interaction parameters between the input prices and the outputs determine the effect of allocative inefficiency on the output elasticity of cost. For example, if capital is under-employed relative to residual inputs, then a positive estimate on the interaction term *TLPK* would indicate that, as *TL* decreases, the costs fall faster for an allocatively inefficient firm. The actual estimated values of the coefficients on all the interaction terms between the outputs and the input prices are close to zero and statistically insignificant. Therefore, the presence of allocative inefficiency is likely to have little effect on the output elasticity of cost.

By definition, allocative inefficiency increases cost. If allocative inefficiency does not affect the output elasticity, then the total effect of allocative inefficiency on the subadditivity test is similar to the effect of technical inefficiency, with the costs of the two inefficient firms being scaled up by a fixed multiplier compared to the cost of two efficient firms. Here the fixed multiplier includes not only the intercept term, but also the sum of all other terms that do not involve the output variables and, therefore, remain the same for the monopoly and the two hypothetical competitive firms.

7. CONCLUSIONS

Though my study indicates that the formal condition for subadditivity of the cost function of local telecommunications industry is violated, the evidence is not as overwhelming as Shin and Ying's (1992). The point estimates for the cost of the two hypothetical firms imply that certain two-firm combinations could have lowered the total cost of the U.S. local telephone industry during the period of consideration. However, it is unclear whether these estimates are statistically significant because the feasibility of different output vectors and the exact forecast variance are unknown.

My estimates of the savings from the division of the existing markets suggest that, while a two-firm industry might be able to provide telecommunications services at lower cost than one firm, the subdivision of the predominantly nonresidential markets might result in efficiency losses. In other words, potential savings from the division of the markets lie mostly in residential areas. The result implies that competition is more desirable in areas with large concentration of residential customers, and that regulators should encourage competition in these markets.

The later finding seem to be inconsistent with the fact that the majority of the actually observed instances of competitive entry takes place in business markets. While the patterns of actual entry are probably caused mainly by lower economic barriers to entry into business markets, the difference in potential savings in the two markets – residential and business – might stem from the differences in scale efficiency. In reality telecommunications companies can adjust their scale of operation and the composition of the output through sale and purchase of individual exchanges (central offices). Business markets are usually served by big companies, while small companies serve mostly residential markets. Existing regulatory conditions, such as the universal service fund and state-averaged access rates, affect the two groups of companies in a different way: while big companies have strong incentives to adjust their scale of operations in order to lower cost, small rural companies do not. Thus, firms in business markets tend to be more scale efficient than firms in residential markets. Therefore, the unnecessary concentration of production in residential markets explains the difference in the potential cost savings from the division of the two markets.

The results of the subadditivity test suggest that the telecommunications monopolies are overly concentrated and diversified. The output combinations that correspond to the maximum cost savings from a two-firm industry include an uneven division of the telephone customers between the two firms and a high degree of specialization in business/residential, as well as local/toll markets. It would be useful to investigate the likelihood of this asymmetric equilibrium for a two-firm industry with a common cost function. The cost-minimizing output combinations might provide some guidance for regulatory authorities.

The modified subadditivity test showed that side by side competition that assumes facilities entry is not necessarily wasteful. Despite the restriction requiring that each of the two hypothetical firms builds its own cable facilities, the maximum possible savings were still positive for the majority of observations and as a total. However, this result might not hold as the number of the competitive firms, and the number of duplicate facilities increases.

The calculated savings from a two-firm industry present a very limited estimate of the possible benefits of competition. The subadditivity test did not consider industry configurations with three or more firms. It is also incapable of estimating benefits from improved service quality or productive efficiency of the telecommunications carriers under competitive pressures. As section 6.2 suggests, the degree of productive inefficiency of the local telephone monopolies is significant. Therefore, a monetary estimate of the benefits of competition in local telecommunications should include not only the potential savings from the increased scale efficiency of section 6.1, but also the potential savings from increased technical and allocative efficiency of section 6.2.

Different approaches to modeling inefficiency result in different ordinal and cardinal inefficiency measures. The error component model estimates a much smaller degree of relative technical inefficiency than the parametric model of fixed intercepts. While the parametric method ranks most Regional Bell Operating Companies high in terms of technical efficiency, the error component method almost reverses the ranking. The introduction of parametric allocative inefficiency changes the technical efficiency order, though still ranking most RBOCs higher than other companies

The generalized cost model resulted in unexpected allocative inefficiency estimates. Contrary to the theoretical predictions and the aggregate estimates of inefficiency in telecommunications obtained by Oum and Zhang (1995), the estimated capital inefficiency parameters indicate that the industry was under-employing capital relative to materials. This result should be treated with caution for several reasons. First, as Farber (1989) found, the generalized cost estimates might be sensitive to the measures of capital price. Second, the specification of shadow input price as proportional to the observed price might be inappropriate. Third, the nonlinear iterative method used in the estimation of the generalized cost function does not always find converged solution. Convergence problems are partially caused by the large number of coefficients to be estimated and by the sensitivity of the method to the choice of the starting values. Because of these problems I was unable to obtain converged estimates of the firm-specific estimates of allocative inefficiency, or to restrict the time trend coefficients to zero.

In order to check whether the estimated inefficiency measures translate into conventional indicators of firm's performance, I compare the efficiency measures generated by different models to the realized rates of return on investment. I translate the estimated efficiency measures into monetary terms, as losses from inefficiency expressed in terms of the percentage of the actual fitted cost. For each holding company, I calculate the average inefficiency losses for the two periods – the years of the federal rate of return regulation (1998-90) and price cap regulation (1991-95). I calculate the realized rates of return following the FCC methodology, as operating revenues minus taxes divided by the accounting value of the net telecommunications plant.

Table 7.1. summarizes the calculations. Holding companies in the first column of the table are divided into two groups, with the companies that switched to the federal price cap regulation listed first. These companies include the seven RBOCs, GTE and Sprint. Columns two and three present the losses from technical inefficiency generated by the DVLS and EC models. These estimates are invariant with respect to time and therefore, are identical for the two periods of regulation. Column four reflects the losses from technical inefficiency in 1988-90 estimated by the generalized cost model. Column five presents the losses from allocative inefficiency for the same period. Column six lists

the losses from scale inefficiency measured as the maximum potential savings from a division of each market between the two hypothetical firms. Column seven contains the realized rates of return averaged for 1988-90. Columns eight through eleven contain information similar to the columns four through seven, but for the years of price cap regulation.

Table 7.1. Losses from Inefficiency and Actual Rates of Return: Comparison*

			Weighted Average for 1988-90**				Weighted Average for 1991-95**			
Holding Company	Technical Inefficiency		Inefficiency in the Generalized Cost Model		Scale Inefficiency	Rate of Return	Inefficiency in the Generalized Cost Model		Scale Inefficiency	Rate of Return
	DVLS Model	ECM	Technical	Allocative			Technical	Allocative		
AM	7%	0%	6%	26%	77%	10%	0%	34%	46%	10%
BA	0%	13%	8%	23%	61%	10%	2%	33%	49%	10%
BS	10%	8%	13%	14%	86%	10%	8%	22%	58%	10%
N	11%	8%	17%	23%	67%	10%	12%	32%	62%	8%
P	13%	8%	15%	13%	44%	9%	10%	20%	54%	7%
SW	13%	8%	14%	8%	86%	9%	9%	22%	89%	9%
W	23%	8%	16%	20%	79%	9%	11%	30%	54%	7%
G	30%	14%	33%	18%	85%	10%	29%	24%	95%	9%
S	18%	19%					11%	26%	49%	10%
C	34%	7%	23%	21%	95%	13%				
CT	14%	7%	0%	13%	85%	9%				
IND	18%	8%	20%	20%	80%	10%				
O	19%	5%	21%	21%	77%	10%	16%	27%	81%	9%
PR	10%	8%					32%	37%	88%	6%
UT	22%	7%	14%	19%	94%	11%	32%	21%	92%	11%
correlation with rate of return in 88-90	0.44	-0.09	0.25	0.37	0.50	1.00				
correlation with rate of return in 91-95	0.06	0.18					-0.22	-0.32	-0.06	1.00

* -- losses from inefficiency are measured as the percent of fitted cost

** -- federal authorities switched from the rate of return to price cap regulation in 1991

The rates of return depend not only on the company's productive efficiency, but also on the prices of the output and the accounting levels of net capital stock. Nevertheless, for each of the two periods I calculate the correlation coefficients between my measures of productive performance and the realized rates of return. The last two rows of the table list the correlation coefficients. In 1988-90 the correlation coefficients for all measures, with the exception of the ECM technical efficiency, are positive. The positive sign indicates that lower productive performance was not translated into lower rates of return during this period. In fact, the absolute values of the correlation coefficients, which range from 0.25 to 0.5, provide certain evidence that less efficient companies were likely to have higher rates of return. This result is not totally unexpected: critics of the rate of return regulation suggest that this system induces inefficiency because it allows the companies to recover increased expenses through an increase in the output prices (see, for example, Loube, 1995).

After 1991 the correlation coefficients change in sign and size. The estimates of the generalized cost model, as well as the subadditivity results, suggest that less efficient firms were likely to have lower rates of return. In general, during this period the relation between the efficiency measures and the rates of return seems to be much weaker. The theory predicts that price cap regulation should improve the firms' efficiency because it allows them to retain savings from decreased costs. The positive correlation between certain efficiency measures and the rates of return supports the theoretical prediction. The weakness of this relation can be attributed to the regulatory lags and restructuring, as well as to the fact that the federal authorities regulate only the interstate jurisdiction.

The estimator that accounts for the theoretical heteroscedasticity in the system of cost and share equations turned out to be extremely computationally intensive but did not generate results qualitatively different from the SUR estimator. The closeness of the two sets of the estimates suggests that the degree of heteroscedasticity in the cost equation is not strong, or that the assumed functional from of heteroscedasticity was incorrect.

The following four areas present directions for the future research. The first direction is to expand the data set. This expansion might include not only addition of observations beyond the period of study 1988-95, but also more detailed representation of the telecommunications companies. Recently, the FCC made publicly available the detailed data bases on the local exchange carriers (the ARMIS data bases) that the agency has been using in the compilation of the *Statistics of Communications Common Carriers.* These data bases include a significantly more detailed accounting and telephone plant statistics, as well as a disaggregated list of companies. For example, *Statistics of Communications Common Carriers* lists US West Communications as one entry in each year, while the original ARMIS data base separates US West, which operates in the fourteen western states, into fourteen companies.

The second direction of the future research is to improve the model variables. As I have already mentioned, my allocative inefficiency estimates might be driven by the measurement errors in the input prices or input shares. In order to check the robustness of my allocative inefficiency estimates, I would like to try different measures of the input prices. Alternatively, subdivision of the 'residual' input into two or more inputs might improve the measurement of the input prices and shares. The inclusion of different proxies for technology, regional cost adjustment coefficients or variables that account for the differences in the regulatory settings might also improve the model.

The third direction for the future research is to use different estimation methods. Application of an estimator with a theoretically consistent error structure to the models of productive inefficiency presents the next logical step. Other potential estimation methods include random specification of allocative inefficiency and the specification of fixed effects as varying over companies, as well as time.

The fourth direction for the future research is to use the estimated cost function to assess the feasibility of different asymmetric equilibria under deregulation and predict the behavior of the firms in response to different demand-side regulatory changes.

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