THREE EMPRICAL ESSAYS ON MERGERS AND REGULATION IN THE TELECOMMUNICATIONS INDUSTRY

by

DAIGYO SEO

B.A., Hanyang University, 1996
M.S., Hanyang University, 1998
M.A., University of Pittsburgh, 2002

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department Of Economics
College of Arts and Science

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2007

Abstract

This empirical dissertation consists of three essays on mergers and regulation in the U.S. telecommunications industry. An abstract for each of the three essays follows.

Essay 1: This study has attempted to measure the productivity growth associated with 25 incumbent local exchange carriers (ILECs) over the period 1996-2005 using a Malmquist productivity index. The average efficiency scores for our sample companies have not changed significantly between 1996 and 2005, which indicates that the average ILECs shows no measurable improvement in terms of optimizing their input-output combinations over time. We find some empirical evidence of a positive merger effect, although this effect diminishes over time. In addition, we find that non-merged firms underperform in terms of average productivity growth.

Essay 2: This study analyzes the merger effects for 25 ILECs over the period 1996-2005 using stochastic frontier analysis with a time-varying inefficiency model. In addition, we conduct a comparison of indices between the stochastic frontier analysis and the Malmquist index method. The empirical results indicate that the sample of telecommunications firms has experienced deterioration in average productivity growth following the mergers. In addition, both approaches suggest that firms that do not merge underperform in terms of average productivity growth.

Essay 3: This essay investigates whether the substitution of price cap regulation (PCR), along with other regulatory regimes, for traditional rate of return regulation (RRR) has had a measurable effect on productivity growth in the U.S. telecommunications industry. A stochastic frontier approach, which differs from previous studies, is employed to compute efficiency

change, technological progress, and productivity growth for 25 LECs over the period 1988-1998. By examining the relationship between the change in productivity growth and regulatory regime variables, while controlling for other effects, we find that PCR and other regulatory regimes have a positive effect on productivity growth. However, only PCR has a significant and positive effect in both contemporaneous and lagged model specifications.

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Acknowledgements

The deepest appreciation goes to my major advisor, Dr. Dennis L. Weisman, who has been my “American father” for many years. Throughout my Ph.D. program, he has constantly guided and encouraged me to challenge the toughest issues in the field of microeconomics. In addition to his academic guidance, his thoughtful consideration and kindness in the way he lives his daily life served as an exceptional lesson to me. I truly believe that having him as my main advisor was one of the luckiest things in my entire life.

Special thanks go to Dr. Allen Featherstone. He has given me the opportunity to learn production economics, which, in fact, turned out to be a significant contribution to my dissertation. I would like to thank Dr. Tracy M. Turner for giving me the opportunity to join her research project, which I very much enjoyed. I would also like to thank my dissertation committee members, Dr. Dong Li, Dr. Philip G. Gayle, and Dr. John M. McCulloh, for their invaluable help and guidance. Finally, I would like to thank my fellow Korean graduate student, Shin-Jae Kang.

Dedication

This dissertation is dedicated to my beloved family, especially to my parents and my wife, Yeonkyung Ha, for endless encouragement, support, and patience.

CHAPTER 1 - Introduction

This dissertation is comprised of three empirical essays that investigate mergers and regulation in the U.S. telecommunications industry. The first two essays address the effect of a series of mergers in the telecommunications industry after the passage of the 1996 Telecommunications Act (1996 Act). The third essay analyzes the effect of implementation of incentive regulation in telecommunications industry.

The primary objective of Chapter 2 is to investigate whether productivity growth has increased among incumbent local exchange carriers (ILECs) that have merged since the 1996 Telecommunications Act and whether the merged firms performed better than firms that did not merge in terms of productivity growth during the period 1996-2005 .

Mergers can be either a pro-competitive or anti-competitive in terms of their effect on industry performance, including productive efficiency. The horizontal merger guidelines (HMG) of the U.S. Department of Justice (DOJ) rely, in part, upon market concentration in evaluating whether particular mergers raise anticompetitive concerns. In addition to market concentration, the HMG also take into account potential adverse competitive effects and entry analysis in evaluating proposed mergers. Specifically, Section 4 of the HMG (revised April 8, 1997) describes the significance of merger efficiencies. When the efficiency gains from a merger, which may result in lower prices or quality improvements, are expected to outweigh the other effects of the merger that may serve to lessen competition, the agency will consider approving the proposed merger. These observations notwithstanding, it is difficult in practice to verify and quantify these merger efficiencies.

A Malmquist productivity growth index introduced by Caves et al. (1982) and further developed by Färe et al. (1994) is employed to compute productivity growth, which is comprised of technical efficiency change and technological change. In addition, this essay measures firm-level technical efficiencies using dynamic data envelope analysis (DEA) to evaluate the ILECs' ability to optimize output over time.

The main findings of this essay indicate that mergers positively affect average productivity growth, but that this effect decreases over time. In addition, firms that have not merged under-perform firms that have merged in terms of average productivity growth.

The primary objective of Chapter 3 is to evaluate the effectiveness of mergers that occurred between 1996 and 2005 using stochastic frontier analysis (SFA). This essay investigates whether productivity growth has increased among ILECs that have merged since the 1996 Act and whether the merged firms performed better than those firms that did not merge. The second objective is to compare the results on productivity growth between the SFA and the Malmquist index approach. This comparison provides useful information on the robustness of the efficiency findings across different approaches.

One of the methods that may be used to examine efficiencies is to measure productivity growth, inclusive of its underlying components--technological progress and changes in technical efficiency. From a policy perspective, the decomposition of productivity growth into these components provides important information for analysis. For example, if policymakers are able to determine the key drivers of productivity growth, they may adopt policies that can significantly improve the performance of firms in the industry and hence the overall economy. Suppose, for example, that a lack of technological progress is the source of low productivity growth. It would then be possible to adopt various policies that serve to stimulate technological innovation and move the technology frontier outward over time. If high rates of technological change associated with low rates of efficiency change are measured, then policy makers may focus on the policy that increases the efficiency of the individual firms.

Chapter 3 finds that the firm sample has experienced deterioration in average productivity growth following the merger. This empirical finding is attributed to technological regression, a finding that may lead policymakers to consider implementing policies that serve to shift out the production frontier over time. In terms of average growth in productivity, the only firm in the sample not to have merged ranks third lowest among the 25 ILECs.

Another component of this chapter is a comparison of indices for the stochastic frontier analysis and the Malmquist index method. This comparison provides useful information on robustness. With the exception of one firm using the Malmquist index method, both methods indicate that every firm in the sample has experienced negative annual growth in technological change. Indices of productivity growth suggest that most of the firms experience negative growth in annual productivity growth following the merger across both methods. However, in terms of productivity growth, it is noteworthy that the only firm not to have merged underperforms relative to the firms that have merged during the post-merger periods. In SFA, annual productivity growth for BellSouth is the third lowest in the sample and the fourth lowest using the Malmquist index method.

The primary objective of Chapter 4 is to measure productivity growth associated with technological progress and changes in technical efficiency in order to examine the improvement in the local exchange carriers' (LECs') productivity growth. In addition, this essay analyzes the effects associated with the adoption of incentive regulation on the LECs' productivity growth rate.

A large volume of research has examined the effects of the implementation of incentive regulation regimes. Schmalensee and Rohlfs (1992) examined the effect of price cap regulation (PCR) on productivity gains. They found that the cumulative productivity gains increased $1.8 billion over the period of price cap regulation (PCR) relative to the pre price-cap period.

Majumdar (1997) employed a non-parametric approach, commonly referred to as data envelopment analysis (DEA), to examine the effect of incentive regulation on the productive performance of 45 local exchange carriers (LECs) over the period 1988-1993. He showed that PCR has a positive but lagged effect on technical efficiency. Uri (2001) used a Malmquist index to measure the change in productivity growth following the implementation of incentive regulation. He found that productivity growth increased by approximately 5 percent per year for the 19 LECs over the period 1988-1999.

Although a number of empirical studies have found that the effect of incentive regulation on productivity growth in the U.S. telecommunications industry is substantially positive, some have concluded that the effect of incentive regulation is ambiguous. For example, Resende (1999) estimated a translog cost function combined with a total factor productivity (TFP) growth decomposition for the period 1989-1994. He found that incentive regulation did not enhance the level of productive efficiency. Uri (2002) employed a corrected ordinary least squares (COLS) approach to measure the efficiency gains associated with the implementation of incentive regulation in the U.S. telecommunications industry. Using data from 19 LECs over the 1988-1999 period, he found no empirical evidence that incentive regulation had enhanced technical efficiency.

The results of Chapter 4 broadly indicate that the adoption of PCR and incentive regulation (IR), more generally, has had a positive impact on operating performance in the U.S.

telecommunications industry. By examining the relationship between productivity growth and regulatory regime variables, while controlling for all other effects, we find that PCR and other forms of incentive regulation have a positive effect on productivity growth. It is noteworthy, however, that only PCR has a significant and positive effect on productivity growth in both contemporaneous and lagged model specifications.

CHAPTER 2 - Productivity Growth and Merger Efficiencies in the U.S. Telecommunications Industry

INTRODUCTION

In 1974, the U.S. Department of Justice (DOJ) initiated an anti-trust suit against AT&T that was ultimately settled on January 8, 1982.[1] On January 1, 1984, AT&T's local operating companies were divested into seven independent Regional Holding Companies known as the Regional Bell Operating Companies (RBOCs). [2, 3] Following this divestiture, AT&T provided long distance service and the seven RBOCs provided primarily local telephone service and intraLATA long-distance service.[4] The RBOCs were prohibited from providing interLATA long-distance service. This *de facto* quarantine imposed on the RBOCs was designed to spur competition in long-distance and telecommunications equipment markets. The expectation was that the gains from the ensuing competition would outweigh the loss of economies of scope that derive from the joint provision of local and long distance telecommunications (Baxter, 1991, p.30).

The passage of the 1996 Telecommunications Act (1996 Act) was the next significant event designed to further stimulate competition in telecommunications markets.[5] This statute required local exchange carriers (LECs) to unbundle their networks and share the component

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[1] See Chapter 2 in Sappington and Weisman (1996) for a detailed history of these industry developments.

[2] The seven RBOCs were Ameritech Corporation, Bell Atlantic Corporation, BellSouth Corporation, NYNEX Corporation, Pacific Telesis Group, Southwestern Bell Corporation and U S West, Inc.

[3] In addition to the seven RBOCs, two smaller companies, Cincinnati Bell and Southern New England Telephone (SNET), became stand-alone companies after the settlement. There were also several operating companies such as GTE, United, Continental and Central telephone system that are known as independent telephone companies because they were never part of the Bell System.

[4] As part of the break-up of AT&T, the U.S. was partitioned into approximately 161 local access transport areas or LATAs. The RBOCs were restricted to providing intraLATA long distance service. This essentially meant that the RBOCs could not provide long distance service across area code boundaries.

[5] The Telecommunications Act of 1996 is divided into seven Sections. Obligations of Incumbent Local Exchange Carriers (ILECs) were in Title I. Additional duties of ILECs include negotiation, interconnection, unbundled access, resale, notice of changes and collocation.

inputs, or “unbundled network elements” (UNEs), with rivals at regulatory prescribed rates if “the failure to provide access to such network elements would impair the ability of the telecommunications carrier seeking access to provide the services that it seeks to offer” (Section 251(d)(2)(B)).[6] Consequently, the 1996 Act gave rise to a new group of communications carriers known as competitive local exchange carriers (CLECs) that compete directly with incumbent local exchange carriers (ILECs).[7] Section 271 of the 1996 Act also provided a mechanism through which the RBOCs could re-enter the interLATA long-distance market.

A significant amount of industry consolidation followed in the aftermath of the passage of the 1996 Act.[8] This consolidation was primarily directed at increasing economies of scale in the provision of local telephone service and also re-capturing the economies of scope that had been sacrificed as part of the AT&T divestiture. Southwestern Bell Corporation (SBC, now at&t) was perhaps the most aggressive RBOC in this consolidation campaign.

SBC acquired Pacific Telesis Group, Southern New England Telephone and Ameritech in 1997, 1998 and 1999, respectively. A merger between Bell Atlantic and GTE formed Verizon in 2000. U.S. West agreed to merge with QWEST Communications in 1999 and this merger was approved by state and federal regulators in 2000. In 2005, AT&T was acquired by SBC communications. Shortly after this merger, the company was renamed at&t Inc. Finally, Verizon acquired MCI in January 2006, followed by at&t’s December 2006 acquisition of

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[6] CLECs can lease UNEs and combine them with their own facilities to provide the retail telecommunications product. UNE-L, or the unbundled network loop, is example of this type of network element. The UNE-L entails leasing the loop, which is the connection from the telephone exchange’s central office to the customer premises. UNE-P, or the unbundled network element platform, is a special type of resale in which the network inputs are combined for the entrant by the incumbent provider. The price for UNE-P is lower than that of pure resale because it is based on TELRIC (total element long-run incremental cost) rather than avoided cost, but the two are functionally indistinguishable otherwise. The Federal Communications Commission began phasing out UNE-P in 2005 because it believed the availability of UNE-P was having an adverse effect on investment in network infrastructure. See FCC (2005).

[7] At the time of the 1996 Act, the ILECs were comprised of local telephone companies, including the Regional Bell Operating Companies (RBOCs).

[8] The history of ILEC mergers from 1996 onward is shown in Table 1.

BellSouth Corporation—the last of the RBOCs to have retained its original corporate name following the 1984 AT&T divestiture.[9, 10]

In general, mergers can be either pro-competitive or anti-competitive in terms of their effect on industry performance, including productive efficiency. The horizontal merger guidelines (HMG) of the U.S. Department of Justice (DOJ) rely, in part, upon market concentration in evaluating whether particular mergers raise anticompetitive concerns. In addition to market concentration, the HMG also take into account potential adverse competitive effects and entry analysis in evaluating proposed mergers. Specifically, Section 4 of the HMG (revised April 8, 1997) describes the significance of merger efficiencies. When efficiency gains from a merger, which may result in lower prices or quality improvements, are expected to dominate the other effects of the merger that may serve to lessen competition, the agency would consider approving the proposed merger. These observations notwithstanding, it is difficult in practice to verify and quantify these merger efficiencies.[11]

A number of empirical studies have computed efficiency scores for the U.S. telecommunications industry, including Majumdar (1995, 1997), Resende (2000) and Resende and Facanha (2005). And yet, most of the studies that examine efficiency in the telecommunications industry have concentrated on either the effects of different regulatory regimes or the impact of the AT&T divestiture.[12] The measurement of efficiency gains with respect to mergers has heretofore been given surprisingly little attention in the literature.

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[9] Cincinnati Bell, which is not part of AT&T break-up, retains its brand name and continues to use the Bell logo.

[10] This trend continues in the wireless industry as well as the wireline industry. For instance, in 2004, AT&T and Cingular Wireless merged and became the largest provider in the wireless industry. Sprint PCS also merged with Nextel and adopted the brand Sprint-Nextel in 2005. See Weisman (2007) for further discussion of these mergers and the economic factors driving them.

[11] The HMG of the DOJ introduced cognizable efficiencies that are merger-specific. The HMG (p. 31) indicate that "Cognizable efficiencies are assessed net of costs produced by the merger or incurred in achieving those efficiencies."

[12] See Shin et al. (1992) and Krouse et al. (1999) for research on the effects of the AT&T divestiture.

In this essay, a Malmquist productivity growth index introduced by Caves et al. (1982) and further developed by Färe et al. (1994) is employed to compute productivity growth, which is comprised of technical efficiency change and technological change.[13] A large number of papers employ the Malmquist index to measure productivity growth for a cross-section of industries.[14] With specific reference to the telecommunications sector in the U.S., Uri (2001, 2002) used a Malmquist index to measure the change in productivity growth following the implementation of incentive regulation. He found that productivity growth increased by approximately 5 percent per year for the 19 LECs over the period 1988-1999.

This study differs from Uri in three critical respects. First, we investigate the effectiveness of mergers over the 1996 to 2005 time period. We seek to determine whether productivity growth has increased for ILECs that have merged since the 1996 Act and whether the merged firms perform better than a firm that did not merge in terms of productivity growth. Employing a Malmquist index, we find that the change in productivity growth for merged firms is higher than that of firms that did not merge, *ceteris paribus*. In contrast to Uri, our findings indicate that productivity growth decreased for most firms in the sample. Second, our sample includes 25 LECs and therefore provides for a more robust analysis. Third, we measure firm-level technical efficiencies using dynamic DEA to evaluate the ILECs' ability to optimize output over time.

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[13] Kwoka (1993) analyzed the impact of different regulatory policies on productivity growth for both AT&T and British Telecom (BT). He found empirical evidence that both the privatization of BT and the divestiture of AT&T had a significant effect on productivity growth. Resende (1999) found no statistically significant relationship between incentive regulation and increased productivity growth. Stranczak et al. (1994) investigated whether privatization and competition affect productivity growth in the telecommunications industry. They found no empirical evidence of a statistically significant relationship between long distance competition and productivity growth.

[14] For example, Färe et al. (1994) examined productivity growth in 17 OECD countries for the 1979-1988 period using the Malmquist index. They found that the country that has the highest productivity growth rate is Japan while that of the U.S. is slightly higher than average. Lall et al. (2002) also used the Malmquist index to measure productivity growth in over 30 countries in the Western Hemisphere over the 1978-1994 period. They found that civil, economic, and political liberty played a significant role in productivity growth for Caribbean countries.

The remainder of this essay is organized as follows. The analytical framework and theory used to measure productivity growth and the decomposition of the Malmquist index are described in Section 2. In Section 3, the data used in this essay are discussed. Section 4 provides the empirical results for the DEA scores and changes in productivity growth. We compare the pre-merger and post-merger productivity growth and technical efficiency change among ILECs that have merged since the 1996 Act relative to the ILEC that did not merge.[15] Finally, Section 5 contains a brief summary of the results and a conclusion.

METHODLOGY

There are two principal approaches to the estimation of production frontiers, the parametric method and the non-parametric method. The Malmquist index approach employed in this essay is of the latter type. One of the important advantages of using this index is the ability to decompose productivity growth rates into technical efficiency change and technological change. In addition, no explicit functional form for the frontier is required since the DEA approach uses linear programming. DEA also allows for multiple inputs and multiple outputs that are not as easily estimated using parametric methods. Another distinct advantage of using the DEA method in measuring productivity growth is that it does not require any price data. Before turning to a discussion of the specific properties of the Malmquist index, we provide an overview of the DEA technique.[16]

DEA is a linear programming method that uses data on the multiple input and output quantities to construct a hypersurface over the data points. This hypersurface is constructed by the solution to a series of linear programming problems. There are input-oriented and output-oriented DEA methods. The former is conducted by reducing the amount of all inputs

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[15] BellSouth Corporation is the only ILEC that had not merged prior to 2005.

[16] The first influential DEA model was developed by Charnes et al. (1978).

proportionally without a reduction in output. The latter is conducted by determining the maximum proportional increase in output for any given level of input.

Output-oriented DEA is depicted in Figure 1. There are two outputs (Y_1, Y_2) and five firms (a, b, c, d, e). Firms a, b and c are efficient since they lie on the production frontier. Calculating the technical efficiency score of firm d is equivalent to:

$$TE_d = \frac{\overline{0d}}{\overline{0d^{'}}}. \tag{1}$$

In similar fashion, the technical efficiency score for firm e is equal to:

$$TE_e = \frac{\overline{0e}}{\overline{0e^{'}}}. \tag{2}$$

Therefore, the value of the efficiency score lies between 0 and 1.

For firm d, the efficient target is $d^{'}$ which lies on the line segment joining points a and b. Firms a and b are typically referred to as the peers of firm d. In similar fashion, firm e's peers are firms b and c. Note that the value of technical efficiency for firms a, b and c are assigned the value of one and each firm is its own peer.

We turn now to discuss the distance function that is required to construct a Malmquist index. Based on Caves et al. (1982), we assume that for each time period $t = 1, \ldots, T$, the production technology F^t maps input vectors, $x^t \in \mathbb{R}_+^n$ into output vectors, $y^t \in \mathbb{R}_+^m$,[17]

$$F^t = \left\{ \left(x^t, y^t \right) : x^t \text{ can produce } y^t \right\}, \tag{3}$$

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[17] The production technology is assumed to satisfy the following axioms in order to be a meaningful model of production: i) the possibility of inaction; ii) monotonicity of the output correspondence; iii) disposability of output; iv) the output set is closed; and v) irreversibility (Färe and Grosskopf, 1994).

where $\mathbb{R}$ is the set of real numbers. The production technology F^t is homogeneous of degree 1 in output. Following Shepard (1970), the output distance function is defined at time t as:

$$D_O^t\left(x^t,y^t\right)=\inf\left\{\theta:\left(x^t,\frac{y^t}{\theta}\right)\in F^t\right\}=\left(\sup\left\{\theta:\left(x^t,\theta y^t\right)\in F^t\right\}\right)^{-1}. \tag{4}$$[18]

The distance function $D_O^t\left(x^t,y^t\right)$ is homogeneous of degree 1 in output. Note that input-output vectors lie below the production technology set, which implies that $D_O^t\left(x^t,y^t\right)\leq 1$ if and only if $\left(x^t,y^t\right)\in F^t$. Moreover, $D_O^t\left(x^t,y^t\right)=1$ if and only if input-output combinations lie on the boundary of the production technology set that is illustrated in Figure 2.[19] The value of the distance function evaluated at $\left(x^t,y^t\right)$ is $\frac{oa_2}{oa_2}=1$, while the value of the distance function evaluated at $\left(x^{t'},y^{t'}\right)$ is $\frac{oa_1}{oa_2}<1$.[20] In order to construct a Malmquist index, another distance function from a different time period is required. This distance function is expressed as:

$$\begin{aligned}D_O^t\left(x^{t+1},y^{t+1}\right)&=\inf\left\{\theta:\left(x^{t+1},\frac{y^{t+1}}{\theta}\right)\in F^t\right\}\\&=\left(\sup\left\{\theta:\left(x^{t+1},\theta y^{t+1}\right)\in F^t\right\}\right)^{-1}.\end{aligned} \tag{5}$$

This distance function measures the maximal proportional change in output required to make $\left(x^{t+1},y^{t+1}\right)$ feasible in relation to the technology at time t. In Figure 2, production $\left(x^{t+1},y^{t+1}\right)$

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[18] The input distance function can be defined as follows:

$$D_I^t\left(x^t,y^t\right)=\sup\left\{\delta:\left(\frac{x^t}{\delta},y^t\right)\in F^t\right\}.$$

[19] Farrell (1957) referred to a firm as "technically efficient" when $D_O^t\left(x^t,y^t\right)=1$.

[20] Refer to Färe and Grosskopf (2000) for additional discussion of distance functions.

occurs outside the production possibility set at time t. The value of the distance function for observation $\left(x^{t+1}, y^{t+1}\right)$ relative to technology F^t is $\frac{oa_4}{oa_3} > 1$.

A Malmquist index is the ratio of two distance functions and is constructed as follows:

$$M_c^t = \frac{D_O^t\left(x^{t+1}, y^{t+1}\right)}{D_O^t\left(x^t, y^t\right)}.^{21} \tag{6}$$

Färe et al. (1994) suggest using the output-based Malmquist index in order to avoid the use of an arbitrary benchmark:

$$M_O\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \sqrt{\left(\frac{D_O^t\left(x^{t+1}, y^{t+1}\right)}{D_O^t\left(x^t, y^t\right)}\right)\left(\frac{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_O^{t+1}\left(x^t, y^t\right)}\right)}. \tag{7}$$

From the production frontier perspective, technical efficiency measures how far below the production frontier a particular firm's technology resides. Technological change implies technological innovation and it measures the extent to which that frontier moves outward/inward over time. In order to decompose a Malmquist index into a technical efficiency change and technological change, (7) can be represented as:

$$M_O\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \frac{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_O^t\left(x^t, y^t\right)} \times \sqrt{\left(\frac{D_O^t\left(x^{t+1}, y^{t+1}\right)}{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)\left(\frac{D_O^t\left(x^t, y^t\right)}{D_O^{t+1}\left(x^t, y^t\right)}\right)}, \tag{8}$$

where $\frac{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_O^t\left(x^t, y^t\right)}$ measures the change in relative efficiency (i.e., whether the production technology is moving closer to or farther away from the production frontier) between periods t

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[21] Technology in period t is treated as the base-case technology.

and $t+1$. $\left(\frac{D_O^t\left(x^{t+1},y^{t+1}\right)}{D_O^{t+1}\left(x^{t+1},y^{t+1}\right)}\right)\left(\frac{D_O^t\left(x^t,y^t\right)}{D_O^{t+1}\left(x^t,y^t\right)}\right)$ measures the shift in the technology frontier between the two periods evaluated at x^t and x^{t+1}.

Therefore, the technical efficiency change (EC) is represented as:

$$EC = \frac{D_O^{t+1}\left(x^{t+1},y^{t+1}\right)}{D_O^t\left(x^t,y^t\right)}, \tag{9}$$

and technological change is represented as:

$$TC = \sqrt{\left(\frac{D_O^t\left(x^{t+1},y^{t+1}\right)}{D_O^{t+1}\left(x^{t+1},y^{t+1}\right)}\right)\left(\frac{D_O^t\left(x^t,y^t\right)}{D_O^{t+1}\left(x^t,y^t\right)}\right)}. \tag{10}$$

Hence, if there is no change in inputs and outputs between periods t and $t+1$, the Malmquist index is one. Note that EC and TC are not necessarily equal to one since the Malmquist index is the product of EC and TC. Increases (decreases) in productivity growth imply that a Malmquist index is greater (less) than one. In a similar manner, values of EC and TC that are greater than one suggest improvements in EC and TC, whereas values less than one suggest deterioration in EC and TC.

A nonparametric linear programming approach is used to calculate the values of the distance functions used to construct a productivity growth index. Assume that there are $i=1,\ldots,I$ firms using $n=1,\ldots,N$ inputs that produce $m=1,\ldots.M$ outputs. Therefore, the individual firm's input and output vectors associated with time t can be represented as $x_n^{i,t}$ and $y_m^{i,t}$, respectively.

The base technology under constant returns to scale (CRS) at time t is modeled using data as:

$$F^t = \left\{ \left(x^t, y^t\right) \text{ such that } y_m^t \leq \sum_{i=1}^{I} z^i y_m^{i,t},\ \sum_{i=1}^{I} z^i x_n^{i,t} \leq x_n^t,\ z^i \geq 0 \right\}, \tag{11}$$

where z^i is the intensity of use of the i^{th} firm's technology. By adding the following convexity condition based on Afriat (1972), the constant returns to scale assumption can be modified to allow for variable returns to scale (VRS):

$$\sum_{i=1}^{I} z^i = 1. \tag{12}$$

One may obtain technical efficiency change under constant returns to scale technology and then decompose it into two components–the pure efficiency component and the residual scale component. The former is due to pure technical inefficiency and the latter is due to scale inefficiency.[22]

In order to calculate a Malmquist index in (8), four different linear programming problems are used to solve for the values of four distance functions. These are given by $D_O^t\left(x^t, y^t\right)$, $D_O^t\left(x^{t+1}, y^{t+1}\right)$, $D_O^{t+1}\left(x^t, y^t\right)$, $D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)$. For firm i',

$$\left(D_O^t\left(x^{i',t}, y^{i',t}\right)\right)^{-1} = \max_{z,\theta} \theta^{i'}$$

$$\begin{aligned} \text{s. t.} \quad & \theta^{i'} y_m^{i',t} \leq \sum_{i=1}^{I} z^i y_m^{i,t} \\ & \sum_{i=1}^{I} z^i x_n^{i,t} \leq x_n^{i',t} \\ & z^i \geq 0. \end{aligned} \tag{13}$$

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[22] The decomposition can be expressed as:

$$M_O\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = TECH \times EFCH$$
$$= TECH \times PEFCH \times SCH,$$

where TECH represents technological change, EFCH represents technical efficiency change, PEFCH represents pure efficiency change and SCH represents scale change. EFCH is computed under CRS while PEFCH is computed under VRS.

$$\text{and } \left(D_O^{t+1}\left(x^{i',t+1}, y^{i',t+1}\right)\right)^{-1} = \max_{z,\theta} \theta^{i'}$$

$$\text{s. t.} \quad \theta^{i'} y_m^{i',t+1} \le \sum_{i=1}^{I} z^{i,t+1} y_m^{i,t+1} \tag{14}$$

$$\sum_{i=1}^{I} z^{i,t+1} x_n^{i,t+1} \le x_n^{i',t+1}$$

$$z^i \ge 0.$$

Two additional distance functions are required to calculate a Malmquist index for the two periods t and $t+1$. The first of these is calculated for firm i' as

$$\left(D_O^{t}\left(x^{i',t+1}, y^{i',t+1}\right)\right)^{-1} = \max_{z,\theta} \theta^{i'}$$

$$\text{s. t.} \quad \theta^{i'} y_m^{i',t+1} \le \sum_{i=1}^{I} z^{i} y_m^{i,t} \tag{15}$$

$$\sum_{i=1}^{I} z^{i} x_n^{i,t} \le x_n^{i',t+1}$$

$$z^i \ge 0.$$

Note that the value of θ in (15) need not be greater than or equal to unity. For example, the observation could lie above the feasible production possibility set since a production combination from period $t+1$ is compared to technology in period *t*. The last linear programming problem entails the same calculations as in (15) with transposed superscripts, *t* and $t+1$, and stated as

$$\left(D_O^{t+1}\left(x^{i',t}, y^{i',t}\right)\right)^{-1} = \max_{z,\theta} \theta^{i'}$$

$$\text{s. t.} \quad \theta^{i'} y_m^{i',t} \le \sum_{i=1}^{I} z^{i} y_m^{i,t+1} \tag{16}$$

$$\sum_{i=1}^{I} z^{i} x_n^{i,t+1} \le x_n^{i',t}$$

$z^i \geq 0$.

DATA

This essay examines observations on the inputs and outputs of 25 ILECs over the period 1996-2005 for which comparable data exist following the passage of the 1996 Act. The data are obtained from the Electronic ARMIS Filing System maintained by the U.S. Federal Communications Commission (FCC) and the Statistics of Communications Common Carriers.[23] Although both physical and financial data values are available as inputs or outputs, we separate the physical and financial data sets because the financial data are required to deflate variables and may result in measurement errors.

Our input and output variable definitions use Majumdar's (1997) approach, which defines 3 outputs and 3 inputs. The output variables are local calls, intraLATA toll calls and interLATA toll calls.[24] Our measures of inputs are the number of total switches, the number of access lines and the number of employees. The use of these three inputs is sufficient to capture the actual network characteristics of the firms that provide telephone service. In the telecommunications industry, telephone switches comprise the system of electronic components that connect telephone calls, while actual messages are distributed by the physical (copper or fiber optic) lines.

The summary statistics for the inputs and outputs for the ILECs examined in this essay over the period 1996-2005 are shown in Table 2. It is noteworthy that the average of each of the outputs has been decreasing since 2000. This reflects the fact that the ILECs lost significant market share to the CLECs following the implementation of the 1996 Act. According to Trends

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[23] ARMIS stands for Automated Reporting Management Information System. This data set may accessed at http://www.fcc.gov/wcb/armis. FCC Report 43-02, the ARMIS USOA Report , FCC Report 43-07, the ARMIS Infrastructure Report and FCC Report 43-08, the ARMIS Operating Data Report were used to construct the data set.

[24] InterLATA calls refers to calls that originate in one Local Access and Transport Area (LATA) and terminate in another LATA. IntraLATA calls refers to calls that originate and terminate in the same LATA. LATAs are some times referred to as the service areas for the Bell Operating Companies. See, for example, Newton (2000).

in Telephone Service (2007), the CLEC share of end-user switched access lines increased from 4.3 percent in 1999 to 17.9 percent in 2005. In addition, significant growth in the number of wireless subscribers and usage has caused the traditional wireline companies to experience significant erosion in their long distance telephone volumes.[25]

EMPIRICAL RESULTS

Results for the efficiency scores and productivity growth indices are reviewed in this section. In Table 3, we provide the technical efficiency scores for all merged and non-merged firms from 1996 through 2005. Note that a firm that lies on the production frontier has a value of one for its efficiency score for each year regardless of improvement or deterioration in its performance. As a result, we are not able to examine the real efficiency change of the frontier firms over the sample period. Despite this complexity, this approach does provide information as to how the efficiency measures for the non-frontier firms are changing over time. When the efficiency score is closer to one, the efficiency of the non-frontier firm is catching up to that of the frontier firms. For example, in Table 3, a technical efficiency score for Qwest of 0.881 in 1996 indicates that Qwest could produce approximately 11.9 percent more output with the same level of inputs if it moved up on to the production frontier.

In Table 4, we identify those firms that define the frontier technology for the first year (1996) and the final year (2005) adjacent to their observed combination of inputs and outputs. In 1996, 12 firms lie on the production frontier, while 11 firms lie on the production frontier in 2005. Table 4 indicates that Southwestern Bell, Nevada Bell, Michigan Bell, Verizon Virginia and Verizon Delaware were all on the production frontier in 1996, and yet all became non-production frontier firms in 2005. In addition, there are changes in the groups of peer firms over

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[25] The Cellular Telecommunications and Internet Association (CTIA)'s survey data (2006) reveals a rapid increase in the number of wireless telephone subscribers, from 44,042,992 in 1996 to 207,896,198 in 2005, or an increase of 372%.

the two periods. For example, the peers for Qwest Corporation were Nevada Bell, BellSouth Corporation and Verizon New Jersey in 1996. However, only Verizon New Jersey remained in the same peer group for Qwest Corporation in 2005. Efficient firms on the frontier that do not appear as a peer for inefficient firms may be considered to be on the frontier as a result of their distinct characteristics in terms of input/output combinations. For Example, Indiana Bell and Michigan Bell do not appear as a peer for any firm in 1996 while Verizon New Jersey appears as a peer for 12 firms.

Table 5 provides the mean values of technical efficiency change, technological change and productivity growth change for the 25 ILECs over the period 1996 to 2005.[26] The firms in the table are presented in descending order of the magnitude of their average productivity growth over the sample period. Verizon South shows a 4.8 percent average growth in productivity, which is due to a 1.2 percent growth in technical efficiency change and a 3.6 percent growth in technological change. It is useful to note the number of companies that improved their performance over the sample period. Only 4 out of 25 companies, Verizon South, Verizon New York, Verizon Florida and Verizon Northwest, realized positive productivity growth over the sample period. For example, Verizon South experienced a 4.8 percent annual growth in productivity over the sample period.

Table 6 reports the average of technical efficiency change, technological change and productivity growth 3 years before and 3 years after the merger. The sample companies are classified by 3 groups. The first group includes firm 1 and firms 11 through 25 for mergers that occurred in 2000. The second group includes firms 2 through 9 for mergers that occurred in

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[26] In this paper, the mean is the geometric mean. Let M_t denote the Malmquist index, where t stands for time and t = 1, 2, . . . , 10. The geometric mean is computed as $\sqrt[10]{\prod_{t=1}^{10} M_t}$.

1999.[27] The last group contains only BellSouth Corporation as it is the only the non-merged firm in the sample. The reason we examine the periods 3 years before and 3 years after the merger is to identify the merger effect for the same time interval.[28]

Seven companies, comprised of firms 1, 11, 12, 14, 15, 16 and 18 from the first group, and two companies, firms 3 and 4 from the second group, have experienced increases in productivity growth. However, the control company, BellSouth Corporation, experienced decreased productivity growth. Five companies, firms 3, 12, 15, 16, and 18, were able to reverse their performance from deterioration 3 years before the merger to improvement for 3 years after their merger. For example, Pacific Bell-California experienced a 3.3 percent average growth in productivity for the 3 years after the merger, but a -4.7 percent average growth in productivity for the 3 years prior to the merger.

Table 7 reports the mean of technical efficiency change, technological change, and productivity growth between the pre-merger and post-merger periods. The mergers occurred in 2000 and 1999 for the first and second groups, respectively. Therefore, in order to compare every firm in each group with a non-merged firm, we compute two measures for BellSouth Corporation. One measure is conducted from 2000 and the other measure is conducted from 1999. When comparing the measures in Table 6, the number of companies that experienced increased productivity growth decreased from 9 to 4. This suggests that the merger effect of increased productivity growth diminishes over time.

It is noteworthy that 3 companies, Verizon Virginia, Southwestern Bell and Michigan Bell, experienced lower average productivity growth after the merger than that of BellSouth

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[27] In fact, Pacific Telesis Group which has Pacific Bell and Nevada Bell operating companies first merged in 1997. Since our sample period begins with 1996 we place theses two companies in the second group.

[28] The maximum number of indexes before the merger for the second group is 3 (i.e., 1997, 1998, and 1999). The 1997 index refers to the change between 1996 and 1997. Therefore, in order to compare the same period, we must use a 3-year data span before and after the merger.

Corporation. The mean productivity growth for BellSouth Corporation was computed for two different time periods. One is computed over 5 years and yields an annual growth rate of -5.2 percent. The other is computed over 6 years and yields an annual growth rate of -5.1 percent. It should be noted that BellSouth Corporation, the only firm that was not part of a merger in our sample, is one of the worst performing ILECs in terms of average productivity growth.

Conclusion

The passage of the 1996 Telecommunications Act ushered in a period of increased consolidation in the U.S. telecommunications industry. Of the seven RBOCs created as a result of the AT&T divestiture, only 3 remain, Qwest, Verizon and AT&T (formerly SBC). In order to examine the efficiencies associated with these mergers, this study attempts to measure the productivity growth associated with 25 ILECs over the period 1996-2005 using a Malmquist productivity index. We also compute technical efficiency scores, which enable us to capture the relative efficiency effects and explain how the efficiency for the non-efficient firm is changing over time. The average efficiency scores for our sample companies have not changed significantly between 1996 and 2005. This implies that the average ILEC shows no measurable improvement in terms of optimizing their input-output combinations over time.

The results of computing a Malmquist productivity index reveal that 9 out of 25 individual firms are shown to have increased their average productivity growth for the 3-year period after the merger. When we partition these firms into pre-merger and post-merger categories, the number of firms that increase productivity growth is reduced to 4 firms. This suggests that the impact on average productivity growth resulting from the mergers decreases over time. In addition, the measure of the Malmquist productivity index for the non-merged firm, BellSouth Corporation, is one of the lowest firms in the sample. The index for BellSouth

Corporation shows about a -5 percent decline in annual productivity growth. These results therefore provide some evidence of a positive merger effect, although this effect appears to diminish over time.

Figure 2.1 Output-Oriented DEA

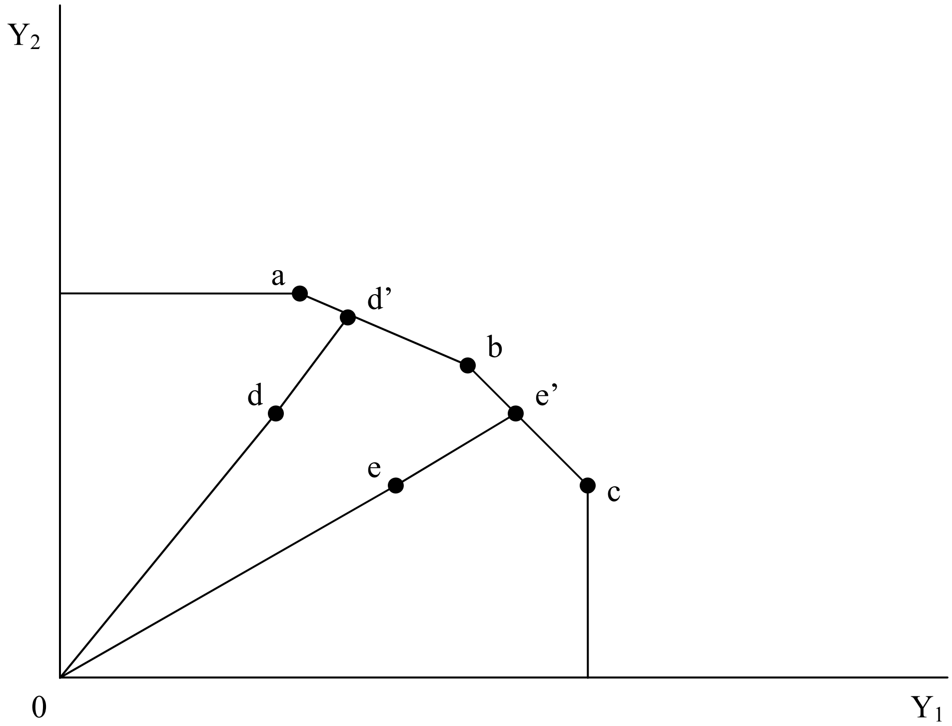

Figure 2.2 Output Distance Function

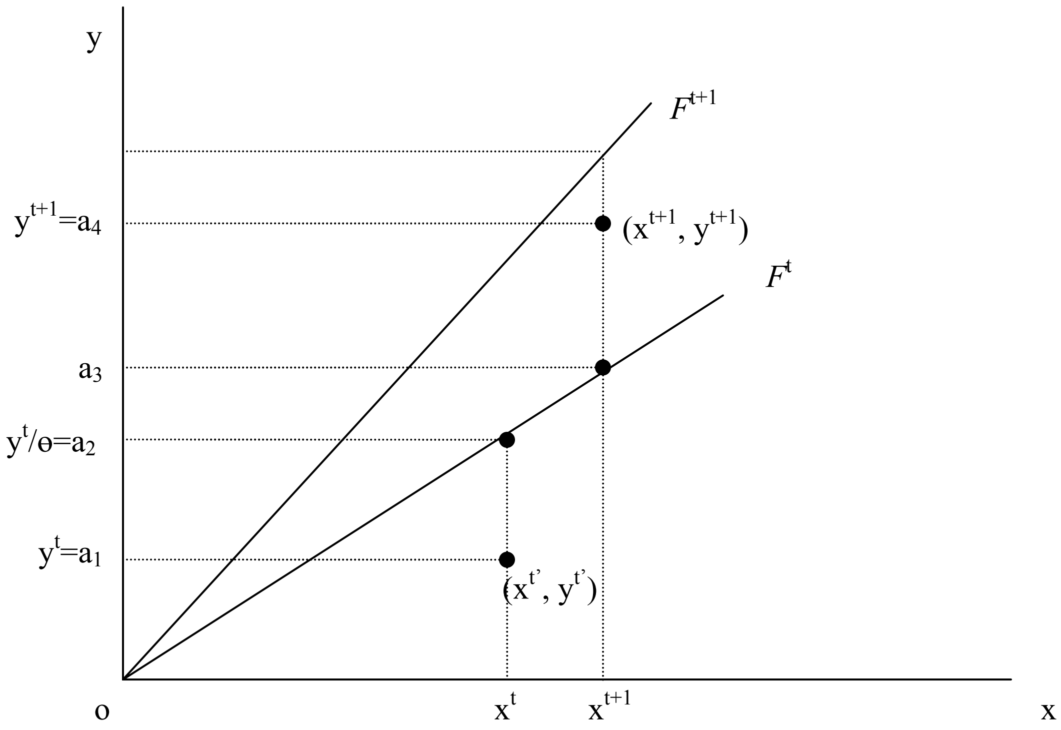

Table 2.1 History of Mergers among RBOCs

Year	Name of RBOC	Action Taken
1996	NYNEX	Acquired Bell Atlantic and branded Bell Atlantic
1997	Pacific Telesis Group	Acquired by SBC
1999	Ameritech	Acquired by SBC
2000	Bell Atlantic	Merged with GTE and formed Verizon
2000	U S West	Merged with Qwest
2006	Verizon	Acquired MCI
2006	Southwestern Bell Corporation (SBC)	Acquired AT&T and branded at&t
2006	BellSouth Corporation	Acquired by at&t

Table 2.2 Summary Statistics

	Local call	Intra LATA toll call	inter LATA toll call	Total switches	Access lines	Employees
1996 Mean	18,568,460	762,654	2,539,546	596	5,644,720	15,254
S.D.	22,134,968	1,045,108	2,368,059	539	5,594,318	16,479
Min	821,576	4,902	236,733	34	361,000	842
Max	94,344,715	4,929,318	9,427,603	1,782	22,017,000	59,486
1997 Mean	19,203,861	745,459	2,737,357	594	5,913,527	15,329
S.D.	22,986,746	1,056,051	2,503,517	536	5,887,640	16,114
Min	961,244	5,453	98,277	33	326,212	870
Max	97,783,674	4,879,781	10,055,171	1,750	23,080,061	53,919
1998 Mean	19,871,661	643,766	2,778,404	591	6,131,493	15,466
S.D.	23,378,880	977,498	2,385,641	534	6,130,918	16,510
Min	1,149,802	4,906	105,215	31	341,508	870
Max	99,324,801	4,807,358	10,695,077	1,770	23,908,672	56,188
1999 Mean	20,267,909	613,354	3,014,317	595	6,279,775	15,562
S.D.	22,999,739	928,092	2,614,382	537	6,258,412	17,178
Min	1,227,627	4,664	96,531	31	363,444	918
Max	97,232,126	4,491,538	10,965,391	1,802	24,457,845	59,457
2000 Mean	19,581,898	548,571	3,208,499	574	6,271,283	15,594
S.D.	22,223,409	875,148	2,665,776	517	6,288,029	16,724
Min	1,017,475	4,728	110,000	30	380,616	921
Max	93,784,438	4,396,675	11,102,561	1,715	24,558,289	61,555
2001 Mean	18,642,513	542,199	3,005,960	575	6,075,592	14,722
S.D.	21,010,357	1,004,990	2,596,988	516	6,057,136	15,947
Min	1,022,195	4,751	128,285	30	367,578	929
Max	89,498,059	5,151,332	10,287,931	1,716	23,756,306	60,535
2002 Mean	16,570,572	475,912	2,933,650	561	5,808,766	12,728
S.D.	18,727,360	997,724	2,723,152	501	5,842,992	13,856
Min	841,740	4,419	182,374	28	365,535	774
Max	82,925,856	5,120,259	9,379,825	1,722	22,954,773	53,461
2003 Mean	15,096,699	415,611	2,675,848	561	5,589,264	11,608
S.D.	17,040,793	841,427	2,535,131	500	5,576,337	13,085
Min	780,677	3,030	180,943	30	361,218	692
Max	75,767,109	4,307,978	8,827,826	1,728	22,206,344	50,393
2004 Mean	13,683,056	345,420	2,514,156	561	5,327,325	11,300
S.D.	15,247,549	674,329	2,314,766	498	5,322,309	12,359
Min	738,430	2,191	179,010	30	359,238	659
Max	67,393,286	3,426,898	8,328,607	1,722	21,316,936	47,678
2005 Mean	12,106,135	311,944	2,357,347	485	4,999,650	11,012
S.D.	13,215,118	595,660	2,271,946	482	5,019,158	12,017
Min	659,198	1,552	172,013	30	351,471	646
Max	58,578,025	2,995,837	9,028,745	1,706	19,943,670	48,391

Table 2.3 Technical Efficiency Scores, 1996-2005

Name	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Qwest Corporation	0.881	0.884	0.855	0.831	0.779	0.794	0.778	0.795	0.814	0.747
AT&T/Southwestern Bell Telephone	1.000	1.000	1.000	1.000	1.000	1.000	0.963	0.967	0.988	0.825
Pacific Bell - California	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Nevada Bell	1.000	0.730	0.803	0.852	0.742	0.727	0.752	0.760	0.776	0.824
Illinois Bell	0.896	0.870	0.906	0.901	0.908	0.893	0.832	0.860	0.922	0.917
Indiana Bell	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Michigan Bell	1.000	1.000	1.000	1.000	1.000	1.000	0.932	0.949	0.930	0.807
Ohio Bell	0.961	0.955	1.000	1.000	1.000	1.000	0.985	0.996	1.000	0.978
Wisconsin Bell	0.856	0.855	0.925	0.911	0.957	0.958	0.872	0.857	0.962	0.943
AT&T/BellSouth Corporation	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Verizon Washington D.C.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Verizon Maryland	1.000	0.965	0.962	0.969	0.941	0.956	1.000	1.000	1.000	1.000
Verizon Virginia	1.000	1.000	1.000	1.000	1.000	1.000	0.971	0.959	0.865	0.824
Verizon West Virginia	0.882	0.872	0.890	0.908	0.902	0.948	0.935	0.935	0.925	0.983
Verizon Delaware LLC	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.950
Verizon Pennsylvania	0.941	0.938	0.957	0.968	0.927	0.902	0.960	0.968	0.974	0.961
Verizon New Jersey	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Verizon New England	1.000	1.000	0.825	1.000	0.899	0.936	1.000	0.980	1.000	1.000
Verizon New York Telephone	0.722	0.675	0.655	0.945	0.955	0.987	1.000	1.000	1.000	1.000
Verizon California	0.995	0.959	0.945	0.979	1.000	1.000	1.000	1.000	1.000	1.000
Verizon Florida LLC	0.860	0.869	0.947	0.989	0.867	0.884	0.879	0.903	0.927	1.000
Verizon North, Inc.	0.862	0.860	0.851	0.859	0.941	0.902	0.791	0.829	0.835	0.825
Verizon Northwest, Inc.	0.843	0.893	1.000	1.000	0.837	0.877	0.864	0.889	0.836	0.882
Verizon South, Inc.	0.895	0.910	0.904	0.947	1.000	1.000	1.000	1.000	1.000	1.000
GTE of The Southwest, Inc. dba Verizon Southwest	0.971	0.987	0.966	1.000	1.000	0.987	0.979	0.991	0.990	0.910
Mean	0.943	0.929	0.936	0.962	0.946	0.950	0.940	0.945	0.950	0.935

Table 2.4 Peers from DEA, 1996-2005

Number	Company	Peers	
		1996	2005
1	Qwest Corporation	17 10 4	21 20 24 17
2	AT&T/Southwestern Bell Telephone	2	24 10
3	Pacific Bell - California	3	3
4	Nevada Bell	4	12 24 20
5	Illinois Bell	17 11 10	21 10 24 17
6	Indiana Bell	6	6
7	Michigan Bell	7	21 20 24 3
8	Ohio Bell	10 11 17 15 12	21 10 24 17
9	Wisconsin Bell	10 12 15 3	20 12 24
10	AT&T/BellSouth Corporation	10	10
11	Verizon Washington D.C.	11	11
12	Verizon Maryland	12	12
13	Verizon Virginia	13	21 20 24 17
14	Verizon West Virginia	17 4 10 13	24 20 12
15	Verizon Delaware LLC	15	11 6 17 24
16	Verizon Pennsylvania	15 12 17 3	24 17
17	Verizon New Jersey	17	17
18	Verizon New England	18	18
19	Verizon New York Telephone	17 13 10	19
20	Verizon California	18 3 17	20
21	Verizon Florida LLC	10 4	21
22	Verizon North, Inc.	17 10 4	18 24 3
23	Verizon Northwest, Inc.	10 17 4	24 20 12
24	Verizon South, Inc.	17 4 10	24
25	GTE of The Southwest, Inc. dba Verizon Southwest	17 4 10	18 24 3

Table 2.5 Mean Technical Efficiency Change, Technological Change and Productivity Change, 1996-2005

Firm #	Firm	Efficiency change	Technological change	Productivity change
24	Verizon South, Inc.	1.012	1.036	1.048
19	Verizon New York Telephone	1.037	0.976	1.013
21	Verizon Florida LLC	1.017	0.986	1.002
23	Verizon Northwest, Inc.	1.005	0.996	1.001
25	GTE of The Southwest, Inc. dba Verizon Southwest	0.993	1.002	0.995
14	Verizon West Virginia	1.012	0.983	0.995
22	Verizon North, Inc.	0.995	0.998	0.993
9	Wisconsin Bell	1.011	0.982	0.993
6	Indiana Bell	1.000	0.989	0.989
16	Verizon Pennsylvania	1.002	0.985	0.987
20	Verizon California	1.001	0.984	0.985
18	Verizon New England	1.000	0.985	0.984
12	Verizon Maryland	1.000	0.983	0.983
8	Ohio Bell	1.002	0.980	0.982
15	Verizon Delaware LLC	0.994	0.987	0.982
11	Verizon Washington D.C.	1.000	0.972	0.972
5	Illinois Bell	1.003	0.968	0.971
13	Verizon Virginia	0.979	0.989	0.968
17	Verizon New Jersey	1.000	0.966	0.966
10	AT&T/BellSouth Corporation	1.000	0.963	0.963
1	Qwest Corporation	0.982	0.980	0.962
7	Michigan Bell	0.976	0.982	0.958
2	AT&T/Southwestern Bell Telephone	0.979	0.977	0.957
3	Pacific Bell - California	1.000	0.956	0.956
4	Nevada Bell	0.979	0.950	0.930

Table 2.6 Mean Technical Efficiency Change, Technological Change, and Productivity Growth Change, 3 Years Before and 3 Years after Merger

Firm #	Firm	3 years before merger			3 years after merger		
		Efficiency change	Technological change	Productivity change	Efficiency change	Technological change	Productivity change
1	Qwest Corporation	0.959	0.994	0.954	1.006	0.958	0.964
11	Verizon Washington D.C.	1.000	0.948	0.948	1.000	0.960	0.960
12	Verizon Maryland	0.992	0.997	0.989	1.021	0.988	1.009
13	Verizon Virginia	1.000	0.998	0.998	0.986	0.978	0.964
14	Verizon West Virginia	1.011	0.996	1.007	1.012	0.997	1.009
15	Verizon Delaware LLC	1.000	0.999	0.999	1.000	1.034	1.034
16	Verizon Pennsylvania	0.996	0.991	0.987	1.014	1.010	1.025
17	Verizon New Jersey	1.000	0.993	0.993	1.000	0.978	0.978
18	Verizon New England	0.965	0.950	0.917	1.029	0.975	1.003
19	Verizon New York Telephone	1.123	0.990	1.112	1.016	0.968	0.983
20	Verizon California	1.014	1.007	1.021	1.000	0.993	0.993
21	Verizon Florida LLC	1.000	1.005	1.005	1.014	0.941	0.954
22	Verizon North, Inc.	1.031	1.032	1.064	0.958	0.974	0.933
23	Verizon Northwest, Inc.	0.979	1.035	1.013	1.020	0.979	0.999
24	Verizon South, Inc.	1.032	1.078	1.112	1.000	1.013	1.013
25	GTE of The Southwest, Inc. dba Verizon Southwest	1.004	1.055	1.060	0.997	0.943	0.940
10	AT&T/BellSouth Corporation	1.000	0.966	0.966	1.000	0.961	0.961
2	AT&T/Southwestern Bell Telephone	1.000	0.976	0.976	0.988	0.966	0.954
3	Pacific Bell - California	1.000	0.953	0.953	1.000	1.033	1.033
4	Nevada Bell	0.948	0.939	0.890	0.959	0.973	0.933
5	Illinois Bell	1.002	1.011	1.013	0.974	0.958	0.933
6	Indiana Bell	1.000	1.020	1.020	1.000	0.969	0.969
7	Michigan Bell	1.000	1.005	1.005	0.977	0.959	0.936
8	Ohio Bell	1.014	1.018	1.032	0.995	0.966	0.961
9	Wisconsin Bell	1.021	1.006	1.026	0.986	0.982	0.968
10	AT&T/BellSouth Corporation	1.000	0.990	0.990	1.000	0.966	0.966

- Firm number 11 through 25 and 1 pertain to the first group. Firm number 2 to 10 pertain to the second group. The third group includes firm number 10.
- Firm number 3 and 4 first merged in 1997. Since our sample period begins with 1996 we place theses two firms in the second group.

Table 2.7 Mean Technical Efficiency Change, Technological Change, and Productivity Growth Change, Pre-merger and Post-merger

Firm #	Firm	Pre-Merger			Post-Merger		
		Efficiency change	Technological change	Productivity change	Efficiency change	Technological change	Productivity change
1	Qwest Corporation	0.970	0.997	0.967	0.991	0.966	0.958
11	Verizon Washington D.C.	1.000	0.961	0.961	1.000	0.980	0.980
12	Verizon Maryland	0.985	1.001	0.986	1.012	0.969	0.981
13	Verizon Virginia	1.000	1.012	1.012	0.962	0.971	0.934
14	Verizon West Virginia	1.006	1.002	1.008	1.017	0.968	0.985
15	Verizon Delaware LLC	1.000	0.991	0.991	0.990	0.985	0.975
16	Verizon Pennsylvania	0.996	0.992	0.988	1.007	0.980	0.987
17	Verizon New Jersey	1.000	0.989	0.989	1.000	0.948	0.948
18	Verizon New England	0.974	0.977	0.952	1.021	0.991	1.012
19	Verizon New York Telephone	1.073	1.005	1.078	1.009	0.954	0.963
20	Verizon California	1.001	1.003	1.004	1.000	0.969	0.969
21	Verizon Florida LLC	1.002	1.015	1.018	1.029	0.962	0.990
22	Verizon North, Inc.	1.023	1.027	1.051	0.974	0.975	0.950
23	Verizon Northwest, Inc.	0.998	1.029	1.027	1.010	0.970	0.980
24	Verizon South, Inc.	1.028	1.063	1.093	1.000	1.014	1.014
25	GTE of The Southwest, Inc. dba Verizon Southwest	1.007	1.047	1.054	0.981	0.969	0.950
10	AT&T/BellSouth Corporation	1.000	0.982	0.982	1.000	0.948	0.948
2	AT&T/Southwestern Bell Telephone	1.000	0.976	0.976	0.968	0.978	0.947
3	Pacific Bell - California	1.000	0.953	0.953	1.000	0.957	0.957
4	Nevada Bell	0.948	0.939	0.890	0.994	0.955	0.950
5	Illinois Bell	1.002	1.011	1.013	1.003	0.948	0.951
6	Indiana Bell	1.000	1.020	1.020	1.000	0.974	0.974
7	Michigan Bell	1.000	1.005	1.005	0.965	0.970	0.936
8	Ohio Bell	1.014	1.018	1.032	0.996	0.961	0.958
9	Wisconsin Bell	1.021	1.006	1.026	1.006	0.970	0.976
10	AT&T/BellSouth Corporation	1.000	0.990	0.990	1.000	0.949	0.949

- Firm number 11 through 25 and 1 pertain to the first group. Firm number 2 to 10 pertain to the second group. The third group includes firm number 10.
- Firm number 3 and 4 first merged in 1997. Since our sample period begins with 1996 we place theses two firms in the second group.

CHAPTER 3 - Market Consolidation and Productivity Growth in U.S. Telecommunications: Stochastic Frontier analysis vs. Malmquist index

INTRODUCTION

In 1996, the Telecommunications Act of 1996 (1996 Act) substantially amended the Communications Act of 1934 (1934 Act)[29]. The primary purpose of the 1996 Act was to stimulate competition in both local and long distance telecommunications markets. Incumbent Local Exchange Carriers (ILECs) were required to open up local exchange telecommunications markets to competition by unbundling their networks and providing the component inputs, known as unbundled network elements (UNEs), to competitive local exchange carriers (CLECs) at prices set by state regulators.[30] As the quid pro quo for such network sharing, the 1996 Act allowed the Regional Bell Operating Companies' (RBOCs) to gain entry into the interLATA long distance market once they satisfied the so-called "Competitive Checklist contained in Section 271 of the Act.[31, 32]

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[29] The 1934 Act empowered Federal Communications Commission (FCC) to regulate the telecommunications industry in the U.S.

[30] CLECs can lease the individual unbundled network elements and combine them with their own facilities to provide the retail telecommunications product. UNE-L, or the unbundled network loop, is example of this type of network element. The UNE-L entails leasing the loop, which is the connection from the telephone exchange's central office to the customer premises equipment. UNE-P, or the unbundled network element platform, is a special type of resale in which the network inputs are combined for the entrant by the incumbent provider. The price for UNE-P is lower than that of pure resale because it is based on TELRIC (total element long-run incremental cost) rather than avoided cost, but the two are functionally indistinguishable otherwise. The Federal Communications Commission began phasing out UNE-P in 2005 because it came to believe that the availability of UNE-P was having an adverse effect on investment in network infrastructure. See FCC (2005).

[31] At the time of the divestiture, 1984, there were seven RBOCs: Ameritech Corporation, Bell Atlantic Corporation, BellSouth Corporation, NYNEX Corporation, Pacific Telesis Group, Southwestern Bell Corporation and U.S. West, Inc.

[32] InterLATA long distance calls refers to calls that originate in one Local Access and Transport Area (LATA), cross over and terminate in another LATA. IntraLATA long distance calls refers to calls that originate and terminate in the same LATA. LATAs are some times referred to as the service areas for the Bell Operating Companies. See Newton (2000).

One of the key trends in the telecommunications industry following the passage of the 1996 Act was a series of business consolidations among ILECs that policy makers did not fully anticipate.[33] Southwestern Bell Corporation (SBC, now at&t) was a leader in this trend. SBC acquired Pacific Telesis Group, Southern New England Telephone and Ameritech in 1997, 1998 and 1999, respectively. U.S. West merged with QWEST Communications in 1999. A merger between Bell Atlantic and GTE formed Verizon in 2000. In 2005, AT&T was acquired by SBC communications and branded at&t Inc. In December 2006, at&t acquired BellSouth Corporation, which is the last of the RBOCs to have retained its original corporate name following the 1984 AT&T divestiture.

The Department of Justice (DOJ) and the Federal Trade Commission (FTC) use the Horizontal Merger Guidelines (HMG) to evaluate horizontal mergers. The HMG take into account a number of factors including market concentration, entry barriers, and merger efficiencies.[34] As long as competition remains vigorous following the merger, measured in terms of little or no discernible increase in market power, the merger is likely to be approved by the DOJ/FTC. Nonetheless, from an operational standpoint, these prospective efficiency gains are difficult to verify and quantify.

One of the methods that may be used to examine efficiencies is to measure productivity growth, inclusive of its underlying components--technological progress and changes in technical efficiency. From a policy perspective, the decomposition of productivity growth into these components provides important information for analysis. For example, if policymakers are able to determine the key drivers of productivity growth, they may adopt policies that can

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[33] Another important trend in the telecommunications industry is vertical integration. See, for example, Weisman (2000).

[34] In order to measure efficiencies, the HMG introduced the "cognizable efficiency" concept which "are assessed net of costs produced by the merger or incurred in achieving those efficiencies." See HMG (p. 31)

significantly improve the performance of firms and the overall economy. Suppose, for example, that the lack of technological progress is the source of low productivity growth. It would then be possible to put in place various policies that stimulate technological innovation and move the technology frontier outwards over time. If high rates of technological change associated with low rates of efficiency change are measured, then policy makers may focus on the policy that increases the efficiency of firms.

To measure the production frontier, we use an output distance function approach introduced by Shepard (1970). The main advantage of the distance function approach is that it allows for a multiple-input and multiple-output technology without requiring price data. The distance function can be estimated in several ways. These include data envelopment analysis (DEA), parametric deterministic linear programming (PLP), corrected ordinary least squares (COLS), and stochastic frontier analysis (SFA).

There are a number of empirical studies that measure productivity growth using SFA across different industries.[35] Kim and Han (2001) measured productivity growth associated with technological change and efficiency changes in Korean manufacturing industries. They found that technological change was the main factor contributing to productivity growth. Coelli et al. (2003) employed SFA to investigate productivity growth in Bangladesh crop agriculture over the period 1961-1992. Using 16 regional data points, they found that productivity growth is affected by the green revolution and agricultural research expenditures. Recently, Resende (2006) conducted an analysis that examined parametric and non-parametric efficiency measures resulting from the implementation of incentive regulation in the U.S. telecommunications industry. He compared efficiency scores obtained from DEA, COLS, and SFA (with time-

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[35] Uri (2002) employed a COLS approach to measure the efficiency gains associated with the implementation of incentive regulation in the U.S. telecommunications industry. Using data from 19 LECs over the 1988-1999 time period, Uri found no empirical evidence that incentive regulation had enhanced technical efficiency.

invariant and time-varying inefficiency effects). He found no significant consistency across the different methods.

Despite a voluminous literature on productivity growth using SFA, the measurement of productivity growth associated with mergers has received surprisingly little attention. Specifically, in the telecommunications industry, no study to date has attempted to measure productivity growth and proceeded to decompose it into its component parts, technological change and efficiency change, using a stochastic frontier model.[36] Therefore, this study provides productivity growth measures associated with the decomposition analysis, which differs from Resende (2006) who examines efficiency scores. In addition, this study compares both the SFA approach and the Malmquist index approach for mergers in the U.S. telecommunications industry.[37]

This study has two principal objectives. The first objective is to evaluate the effectiveness of mergers that occurred between 1996 and 2005 using SFA. We investigate whether productivity growth has increased among ILECs that have merged since the 1996 Act and whether the merged firms performed better than those firms that did not merge. The second objective is to compare productivity growth results between SFA and a Malmquist index approach. This comparison provides useful information on the robustness of the efficiency findings across different approaches.

The remainder of this essay is organized as follows. Section 2 discusses the multiple output distance function and presents the models used in the study. In Section 3, we discuss the data. The empirical results are presented and compared in Section 4. Section 5 contains a brief summary and conclusion.

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[36] Seo and Weisman (2007) investigated the same issue with a non-parametric approach.

[37] There are number of empirical studies that compare parametric and non-parametric methods in various industries. See, for example, Aigner and Chu (1968), and Kopp and Smith (1980).

Methodology

Distance Function

In order to define the output distance function, we first introduce the production technology. We assume that for each time period $t = 1, \ldots, T,$ the production technology F^t maps input vectors, $x_t \in \mathbb{R}_+^n$, into output vectors, $y_t \in \mathbb{R}_+^m$,

$$F^t = \left\{ \left(x_t, y_t \right) : x_t \text{ can produce } y_t \right\}, \tag{1}$$

where $\mathbb{R}$ is the set of real numbers.[38] The production technology F^t is homogeneous of degree one in output. Following Shepard (1970), the output distance function is defined at time t as:

$$D_{Ot}\left(x_t, y_t \right) = \inf \left\{ \theta : \left(x_t, \frac{y_t}{\theta} \right) \in F^t \right\} = \left(\sup \left\{ \theta : \left(x_t, \theta y_t \right) \in F^t \right\} \right)^{-1}. \tag{2}$$

According to Lovell et al. (1994), the output distance function $D_{Ot}\left(x_t, y_t \right)$ is non-decreasing, positively linearly homogeneous[39] and convex in y and decreasing in x.[40] Note that input-output vectors lie below the production technology set. This implies that $D_{Ot}\left(x_t, y_t \right) \le 1$ if and only if $\left(x_t, y_t \right) \in F^t$. Moreover, $D_{Ot}\left(x_t, y_t \right) = 1$ if and only if input-output combinations lie on the boundary of the production technology set, which is illustrated in Figure 1. The value of the

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[38] The production technology must satisfy the following axioms in order to be a meaningful model of production: i) the possibility of inaction. ii) monotonicity of the output correspondence iii) disposability of output iv) the output set is closed v) irreversibility (Färe, R., and S. Grosskopf. 1994).

[39] In Section 2.2, we assume homogeneity of degree one in y.

[40] One can define the input distance function as follows:

$$D_{It}\left(x_t, y_t \right) = \sup \left\{ \delta : \left(\frac{x_t}{\delta}, y_t \right) \in F^t \right\}.$$

distance function evaluated at $\left(x_t, y_t\right)$ is $\frac{oa_2}{oa_2} = 1$, whereas the value of the distance function evaluated at $\left(x_t^{'}, y_t^{'}\right)$ is $\frac{oa_1}{oa_2} < 1$.[41]

Stochastic Frontier Model

Aigner et al. (1977) and Meeusen and van den Broeck (1977) simultaneously published an analysis of the Stochastic Frontier Model (SFM) in different outlets. Technical efficiency, as well as random shocks, is considered and specified in this model. The main advantage of SFM is that it accounts for the possible influence of noise on the shape and positioning of the frontier, something that deterministic frontier models are unable to do. In other words, issues such as measurement error and other random factors can be separated from the sources of variation in technical efficiency. SFM posits a production function with an error term associated with two components. These two components consist of a symmetric error term accounting for noise and an asymmetric error term accounting for technical inefficiency.

In order to estimate the stochastic frontier, a distance function must be specified. Based on Coelli and Perelman (2000), the multiple output distance function is specified in translog functional form and is given by[42]:

$$\ln(D_{Oi}) = \alpha_0 + \sum_{j=1}^{J} \alpha_j \ln y_{ij} + \sum_{l=1}^{L} \beta_l \ln x_{il} + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{J} \alpha_{jk} \ln y_{ij} \ln y_{ik}$$

$$+ \frac{1}{2} \sum_{l=1}^{L} \sum_{m=1}^{L} \beta_{lm} \ln x_{il} \ln x_{im} + \frac{1}{2} \sum_{j=1}^{J} \sum_{l=1}^{L} \delta_{jl} \ln y_{ij} \ln x_{il}, \qquad i = 1, 2, \ldots, I \qquad (3)$$

where J is the number of outputs, L is the number of inputs, and i denotes the ith firm in the sample. The restrictions required for homogeneity of degree one in outputs are

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[41] Refer to Coelli et al. (1998) and Kumbhakar and Lovell (2000) for further discussion of distance functions.

[42] In this study, we use 3 outputs and 3 inputs.

$$\sum_{j=1}^{J}\alpha_j = 1 \tag{4}$$

and

$$\sum_{k=1}^{J}\alpha_{jk} = 0,\quad j = 1,2,\ldots,J \text{ and } \sum_{l=1}^{L}\delta_{jl} = 0, \qquad l = 1,2,\ldots,L. \tag{5}$$

The restrictions required for symmetry are

$$\alpha_{jk} = \alpha_{kj}, \qquad j,k = 1,2,\ldots,J \text{ and } \beta_{lm} = \beta_{ml}, \qquad l,m = 1,2,\ldots,L. \tag{6}$$

Lovell et al. (1994) proposed a convenient method for imposing the homogeneity restriction in (3). Homogeneity implies that

$$D_O\left(x,\lambda y\right) = \lambda D_O\left(x,y\right), \text{ for any } \lambda > 0. \tag{7}$$

Hence, we arbitrarily choose one of the outputs, the J th output, and normalize on it. This, in turn, allows us to obtain

$$D_O\left(x,\frac{y}{y_J}\right) = \frac{D_O\left(x,y\right)}{y_J}. \tag{8}$$

The translog function can be written as:

$$\ln\left(\frac{D_{oi}}{y_{iJ}}\right) = \alpha_0 + \sum_{j=1}^{J-1}\alpha_j \ln y_{ij}^{*} + \sum_{l=1}^{L}\beta_l \ln x_{il} + \frac{1}{2}\sum_{j=1}^{J-1}\sum_{k=1}^{J-1}\alpha_{jk}\ln y_{ij}^{*}\ln y_{ik}^{*}$$

$$+\frac{1}{2}\sum_{l=1}^{L}\sum_{m=1}^{L}\beta_{lm}\ln x_{il}\ln x_{im} + \frac{1}{2}\sum_{j=1}^{J-1}\sum_{l=1}^{L}\delta_{jl}\ln y_{ij}^{*}\ln x_{il}, \qquad i = 1,2,\ldots,I, \tag{9}$$

where $y_{ij}^{*} = \frac{y_{ij}}{y_{iJ}}$.[43] Equation (9) can be rewritten in the following functional form

$$-\ln(y_{iJ}) = TL\left(y^{*},x,\alpha,\beta\right) - \ln\left(D_{Oi}\right)^{44} \tag{10}$$

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[43] Note that the value of Jth output, $\ln\left(\frac{y_{iJ}}{y_{iJ}}\right)$, is 0. This implies that the summations involving outputs are comprised of J-1 terms.

SFM has two error components that are comprised of a two-sided noise component and a non-negative technical inefficient component. We append the noise term v_i and change the notation from $\ln\left(D_{Oi}\right)$ to $-u_i$. This transformation yields the stochastic frontier function associated with the time trend for panel data and is expressed as follows:

$$
\begin{aligned}
-\ln(Y_{it}) &= \alpha_0 + \alpha_T t + \sum_{j=1}^{J-1}\alpha_j \ln y^*_{ijt} + \sum_{l=1}^{L}\beta_l \ln x_{ilt} + \frac{1}{2}\alpha_{TT}t^2 \\
&+ \frac{1}{2}\sum_{j=1}^{J-1}\sum_{k=1}^{J-1}\alpha_{jk}\ln y^*_{ijt}\ln y^*_{ikt} + \frac{1}{2}\sum_{l=1}^{L}\sum_{m=1}^{L}\beta_{lm}\ln x_{ilt}\ln x_{imt} + \frac{1}{2}\sum_{j=1}^{2}\alpha_{Tj}t\ln y^*_{ijt} \\
&+ \frac{1}{2}\sum_{l=1}^{L}\beta_{Tl}t\ln x_{ilt} + \frac{1}{2}\sum_{j=1}^{J-1}\sum_{l=1}^{L}\delta_{jl}\ln y^*_{ijt}\ln x_{ilt} + v_{it} + u_{it}.^{45} \qquad (11)
\end{aligned}
$$

where $t = 1, 2, \ldots, T$ is a time trend. Y_{it} and y^*_{ijt} are the output and arbitrarily normalized output for firm i, respectively. Subscripts j, k index outputs; α, β, δ are parameters to be estimated; x variables are inputs. Subscripts l, m index inputs; the v_{it} s are the error components and are assumed to be independently and identically distributed as $N\left(0, \sigma_v^2\right)$. The u_{it} 's are the technical inefficiency components.

Following Battese and Coelli (1992), the technical inefficiency error term is defined by

$$u_{it} = u_i \exp\left[-\eta\left(t - T\right)\right], \qquad i = 1, 2, \ldots, I; t = 1, 2, \ldots, T, \qquad (12)$$

where the u_i s are assumed to be a non-negative truncation of the normal distribution $N\left(\mu, \sigma_\mu^2\right)$ associated with technical inefficiency in production.[46] u_i is the technical inefficiency effect for

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[44] Note that $D_{oi} = 1$ implies that the boundary of the frontier.

[45] Note that as suggested by Morrison-Paul et al. (2000), one can change the sign of dependent variable. This change allows for interpreting estimates that conform to the standard SFA framework.

[46] There are other distributional assumptions imposed on the inefficiency error term, such as half-normal, exponential, and gamma-halton. See, for example, Kumbhakar and Lovell (2000).

firm i for the last period of the sample;[47] η is an unknown parameter to be estimated and represents the rate of change in technical inefficiency. Therefore, a positive value, $\eta > 0$, implies that the technical inefficiency effects are decreasing over time.[48] One of the advantages of using the error term in (12) is that any technical inefficiency changes over time can be separated from technical change. In this essay, the maximum likelihood estimates of the unknown parameters and the technical inefficiency, defined by (11) and (12), are obtained using the FRONTIER 4.1 computer program.[49]

Following Coelli et al. (1998) and given estimates for (11) and (12), the technical efficiencies of production for each firm in the t th year can be predicted as:

$$TE_{it} = \exp\left(-u_{it}\right).^{50} \tag{13}$$

Therefore, the technical efficiency change between periods t and $t-1$ is calculated as:

$$EC_{it} = \frac{TE_{it}}{TE_{it-1}}. \tag{14}$$

With the estimates of the parameters in (11) and (12), the index of the technological change for firm i is calculated by evaluating the partial derivative of the production function with respect to time. The calculation of technological change is computed according to:

$$TC_{it} = \sqrt{\left[1 + \frac{\partial f\left(y_{is}^{*}, x_{is}, t, \alpha^{*}, \beta^{*}\right)}{\partial s}\right] \times \left[1 + \frac{\partial f\left(y_{it}^{*}, x_{it}, t, \alpha^{*}, \beta^{*}\right)}{\partial t}\right]}.^{51} \tag{15}$$

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[47] In the last period, T, the value of the exponential function is 1 which implies that $u_{iT} = u_i$.

[48] If $\eta > 0$ then $-\eta(t - T) \equiv -\eta(t - T)$ and $u_{it} > u_i$. However, the value of the exponential function is decreasing monotonically towards the value of the last period in the sample. If $\eta = 0$, the translog specification in (11) becomes a time-invariant inefficiency model.

[49] See Coelli (1996a).

[50] The predicted values of technical efficiency lie between zero and one. The value of one implies that the firm lies on the boundary of the production possibility set.

Finally, the TFP index can be obtained by the product of the index of technical efficiency change and the index of technological change calculated from (14) and (15):

$$TFP_{it} = EC_{it} \times TC_{it} . \tag{16}$$

A Malmquist Index Approach

A Malmquist index approach is a non-parametric method for measuring productivity growth that allows for a decomposition in terms of technological progress and efficiency change. One of the important advantages of using this index is that no explicit functional form for the frontier is required since the DEA approach uses linear programming. In addition, the DEA method does not require any price data.[52]

Following Caves et al. (1982), a Malmquist index, which is computed as the ratio of two output distance functions, is constructed as:

$$M_S = \frac{D_{Ot}\left(x_t, y_t\right)}{D_{Os}\left(x_s, y_s\right)},^{53} \tag{17}$$

where t and s are adjacent periods. Färe et al. (1994) suggested using the output-based Malmquist index in order to avoid the use of an arbitrary benchmark:

$$M_O\left(x_t, y_t, x_s, y_s\right) = \sqrt{\left(\frac{D_{Os}\left(x_t, y_t\right)}{D_{Os}\left(x_s, y_s\right)}\right)\left(\frac{D_{Ot}\left(x_t, y_t\right)}{D_{Ot}\left(x_s, y_s\right)}\right)} . \tag{18}$$

In order to decompose a Malmquist index into technical efficiency change and technological change, (18) can be rearranged as:

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[51] Equation (15) differs from Nishimizu and Page (1982) in two respects. First, the former uses a stochastic frontier approach to estimate the technology, while the latter uses deterministic model. Second, the former uses a geometric mean whereas the latter uses an arithmetic mean.

[52] Although a distance production approach does not require price data for both parametric and non-parametric methods, revenue, cost, and profit approaches which employ parametric estimation do require price data.

[53] Technology in period t is treated as the base-case technology.

$$M_O\left(x_t, y_t, x_s, y_s\right)=\frac{D_{Ot}\left(x_t, y_t\right)}{D_{Os}\left(x_s, y_s\right)} \times \sqrt{\left(\frac{D_{Os}\left(x_t, y_t\right)}{D_{Ot}\left(x_t, y_t\right)}\right)\left(\frac{D_{Os}\left(x_s, y_s\right)}{D_{Ot}\left(x_s, y_s\right)}\right)}, \tag{19}$$

where $\frac{D_{Ot}\left(x_t, y_t\right)}{D_{Os}\left(x_s, y_s\right)}$ measures whether the production technology is getting closer to or farther away from the production frontier between adjacent periods s and t.

$\left(\frac{D_{Os}\left(x_t, y_t\right)}{D_{Ot}\left(x_t, y_t\right)}\right)\left(\frac{D_{Os}\left(x_s, y_s\right)}{D_{Ot}\left(x_s, y_s\right)}\right)$ measures the move of the technology frontier between the two periods evaluated at x_s and x_t.

Therefore, the technical efficiency change (EC) is expressed as:

$$EC=\frac{D_{Ot}\left(x_t, y_t\right)}{D_{Os}\left(x_s, y_s\right)}, \tag{20}$$

and technological change is expressed as:

$$TC=\sqrt{\left(\frac{D_{Os}\left(x_t, y_t\right)}{D_{Ot}\left(x_t, y_t\right)}\right)\left(\frac{D_{Os}\left(x_s, y_s\right)}{D_{Ot}\left(x_s, y_s\right)}\right)}. \tag{21}$$

A Malmquist index of one indicates that there is no change in inputs and outputs between adjacent periods s and t. It should be noted, however, that, EC and TC are not necessarily equal to one because the Malmquist index is the product of EC and TC. A value for the Malmquist index greater than one indicates that productivity growth is positive, whereas a Malmquist index value less than one implies that productivity growth is negative.

In this study, linear programming is used to calculate values of the distance functions which, in turn, determine the productivity growth index. The DEA procedures used here follow Färe et al. (1994). In order to calculate a Malmquist index in (19), four different linear programming problems are used to solve for the values of four distance functions. These distance functions are given by $D_{Os}\left(x_s, y_s\right)$, $D_{Os}\left(x_t, y_t\right)$, $D_{Ot}\left(x_t, y_t\right)$ and $D_{Ot}\left(x_s, y_s\right)$. The computations for the linear programming are carried out using the DEAP 2.1 computer program.[54]

DATA

The data used in this analysis represents a balanced panel that consists of annual data for 25 ILECs over the 1996-2005 time period. The sample period starts with 1996 because this essay focuses on mergers among ILECs following the 1996 Act. The year 2005 is chosen as the ending period as it was necessary to exclude two merger cases where data were limited or unavailable.[55] The primary sources of data are obtained from the Electronic ARMIS Filing System and the Statistics of Communications Common Carriers maintained by the U.S. Federal Communications Commission (FCC).[56]

Local calls, intraLATA toll calls and interLATA toll calls are the output variables since these are the core services provided by ILECs. The measures of inputs are the number of total switches, the number of access lines, and the number of employees.[57] The use of these three inputs captures the actual industry characteristic for providing telephone service. In the telecommunications industry, telephone switches, represent the system of electronic components that connect telephone calls, while actual messages are distributed by the telephone lines, sometimes referred to as local loops.

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[54] See Coelli (1996b).
[55] Those two mergers occurred in December 2005 and 2006.
[56] ARMIS is the acronym for Automated Reporting Management Information System. One may refer to http://www.fcc.gov/wcb/armis to access the data set. FCC Report 43-02, the ARMIS USOA Report, FCC Report 43-07, the ARMIS Infrastructure Report and FCC Report 43-08, the ARMIS Operating Data Report were used to populate the data set.
[57] Majumdar (1997) also introduced the same classification for outputs and inputs.

We use a stochastic frontier model with homogeneity imposed on (9). IntraLATA toll calls are chosen as the output measure used to normalize all other outputs. We, therefore, specify the variables used in (11) as follows:

Y is intraLATA toll calls;

y_1^* is local calls divided by intraLATA toll calls;

y_2^* is interLATA toll calls divided by intraLATA calls;

x_1 is number of switches;

x_2 is number of access lines;

and x_3 is number of employees.

The summary statistics for the inputs and outputs for the ILECs from 1996-2005 are presented in Table 1. It should be noted that the average of each of the outputs has been decreasing since 2000. This is plausible because competitive local exchange carriers (CLECs) have continued to encroach on the ILECs' local telephone service markets following the implementation of the 1996 Act. According to *Trends in Telephone Service* (2007) published by FCC, the CLEC share of end-user switched access lines are 4.3 percent and 17.9 percent in 1999 and 2005, respectively. In addition, significant growth in the number of wireless subscribers and associated usage has caused the traditional wireline companies to experience pronounced reductions in their long distance telephone volumes.[58]

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[58] Based on Cellular Telecommunications and Internet Association (CTIA)'s survey data (2006), there is clear evidence of a rapid increase in the number of wireless telephone subscribers. In fact, the number of wireless subscribers has increased by 372% (i.e., from 44,042,992 subscribers to 207,896,198 subscribers) from 1996 to 2005.

EMPIRICAL RESULTS

The test results for various null hypotheses presented in Table 2 are conducted using log-likelihood ratio (LR) tests. The LR test statistic is calculated by $-2\times\left[L\left(H_0\right)-L\left(H_A\right)\right]$, where $L\left(H_0\right)$ and $L\left(H_A\right)$ are the log-likelihood values under the null and alternative hypotheses, respectively. Given the stochastic frontier specification, we first test for changes in technical inefficiency. The null hypothesis $\left(\gamma=\mu=\eta=0\right)$ is rejected at the 1% significance level. This implies technical inefficiency effects are statistically significant. The second null hypothesis, that there is no technological change, is strongly rejected at the 1% significance level. This result suggests that technological change exists in the model. The third hypothesis, testing that technical inefficiency effects have a half-normal distribution is not rejected, indicating that the technical inefficiency effects can be represented by a half normal distribution. The last set of hypothesis tests focuses on whether technical inefficiency is time-invariant. This hypothesis is rejected at the 1% statistical significance level, implying that technical inefficiency varies over time. In addition, the estimate of η is statistically significant.

The maximum likelihood estimates (MLE) of the parameters in the translog stochastic frontier production function defined by (11) and (12) are presented in Table 3. Note that the parameter $\gamma\left(\gamma=\dfrac{\sigma_\mu^2}{\sigma_\mu^2+\sigma_v^2}\right)$ is the ratio of the error variances from (11). Therefore, the value of γ must lie between zero and one. If $\gamma=0$, no technical inefficiency is present, while $\gamma=1$ indicates that there exists no random noise. Thus, our estimate of γ = 0.872 implies that the technical inefficiency component dominates the random noise component. The significant and positive estimate of the time varying inefficiency effect, $\eta=0.0964$, indicates that the technical inefficiency effects are decreasing monotonically over time. These results further substantiate the claim that there are time variant technical inefficiency effects in the error term that are decreasing over time.

The indices for average productivity growth, efficiency, and technological change for the period 1996-2005 are shown in table 4. The average efficiency change for all firms is greater than one. The estimates of the inefficiency error term indicate that technical efficiency has occurred at a positive rate while the rate of growth decreased continuously during the sample period. However, indices of average productivity growth for each firm indicate negative growth in productivity. For example, Qwest Corporation exhibits a -3.5 percent growth in annual productivity. It is noteworthy that BellSouth (firm 10), the only firm that has not merged in the sample, experienced the second lowest average productivity growth.

Table 5 provides technological change estimates for each firm across each time period. Only three companies, Qwest Corporation, Southwestern Bell, and BellSouth have shown persistent declines in technological change. All of the indices of technological change are less than one indicating technological regression over time. One way of interpreting technological regression in this study is that it may be the result of structural changes in the telecommunications industry. Production in the conventional sectors, which is our main focus, reveals no improvement, while the shift into new business models associated with new products such as satellite TV, broadband, and voice over internet protocol (VoIP) that require high technology grows rapidly.[59]

Table 6 presents the average productivity, efficiency, and technological change for each individual firm during the pre-merger and post-merger periods. The duration of the post-merger

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[59] See Neuchterlein and Weiser (2005) for a comprehensive analysis of the technological dynamics of the telecommunications industry and its economic implications.

period is 5 and 6 years for the first and second group, respectively. Therefore, in order to compare every firm in each group with a firm that has not merged, we compute two measures for BellSouth Corporation. One is calculated from 2000 and the other is calculated from 1999. When examining the indices in Table 6, it is noteworthy that every company experienced a decline in every index after a merger. Specifically, BellSouth experienced a -5.2 percent annual growth in productivity after the merger. Only firms 11 and 20 experience lower annual growth in productivity than that of BellSouth during the post-merger periods.

We examine the robustness of these results by comparing the SFA and the Malmquist index. These results are presented in Table 7 and Table 8. Table 7 compares the mean efficiency change and the mean technological change between the SFM and the Malmquist index method during the pre-merger and post-merger periods. There is a common trend in indices of mean technological change. Using the Malmquist index method, only Verizon South has shown positive (1.4 percent per year) growth in technological change after the merger. Otherwise, both methods indicate negative growth in technological change over the post-merger period. There are some inconsistent results for the mean efficiency change between the two methods. Using the SFM, each firm experiences positive growth in annual efficiency change over the post-merger period. However, the Malmquist index method indicates that 9 out of 25 individual firms exhibit negative growth in annual efficiency change. The differences between two methods are likely attributable to the particular specification of the inefficiency error term in SFM.

In Table 8, the Malmquist index method indicates that 4 out of 25 individual firms have experienced increases in average productivity growth. In contrast, the stochastic frontier estimation approach indicates that every firm has experienced decreases in average productivity growth after the merger. Only firms 18 and 24 measured by the Malmquist index method exhibit a 1.2 percent and 1.4 percent average growth in productivity, respectively. The remainder of the firms has experienced negative growth in productivity. These results imply that most of the firms experience deterioration in productivity following their mergers. Another interesting result concerns the number of companies that experience productivity performance worse than BellSouth, which is a non-merged control company. In terms of productivity growth, only 2 companies perform worse than BellSouth using the SFM approach, while 3 companies perform worse than BellSouth using the Malmquist index.

CONCLUSION

This study analyzes the merger effects for 25 ILECs over the period 1996-2005 using stochastic frontier analysis with a time varying inefficiency model. We find that our sample has experienced deterioration in average productivity growth following the merger. This empirical finding is attributed to technological regression, a finding that may lead policymakers to consider implementing policies that serve to shift out the production frontier over time. In terms of average growth in productivity, the performance of BellSouth, the only firm in the sample not to have merged, ranks third lowest among the 25 ILECs.

Another component of this study is a comparison of indices for the stochastic frontier analysis and the Malmquist index method. This comparison provides useful information on robustness. With the exception of one firm using the Malmquist index method, both methods indicate that every firm in the sample has experienced negative annual growth in technological change. Indices of productivity growth suggest that most of the firms experience negative growth in annual productivity after the merger according to both methods. However, in terms of productivity growth, it is noteworthy that the only firm not to have merged underperforms during post-merger periods. In SFM, annual productivity growth for BellSouth is the third lowest company in the sample and the fourth lowest using the Malmquist index method.

In the telecommunications industry, the traditional wireline telecommunications sector has experienced a shift toward a new business model involving satellite TV, Voice over Internet Protocol (VoIP) and broadband internet. This study is not able to fully examine the far-reaching effects of these phenomena. Hence, further research is necessary to investigate the impact of these structural changes on the performance of the U.S telecommunications industry.

Figure 3.1 Output Distance Function

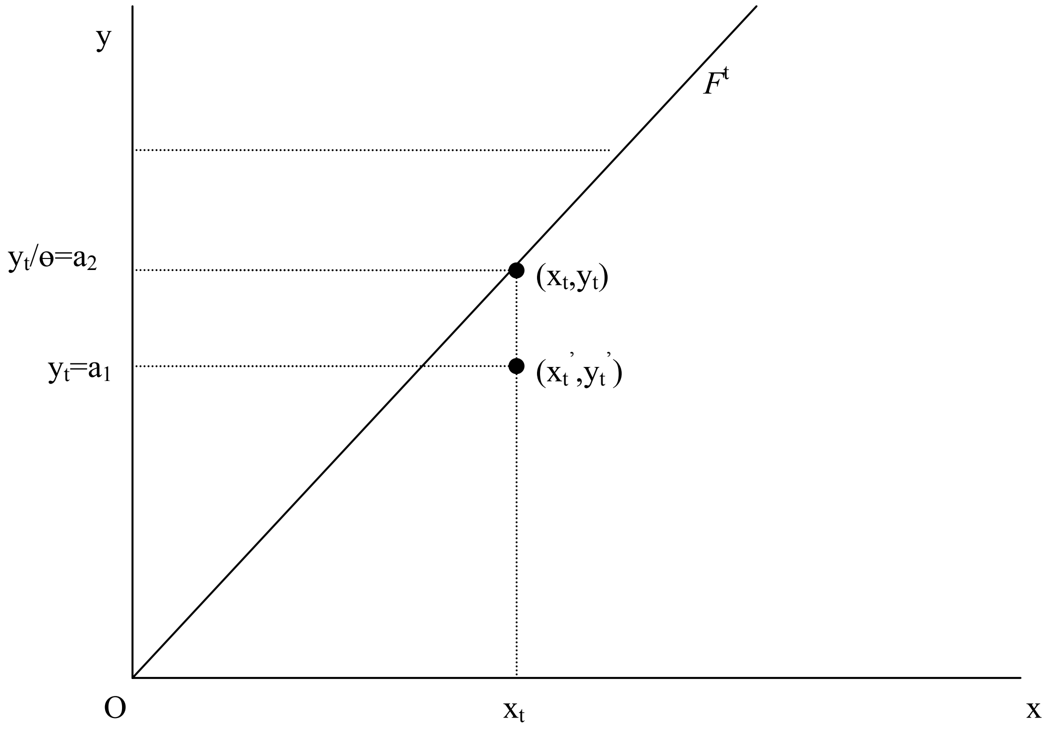

Table 3.1 Summary Statistics

	Local call	intraLATA toll call	InterLATA toll call	Total switches	Access lines	Employees
1996 Mean	18,568,460	762,654	2,539,546	596	5,644,720	15,254
S.D.	22,134,968	1,045,108	2,368,059	539	5,594,318	16,479
Min	821,576	4,902	236,733	34	361,000	842
Max	94,344,715	4,929,318	9,427,603	1,782	22,017,000	59,486
1997 Mean	19,203,861	745,459	2,737,357	594	5,913,527	15,329
S.D.	22,986,746	1,056,051	2,503,517	536	5,887,640	16,114
Min	961,244	5,453	98,277	33	326,212	870
Max	97,783,674	4,879,781	10,055,171	1,750	23,080,061	53,919
1998 Mean	19,871,661	643,766	2,778,404	591	6,131,493	15,466
S.D.	23,378,880	977,498	2,385,641	534	6,130,918	16,510
Min	1,149,802	4,906	105,215	31	341,508	870
Max	99,324,801	4,807,358	10,695,077	1,770	23,908,672	56,188
1999 Mean	20,267,909	613,354	3,014,317	595	6,279,775	15,562
S.D.	22,999,739	928,092	2,614,382	537	6,258,412	17,178
Min	1,227,627	4,664	96,531	31	363,444	918
Max	97,232,126	4,491,538	10,965,391	1,802	24,457,845	59,457
2000 Mean	19,581,898	548,571	3,208,499	574	6,271,283	15,594
S.D.	22,223,409	875,148	2,665,776	517	6,288,029	16,724
Min	1,017,475	4,728	110,000	30	380,616	921
Max	93,784,438	4,396,675	11,102,561	1,715	24,558,289	61,555
2001 Mean	18,642,513	542,199	3,005,960	575	6,075,592	14,722
S.D.	21,010,357	1,004,990	2,596,988	516	6,057,136	15,947
Min	1,022,195	4,751	128,285	30	367,578	929
Max	89,498,059	5,151,332	10,287,931	1,716	23,756,306	60,535
2002 Mean	16,570,572	475,912	2,933,650	561	5,808,766	12,728
S.D.	18,727,360	997,724	2,723,152	501	5,842,992	13,856
Min	841,740	4,419	182,374	28	365,535	774
Max	82,925,856	5,120,259	9,379,825	1,722	22,954,773	53,461
2003 Mean	15,096,699	415,611	2,675,848	561	5,589,264	11,608
S.D.	17,040,793	841,427	2,535,131	500	5,576,337	13,085
Min	780,677	3,030	180,943	30	361,218	692
Max	75,767,109	4,307,978	8,827,826	1,728	22,206,344	50,393
2004 Mean	13,683,056	345,420	2,514,156	561	5,327,325	11,300
S.D.	15,247,549	674,329	2,314,766	498	5,322,309	12,359
Min	738,430	2,191	179,010	30	359,238	659
Max	67,393,286	3,426,898	8,328,607	1,722	21,316,936	47,678
2005 Mean	12,106,135	311,944	2,357,347	485	4,999,650	11,012
S.D.	13,215,118	595,660	2,271,946	482	5,019,158	12,017
Min	659,198	1,552	172,013	30	351,471	646
Max	58,578,025	2,995,837	9,028,745	1,706	19,943,670	48,391

Table 3.2 LR Tests of hypotheses for parameters of stochastic production frontier model

No	Null Hypothesis	Test statistics	Critical value	Decision
(1)	$\gamma = \mu = \eta = 0$	146.629	10.501*	Reject H_0
(2)	$\alpha_T = \alpha_{TT} = \alpha_{T1} = \alpha_{T2} = \beta_{T1} = \beta_{T2} = \beta_{T3} = 0$	92.333	$\chi^2_{7,0.01} = 18.475$	Reject H_0
(3)	$\mu = 0$	0.042	$\chi^2_{1,0.05} = 3.84$	Accept H_0
(4)	$\eta = 0$	11.998	$\chi^2_{1,0.01} = 6.63$	Reject H_0

* The critical values for this test are obtained from Table 1 of Kodde and Palm (1986) for mixed $\chi^2_{v,0.01}$.

Table 3.3 Estimated parameters for stochastic production frontier model

Log-likelihood = 342.4692

Number of observations = 250
Number of firms = 25
Number of years = 10

Parameters	Coefficient	Standard error
α_0	21.7045***	7.5514
α_T	0.2024***	0.0696
α_1	1.5716**	0.7308
α_2	-1.5097**	0.7591
β_1	-0.4881	0.5813
β_2	5.2046***	1.7148
β_3	-2.5032*	1.4291
α_{TT}	-0.0001	0.0008
α_{11}	0.0113	0.0605
α_{22}	0.0994	0.0816
α_{12}	-0.0773	0.0665
β_{11}	-0.1032***	0.0370
β_{22}	-0.3456*	0.2073
β_{33}	0.0937	0.2060
β_{12}	0.1057	0.0747
β_{13}	-0.1030*	0.0626
β_{23}	0.1290	0.1928
α_{T1}	-0.0320*	0.0164
α_{T2}	0.0490***	0.0180
β_{T1}	-0.0038	0.0081
β_{T2}	0.0624***	0.0195
β_{T3}	-0.0452**	0.0208
δ_{11}	0.3297***	0.0745
δ_{12}	-0.5105**	0.2141
δ_{13}	0.1479	0.2131
δ_{21}	-0.2331**	0.0909
δ_{22}	0.2730	0.2291
δ_{23}	0.0330	0.2314
μ	-	-
η	0.0964***	0.0163
$\gamma = \sigma_\mu^2 / (\sigma_\mu^2 + \sigma_v^2)$	0.8719	0.0536
$\sigma^2 \left(= \sigma_\mu^2 + \sigma_v^2 \right)$	0.0183	0.0073

Note: *** = significant at 1% level ($p<0.01$).
** = significant at 5% level ($p<0.05$).
* = significant at 10% level ($p<0.10$).

Table 3.4 Mean Technical Efficiency change, Technological change and Productivity change for SFM, 1996-2005

Firm #	Firm	Technological change	Efficiency change	Productivity change
1	Qwest Corporation	0.944	1.022	0.965
2	AT&T/Southwestern Bell Telephone	0.960	1.013	0.973
3	Pacific Bell - California	0.960	1.012	0.971
4	Nevada Bell	0.968	1.016	0.984
5	Illinois Bell	0.943	1.030	0.972
6	Indiana Bell	0.956	1.011	0.966
7	Michigan Bell	0.962	1.012	0.974
8	Ohio Bell	0.952	1.012	0.963
9	Wisconsin Bell	0.956	1.023	0.977
10	AT&T/BellSouth Corporation	0.950	1.001	0.951
11	Verizon Washington D.C.	0.939	1.002	0.941
12	Verizon Maryland	0.941	1.019	0.960
13	Verizon Virginia	0.940	1.019	0.958
14	Verizon West Virginia	0.960	1.015	0.974
15	Verizon Delaware LLC	0.960	1.004	0.963
16	Verizon Pennsylvania	0.951	1.017	0.967
17	Verizon New Jersey	0.943	1.028	0.969
18	Verizon New England	0.950	1.024	0.973
19	Verizon New York Telephone	0.939	1.056	0.992
20	Verizon California	0.952	1.005	0.958
21	Verizon Florida LLC	0.951	1.029	0.978
22	Verizon North, Inc.	0.958	1.002	0.960
23	Verizon Northwest, Inc.	0.961	1.010	0.971
24	Verizon South, Inc.	0.961	1.002	0.963
25	GTE of The Southwest, Inc. dba Verizon Southwest	0.966	1.003	0.969

Table 3.5 Technological Change for SFM, 1996-2005

Firm	1997*	1998	1999	2000	2001	2002	2003	2004	2005
Qwest Corporation	0.959	0.955	0.952	0.947	0.942	0.939	0.938	0.936	0.932
AT&T/Southwestern Bell Telephone	0.977	0.977	0.976	0.973	0.966	0.955	0.945	0.939	0.937
Pacific Bell - California	0.962	0.967	0.971	0.966	0.963	0.957	0.952	0.951	0.949
Nevada Bell	0.975	0.990	0.989	0.988	0.978	0.961	0.949	0.945	0.940
Illinois Bell	0.951	0.943	0.939	0.940	0.947	0.948	0.943	0.941	0.936
Indiana Bell	0.964	0.959	0.956	0.956	0.958	0.957	0.955	0.951	0.944
Michigan Bell	0.970	0.965	0.959	0.956	0.961	0.965	0.965	0.962	0.958
Ohio Bell	0.959	0.954	0.951	0.950	0.955	0.954	0.950	0.948	0.945
Wisconsin Bell	0.963	0.957	0.953	0.952	0.957	0.959	0.958	0.953	0.947
AT&T/BellSouth Corporation	0.957	0.954	0.951	0.950	0.950	0.950	0.948	0.945	0.942
Verizon Washington D.C.	0.946	0.944	0.941	0.941	0.942	0.941	0.936	0.932	0.930
Verizon Maryland	0.950	0.947	0.945	0.944	0.942	0.938	0.936	0.936	0.937
Verizon Virginia	0.946	0.940	0.938	0.939	0.939	0.937	0.937	0.941	0.944
Verizon West Virginia	0.973	0.969	0.966	0.963	0.959	0.955	0.952	0.952	0.953
Verizon Delaware LLC	0.969	0.965	0.961	0.960	0.959	0.957	0.956	0.955	0.959
Verizon Pennsylvania	0.957	0.952	0.950	0.950	0.951	0.950	0.949	0.950	0.951
Verizon New Jersey	0.953	0.948	0.944	0.943	0.940	0.938	0.937	0.939	0.943
Verizon New England	0.964	0.964	0.960	0.954	0.949	0.944	0.939	0.940	0.940
Verizon New York Telephone	0.951	0.951	0.946	0.941	0.939	0.933	0.928	0.929	0.933
Verizon California	0.970	0.967	0.964	0.956	0.950	0.946	0.941	0.937	0.941
Verizon Florida LLC	0.962	0.959	0.956	0.951	0.947	0.945	0.945	0.946	0.949
Verizon North, Inc.	0.970	0.965	0.962	0.957	0.951	0.954	0.953	0.951	0.956
Verizon Northwest, Inc.	0.972	0.967	0.965	0.963	0.958	0.958	0.956	0.955	0.956
Verizon South, Inc.	0.969	0.965	0.960	0.958	0.958	0.960	0.960	0.959	0.959
GTE of The Southwest, Inc. dba Verizon Southwest	0.972	0.971	0.967	0.962	0.960	0.962	0.963	0.966	0.972

* 1997 implies technological change between period 1996-1997.

Table 3.6 Mean Technical Efficiency Change, Technological Change, and Productivity Growth Change for SFM, Pre-merger and Post-merger

Firm #	Firm	Pre-Merger			Post-Merger		
		Technological change	Efficiency change	Productivity change	Technological change	Efficiency change	Productivity change
1	Qwest Corporation	0.953	1.028	0.979	0.938	1.018	0.954
11	Verizon Washington D.C.	0.943	1.002	0.945	0.936	1.001	0.937
12	Verizon Maryland	0.946	1.024	0.969	0.937	1.015	0.952
13	Verizon Virginia	0.941	1.024	0.964	0.940	1.016	0.954
14	Verizon West Virginia	0.968	1.018	0.985	0.954	1.012	0.966
15	Verizon Delaware LLC	0.964	1.004	0.968	0.957	1.003	0.960
16	Verizon Pennsylvania	0.952	1.021	0.972	0.950	1.014	0.963
17	Verizon New Jersey	0.947	1.035	0.980	0.939	1.022	0.960
18	Verizon New England	0.961	1.030	0.989	0.942	1.019	0.960
19	Verizon New York Telephone	0.947	1.070	1.014	0.932	1.045	0.974
20	Verizon California	0.964	1.007	0.971	0.943	1.004	0.947
21	Verizon Florida LLC	0.957	1.036	0.991	0.946	1.023	0.968
22	Verizon North, Inc.	0.963	1.003	0.966	0.953	1.002	0.955
23	Verizon Northwest, Inc.	0.967	1.013	0.979	0.956	1.008	0.964
24	Verizon South, Inc.	0.963	1.003	0.965	0.959	1.002	0.961
25	GTE of The Southwest, Inc. dba Verizon Southwest	0.968	1.004	0.972	0.965	1.002	0.967
10	AT&T/BellSouth Corporation	0.953	1.002	0.954	0.947	1.001	0.948
2	AT&T/Southwestern Bell Telephone	0.976	1.017	0.993	0.953	1.011	0.963
3	Pacific Bell – California*	0.966	1.015	0.981	0.956	1.010	0.966
4	Nevada Bell *	0.985	1.021	1.005	0.960	1.014	0.973
5	Illinois Bell	0.944	1.039	0.982	0.943	1.026	0.967
6	Indiana Bell	0.960	1.014	0.973	0.953	1.009	0.962
7	Michigan Bell	0.965	1.016	0.980	0.961	1.011	0.971
8	Ohio Bell	0.955	1.016	0.970	0.950	1.010	0.960
9	Wisconsin Bell	0.958	1.030	0.986	0.954	1.019	0.973
10	AT&T/BellSouth Corporation	0.954	1.002	0.956	0.947	1.001	0.948

* Firm number 3 and 4 first merged in 1997. Since our sample period begins with 1996 we place theses two firms in the second group.

- Firm number 11 through 25 and 1 pertain to the first group. Firm number 2 to 10 pertain to the second group. The third group contains firm number 10.

Table 3.7 Mean Efficiency Change and Technological Change between Stochastic Frontier Model and Malmquist Index, Pre-merger and Post-merger

Firm #	Firm	Technological Change				Efficiency Change			
		SFM		Malmquist		SFM		Malmquist	
		Pre-Merger	Post-Merger	Pre-Merger	Post-Merger	Pre-Merger	Post-Merger	Pre-Merger	Post-Merger
1	Qwest Corporation	0.953	0.938	0.997	0.966	1.028	1.018	0.970	0.991
11	Verizon Washington D.C.	0.943	0.936	0.961	0.980	1.002	1.001	1.000	1.000
12	Verizon Maryland	0.946	0.937	1.001	0.969	1.024	1.015	0.985	1.012
13	Verizon Virginia	0.941	0.940	1.012	0.971	1.024	1.016	1.000	0.962
14	Verizon West Virginia	0.968	0.954	1.002	0.968	1.018	1.012	1.006	1.017
15	Verizon Delaware LLC	0.964	0.957	0.991	0.985	1.004	1.003	1.000	0.990
16	Verizon Pennsylvania	0.952	0.950	0.992	0.980	1.021	1.014	0.996	1.007
17	Verizon New Jersey	0.947	0.939	0.989	0.948	1.035	1.022	1.000	1.000
18	Verizon New England	0.961	0.942	0.977	0.991	1.030	1.019	0.974	1.021
19	Verizon New York Telephone	0.947	0.932	1.005	0.954	1.070	1.045	1.073	1.009
20	Verizon California	0.964	0.943	1.003	0.969	1.007	1.004	1.001	1.000
21	Verizon Florida LLC	0.957	0.946	1.015	0.962	1.036	1.023	1.002	1.029
22	Verizon North, Inc.	0.963	0.953	1.027	0.975	1.003	1.002	1.023	0.974
23	Verizon Northwest, Inc.	0.967	0.956	1.029	0.970	1.013	1.008	0.998	1.010
24	Verizon South, Inc.	0.963	0.959	1.063	1.014	1.003	1.002	1.028	1.000
25	GTE of The Southwest, Inc. dba Verizon Southwest	0.968	0.965	1.047	0.969	1.004	1.002	1.007	0.981
10	AT&T/BellSouth Corporation	0.953	0.947	0.982	0.948	1.002	1.001	1.000	1.000
2	AT&T/Southwestern Bell Telephone	0.976	0.953	0.976	0.978	1.017	1.011	1.000	0.968
3	Pacific Bell - California *	0.966	0.956	0.953	0.957	1.015	1.010	1.000	1.000
4	Nevada Bell *	0.985	0.960	0.939	0.955	1.021	1.014	0.948	0.994
5	Illinois Bell	0.944	0.943	1.011	0.948	1.039	1.026	1.002	1.003
6	Indiana Bell	0.960	0.953	1.020	0.974	1.014	1.009	1.000	1.000
7	Michigan Bell	0.965	0.961	1.005	0.970	1.016	1.011	1.000	0.965
8	Ohio Bell	0.955	0.950	1.018	0.961	1.016	1.010	1.014	0.996
9	Wisconsin Bell	0.958	0.954	1.006	0.970	1.030	1.019	1.021	1.006
10	AT&T/BellSouth Corporation	0.954	0.947	0.990	0.949	1.002	1.001	1.000	1.000

* Firm number 3 and 4 first merged in 1997. Since our sample period begins with 1996 we place theses two firms in the second group.

- Firm number 11 through 25 and 1 pertain to the first group. Firm number 2 to 10 pertain to the second group. The third group contains firm number 10.

Table 3.8 Comparison of Mean Productivity Growth Change between Stochastic Frontier Model and Malmquist Index, Pre-merger and Post-merger

Firm #	Firm	Stochastic Frontier Model		Malmquist Index	
		Pre-Merger	Post-Merger	Pre-Merger	Post-Merger
1	Qwest Corporation	0.979	0.954	0.967	0.958
11	Verizon Washington D.C.	0.945	0.937	0.961	0.980
12	Verizon Maryland	0.969	0.952	0.986	0.981
13	Verizon Virginia	0.964	0.954	1.012	0.934
14	Verizon West Virginia	0.985	0.966	1.008	0.985
15	Verizon Delaware LLC	0.968	0.960	0.991	0.975
16	Verizon Pennsylvania	0.972	0.963	0.988	0.987
17	Verizon New Jersey	0.980	0.960	0.989	0.948
18	Verizon New England	0.989	0.960	0.952	1.012
19	Verizon New York Telephone	1.014	0.974	1.078	0.963
20	Verizon California	0.971	0.947	1.004	0.969
21	Verizon Florida LLC	0.991	0.968	1.018	0.990
22	Verizon North, Inc.	0.966	0.955	1.051	0.950
23	Verizon Northwest, Inc.	0.979	0.964	1.027	0.980
24	Verizon South, Inc.	0.965	0.961	1.093	1.014
25	GTE of The Southwest, Inc. dba Verizon Southwest	0.972	0.967	1.054	0.950
10	AT&T/BellSouth Corporation	0.954	0.948	0.982	0.948
2	AT&T/Southwestern Bell Telephone	0.993	0.963	0.976	0.947
3	Pacific Bell - California *	0.981	0.966	0.953	0.957
4	Nevada Bell *	1.005	0.973	0.890	0.950
5	Illinois Bell	0.982	0.967	1.013	0.951
6	Indiana Bell	0.973	0.962	1.020	0.974
7	Michigan Bell	0.980	0.971	1.005	0.936
8	Ohio Bell	0.970	0.960	1.032	0.958
9	Wisconsin Bell	0.986	0.973	1.026	0.976
10	AT&T/BellSouth Corporation	0.956	0.948	0.990	0.949

* Firm number 3 and 4 first merged in 1997. Since our sample period begins with 1996 we place theses two firms in the second group.

- Firm number 11 through 25 and 1 pertain to the first group. Firm number 2 to 10 pertain to the second group. The third group contains firm number 10.

Chapter 4 - The Impact of Incentive Regulation on the U.S. Telecommunications Industry: A Stochastic Frontier Approach

INTRODUCTION

Since the late 1980s, one of the most important trends in regulatory policy in the U.S. telecommunications industry has been the transition from traditional rate-of-return regulation (RRR) to alternative forms of regulation, so called incentive regulation (IR).[60,61] Regulators in the telecommunications industry anticipated that the adoption of incentive regulation would lower prices, enhance technical innovation, encourage firms to operate with efficient technology and reduce the administrative costs of regulation.

A large volume of research has examined the effects associated with the implementation of incentive regulations.[62] Schmalensee and Rohlfs (1992) examined the effect of price cap regulation (PCR)[63] on productivity gains. They compared AT&T's productivity gains on switched services in the period prior to the implementation of PCR (1986-1988) with the period following the implementation of PCR (1989-1991). Schmalensee and Rholfs found that the

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[60] Economists have long criticized the incentive properties of RRR. For example, Braeutigam and Panzar (1989) describe potential problems of RRR, including: (1) incentives to misreport cost allocations; (2) choose an inefficient technology mix; (3) underinvestment in cost-reducing innovation; (4) underproduce in the non-core market; (5) inefficient diversification. Sappington (2001) has analyzed potential flaws in RRR to include: (1) firms are not likely to perform fully in terms of incentives for innovation and cost minimization; (2) over capitalization; (3) regulatory cost are high; (4) consumers bear excessive risk; (5) cost shifting; (6) distortion of diversification and innovation; (7) operate with inefficient technology; and (8) insufficient pricing flexibility. See also Weisman (1996) for a discussion of similar drawback associated with price cap regulation with earnings sharing.

[61] In this essay, we examine 4 different types of IR. These are Earnings Sharing, Hybrid Price Caps, Price Caps, and Other Forms of IR. See Sappington and Weisman (1996) for a discussion of incentive regulation in the telecommunications industry.

[62] Empirical analyses of the effects of incentive regulation have focused on performance metrics such as services prices, production costs, productivity, investment in infrastructure, service quality, company profits, service penetration rates and new services in the telecommunications industry. See Kridel et al. (1996) for further review.

[63] PCR is the dominant regulatory regime among incentive regulation regimes. Substituting PCR for RRR provides for Pareto-superior change for all primary economic entities: the regulator, consumers, and competitors. See Weisman (2000b).

cumulative productivity gains were $1.8 billion higher during the PCR period relative to the RRR period.[64]

Majumdar (1997) employed a non-parametric approach, commonly referred to as data envelopment analysis (DEA), to examine the effect of incentive regulation on the productive performance of 45 local exchange carriers (LECs) over the period 1988-1993. He showed that PCR has a positive but lagged effect on technical efficiency.[65] Uri (2001) used a Malmquist index to measure the change in productivity growth following the implementation of incentive regulation. He found that productivity growth increased by approximately 5 percent per year for the 19 LECs over the period 1988-1999.

Although a number of empirical studies have concluded that the effect of incentive regulation on productivity growth in the U.S. telecommunications industry is substantially positive, some studies find that the effect of incentive regulation is ambiguous. For example, Resende (1999)[66] estimated a translog cost function combined with total factor productivity (TFP) growth decomposition for the period 1989-1994. He found that incentive regulation did not enhance the level of productive efficiency. Uri (2002) employed a corrected ordinary least

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[64] Kwoka (1993) analyzed the impact of different regulatory policies on productivity growth of British Telecom (BT). He found empirical evidence that the combination of privatization and price cap regulation for BT substantially affected productivity increases from 1984 to 1987. Tardiff and Taylor (1993) examined the effects of the implementation of incentive regulation on the local telecommunications firms in the U.S. They found that firms operating incentive regulation improved their annual total factor productivity (TFP) growth rate by 2.8 percentage points. This increase is attributed to the gains in output productivity and reduction in the growth rate of input under incentive regulation. Ai and Sappington (2002) used a fixed-effects estimation to examine the effect of incentive regulation on the U.S. telecommunications industry. They find that the incentive regulation improves network modernization and lowered costs.

[65] Kang (2000) introduced both static and dynamic DEA to investigate the effects of the implementation of incentive regulatory regimes at the state level for 28 local exchange carriers (LECs) over the period 1988 and 1998. He found that state level PCR had a positive effect on pure technical efficiency—an estimated improvement on average of 4 % in terms of the LECs' technical efficiency. Jung (2005) also employed both static and dynamic DEA to examine the effects of the implementation of incentive regulatory regimes for the period 1988-2000. His empirical findings, including various efficiency scores, indicated that only pure price cap regulation has a positive influence on improving efficiency scores.

[66] Resende (2000) used DEA to analyze the impact of alternative forms of regulation in the U.S. telecommunications industry. He found no empirical evidence in support of the claim that price cap regulation had a positive effect on technical efficiency.

squares (COLS) approach to measure the efficiency gains associated with the implementation of incentive regulation in the U.S. telecommunications industry. Using data from 19 LECs over the 1988-1999 time period, he found no empirical evidence that incentive regulation had enhanced technical efficiency.

In an attempt to resolve the extant ambiguity in the literature concerning the effect of incentive regulation on productivity growth, this essay investigates whether the substitution of PCR along with other incentive regulatory regimes for RRR enhanced the productive efficiency in the U.S. telecommunications industry using a stochastic frontier analysis (SFA). Specifically, we measure the productivity growth for 25 local exchange carriers' (LECs), inclusive of its underlying components -- technological progress and changes in technical efficiency over the period 1988 to 1998.

This study has two principal objectives. First, using SFA, this essay measures productivity growth associated with technological progress and changes in technical efficiency to examine the improvement in the LECs' productivity growth. Although previous studies provide some useful results in terms of productivity growth, employing the SFA approach differs from previous studies in material ways. Second, this essay analyzes the effects associated with the adoption of incentive regulation on the LECs' productivity growth rate.

The remainder of this essay is organized as follows. Section 2 discusses the multiple output distance function and presents the models used in the study. In Section 3, we discuss the data set, hypothesis tests and productivity growth changes. The estimates of the factors, including various regulatory regime variables, that explain changes in productivity growth are presented and discussed in Section 4. Section 5 provides a brief summary and conclusion.

THEORY OF STOCHASTIC FRONTIER ANALYSIS

Distance Function

To measure the production frontier, an output distance function is employed. The main advantage of the distance function approach is that it allows for a multiple-input and multiple-output technology without requiring price data, which is typically a constraint in working with telecommunications industry data.[67]

In order to define the output distance function, we first introduce the production technology. We assume that for each time period $t = 1,\ldots,T,$ the production technology F^t maps input vectors, $x_t \in \mathbb{R}_+^n$, into output vectors, $y_t \in \mathbb{R}_+^m$,

$$F^t = \left\{ \left(x_t, y_t \right) : x_t \text{ can produce } y_t \right\}, \tag{1}$$

where $\mathbb{R}$ is the set of real numbers.[68] The production technology F^t is homogeneous of degree one in output. Following Shepard (1970), the output distance function is defined at time t as:

$$D_{Ot}\left(x_t, y_t\right) = \inf\left\{ \theta : \left(x_t, \frac{y_t}{\theta} \right) \in F^t \right\} = \left(\sup\left\{ \theta : \left(x_t, \theta y_t \right) \in F^t \right\} \right)^{-1}. \tag{2}$$

According to Lovell et al. (1994), the output distance function $D_{Ot}\left(x_t, y_t\right)$ is non-decreasing, positively linearly homogeneous and convex in y and decreasing in x.[69] Note that the input-output vectors lie below the production technology set. This implies that

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[67] The distance function can be estimated in several ways. These include data envelopment analysis (DEA), parametric deterministic linear programming (PLP), corrected ordinary least squares (COLS), and stochastic frontier analysis (SFA).

[68] The production technology must satisfy following axioms in order to be a meaningful model of production: i) the possibility of inaction; ii) monotonicity of the output correspondence; iii) disposability of output iv); the output set is closed v); irreversibility (Färe, R., and S. Grosskopf. 1994).

[69] Refer to Coelli et al. (1998) for further discussion of distance functions.

$D_{Ot}(x_t, y_t) \leq 1$ if and only if $(x_t, y_t) \in F^t$. Moreover, $D_{Ot}(x_t, y_t) = 1$ if and only if (x_t, y_t) lie on the boundary of the production technology set.

Stochastic Frontier Analysis

There are two main approaches employed in efficiency analysis: econometric methods and the non-parametric DEA method. Depending upon the assumed property of the error term, the econometric method is categorized by a deterministic approach or a stochastic approach. The main advantage of stochastic frontier analysis (SFA) is that it accounts for the possible influence of noise on the shape and positioning of the frontier, something that deterministic frontier models are unable to do. In other words, issues such as measurement error and other random factors can be separated from the sources of variation in technical efficiency. SFA posits a production function with an error term associated with two components. These two components consist of a symmetric error term accounting for noise and an asymmetric error term accounting for technical inefficiency.

Based on Coelli and Perelman (2000), the multiple output distance function is specified in translog functional form and is given by:

$$\ln(D_{Oi}) = \alpha_0 + \sum_{j=1}^{J} \alpha_j \ln y_{ij} + \sum_{l=1}^{L} \beta_l \ln x_{il} + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} \alpha_{jk} \ln y_{ij} \ln y_{ik}$$

$$+ \frac{1}{2}\sum_{l=1}^{L}\sum_{m=1}^{L} \beta_{lm} \ln x_{il} \ln x_{im} + \frac{1}{2}\sum_{j=1}^{J}\sum_{l=1}^{L} \delta_{jl} \ln y_{ij} \ln x_{il}, \qquad i = 1, 2, \ldots, I \tag{3}$$

where J is the number of outputs, L is the number of inputs, and i denotes the ith firm in the sample. The restrictions required for homogeneity of degree one in outputs are

$$\sum_{j=1}^{J} \alpha_j = 1, \tag{4}$$

and

$$\sum_{k=1}^{J}\alpha_{jk}=0,\quad j=1,2,\ldots,J \text{ and } \sum_{l=1}^{L}\delta_{jl}=0,\qquad l=1,2,\ldots,L. \tag{5}$$

The restrictions required for symmetry are

$$\alpha_{jk}=\alpha_{kj},\qquad j,k=1,2,\ldots,J \text{ and } \beta_{lm}=\beta_{ml},\qquad l,m=1,2,\ldots,L. \tag{6}$$

Lovell et al. (1994) proposed a convenient method for imposing the homogeneity restriction in (3). Homogeneity implies that

$$D_O(x,\lambda y)=\lambda D_O(x,y),\text{ for any } \lambda>0. \tag{7}$$

Hence, we arbitrarily choose one of the outputs, and set $\lambda=\frac{1}{y_J}$, which allows us to obtain

$$D_O\left(x,\frac{y}{y_J}\right)=\frac{D_O(x,y)}{y_J}. \tag{8}$$

The translog function can be written as:

$$\ln\left(\frac{D_{oi}}{y_{iJ}}\right)=\alpha_0+\sum_{j=1}^{J-1}\alpha_j\ln y^*_{ij}+\sum_{l=1}^{L}\beta_l\ln x_{il}+\frac{1}{2}\sum_{j=1}^{J-1}\sum_{k=1}^{J-1}\alpha_{jk}\ln y^*_{ij}\ln y^*_{ik}$$

$$+\frac{1}{2}\sum_{l=1}^{L}\sum_{m=1}^{L}\beta_{lm}\ln x_{il}\ln x_{im}+\frac{1}{2}\sum_{j=1}^{J-1}\sum_{l=1}^{L}\delta_{jl}\ln y^*_{ij}\ln x_{il},\qquad i=1,2,\ldots,I, \tag{9}$$

where $y^*_{ij}=\frac{y_{ij}}{y_{iJ}}$. Equation (9) can be rewritten in the following functional form

$$-\ln(y_{iJ})=TL\left(y^*,x,\alpha,\beta\right)-\ln\left(D_{Oi}\right) \tag{10}$$ [70]

We append the noise term v_i and change the notation from $\ln(D_{Oi})$ to $-u_i$. This transformation yields the stochastic frontier function associated with the time trend for the panel data and is expressed as follows:

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[70] Note that $D_{oi}=1$ implies that the firm lies on the boundary of the frontier.

$$-\ln(Y_{it}) = \alpha_0 + \alpha_T t + \sum_{j=1}^{J-1} \alpha_j \ln y_{ijt}^* + \sum_{l=1}^{L} \beta_l \ln x_{ilt} + \frac{1}{2}\alpha_{TT} t^2$$

$$+\frac{1}{2}\sum_{j=1}^{J-1}\sum_{k=1}^{J-1} \alpha_{jk} \ln y_{ijt}^* \ln y_{ikt}^* + \frac{1}{2}\sum_{l=1}^{L}\sum_{m=1}^{L} \beta_{lm} \ln x_{ilt} \ln x_{imt} + \frac{1}{2}\sum_{j=1}^{2} \alpha_{Tj} t \ln y_{ijt}^*$$

$$+\frac{1}{2}\sum_{l=1}^{L} \beta_{Tl} t \ln x_{ilt} + \frac{1}{2}\sum_{j=1}^{J-1}\sum_{l=1}^{L} \delta_{jl} \ln y_{ijt}^* \ln x_{ilt} + v_{it} + u_{it}\,,^{71} \qquad (11)$$

where $t = 1, 2, \ldots, T$ is a time trend. Y_{it} and y_{ijt}^* are the output and arbitrarily normalized output for firm i, respectively. Subscripts j, k index outputs; α, β, δ are parameters to be estimated; x variables are inputs. Subscripts l, m index inputs; the v_{it} s are the error components and are assumed to be independently and identically distributed as $N\left(0, \sigma_v^2\right)$. The u_{it} 's are the technical inefficiency components.

Following Battese and Coelli (1992), the technical inefficiency error term is defined by

$$u_{it} = u_i \exp\left[-\eta\left(t - T\right)\right], \qquad i = 1, 2, \ldots, I; t = 1, 2, \ldots, T, \qquad (12)$$

where the u_i s are assumed to be a non-negative truncation of the normal distribution $N\left(\mu, \sigma_\mu^2\right)$ associated with technical inefficiency in production. u_i is the technical inefficiency effect for firm i for the last period of the sample; η is an unknown parameter to be estimated and represents the rate of change in technical inefficiency. Therefore, a positive value, $\eta > 0$, implies that the technical inefficiency effects are decreasing over time.[72] One of the advantages of using

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[71] Note that as suggested by Morrison-Paul et al. (2000), one can change the sign of dependent variable. This change allows for interpreting estimates that conform to the standard SFA framework.

[72] If $\eta > 0$ then $-\eta\,(t\text{-}T) \equiv \eta(T\text{-}t)$ and $u_{it} > u_i$. However, the value of the exponential function is decreasing monotonically towards the value of the last period in the sample. If $\eta = 0$, the translog specification in (11) becomes a time-invariant inefficiency model.

the error term in (12) is that any technical inefficiency changes over time can be separated from technical change.

Following Coelli et al. (1998) and given the estimates for (11) and (12), the technical efficiencies of production for each firm in the tth year can be predicted as:

$$TE_{it} = \exp\left(-u_{it}\right).^{73} \tag{13}$$

Therefore, the technical efficiency change between adjacent periods t and s is calculated as:

$$EC_{it} = \frac{TE_{it}}{TE_{is}}. \tag{14}$$

With the estimates of the parameters in (11) and (12), the index of the technological change for firm i is calculated by evaluating the partial derivative of the production function with respect to time. The calculation of technological change is computed according to:

$$TC_{it} = \sqrt{\left[1 + \frac{\partial f\left(y_{is}^{*}, x_{is}, t, \alpha^{*}, \beta^{*}\right)}{\partial s}\right] \times \left[1 + \frac{\partial f\left(y_{it}^{*}, x_{it}, t, \alpha^{*}, \beta^{*}\right)}{\partial t}\right]}. \tag{15}$$

Finally, the TFP index can be obtained by the product of the index of technical efficiency change and the index of technological change calculated from (14) and (15):

$$TFP_{it} = EC_{it} \times TC_{it}. \tag{16}$$

Data and Productivity Growth

The data used in this analysis represent a balanced panel that consists of annual data for 25 ILECs over the 1988-1998 period.[74] The primary sources of data are obtained from the

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[73] The predicted values of technical efficiency lie between zero and one. A value of one implies that the firm lies on the boundary of the production possibility set.

[74] Starting with the year 1988, the accounting system that tracks these data was changed.

Electronic ARMIS Filing System and the Statistics of Communications Common Carriers maintained by the U.S. Federal Communications Commission (FCC).[75]

Local calls, intraLATA toll calls, and interLATA toll calls are the output variables since these are the core services provided by ILECs.[76] The measures of inputs are the total number of switches, the number of access lines, and the number of employees.[77] The use of these three inputs captures the actual industry characteristics for producing telephone service.

We use a stochastic frontier model with homogeneity imposed on (9). IntraLATA toll calls are chosen as the output measure used to normalize all other outputs. We therefore specify the variables used in (11) as follows:

Y is intraLATA toll calls;

y_1^* is local calls divided by intraLATA toll calls;

y_2^* is interLATA toll calls divided by intraLATA calls;

x_1 is number of switches;

x_2 is number of access lines;

and x_3 is number of employees.

The test results for various null hypotheses presented in Table 1 are conducted using log-likelihood ratio (LR) tests.[78] Given the stochastic frontier specification, we first test for changes

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[75] ARMIS is the acronym for Automated Reporting Management Information System. One may refer to http://www.fcc.gov/wcb/armis to access the data set. FCC Report 43-02, the ARMIS USOA Report, FCC Report 43-07, the ARMIS Infrastructure Report and FCC Report 43-08, the ARMIS Operating Data Report were used to populate the data set.

[76] As part of the break up of AT&T in 1984, the U.S. was partitioned into approximately 161 local access transport areas or LATAs. The RBOCs were restricted to providing intraLATA long distance service which essentially meant that they could not provide long distance service across area code boundaries. Section 271 of the 1996 Telecommunications Act specified the terms and conditions that would enable the RBOCs to re-enter the interLATA long distance market.

[77] Majumdar (1997) also introduced the same classification for outputs and inputs.

[78] The LR test statistic is calculated by -2x[L(H_0) - L(H_A)], where L(H_0) and L(H_A) are the log-likelihood values under the null and alternative hypotheses, respectively.

in technical inefficiency. The null hypothesis $(\gamma = \mu = \eta = 0)$ is rejected at the 1% significance level. This implies that OLS does not fit the actual frontier well due to the technical inefficiency effects. The second null hypothesis, that there is no technological change, is strongly rejected. This result suggests that technological change exists in the model. The third hypothesis test that technical inefficiency effects have a half-normal distribution is also rejected. The last set of hypothesis tests focuses on whether technical inefficiency is time-invariant. This hypothesis is rejected at the 1% level of statistical significance, implying that there is no time-invariance in technical inefficiency.

Table 2 reports the maximum likelihood estimates (MLE) of the parameters in the translog stochastic frontier production function defined by (11) and (12). Note that the parameter $\gamma \left(\gamma = \frac{\sigma_\mu^2}{\sigma_\mu^2 + \sigma_v^2} \right)$ is the ratio of the error variances from (11). Therefore, the value of γ must lie between zero and one. If $\gamma = 0$, no technical inefficiency is present, while $\gamma = 1$ indicates that there exists no random noise. Thus, our estimate of γ=0.853 implies that the technical inefficiency component dominates the random noise component. The significant and positive estimate of the time varying inefficiency effect, $\eta = 0.0292$, indicates that the technical inefficiency effects are monotonically decreasing over time. These results further substantiate the claim that there are time variant technical inefficiency effects in the error term that are decreasing over time.

Table 3 reports the indices for the sample mean of technical efficiency, technological change, and productivity growth changes for the period from 1988 to 1998. The index of efficiency change is greater than one over this time period. The estimates of the inefficiency error term indicate that technical efficiency has occurred at a positive rate while the rate of growth decreased continuously during the sample period. The index for technological change decreases until 1991 and then reflects an overall improvement in technology. In addition, technological change is a dominant factor in the decomposition. Thus, the sample mean for the productivity growth change, which declined initially, is increasing from 1991. This may be attributed to the change in the regulatory regime since price cap regulation for interstate access went into effect in 1991.

Table 4 presents the measures for average productivity, efficiency, and technological change for each individual firm during the 1988-1990 and 1991-1998 periods. Since price caps for interstate access went into effect in 1991, it is important to determine whether the adoption of this new regulatory regime affects productivity growth over the 1991-1998 time period.

Each LEC in the sample, with the exception of Qwest, experienced increases in mean technological change following the implementation of the incentive regulatory regime. This result implies that there was improvement in technology. In addition, with the exception of Qwest and Illinois Bell, each individual firm experienced an increase in annual productivity growth. For example, Pacific Bell-California experienced a 4.1 percent average growth in productivity over the period 1991-1998, but only a 1.4 percent average growth in productivity prior to 1991. It is noteworthy that only Verizon Hawaii experienced negative growth in productivity in both sample periods, although Verizon Hawaii improved its performance over the sample periods. These empirical findings strongly suggest that the substitution of incentive regulation for traditional RRR enhanced performance in the U.S. telecommunications industry over the sample periods. In the next section, we discuss the relationship between productivity growth change and selected independent variables.

THE EFFECTS OF PCR ON THE PRODUCTIVITY GROWTH CHANGE

Regulatory Regime Variables

In this essay, the various regulatory regimes are classified into five groups: rate of return (RRR), earnings sharing (ESHARE), hybrid price caps (HPCR), pure price caps (PCR), and other incentive regulations (OIR). RRR includes only traditional RRR. ESHARE contains all forms of earnings sharing such as banded rate of return with earnings sharing. Price caps with earnings sharing and revenue sharing are categorized by HPCR. Price caps with pricing flexibility and indexed price caps are classified as PCR. OIR contains banded RRR, rate freeze (with pricing flexibility) and all other hybrid types of incentive regulation.[79]

It should be noted that there is a measurement issue associated with matching each firm with a particular regulatory regime. That is, LECs that operates across different states may be subject to disparate regulatory regimes. For example, in 1988, Qwest, then-US West, operated 15 local companies over 14 different states. Qwest in Colorado was under RRR with pricing flexibility while Qwest in Idaho was under traditional RRR. To solve this problem, we use the percentage ratio of a firm's total loops in a specific state to that firm's total number of loops in different states as a proxy.[80]

Control Variables

In addition to the regulatory regime variables, we introduce 8 explanatory variables: FIBER, TOLLC, BSLINE, SIZE, BELL, HUMCAP, CORCO, and COCS.[81]

FIBER is used to control for the effects of network modernization. There are two principal technology types in the development of telecommunications networks: transmission

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[79] We follow Kang (2000)'s classification. The data source is based on Abel and Clements (1998).

[80] Based on Kang (2000) and Resende (2000), we employ these regulatory variables.

[81] Control variables used in this essay are based on Majumdar (1997) and Kang (2000) with a few exceptions as noted.

facilities and switching facilities. Due to data limitations, we compute the ratio of sheath kilometers of fiber deployed in the cable to sheath kilometers of total cable as a measure of network modernization.

TOLLC is computed as the percentage ratio of number of toll calls to total number of calls. TOLLC is used to control for the effects of competition in long distance service.

BSLINE is used to control for the effects of competition in the exchange access service market. Bypass is a form of competition in local exchange access markets which can lead to pronounced losses in LEC revenues without corresponding reductions in LEC costs.[82] Business customers tend to have greater opportunities to bypass the local network because of their location in the urban cores with high teledensity (local loops per square mile). Thus, this measure is computed as the percentage ratio of business access lines to total access lines.

SIZE is employed as an explanatory variable to control for scale effects among LECs. SIZE is computed as the log of deflated total revenue.[83]

BELL is used to distinguish regional bell operating company (RBOC) and independent LECs. BELL is a dummy variable which takes on the value 1 if the LEC is an RBOC and the value of 0 otherwise.

HUMCAP is used to capture the difference in worker quality among the LECs. In theory, high-quality employees are likely to receive a higher rate of compensation, whereas low quality

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[82] The nature of the telecommunications production process is that the vast majority of costs are incurred in providing for the option of use rather than actual use. This implies, of course, that reductions in demand and revenues do not translate into comparable reduction in LEC costs. As Mitchell and Vogelsang (1997, p. 9) observe:

> In telecommunications networks, production facilities have well-determined capacities, and the costs of operation are nearly independent of the flow of services through those facilities . . . Consequently, . . . variable costs are very small.

[83] Total revenues are deflated by the CPI for overall telephone services (base year = 1984).

employees are likely to receive a somewhat lower rate of compensation. Thus, as a proxy for worker quality, we use average real compensation per employee.[84]

CORCO is used to control for the effects of differences in the firm's long-run business investment. This variable is computed as the percentage ratio of planning, human resources, and research and development expenses to total operating expenses.

COCS is used to explain the effects of differences in the LEC's level of customer service. The higher the quality of service the firm provides the higher the demand for its services, *ceteris paribus*. As a proxy for the firm's level of customer service, we use the percentage ratio of customer operating expenses to total operating expenses.[85]

Econometric specification

In the previous section, we defined the regulatory regime variables along with seven explanatory variables. In this section, we turn to investigate the relationship between productivity growth change and the regulatory regime variables. In addition, it is interesting to ascertain whether the lagged values of the regulatory variables have substantially influenced the firm's performance in the near term since the change in regulatory policy and the individual firm's reaction to the new policy may occur over time. Thus, our model includes two-period lagged regulatory variables and is specified as follows:

$$TFP_{it} = \alpha + \sum_{j=1}^{4}\sum_{l=0}^{2}\beta_{j,t-l}R_{j,i,t-l} + \sum_{k=1}^{8}\delta_k X_{k,it} + \varepsilon_{it} \qquad (17)$$

$$\varepsilon_{it} \sim N(0,\sigma_{\varepsilon}^{2})$$

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[84] To obtain real compensation of labor, total compensation of labor was deflated by the employment cost indexes in communications obtained from the U.S. Department of Labor, Bureau of Labor Statistics

[85] Summary statistics for the explanatory variables are reported in Table 5.

where the subscript *i* indexes the individual firm. TFP_{it} is the total factor productivity index in the *t* th year, and $R_{j,i,t-l}$ represents a dummy variable for the *j* th regulatory regime in the *t-k* th year. $X_{k,it}$ represents the *k*th control variable, as defined in the previous section, in the *t-k* th year. α, β, δ are parameters to be estimated. ε_{it} is the error term.

Generally speaking, our *a priori* expectation is that FIBER, TOLLC, BELL, HUMCAP, CORCO, and COCS will have positive effects, while BSLINE will have negative effects. The OLS estimates of these regulatory variables along with the control variables are reported in Table 6. Model 1 includes no time lags, while Model 2 and Model 3 include a one-period time lag and a two-period time lag, respectively.

Except ESHRE, all estimates of the incentive regulation regime variables in Model 1 are positive and statistically significant. This implies that the adoption of incentive regulation has a positive effect on productivity growth. It is noteworthy that the coefficient on PCR indicates a substantially positive relationship with TFP growth. Moreover, only PCR is positively related to productivity growth at the 1% significance level in all three models. That is PCR shows a consistent result across the various specification of the time lag. This result implies that there is a pronounced positive effect of PCR on productivity growth. In practice, PCR plays an instrumental role in enhancing productivity growth relative to the other regulatory regimes.

FIBER is positively related to the productivity growth change at the 1% significance level in all three models. This indicates that network modernization in the form of investment in fiber optic cables positively enhanced productivity growth.

The contribution of toll call (TOLLC) to productivity growth has a positive impact and is significant at the 1% significance level in all three models. Since toll markets are more lucrative than local markets, increasing competition in the toll service market induces more entry in the market. Thus, firms operating with a high proportion of toll services are likely to encounter intense competition that, in turn, drives them to be more productive.

Business line (BSLINE) is negatively related to productivity growth. Business markets are more susceptible to bypass competition due to high measures of teledensity. This can lead to a large loss of LEC revenues without a corresponding reduction in LEC costs.

Baby Bells (BELL) variable is positively related to the change in productivity growth. This implies that regional bell operating companies (RBOCs) performed better in terms of productivity growth change relative to non-RBOCs.

On the other hand, corporate cost (CORCO) is negatively related to the change in productivity growth at the 1% significance level in all three models. This result implies that increasing levels of investment in human capital and research has no measurable, positive impact on productivity growth. Rather, physical (capital) investment may be the dominant factor in terms of enhancing production performance in the telecommunications industry.

The human capital (HUMCAP), customer cost (COCS) and SIZE are negatively related to productivity growth. However, with the lone exception of model 3, these estimates are not statistically significant.

CONCLUSION

The pervasive adoption of PCR and IR is one of the outstanding achievements of regulatory economics in the United States and throughout the western world. In theory, PCR is superior to RRR in that it provides stronger incentives for operating efficiency. The theoretical literature notwithstanding, the empirical evidence concerning the effect of incentive regulation on productivity growth has been mixed. Hence, the primary objective of this essay is to investigate whether the implementation of PCR along with other regulatory regime variables has had a positive effect on productivity growth in the U.S. telecommunications industry. In addition, this essay employs a stochastic frontier approach, which differs from previous studies, to compute efficiency change, technological progress, and productivity growth for 25 LECs over the 1988-1998 sample periods.

Every LEC in the sample, with the exception of Qwest, experienced an increase in mean technological change following the implementation of incentive regulation. Furthermore, with the exception of Qwest and Illinois Bell, each firm in the sample experienced an increase in annual productivity growth following the implementation of incentive regulation. This may imply that the adoption of PCR and IR, more generally, has had positive impact on operating performance in the U.S. telecommunications industry.

By examining the relationship between productivity growth, regulatory regime variables and a set of control variables, we find that PCR and other regulatory regimes have a positive effect on productivity growth. However, only PCR has a significant and positive effect on productivity growth in both contemporaneous and lagged model specifications.

Table 4.1 LR Tests of hypotheses for parameters of stochastic production frontier model

No	Null Hypothesis	Test statistics	Critical value	Decision
(1)	$\gamma = \mu = \eta = 0$	216.554	10.501*	Reject H_0
(2)	$\alpha_T = \alpha_{TT} = \alpha_{T1} = \alpha_{T2} = \beta_{T1} = \beta_{T2} = \beta_{T3} = 0$	92.333	$\chi^2_{7,0.01} = 18.475$	Reject H_0
(3)	$\mu = 0$	88.835	$\chi^2_{1,0.01} = 6.63$	Reject H_0
(4)	$\eta = 0$	8.403	$\chi^2_{1,0.01} = 6.63$	Reject H_0

* The critical values for this test are obtained from Table 1 of Kodde and Palm (1986) for mixed $\chi^2_{v,0.01}$.

Table 4.2 Estimated Parameters for Stochastic Production Frontier Model

Number of observations = 275
Number of firms = 25
Log-likelihood = 355.7185
Number of years = 11

Parameters	Coefficient	Standard error
α_0	-4.9072***	1.0336
α_T	-0.3616***	0.0796
α_1	-3.2244***	0.3102
α_2	2.5044***	0.4299
β_1	2.5263***	0.678
β_2	1.9386***	0.5842
β_3	-4.0434***	0.9954
α_{TT}	-0.0034***	0.001
α_{11}	0.3834***	0.0237
α_{22}	0.312***	0.0464
α_{12}	-0.3043***	0.0347
β_{11}	0.1631***	0.0393
β_{22}	-0.7495***	0.1564
β_{33}	-0.9752***	0.243
β_{12}	-0.3336***	0.0971
β_{13}	0.1401*	0.0816
β_{23}	0.9273***	0.2004
α_{T1}	-0.0637***	0.0114
α_{T2}	0.058***	0.0121
β_{T1}	0.032**	0.0143
β_{T2}	0.1638***	0.0309
β_{T3}	-0.1839***	0.0361
δ_{11}	0.0507	0.0563
δ_{12}	0.9853***	0.1266
δ_{13}	-0.9024***	0.1439
δ_{21}	-0.105*	0.0555
δ_{22}	-0.7191***	0.1417
δ_{23}	0.7901***	0.1569
μ	0.2623***	0.032
η	0.0292***	0.0071
$\gamma = \sigma_{\mu}^{2} / (\sigma_{\mu}^{2} + \sigma_{v}^{2})$	0.8534	0.0242
$\sigma^{2} \left(= \sigma_{\mu}^{2} + \sigma_{v}^{2} \right)$	0.0202	0.0017

Note: *** = significant at 1% level (p<0.01).
** = significant at 5% level (p<0.05).
* = significant at 10% level (p<0.10).

Table 4.3 Sample Mean of Technical Efficiency Change, Technological Change, and Productivity Growth Change Using a Stochastic Frontier Approach

Year	Efficiency change	technological change	productivity growth change
1988	1.000	1.000	1.000
1989	1.012	0.995	1.007
1990	1.011	0.994	1.006
1991	1.011	0.993	1.004
1992	1.011	0.998	1.009
1993	1.011	1.004	1.015
1994	1.010	1.013	1.023
1995	1.010	1.025	1.036
1996	1.010	1.033	1.043
1997	1.009	1.035	1.045
1998	1.009	1.036	1.045

Note: Indices for year 1988 reflect change between 1987 and 1988. Since no data is available prior to 1988 in our sample, we assign a value 1.

Table 4.4 Mean Technical Efficiency Change, Technological Change, and Productivity Growth Change, 1988-1990 and 1991-1998

Firm #	Firm	1988-1990			1991-1998		
		Technological change	Efficiency change	Productivity change	Technological change	Efficiency change	Productivity change
1	Qwest Corporation	1.022	1.010	1.033*	1.015	1.009	1.024
2	AT&T/Southwestern Bell	0.985	1.016	1.001	1.000	1.014	1.014
3	Pacific Bell - California	0.999	1.015	1.014	1.027	1.013	1.041
4	AT&T/SNET	0.970	1.018	0.988	0.989	1.016	1.004
5	Illinois Bell	1.018	1.014	1.032	1.018	1.012	1.031
6	Indiana Bell	1.020	1.012	1.032	1.034	1.011	1.045
7	Michigan Bell	1.018	1.016	1.034	1.026	1.014	1.040
8	Ohio Bell	1.016	1.015	1.032	1.022	1.013	1.036
9	Wisconsin Bell	1.018	1.010	1.028	1.032	1.009	1.041
10	AT&T/BellSouth	0.990	1.018	1.008	1.008	1.015	1.023
11	Verizon Washington D.C.	0.958	1.013	0.971	0.995	1.011	1.006
12	Verizon Maryland	0.991	1.014	1.004	1.027	1.012	1.039
13	Verizon Virginia	1.003	1.012	1.015	1.034	1.010	1.045
14	Verizon West Virginia	0.981	1.007	0.988	1.006	1.006	1.012
15	Verizon Delaware LLC	1.025	1.004	1.029	1.045	1.003	1.048
16	Verizon Pennsylvania	1.026	1.012	1.038	1.038	1.010	1.049
17	Verizon New Jersey	1.013	1.017	1.030	1.043	1.015	1.058
18	Verizon New England	1.016	1.011	1.027	1.032	1.010	1.042
19	Verizon New York	1.000	1.001	1.001	1.007	1.000	1.007
20	Verizon Florida LLC	0.969	1.003	0.972	0.999	1.002	1.001
21	Verizon Hawaii	0.900	1.006	0.906	0.946	1.005	0.951
22	Verizon North, Inc.	0.992	1.014	1.006	1.022	1.012	1.034
23	Verizon Northwest, Inc.	0.996	1.011	1.007	1.021	1.010	1.031
24	Verizon South, Inc.	0.974	1.013	0.986	1.022	1.012	1.034
25	GTE of The Southwest, Inc.	0.967	1.009	0.976	1.019	1.008	1.027

Note: 1) The mean is the geometric mean.
2) 1.033 implies a 3.3% annual growth in productivity over the period 1988-1990.

Table 4.5 Summary Statistics for Explanatory Variables

	Independent Variable	MEAN	STDV	MIN	MAX
ESHARE	Earnings Sharing	0.29	0.42	0.00	1.00
HPCR	Hybrid Price Cap Regulation	0.17	0.34	0.00	1.00
PCR	Price Cap Regulation	0.06	0.22	0.00	1.00
OIR	Other Incentive Regulation	0.26	0.42	0.00	1.00
FIBER	Fiber Km per Sheath Km of Cable	6.33	3.62	0.02	16.48
TOLLC	% Toll Calls	15.34	7.23	3.35	89.78
BSLINE	% Business Access Lines	31.41	8.74	16.80	69.61
SIZE	Logged Total Revenue	26.73	27.04	1.83	122.84
BELL	Regional Operating Bell Company	0.72	0.45	0.00	1.00
HUMCAP	Compensation per Employee (in thousands)	70.57	9.40	15.60	104.27
CORCO	% R & D Expenses	1.75	0.51	0.87	3.14
COCS	% Customer Operations Expenses	18.21	3.24	12.20	26.90

Table 4.6 Factors Explaining Productivity Growth Change

	Model 1		Model 2		Model 3	
	Coefficient	Expected Sign	Coefficient	Expected sign	Coefficient	Expected sign
CONSTANT	1.0101***		1.013***		1.0119***	
	(0.0166)		(0.0166)		(0.0171)	
OIR	0.0104**		0.0052		0.0028	
	(0.0049)		(0.0072)		(0.0073)	
OIR $_{t-1}$			0.0069		-0.0006	
			(0.0068)		(0.0089)	
OIR $_{t-2}$					0.0113*	
					(0.0062)	
ESHARE	0.0084		0.0023		-0.0002	
	(0.0052)		(0.007)		(0.0068)	
ESHARE $_{t-1}$			0.009		0.0025	
			(0.0068)		(0.0082)	
ESHARE $_{t-2}$					0.0106*	
					(0.0063)	
HPCR	0.0231***		-0.0011		-0.0073	
	(0.007)		(0.0116)		(0.0108)	
HPCR $_{t-1}$			0.0316***		-0.0002	
			(0.0119)		(0.0146)	
HPCR $_{t-2}$					0.0331***	
					(0.00109)	
PCR	0.027***		0.0211***		0.0173***	
	(0.005)		(0.0072)		(0.0068)	
PCR $_{t-1}$			0.0096		0.0045	
			(0.0073)		(0.0084)	
PCR $_{t-2}$					0.0083	
					(0.0069)	
FIBER	0.0018***	O	0.0017***	O	0.0016***	O
	(0.0005)		(0.0005)		(0.0006)	
TOLLC	0.1405***	O	0.1361***	O	0.256***	O
	(0.0194)		(0.0194)		(0.0265)	
BSLINE	-0.0635***	O	-0.0616***	O	-0.0381	O
	(0.0194)		(0.0195)		(0.0191)	
SIZE	-3.49E-08		-5.76E-08		-7.32E-08	
	(6.05E-08)		(6.12E-08)		(5.93E-08)	
BELL	0.0222***	O	0.0227***	O	0.0236***	O
	(0.0047)		(0.0047)		(0.0046)	
HUMCAP	-0.0042	X	-0.0117	X	-0.0402**	X
	(0.0163)		(0.0166)		(0.0171)	
CORCO	-1.0197***	X	-0.9634***	X	-0.8206**	X
	(0.3553)		(0.3542)		(0.3501)	
COCS	-0.0405	X	-0.0383	X	-0.071	X
	(0.0511)		(0.0514)		(0.0478)	
Adjusted R^2	0.5585		0.5648		0.6451	

Note: Numbers in parentheses are standard errors.

O (X) indicates that expected signs and actual signs are the same (different)

*** = significant at 1% level. ** = significant at 5% level. * = significant at 10% level.

CHAPTER 5 - Conclusion

This dissertation is comprised of three empirical essays that investigate the effect of mergers and regulation in the U.S. telecommunications industry. The first two essays, chapters 2 and 3, respectively, address the effect of a series of mergers in the telecommunications industry following the passage of the 1996 Telecommunications Act (1996 Act). The third essay, chapter 4, investigates the effect of the implementation of incentive regulation in the telecommunications industry.

The primary objective of chapter 2 is to determine whether productivity growth has increased among ILECs that have merged since the 1996 Telecommunications Act and whether the merged firms performed better than firms that did not merge in terms of productivity growth during the period 1996-2005. The empirical results of this chapter suggest that mergers positively affected average productivity growth over the sample period.

The primary objective of Chapter 3 is to evaluate the effectiveness of mergers that occurred between 1996 and 2005 using SFA. This chapter also compares productivity growth results between the SFA and the Malmquist index approach. Both methods indicate that every firm in the sample has experienced negative annual growth in technological change. Furthermore, both methods indicate that most of the firms in the sample experience negative annual productivity growth following the merger.

Chapters 2 and 3 suggest that consolidation reduces deterioration in productivity growth. This result is of potential value to both government and industry as further consolidation may be in the offing.

The primary objective of Chapter 4 is to measure productivity growth associated with technological progress and changes in technical efficiency in order to examine the improvement in the LECs' productivity growth following the adoption of incentive regulation. The results of Chapter 4 indicate that the adoption of PCR and IR, more generally, has had positive impact on operating performance in the U.S. telecommunications industry. In addition, PCR has a significant and positive effect on productivity growth in both contemporaneous and lagged model specifications.

Chapter 4, in contrast to the other literature, provides strong empirical evidence in support of the theoretical literature concerning the superiority of price cap over traditional rate-of-return regulation.

Broadly speaking, the contributions of this dissertation are two fold. First, measuring the efficiency gains associated with consolidation in the U.S. telecommunications industry has been given relatively little attention in the literature heretofore. Two of the essays address whether the efficiency gains expected from these mergers were, in fact, realized. Second, the stochastic frontier analysis employed in this dissertation has not been applied pervasively in the analysis of the telecommunications sector. Therefore, these three empirical essays collectively provide a rigorous analysis of timely issues that may be employed by regulators charged with implementing public policy in the telecommunications sector—a sector of the economy that is responsible for a significant and increasing share of gross domestic product.[86]

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[86] According to Bureau of Economic Analysis, the broadcasting and telecommunications sector in the U.S. generated $304.1 billion dollars of GDP in 2005.

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