Effect of regulatory reform on the efficiency of mobile telecommunications *

by

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Abstract

Regulatory reform of the mobile telecommunications sector has been introduced to improve productivity and competitiveness. We use Data Envelopment Analysis and Stochastic Frontier Analysis, and a second-stage econometric analysis to identify the effect of different aspects of reform on productivity and its constituent parts across twenty-two firms from seven countries over 1998-2007. While measures of firm performance are sensitive to the choice of methodology, we find robust evidence that competition and independent regulation improve firm efficiency. Privatized firms are not necessarily more efficient, but can improve productivity more quickly than their public counterparts.

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1. Introduction

Regulatory reform of network industries to improve their productivity and national competitiveness has been widespread in developed, developing and transition economies over the past two decades. Reform is introduced at least in part to improve productivity by changing the utilities' incentives and providing the appropriate economic environment within which management responds to these incentives (Vickers and Yarrow 1984). A number of empirical studies have assessed the effect both of overall reform programmes and their constituent elements in utilities (see e.g., Markou and Waddams Price, 1999 for an early assessment, Parker 2004 for a survey of studies in the UK, and Newbery, 2004, for an international comparison). These studies generally conclude that privatisation increases productivity only in the context of either a competitive market or independent regulation – change of ownership alone does not improve efficiency.

While early studies of regulatory reform focused on ownership, it became clear that the role of the independent regulator was a crucial factor in performance. Gilardi (2002) argued that greater independence would lend credibility to the regulator's actions and increase the environmental stability for the regulatees, enabling them to improve productivity. Eschenbach and Hoekman (2005) show that independent regulation, including in the telecoms sector, is associated with higher macro economic performance in transition countries. Fink et al. (2003) find that a comprehensive reform programme including independent regulation is the most effective in improving efficiency in a large sample of developing countries. Wallsten (2001) had found similar effects from separate regulation in developing countries, but noted the need for refinement of the 'independent regulator' variable.

Reform in the telecommunications sector, typically involving privatisation, introduction of competition and establishment of an independent regulator, has been dominated by the mobile market in recent years. Telecommunications provide both the basis for overall economic development (Rőller and Waverman, 2001), and efficient delivery of telecoms services reduces transactions costs and accelerates information diffusion, and has experienced a wave of reforms across its markets Arnold et al. (2008) demonstrate that inappropriate information and communications regulation can inhibit growth in other sectors of the economy, and Eschenbach and Hoekman (2005) note the importance of service industry reform on economic growth in transition economies. More recently, attention has focused on mobile telecommunications sector reform, typically including privatizing incumbent mobile telecoms providers, introducing competition, and establishing an independent industry regulator. If such reform is to deliver benefits, analysis of its impact on performance offers important policy insights for countries where reform is incomplete or nonexistent. Regulators most commonly use operating efficiency and total factor productivity (TFP) change to evaluate the effectiveness of either broad reform programmes or certain specific regulations.[2]

Prior studies on telecoms reforms and TFP/efficiency have confirmed the general findings for utilities that competition, where it can be effectively introduced, is better able to deliver innovation, enhanced TFP and lowered prices (e.g. Armstrong and Sappington, 2006). The transfer of telecoms from the public to the private sector and the establishment of an independent regulator have also become an important strategy of improving telecoms performance, and these policies are the focus of our analysis.

Many studies have used within-country data to examine the relationship between telecommunications sector reform and TFP/efficiency. Kwoka (1993) found that the competition for AT&T in the US and the privatisation of British Telecom in the UK had delivered significant improvement in the firms' TFP. The findings for the US were also confirmed by Oum and Zhang (1995) who suggested that competition improved the allocative efficiency of the incumbent firms, reducing the Averch-Johnson effect generated by rate-of-return regulation. Gort and Sung (1999) also found a positive effect of competition on TFP growth by comparing the performance of firms in competitive and monopolistic markets, using data for the AT&T long lines and eight local exchange monopolies.

Studies from other countries confirmed these findings. Shin and Ying (1992) suggested that increased competition after breaking up the former Bell system in Canada resulted in significant productivity gains. Boer and Evans (1996) found substantial network TFP growth, cost reduction and consumer welfare gains after the New Zealand telecoms market deregulation and elimination of the incumbent firm's statutory monopoly in 1989. In Japan, Oniki *et al*. (1994) also suggested that there was a significantly faster TFP improvement for Nippon Telegraph and Telephone (NTT) after liberalization.

Several studies have examined the relation between productivity and reform in the telecoms sector across countries. Staranczak *et al.* (1994) examined the impact of private ownership and competition on telecommunications industry TFP growth, using panel data for 10 OECD member countries over a five-year period, 1983-1987, and concluded that TFP growth was increased by private ownership; they could find no significant relationship between productivity growth and competition, but argued that this might be because of low levels of competition at the time in the countries examined. More recently, Madden and

[2] Note that the TFP measurement can be decomposed into the catch-up and innovation components, which subsequently allows for disentangling the factors that explain productivity variations across carriers.

Savage (1999, 2001) employed a Malmquist index to calculate telecommunications TFP growth for 74 countries over 1991-1995, and then estimated a model relating TFP growth to a series of measures of industry development/environment. They concluded that increased privatisation and competition were conducive to productivity growth, technology catch-up and innovation. Madden *et al.*'s (2003) study confirmed the findings of their earlier empirical work, that competition and private ownership improve carriers' TFP growth, based on 12 Asia-Pacific telecommunications carriers during 1987-1990. Tsai et al (2006) use DEA to compare efficiencies of global telecoms operators, and conclude that competition enhances productivity efficiency.

We extend these studies of fixed line markets to examine the mobile sector, which is rapidly replacing fixed line telephony in size and significance. We also follow more recent literature to include a new variable in the industry landscape, the existence of an independent industry regulator, to test for evidence of its importance in good regulatory governance. Cubbin and Stern (2006), Gasmi *et al*. (2006), Gual and Trillas (2003), Guttierez (2003a, 2003b), Gutierrez and Berg (2000), and Stern and Holder (1999) all focus on identifying the characteristics of regulatory institutions which are associated with higher levels of various performance measures, such as fixed-line penetration or electricity generation. These studies suggest that the existence of a strong and independent judiciary, which is able to make decisions independently and is backed by legislation rather than executive decree, is a crucial institutional element of good regulatory governance. Li and Lyons (2011) examined the relationship used panel-data for 29 OECD counties and China from 1991-2006, and found that the presence of an independent industry regulator affected mobile network penetration and expansion positively.

The present study follows Madden *et al.* (2003), the only other study to use firm-level data in a cross-country study, but extends the approach both to the mobile market and by including non dominant providers for each country. Furthermore, unlike previous studies in this area[3], we exploit the difference between methodologies to add robustness to our conclusions, by applying both a stochastic production frontier function approach and a DEA methodology to compare the results and address some of the criticisms which have been levelled at each methodology.[4]

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[3] None of the telecoms TFP/efficiency papers listed has applied stochastic frontier analysis (SFA) which can handle measurement errors in the data.

[4] For example, Nadiri and Nandi (1999) examined TFP growth for the US telecommunications industry from 1935-1987, using an integrated multi-output/multi-inputs translog variable cost function, and compared to the traditional Divisia index approach, they found that TFP growth rate as conventionally measured was a seriously biased measure of the rate of technical change in this industry.

This study identifies mobile sector performance (TFP/efficiency) for 22 mobile carriers from seven countries over the time period 1998-2007 and examines the impact of an independent industry regulator, as well as the effects of competition and privatization. Efficiency and TFP change are measured using two different frontier approaches – non-parametric data envelopment analysis (DEA) and parametric stochastic frontier analysis (SFA) (where a translog stochastic production frontier model is applied). The estimated TFP change itself is decomposed into two components – efficiency change (catch-up effect) and technical change (innovation). All the estimated measures of efficiency, TFP change, efficiency catch-up and technological innovation under the two approaches are further analyzed econometrically in relation to the impact of mobile sector reforms.

Our dual approach to measurement of efficiency and TFP change is justified by their sensitivity to the choice of methodology (DEA vs. SFA). However the second-stage econometric analysis provides robust results, suggesting that competition and the presence of independent regulation improve firm efficiency. The results also imply that it is not necessary for firms to be privatized to be more technically efficient, but privatized firms are more capable of enhancing their TFP growth, efficiency catch-up and technological innovation in the production process in a shorter time period compared with their public counterparts.

The remainder of this paper is structured as follows. The next section elaborates both the methodologies of DEA and SFA approaches, and theoretical expectations of the sector reform. Section 3 describes the data. Section 4 presents and discusses the empirical results. Section 5 concludes the paper with methodological and policy implications.

2. Methodology

In this section we describe the concept of frontier measurement, the two methodologies which we have used and how we have related our findings on firm efficiency to regulatory reforms in the firms' environments.

Frontier-based benchmarking methods have been widely used to identify and estimate the efficient performance frontier from best practice in a sample of firms. Two approaches to measuring frontier models, based upon Farrell's (1957) work, have been well documented, and applied primarily to utilities and infrastructure industries (such as electricity, gas, telecommunication and water). Non-parametric Data Envelopment Analysis (DEA) and parametric Stochastic Frontier Analysis (SFA) have often been presented as competing methodologies, since they use rather different procedures to define the efficient frontier.[5] The debate on robustness of these two performance measurements is receiving growing academic attention (Whiteman, 1995; 1998; Kirkpatrick et al. 2006; Lin and Berg, 2008), and we respond to this debate by measuring the performance of mobile carriers using both DEA and SFA approaches to check for robustness.

2.1. Malmquist Total Factor Productivity index

We use the Malmquist TFP index approach defined in Caves *et al*. (1982) and Färe *et al*. (1994), using distance functions, to calculate the total factor productivity change.[6] For the advantage of utilising this approach, see Arocena and Waddams Price (2002). In this study, a single-output and multi-input technology is required.[7] Following Färe *et al*. (1994), the Malmquist TFP index between period *t* (the base period) and period *t+1* is given by:[8]

$$M_o\left(y^{t+1}, x^{t+1}, y^t, x^t\right) = \left[\frac{d_c^t\left(x^{t+1}, y^{t+1}\right)}{d_c^t\left(x^t, y^t\right)} \times \frac{d_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{d_c^{t+1}\left(x^t, y^t\right)}\right]^{1/2}, \quad (1)$$

where the notation $d_c^t\left(x^{t+1}, y^{t+1}\right)$ represents the distance from the period *t+1* observation to the period *t* technology. A value of M_o greater than unity indicates positive TFP growth from the periods *t* to *t+1*, while a value less than unity indicates a TFP decline. Note that the Malmquist TFP index is, in fact, the geometric mean of two TFP indices. The first is measured with respect to period *t* technology and the second with respect to period *t+1* technology.[9]

We adopt a two-part decomposition of the Malmquist TFP index in which the components represent technical efficiency change ($EFFCH_c$) and technological change ($TECHCH_c$) respectively.[10] An equivalent way of writing this TFP index is:

$$M_o\left(y^{t+1}, x^{t+1}, y^t, x^t\right) = \frac{d_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{d_c^t\left(x^t, y^t\right)}\left[\frac{d_c^t\left(x^{t+1}, y^{t+1}\right)}{d_c^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{d_c^t\left(x^t, y^t\right)}{d_c^{t+1}\left(x^t, y^t\right)}\right]^{1/2}, \quad (2)$$

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[5] For DEA models, see Charnes, Cooper and Rhodes (1978). Lovell (1993) provides a good review. See also Ali and Seiford (1993), Färe *et al.* (1994), Lovell (1994), Seiford and Thrall (1990), and Seiford (1996). For SFA models, see Aigner *et al*. (1977), Greene (1990), Meeusen and van der Broeck (1977) and Stevenson (1990). For a review, see Bauer (1990) and Greene (1993, 1997, 2005). For the methodological comparisons, see Bjurek, Hjalmarsson and Forsund (1990), Ferrier and Lovell (1990), Hjalmarsson, Kumbhakar and Heshmati (1996), Gong and Sickles (1992), Oum and Waters (1996).

[6] We follow the distance function notation in the literature.

[7] In the case of a single-output technology, the (output-oriented) distance function is equivalent to the ratio of the observed output to the predicted frontier output for the observed input vector (i.e. the distance measure is equal to the traditional TE measure).

[8] The subscript ‘o’ denotes the Malmquist TFP index is an output-orientated measure. The subscript ‘c’ denotes these distance measures are under the CRS assumption.

[9] Intuitively, the productivity change is firm’s movement towards the frontier defined by the performance of the most efficient firms (best practices in a sample of firms).

[10] See Appendix 1 for the argument of the two-part decomposition.

Where ,

$$EFFCH_c = \frac{d_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{d_c^t\left(x^t, y^t\right)}, \tag{3}$$

and

$$TECHCH_c = \left[\frac{d_c^t\left(x^{t+1}, y^{t+1}\right)}{d_c^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{d_c^t\left(x^t, y^t\right)}{d_c^{t+1}\left(x^t, y^t\right)}\right]^{1/2}. \tag{4}$$

Below, the distance functions are estimated using SFA and DEA models to obtain the measures of technical efficiency (TE) for each firm in each of the observation years. Information on technical efficiency change and technological change are combined to measure the TFP change index.

2.2. SFA Model

Given a panel dataset we have, this study considers a 'true' fixed effects stochastic production frontier model specified for panel data as proposed by Greene (2004, 2005):[11]

$$y_{it} = \alpha_i + \beta' x_{it} + v_{it} - u_{it}, i = 1, 2,..., N; t = 1, 2,..., T, \tag{5}$$

where y_{it} is the (logarithm) output of the *i*-th DMU in the *t*-th year; x_{it} is a vector of (logarithm) inputs of the *i*-th DMU in the *t*-th year; β is a vector of unknown parameters; α_i is the DMUs' individual specific effects, v_{it} is the random error term which is assumed to be i.i.d. (independent and identically distributed) with $N(0, \sigma_v^2)$ distribution, and independent of u_{it} – the technical *in*efficiency. This model is fitted by maximal likelihood and allows time-varying technical efficiency.[12] All time invariant effects, such as unobserved heterogeneity are captured by α_i (the DMUs' individual specific component) and the technical *in*efficiency varies freely through time with $N(\mu_{it}, \sigma_u^2)$ distribution.[13] Note that in this parametric

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[11] This model has several distinct advantages: (1) allowing technical *in*efficiency effects to vary freely through time; (2) dispensing with the undesirable assumption that the firm inefficiency and heterogeneity are uncorrelated with the input variables; (3) controlling the effect of unobservable & time invariant heterogeneity on measuring *in*efficiency. See Greene (2004a, b; 2005) for a comprehensive discussion and comparison of different stochastic frontier models.

[12] The 'true' fixed effects model needs to be fitted twice with firstly estimating the model using pooled data to provide the starting values for the second estimation (see Greene, 2007).

[13] This is a more general case of a true fixed-effects, normal-truncated normal model, where the u_i are non-negative truncations of the $N(\mu_{it}, \sigma_u^2)$ distribution where $\mu_{it} = \mu(nonzero)\ or\ \delta' z_{it}$. Since the z_{it} factor in this study is not considered, so we have $\mu_{it} = \mu$, a constant for the simple case of truncated normal model. The μ is unknown and is estimated for my data. When the μ estimates are not significantly different from zero, then the normal-half normal distribution is assumed for the *in*efficiency effects, i.e. $u_i \sim N(0, \sigma_u^2)$. In addition, Greene (2004) argued that the *in*efficiency, u_{it}, would be absorbing a large amount of cross-country heterogeneity that would inappropriately be measured as *in*efficiency. Therefore, another possibility allowing the heterogeneity to enter the mean of the *in*efficiency distribution is considered. In this case, the simple normal-

approach, the primary objective is not the estimation of the model parameters, but the estimation of the *in*efficiency term, u_{it}, and thus to predict the technical efficiencies.

To compare different functional forms for the parametric SFA approach, we conduct three likelihood ratio (LR) tests: the model specification test of the Cobb-Douglas functional form versus the translog functional form; time effects that indicate the existence of significant technical change in the period of the firms being studied; and distribution form of *in*efficiency term (see Appendix 2 for the test results). The empirical stochastic production frontier model for our study is specified as a translog normal-truncated normal form with time effects:

$$\begin{aligned}\ln y_{it} = \alpha_i + \sum_{k=1}^{3}\beta_k \ln x_{kit} + \beta_\tau T + \frac{1}{2}\left\{\sum_{k=1}^{3}\sum_{j=1}^{3}\beta_{kj}\ln x_{kit}\ln x_{jit} + \beta_{\tau\tau}T^2\right\},\\ + \sum_{k=1}^{3}\beta_{k\tau}\ln x_{kit}T + v_{it} - u_{it},\ \left(i = 1, 2, ..., N; t = 1, 2, ..., T\right)\end{aligned} \tag{6}$$

Writing the expanded form as:

$$\begin{aligned}\ln Output_{it} &= \alpha_i + \beta_1 \ln L_{it} + \beta_2 \ln M_{it} + \beta_3 \ln K_{it} + \beta_4 T\\ &+ \frac{1}{2}\beta_{11}(\ln L_{it})^2 + \frac{1}{2}\beta_{22}(\ln M_{it})^2 + \frac{1}{2}\beta_{33}(\ln K_{it})^2 + \frac{1}{2}\beta_{44}T^2 \quad ,\\ &+ \beta_{12}\ln L_{it}\ln M_{it} + \beta_{13}\ln L_{it}\ln K_{it} + \beta_{23}\ln M_{it}\ln K_{it}\\ &+ \beta_{14}\ln L_{it}T + \beta_{24}\ln M_{it}T + \beta_{34}\ln K_{it}T + v_{it} - u_{it},\ \left(i = 1, 2, ..., N; t = 1, 2, ..., T\right)\end{aligned} \tag{7}$$

where the one output and three inputs of the *i*-th firm in the *t*-th year are all measured in *quantities* and in logarithm form (L_{it}, M_{it} and K_{it} denote the quantities of the labour input, material input and capital input of the *i*-th firm in the *t*-th year, respectively). The time trend variable, *T*, is included to capture the technical change which may affect the location of production frontier. The *in*efficiency term, u_{it}, is estimated to predict the TE scores for each firm in each observation year.[14] Since u_{it} is a non-negative random variable, the predicted TE scores are between 0 and 1, with a value of one indicating the full technical efficiency.

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truncated normal model (no z_{it} factors included) has $u_i \sim N(\mu_i, \sigma_u^2), \mu_i = \alpha_i + \mu$, where α_i is the cross-country heterogeneity. Finally, there is also another additional possible distribution of u_i may hold in which allows the heterogeneity to be shifted to the variance of the *in*efficiency distribution (e.g., the case of the simple exponential model or the simple heteroscedasticity model (no z_{it} factors included), $u_i \sim N(0, \sigma_{ui}^2), \sigma_{ui}^2 = \sigma_u^2 \times \exp\left(\alpha_i + \mu\right)$). However, data used in this study are not very well matched for such models – the estimators all terminated at maximum iterations without convergence (i.e. the likelihood function became quite flat and the function was no longer increasing). Therefore, in the application in this study, eventually, the true fixed effects, normal-truncated normal model is applied with allowing heterogeneity to enter the mean of the *in*efficiency distribution, i.e. $u_i \sim N(\mu_i, \sigma_u^2), \mu_i = \alpha_i + \mu$, such that the unobserved cross-country heterogeneity can be better controlled and thus the 'cleaner' *in*efficiency, u_{it}, can be estimated.

[14] The TE scores of each DMU in each year can be predicted using the conditional expectation of $\exp(-u_{it})$, given the value of $e_{it} = v_{it} - u_{it}$. According to the Debreu (1951)-Farrell (1957) measure of TE, we have a production model, $y_i = f(x_i, \beta)TE_i$. Since the production model will usually be linear in the logs of the variables, the empirical counterpart will be of the form, $\ln y_i = \ln f(x_i, \beta) + \ln TE_i = \ln f(x_i, \beta) - u_i$, where $u_i \geq 0$ is the measure of technical *in*efficiency as $u_i = -\ln TE_i \approx 1 - TE_i$. Hence, $TE_i = \exp(-u_i)$.

The Malmquist TPF index can be calculated via equations (2)-(4) using the measures of technical efficiency change and technological change obtained from estimating the above particular stochastic production frontier model. The TE estimates, $TE_{it} = E(exp(u_{it})|e_{it})$, are used to calculate the technical efficiency change component. That is, by observing that $d^t\left(x_i^t, y_i^t\right) = TE_{it}$ and $d^{t+1}\left(x_i^{t+1}, y_i^{t+1}\right) = TE_{it+1}$, the technical efficiency change is calculated as:

$$TE\ change = \frac{TE_{it+1}}{TE_{it}}. \tag{8}$$

This measure can be directly compared to Equation (3).

The technological change between adjacent periods t and $t+1$ for the i-th firm can be calculated directly from the estimated parameters from model (7) by partially differentiating the production function with respect to time (at a particular data point). By observing the period t technical change is $\frac{\partial \ln y_{it}}{\partial T} = \beta_\tau + \beta_{\tau\tau} T + \sum_{k=1}^{3} \beta_{k\tau} \ln x_{kit}$ and the period $t+1$ technical change is $\frac{\partial \ln y_{it+1}}{\partial (T+1)} = \beta_\tau + \beta_{\tau\tau}(T+1) + \sum_{k=1}^{3} \beta_{k\tau} \ln x_{kit+1}$, the technological change[15] between adjacent periods t and $t+1$ can be estimated using a geometric mean, that is,

$$\begin{aligned} Technical\ change &= \left\{ \left(1 + \frac{\partial \ln y_{it}}{\partial T}\right) \times \left(1 + \frac{\partial \ln y_{it+1}}{\partial (T+1)}\right) \right\}^{1/2} \\ &= \left\{ \left(1 + \beta_\tau + \beta_{\tau\tau} T + \sum_{k=1}^{3} \beta_{k\tau} \ln x_{kit}\right) \times \left(1 + \beta_\tau + \beta_{\tau\tau}(T+1) + \sum_{k=1}^{3} \beta_{k\tau} \ln x_{kit+1}\right) \right\}^{1/2}. \end{aligned} \tag{9}$$

This measure can be directly compared with Equation (4). Then, the measures of TE change and technological change from equations (8) and (9) can be multiplied to obtain the Malmquist TFP index as defined in Equation (2).[16]

2.3. DEA Model

In the non-parametric case, following Färe *et al*. (1994), the TFP index can be computed as the solution of four linear programming problems provided in Appendix 3, given that suitable panel data are available. Note that the calculation of the Malmquist TFP index requires strictly balanced panel data. That means all firms must be observed in all time periods. Since our sample is unbalanced, this would restrict us to use only the time period of 2002-2007 (with

[15] The technological change is non-neutral in our model; it may vary for different input vectors, unless if $\sum_k \beta_{k\tau} = 0$, then the technical change holds neutral.

[16] Note that the CRS assumption has not been imposed upon the estimated production frontier, meaning that the SFA TFP index will not capture any scale-related productivity changes. However, given that I find the scale economies are very close to 1 in this empirical work, we expect that any scale effects would be minimal. And hence, two DEA TFP and SFA TFP measures are expected to be comparable.

twenty firms observed), which substantially reduces the research sample size. We therefore extend innovatively the methodology above by constructing a series of six overlapping balanced sub-panels, and use each of these to calculate the Malmquist TPF index. The TFP measures for each firm in each two adjacent periods are recorded based on a common rule of selecting the measures obtained from the sub-panels with the most firms observed for those periods. By this sub-panel-by-time-group approach, there is no reduction in the sample size (all annual data information of all firms in the panel is utilized in measuring the TFP change). The TFP change is thus measured for each firm in each pair of adjacent years during all periods in which it can be observed, and the year-by-year TE scores for each firm are also obtained.

In summary, both parametric SFA and non-parametric DEA methods are applied in this firm-level efficiency and TFP study. Conventional and innovative approaches are adopted for DEA to deal with the unbalanced panel data in measuring technical efficiency and TFP change index. In order to keep the consistency of efficiency and Malmquist TFP measures, the output-oriented measure has been chosen. And finally, technical efficiency (TE), technical efficiency change (EFFCH) (catch-up effect), technological change (TECHCH) (innovation) and the Malmquist TFP change index (TFPCH) for each firm in each observed period are obtained and reported by the two approaches.

2.4. Econometric model for reform effects

We anticipate that the efficiency level and productivity growth of firms measured through DEA and SFA will be affected by regulatory reform. We use three indicators of such reform, measuring competition, ownership and independent regulation.

$Competition_{it}$ is measured by the number of mobile network operators (NoF_{it}) in a mobile market. Li and Lyons (2011) argue a non-monotonic effect of market structure on mobile network penetration, and find that three-to-five firms maximize consumer uptake. We examine the quadratic form of our competition measure in the model to explore further the potential nonlinear relationship between competition and the measures of carrier performance. There is well-established principle that competition stimulates productivity growth and results in technical and allocative efficiencies. As argued by North (1990), Levy and Spiller (1996) and Ros (1999), competitive prices and profits signal important information about the costs of an enterprise and the efficiency of inputs, which assists the principal in determining equipment inputs required to compete effectively. Hence, we expect a positive sign for the coefficient associated with the linear measure of competition (i.e. NoF_{it}). There is no *a priori* expectation for the sign associated with the nonlinear measures of competition (i.e. $sqNoF_{it}$).

$Private_{it}$ is a dummy variable indicating whether the firm is at least 50% privately owned. There is no *a priori* expectation for the sign of the coefficient associated with the privatisation dummy, since the existing literature on privatisation provides mixed results and arguments, even though policy-makers in many developed countries believe private ownership supports greater efficiency, innovation and improved customer service (Wellenius and Stern 1994). The conventional privatisation theory suggests that the transfer of public to private ownership should result in important efficiency gains, since changes in the principal-agent relationship and allocation of residual profits can drive a different structure of incentives for management supervision and financial decision-making (Laffont and Tirole, 1993; Shleifer, 1998). Management supervision and monitoring is costly. With public ownership, non-commercial objectives are pursued and less effort is exerted to use resources efficiently. Under private ownership, in contrast, the primary objective is to achieve profit maximization, and thus private ownership is associated with a higher level of management supervision and more commercial and timely financial decision-making. However, the conventional theory has been confronted with increasingly serious challenges by the recent contrary empirical evidence that state-owned firms are not intrinsically less efficient than privately-owned firms and that competition and regulatory policy are more influential determinants of firm performance and efficiency than ownership *per se*.[17] Yarrow (1986), Levy and Spiller (1994, 1996), Ramamurti (2000) and Villalonga (2000) argued that the success or failure of privatisation is highly dependent on political and economic environments in general and the post-privatisation regulatory framework in particular. A survey of the privatisation study by Megginson and Netter (2001) also suggests that the impact of privatisation alone is less clear, but the combination of privatisation and deregulation/liberalization is positively correlated with telecoms performance.

$Regulator_{it}$ is a dummy variable indicating whether an independent industry regulator exists in a mobile market. Given the pro-competition principle of industry regulator, a positive sign is expected for the coefficient associated with the independent regulator dummy. The relevant theory for this variable is the economic theory for regulatory institution and

[17] Early empirical works by Caves and Christensen (1980), Martin and Parker (1995), Kole and Mulherin (1997), Anderson, *et al*. (1997) and others suggest that in competitive market environments public and private firms are equally efficient. More recently, Dewenter and Malatesta (2001) conduct cross-sectional comparisons of government and private firms as well as time-series analysis of privatized firms using a large sample of accounting data reported in *Fortune* magazine, and find that the performance improvements largely occurs during the three years just before privatization and the evidence of further improvements after privatization is not very robust. They thus conclude that "the true rationale for privatization may not be to achieve efficiency gains, but to perpetuate them in the face of changing political circumstance" (p.334).

governance. The theory suggests that good regulatory governance tends to be associated with higher levels of certain performance measures, due to its more effective/credible commitment to private investments and pro-competitive regulatory principles (North, 1990; Levy and Spiller, 1996). And the empirical work on the determinants of the quality of regulatory governance in utility sectors suggests that the existence of a strong and independent judiciary is a crucial institutional element bearing on such good regulatory governance (see e.g., Cubbin and Stern, 2006; Gasmi *et al.*, 2006; Gual and Trillas, 2003; Guttierez, 2003a, b; Gutierrez and Berg, 2000; and Stern and Holder, 1999). Nevertheless, the existing literature pays little attention, with rare exceptions, to the explicit impacts of an independent regulator, *per se*, on the performance of mobile sector in general and of its firm-level in particular.[18] In the current global telecoms climate characterized by massive privatisation, to address this issue becomes increasingly important and has profound policy and managerial implications. That is because, firstly, in a fully privatized market, more credible government's commitment to industry investments and effective pro-competitive regulatory principles – delivered often by good regulatory governance – appear to be particularly important (Armstrong and Sappington, 2006; Levy and Spiller, 1994; 1996; Ramamurti, 2000 and Villalonga, 2000).[19] And the existence of an independent regulator is a key element of ensuring such good regulatory governance and in turn signals, to certain extent, the credibility of a government's commitment to private investments and the propensity to effective pro-competition. Secondly, in many developing countries, it is difficult and unrealistic to achieve a high quality of overall regulatory governance in a short time period when they just privatized or intend to privatize their telecom markets. Thus, one may inquire if establishing an independent industry regulator is the least effort to promote effective competition and deliver certain confidence to private investors. Therefore, this study addresses this issue by examining directly the impact of an independent regulator on mobile carrier TFP change and technical efficiency.

We employ the Feasible Generalized Least Squares (FGLS) procedure for panel data in the second stage which fits well with linear panel-data models and allows estimation in the presence of autocorrelation within panels and cross-sectional correlation and

[18] To the best of the author's knowledge, to the date this study is conducted, there are only two empirical works devoted to exploring the relationship between an independent regulator and mobile sector performance (Li, 2008; Maiorano and Stern, 2007). Both studies used the national-level mobile penetration rate as the measure of mobile sector performance, and suggested that the existence of an autonomous industry regulator has positive effects on the mobile penetration and expansion. However, there is no study examining the impact of an independent regulator on telecoms firm-level performance.

[19] Armstrong and Sappington (2006) argued that in settings where the government's commitment powers are limited, partial privatization of state ownership is preferable to full privatization, since when the government retains an ownership stake in the firm, the government will be the same as private investors – i.e. it will suffer financially – if it implements policies that reduce the firm's earnings. As a consequence, a promise by the government not to expropriate private investors may be more credible when the firm is partially privatized than when it is fully privatized.

heteroscedasticity across panels.[20] The FGLS procedure also allows the regression parameters to be estimated with spatially corrected error components.[21]

The econometric model for exploring the effects of mobile sector reform (including competition, privatisation and independent regulation) on the measures of mobile carrier performance is specified below,

$$y_{it} = \alpha_i + \beta_1(NoF_{it}) + \beta_2(sqNoF_{it}) + \beta_3(private_{it}) + \beta_4(regulator_{it}) + \theta'(Z_{it}) + \upsilon_i + \varepsilon_{it}, \quad (i = 1, ..., N;\ t = 1, ..., T) \tag{10}$$

where the dependent variable, y_{it}, is the estimated measures of mobile performance (under the SFA and DEA approaches) for the firm *i* at the time *t*; α_i is the intercept term for the firm *i*; $\beta_1, \beta_2, \beta_3, \beta_4$ and the vector of θ are the parameters to be estimated; NoF_{it}, $sqNoF_{it}$, $private_{it}$, and $regulator_{it}$ are the three reform variables indicating competition, privatisation and independent regulator for the firm *i* at the time *t*. We return to this below. Z_{it} is a vector of exogenous control factors (including GDP growth, time trend and regional dummies) – may affect performance – for the firm *i* at the time *t*; υ_i is the firm specific effects error term; and ε_{it} is white-noise error term. This model is estimated four times using different estimated measures of firm performance as dependent variables, including TE scores, TFP change, efficiency change (catch-up) and technological change (innovation) indices. We estimate each regression model twice, with each of the DEA and SFA derived measures, to check for robustness.

Detailed data information on mobile carriers' outputs and inputs and mobile sector reform indicators are described in the next section.

3. Data and performance estimation results

Mobile telecommunications carrier data are collected for the twenty-two mobile network providers[22] from seven countries selected to represent different regions and major economic

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[20] In the literature, a censored (Tobit) model has been predominantly used in regression of non-parametric estimates of productive efficiency on environmental variables in two-stage procedures to account for exogenous factors that might affect firms' performances. However, according to Simar and Wilson (2007), the tobit model employed in the second stage regression in the existing two-stage studies are invalid due to complicated, unknown serial correlation among the estimated efficiencies. A truncated regression model was used and demonstrated better performance in their study, but it does not fit panel data estimation applied in this study. Furthermore, since the distribution of the DEA estimated efficiency scores in this empirical work does not have a mass of points at 1.0, to keep the comparability between the regression results of the DEA and SFA estimates, these points are thus not censored.

[21] See Kapoor, Kelejian and Prucha (2007) for detailed theoretical and technical points.

[22] The twenty-two mobile network providers cover the main mobile network operators in each selected country, based on their market share. Most selected network providers are ranked as the top twenty mobile operators by the International Telecommunications Union (ITU).

powers, including the USA, Canada, the UK, France, Germany, China and Korea.[23] The data used for estimating mobile carrier TE and TFP change are drawn from 213 carrier annual reports over 1998-2007. Different national output and input definitions and accounting standards present challenges in constructing consistent measures of carriers' TE and TFP.[24] To meet this challenge and maximise our sample size, we use relatively aggregated measures of output and input data. Regional and company information is used wherever possible, and consolidated information used for two country carriers – France Telecom (Orange) and Deutsche Telekom (T-Mobile). Balancing the most available and useable data information, we obtain a firm-level unbalanced panel dataset with 178 observations, comprising yearly data information on one output and three inputs for twenty-two decision making units (i.e. mobile carriers) from seven national mobile markets over the time period 1998-2007. Table 1 lists the names of these mobile carriers and the regional operating markets observed as well as the time periods covered.[25]

-- *Please insert Table 1 about here* --

- *Output measures*

Output value is measured by total operating revenue from the mobile service segment. It typically consists of network service revenue (i.e. voice services, messaging and other data services) and sales of terminal equipment and excludes interest income, disposals, capital gains/losses and dividends[26].

Output price is used to deflate the value of output into a quantity measure that is consistent across DMUs. Output price is based on the national average mobile price index, calculated for each sample country and collected from ITU.

Output quantity is measured by total operating revenue deflated by the average mobile price index in each country in US$s at 2000 prices.

- *Input measures*

(i) Labour quantity is the number of employees working in the mobile service segment.

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[23] Seven representative countries (i.e. six from the OECD members plus China) are selected to conduct this firm-level efficiency and productivity study, involving two North-American countries, three European countries and two East-Asian countries (the Japanese mobile carriers are not included primarily due to severe lack of data information on the inputs).

[24] For instance, sometimes detailed information on outputs and inputs are reported while for others information is offered in aggregated form; sometimes regional information is reported while for others information is provided in consolidated form; and sometimes company information is reported while for others information is provided also in consolidated form.

[25] The output and inputs are recorded as what happened in the individual specific operating market of each DMU. For example, we record the inputs used by Vodafone in the UK mobile market for producing the output in the UK mobile market only as the inputs and output for Vodafone UK; and record the inputs used by Vodafone in the German mobile market for producing the output in the German mobile market only as the inputs and output for Vodafone Germany; and so forth. In addition, all output and inputs information used in this current study is for the mobile phone service segment only.

[26] The information on the sales of terminal equipment are only provided separately by a few carriers in our sample. We cannot separate them from the total operating revenue. But, based on the information, equipment sales only count very small proportion of the total revenue.

(ii) Material cost is measured by non-personnel operating expenses in the mobile service segment. It consists primarily of consumption of goods and merchandise, services obtained from outside suppliers, materials, cost of acquisition and maintenance of customer services, and administration.

Material price is used to deflate material cost into quantity measure that is consistent across carriers. Material price is proxied by a producer price index (PPI) for a manufacturing products basket (2000 = 100). The PPI data are available for all sample countries in this study at the OECD online statistical database.

Material quantity is PPI deflated non-personnel operating expenses.

(iii) Capital cost is measured by the total depreciation and amortization of property, plant and equipment in the mobile service segment in each year.

Capital price is proxied by the weighted average cost of borrowings reported in carrier annual reports.[27]

Capital quantity is calculated by dividing capital cost by capital price.

-- Please insert Table 2 about here --

Table 2 presents the summary statistics of the output and input measures (labour, material and capital) over the period of 1998-2007 (i.e. calculated means across twenty-two carriers by year). The quantities are listed in the first four columns, and values are followed in the same order. The quantity measures of the (single) output and (three) inputs are used for the DEA and SFA models to estimate TE scores and TFP change indices (and its two components) for the twenty-two mobile carriers over ten observation years.

Following the literature, three reform variables are included. The first is mobile market competition, measured by the number of mobile network operators (*NoF*) in an observed national/regional market. The second, a privatisation dummy equals one if the mobile carrier is privately owned (i.e. at least 50% of assets are held by the private sector), and equals zero otherwise. Thirdly, an independent regulation dummy equals one if the observed national mobile market has a statutory industry regulator which claimed independence of any other

[27] There is a debate in measuring the price (cost) of capital. In the existing literature of telecoms efficiency and productivity study, various measures are used – two in particular. The first one is related to the rate of depreciation. The second one uses PPI as a deflator of capital expense. Since I have treated PPI as a proxy of material price to deflate material expense, and in turn obtain the quantity of material input, the second measure is certainly not preferred if a better one can be used. Regarding the first one, any measure related to depreciation rate is unsuitable for measuring the capital price in the mobile network industry. That is because the depreciation rate for mobile network carriers is very high, and sometimes even exceeds 100%. Therefore, the result can be distorted, if depreciation rate related measure of capital price is used in estimating TE and TFP.

Despite that to the authors' knowledge, the method of weighted average cost of capital (WACC) is a common practice used in accounting and finance to approach cost of capital (see e.g., Bruner et al. 1998; Truong et al. 2008); this approach cannot be applied in this study as a result of lack of financial and stock market information for most of my sample mobile carriers. Accordingly, the closest measure – weighted average cost of borrowings (WACB) – is used as a proxy of capital price.

political power, and equals zero otherwise. Each of these reform variables is compiled as time-series, mainly using the regulatory information provided by the International Telecommunications Union (ITU) online regulatory database, and complemented by country telecoms regulators' and mobile carriers' websites.[28]

Other exogenous factors that may affect mobile carriers' performances are also used as control variables in our econometric model. GDP growth (available online from the OECD) is used to capture the national economic environment. A time variable, *T*, is also included to account for possible unmeasured dynamic changes. Two region dummies indicating Europe and North-America are used for regional comparison, using East-Asia as the base case.

Table 3 presents a summary of ownership status, market regulatory environments, GDP growth and the estimated TE scores and TFP change indices across the mobile carriers over their observation periods. In the sample, all European and North-American mobile carriers are privately owned throughout the period. In East-Asia, only the two Chinese firms remain state-owned, after Korea fully privatized its mobile telecoms sector in 2002. In addition, along with the long-established independent regulators in the UK, the US and Canada, France, Korea and Germany had all created independent industry regulators by 1998, but China was still without one at the end of the period. By 2007, an oligopolistic market structure was dominant in most countries in the sample, though in China the mobile market remained a duopoly.

The technical efficiency scores, measured by DEA and SFA are presented in Table 3, and all estimated performance measures in Appendix 4.

-- Please insert Table 3 about here –

The technical efficiency scores measured by TPA and SFA are shown in table 3. While there is considerable variation between the sizes of the two measures, both show greater productivity growth in European and North American firms than in Asia. However the two measures differ in their assessment of direction of growth in East Asia. For China, DEA indicates negative growth for the two firms, while SFA suggests positive growth, while the reverse is true for two South Korean firms.

-- Please insert Table 4 about here --

[28] Given the existence of a substantial time-lag between the government's announcement of a policy and an observed result, some researchers (e.g. Fink et al., 2001) have considered to apply a one-year-lag effect of policy changes in their studies. For instance, they used to record privatization not in the year it was announced by government but in the year after the sale of equity was completed; moreover, if the sale was completed relatively late in the year, they treat the privatization as effective from the following calendar year. Similarly, they observed the effective competition not in the year the new operators just commenced services if they entered the market relatively late in that year, but in the following year. We follow this idea plus a consideration of the time of *learning by doing* for new entries in this study. Therefore, as a rule, we record all reform variables as effective from the following year they occurred, since it is the least ambiguous criterion that they can take effect in the following year. In doing so, for example, we observe privatization in a given year was taken as effective from the following year; observe any entries (exits) in the following year that they commenced (stopped) services in the markets, and thus any changes in the number of mobile carriers in a market are recorded in the following observed year; and record the starting year of an independent regulator as one year after it was established.

Table 4 summarizes the trends of mobile carriers' performance measures by region (i.e. the calculated means of estimated TE scores, TFP change, efficiency catch-up and technological innovation from the mobile carriers in the sample). The two approaches suggest similar trend patterns in each of those estimated performance measures across the three regions, but the DEA approach produces some extreme results, especially for those periods with very few observations. For this reason discussion of trends in carriers' performances across regions is based on the SFA results. The East-Asian mobile carriers, on average, exhibit worse performances than European and North-American carriers in our sample. Over the ten-year period, the average technical efficiency of the East-Asian firms decreased from 0.87 to 0.82 (i.e. an average 0.64% decrease per annum). Moreover, the average TFP growth and technological progress (innovation) in the East-Asian firms were low, only an average 1.26% and 1.79% increase per annum respectively, while the average efficiency declined by 0.53%. In contrast, the firms in the European and North-American regions demonstrated a strong increasing trend in efficiency catch-up and innovation over the years observed, combining into a part. European firms, on average, achieved a 4% per annum increase in their TFP, mainly due to a yearly 2.5% increase in innovation, while North-American firms made an even higher average increase of 5.7% per annum in their TFP (over a 10-year period, 1998-2007), contributed by an annual 2.5% increase in efficiency catch-up and an annual 3% increase in innovation as well.

4. Empirical findings of reform effects

In this section we identify how the four different measures of firm performances (from DEA and SFA approaches), are influenced by the mobile sector reforms and other control variables, basing our analysis on equation (10) above.

4. 1. Technical efficiency

-- Please insert Table 5 about here --

Table 5 presents the estimated relationship between each of the two measures of total efficiency and the reform and other variables. Likelihood ratio tests indicate that the quadratic form of number of firms is preferred to the linear form, and across the two measures a clear inverted U-shaped relationship is found between the number of firms and firms' technical efficiencies, with the highest level of technical efficiency where four or five firms compete in a market.[29] An independent regulator exerts a significant positive effect on technical efficiency, but privatisation alone seems to have little effect. Indeed it has a weakly negative effect in the DEA specification.

With both DEA and SFA measures, technical efficiency increases with time, but GDP growth has no significant effect on firms' technical efficiencies. There is a positive time trend in both specifications. The coefficients associated with regional dummies indicate that on average, the European and North-American firms are less technically efficient than the East-Asian firms when other determinants are included.

4.2. TFP change, catch-up and innovation

We next explore the effect of reform variables on changes in total productivity, and on its constituent parts of efficiency change (catch-up) and technical change (innovation).

-- Please insert Table 6 about here --

Table 6 presents the results of estimating equation (10) using (DEA and SFA) productivity related measures. The estimation results reveal significant and positive effects of competition and privatisation on firms' TFP growth and on both its two components (catch-up and innovation). The effect of competition (number of firms) is slightly stronger on catch-up than on innovation, while the effect of privatisation seems similar across all measures of productivity change. Note that the lack of significance of privatisation in determining efficiency levels, and its strong positive effect on productivity growth, imply that it is not necessary for firms to be privatized to perform more technically efficiently, but privatized firms may be more capable of enhancing their TFP growth through technological innovation in the production process and efficiency catch-up than their public counterparts.

While competition and privatisation have a strong positive effect on growth, independent regulation has a consistently negative effect. We have checked that this is not a result of regional dummies, and that it is distinct from the positive effect of privatisation. Combined with the positive effect of independent regulation on efficiency *levels*, this suggests that independent regulation enables firms to establish higher levels of efficiency than where such regulation is not present, but inhibit further growth in productivity.

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[29] That is calculated by maximizing technical efficiency with respect to the number-of-firm, i.e. $\frac{\partial TE}{\partial NoF} = 0.246 - 2 \times (0.028) NoF = 0,$ and thus, NoF = 4.4 (for the DEA estimates). And similar calculation using the SFA estimates, we have NoF = 4.6.

Regarding the effects of other control variables on the TFP change, catch-up and innovation indices, TFP is little affected by a time trend, since it has opposite on each of its component parts. Technical change, reflecting innovation, changes positively with time, but catching up deteriorates, leaving a neutral net effect by both DEA and SFA measures. GDP growth is positively and significantly correlated with increases in the TFP, the pace of catch-up and innovation. There is no significant difference in growth rates or constituents across the different regions. We note considerable consistency between the results from the DEA and SFA methodologies in these regressions.

In sum, the empirical results confirm the positive effect of competition in enhancing both the level of firms' efficiency, and productivity growth in the mobile telephone firms. Privatisation seems to have little effect on level of efficiency, but enhances growth; while the presence of an independent regulator is associated with higher levels of efficiency, but lower productivity growth.

5. Conclusions

We have examined the relationship between a series of mobile carrier performance measures (technical efficiency, TFP change, efficiency catch-up and technological innovation) and mobile sector reforms (competition, privatisation and independent regulation), using unbalanced panel data for twenty-two mobile carriers from seven countries over the time period 1998-2007. We first estimated firm performance measures using both nonparametric (DEA) and parametric (SFA) frontier approaches, and then analyzed econometrically how the estimated firm performance measures related to measures of mobile sector reform. Our empirical results reveal that although the measures of firm performance (i.e. technical efficiency, TFP change, efficiency catch-up, and technological innovation) are sensitive to the choice of methodology (DEA or SFA), the econometric analyses provide robust results. We discuss the effect of each of the reform variables in turn.

Competition

Our main finding is the strong and robustly positive effect of competition. The higher the level of competition in a mobile market, the greater is the level of efficiency of a firm, and the faster is TFP growth, efficiency catch-up and technological innovation. However the effect of competition is not linear, but levels off. The highest technical efficiency and growth within firms occurs when a mobile market is served by a four- or five-firm oligopoly. Our results confirm the findings of Li's (2008) and Li and Lyons's (2011) empirical work on national level mobile network penetration, which also suggests a deleterious effect of new entry beyond the fifth firm, with the third to fifth entrant apparently having little different effect in contributing to penetration. The reflection of these national findings at firm level both illustrates one mechanism through which market level performance levels off, and how incentives which are stimulated by competition between few firms have a reverse effect as competitor numbers exceed four. Intermediate levels of competition drive the highest economic efficiency, confirming suggestions by Motta (2004) and some empirical evidence (Cave and Barton, 1990; Green and Mayes, 1991; Aghion et al., 2002).

Privatisation

Privatisation exerts complex effects on mobile carrier performances. On one hand, privatisation is associated with few benefits in the levels of efficiency. Indeed there is weak evidence from the DEA analysis that privately owned firms are likely to have lower levels of efficiency than state owned ones. However levels of growth, measured by innovation, catching up and overall TFP, are all positively related to private ownership. This could be explained by higher investment in the development of mobile network technology by private firms, which would reduce static levels of efficiency in the short run because of the greater inputs with no immediate reward. This is consistent with the observation by Madden and Savage (2001) that higher rates of digitisation (in the short run) create inefficiency due to the initial adjustment costs of technology adoption. On the other hand, private ownership is associated with significantly enhanced TFP growth, efficiency catch-up and technological innovation. Our empirical results imply that it is not necessary for firms to be privatized to perform higher technical efficiency, but privatized firms are more capable of enhancing their TFP growth, efficiency catch-up and innovation in the production process in a shorter time period than their public counterparts.

Independent regulation

The findings on independent regulation may appear somewhat surprising at first sight. The presence of an independent regulator has a clear positive effect on efficiency, showing that those firms subject to independent regulation have a higher level of productivity. But productivity growth is persistently lower amongst firms subject to independent regulation than in those which are not. This could be interpreted as a restrictive effect of the regulator, perhaps in introducing some rules which inhibit innovation, perhaps to aid vested interests, and is at odds with other research, particularly in developing countries, which has found the effect of a regulator on technology growth rates of firms to be positive.[30] Our results may reflect the relative maturity of the regulatory system, since no new regulators were established during the period of the study. Our findings are consistent with an initial one off positive effect from the regulator's creation (before the first observations in our series), which raises the efficiency level of firms. In markets without an independent regulator, firms experience a more gradual move towards improved efficiency which is reflected in higher growth of efficiency measures.

However in interpreting these results we should note that the only firms without an independent regulator during our time period are those in China, so the findings may reflect the relatively low level of efficiency in Chinese firms at the beginning of the period and their high increases in efficiency (relative to other firms in our sample) during the ten years of the study.[31] The absence of an independent regulator is only one factor which may have affected the Chinese firms' relative position, though some local factors have been controlled for through use of regional dummies.

5.1. Methodological note

In this study, both DEA and SFA methods are used to estimate mobile carrier technical efficiency scores and TFP change indices. The overall comparison between the DEA and SFA results suggests that the measures of efficiency and TFP are somewhat sensitive to the choice of methodology. In particular, the DEA approach may produce meaningless or unrealistic results when the number of observations is small or substantial unobserved heterogeneity (or other statistic noise) exist across carriers/countries in the dataset. The SFA approach, in contrast, can deal efficiently with the statistical noise (measurement errors) in the data, and thus reports more manageable and reliable results. Therefore, when examining industry/firm efficiency and TFP, it is important to pay close attention to the choice of methodology,

[30] See, Cubbin and Stern, 2006; Gasmi *et al.*, 2006; Gual and Trillas, 2003; Guttierez, 2003ab; Gutierrez and Berg, 2000; and Stern and Holder, 1999.
[31] A similar comment applies (though less strongly) to the findings on private ownership, since only the Chinese firms were state owned throughout. However there is more variation in this variable since the South Korean firms were privatised during the period of study.

especially when the industry/sector studied is volatile and undergoing fast growth as here in the mobile network industry. To be confident in the outcomes, comparisons of performance across decision making units (and years) need to be checked for robustness using different methodologies.

5.2. Policy Implications

We have presented evidence from twenty-two mobile phone firms and seven countries of the effect of three reform variables on measures of efficiency and growth. Reforms are undertaken for a variety of reasons, both political and economic. Our evidence shows the different effects of reform on the level and the growth in efficiency, and suggests there may be a trade-off between the short term and long term efficiency: privatisation does not seem to lead to higher levels of efficiency, but does lead to higher efficiency growth; an independent regulator has exactly the reverse effect. But the most robust finding is the positive effect on both levels and growth in firm efficiency of competition, which has profound implications for the design of markets. In an area which is sensitive both from a political and business perspective, governments and regulators should encourage active rivalry between four or five firms, but extending such competition to more entrants may have little, or negative impact on the productivity of the participants. Such evidence is crucial as firms may seek consolidation to enhance market power, and governments and competition authorities consider the most appropriate market structure.

Table 1: List of the names, operating markets and years for observed mobile carriers

Unit-code	Firm name	Regional market	Periods covered	No. years	Unit-code	Firm name	Regional market	Periods covered	No. years
D1	China Mobile	China	98-07	10	D12	E-plus	DE	02-07	6
D2	China Unicom	China	98-07	10	D13	Orange France	FR	02-07	6
D3	Vodafone UK	UK	99-07	9	D14	Bouygues Telecom	FR	01-07	7
D4	O2UK	UK	99-07	9	D15	SFR	FR	98-07	10
D5	Orange UK	UK	02-07	6	D16	SK Telecom	Korea	98-07	10
D6	Orange FT	--	99-07	9	D17	KTF	Korea	98-07	10
D7	T-mobile	--	01-07	7	D18	LG Telecom	Korea	98-07	10
D8	T-mobile Europe	Europe	05-07	3	D19	Sprint Nextel	US	98-07	10
D9	T-mobile USA	US	05-07	3	D20	Verizon Wireless	US	98-07	10
D10	O2Germany	DE	00-07	8	D21	Rogers Wireless	Canada	98-07	10
D11	Vodafone Germany	DE	02-07	6	D22	Telus (Mobility)	Canada	99-07	9

Note: Consolidated information is used for DMU6 and DMU7.

Table 2: Summary statistics of output and inputs for twenty-two mobile carriers from 1998 to 2007

	OutputQ	LQ	MQ	KQ	OutputV	LV	MV	KV
	Mean							
1998	23.13	7890.11	15.07	70.74	2217.42	291.24	1467.84	458.79
1999	34.30	9980.46	23.86	88.26	3351.74	362.25	2315.60	571.66
2000	46.94	14744.36	29.51	126.65	4694.43	468.33	2951.40	809.09
2001	61.24	18211.00	38.64	223.92	6282.31	656.59	3870.76	1321.48
2002	69.66	17336.25	41.30	537.59	7265.85	697.77	4114.11	3172.00
2003	86.20	17802.60	49.82	251.06	9183.40	852.65	5036.10	1437.22
2004	101.63	20665.05	58.69	345.41	11068.81	1033.38	6152.10	1858.38
2005	119.37	22620.09	69.49	425.45	13342.51	1191.90	7587.28	2237.05
2006	134.32	23816.05	75.05	460.50	15398.83	1511.33	8467.77	2640.58
2007	152.31	25495.64	86.14	462.32	17812.51	1672.61	9991.60	2864.78
Average annual change rate	23.82%	14.83%	22.16%	33.47%	26.58%	21.82%	24.46%	32.34%

Note: OutputQ is the quantity of output; LQ, MQ and KQ are the quantities of labour, material and capital inputs, respectively. OutputV is the value of output; LV, MV and KV are the values of labour, material and capital inputs, respectively; all values are measured in million (USD).

Table 3: Summary of mobile reform and firm performance across observed mobile carriers

Firm	Ownership	Independent regulator	Number MNOs by 2007	Technical efficiency 2007 (DEA)	Technical efficiency 2007 (SFA)	Average annual TFP change (DEA)	Average annual TFP change (SFA)	Average annual GDP growth
China		No	2					9.24%
China Mobile	state			0.8331	0.9242	-0.06%	5.70%	
China Unicom	state			0.5456	0.5917	-0.31%	4.88%	
Korea		Yes	3					4.33%
SK Telecom	private (2002)			0.8035	0.8968	1.63%	1.07%	
KTF	private (2002)			1.0000	0.8368	2.39%	-2.73%	
LG Telecom	private (2002)			0.8145	0.8524	2.10%	-2.64%	
Unite Kingdom		Yes	5					2.76%
Vodafone UK	private			0.7885	0.8760	-2.25%	0.87%	
O2UK	private			0.8446	0.9103	-0.28%	2.09%	
Orange UK	private			1.0000	0.9326	6.82%	2.84%	
Deutschland		Yes	4					1.34%
O2Germany	private			1.0000	0.9045	49.13%	9.35%	
Vodafone Germany	private			1.0000	0.9742	1.64%	3.41%	
E-plus	private			0.9780	0.9533	8.64%	4.10%	
France		Yes	3					2.15%
Orange France	private			1.0000	0.9741	5.66%	1.21%	
Bouygues Telecom	private			0.7547	0.8413	-4.53%	1.40%	
SFR	private			0.9735	0.9429	3.36%	2.75%	
Unite Sates		Yes	6					2.98%
T-mobile USA	private			0.8163	0.8962	4.25%	4.36%	
Sprint Nextel	private			0.7914	0.7838	16.37%	6.12%	
Verizon Wireless	private			1.0000	0.9803	2.22%	5.54%	
Canada		Yes	5					3.26%
Rogers wireless	private			1.0000	0.9689	3.30%	3.49%	
Telus (Mobility)	private			0.9921	0.8773	7.46%	8.05%	

Note: parentheses in the ownership and independent regulator columns show the year of the events happened if they occurred during the period being studied.

Data source: ITU online regulatory information database, countries' regulatory websites, mobile carriers' websites, OECD online statistical database, firm performance data are from author's calculation.

Table 4: Trends of mobile performance by region 1998-2007

DEA estimates	**Technical efficiency**			**TFP change**			**Efficiency change (catch-up effect)**			**Technical change (innovation)**		
	East-Asia	Europe	North-America	East-Asia	Europe	North-America	East-Asia	Europe	North-America	East-Asia	Europe	North-America
1998	0.9418	0.9469	0.7428									
1999	0.9342	0.9134	0.7637	-1.46%	-9.10%	16.40%	2.04%	-3.80%	21.50%	-3.50%	-5.50%	-4.37%
2000	0.9779	0.7529	0.7528	4.60%	2.20%	3.13%	4.88%	-1.20%	2.55%	-0.50%	3.53%	0.00%
2001	0.9731	0.8316	0.7708	4.56%	48.68%	1.30%	-0.56%	59.14%	3.68%	5.08%	-5.62%	-2.20%
2002	0.9572	0.8443	0.8671	-10.36%	-0.61%	16.65%	-1.20%	7.83%	21.68%	-9.24%	-7.97%	-3.95%
2003	0.8823	0.8589	0.8604	-6.54%	11.03%	6.58%	-8.22%	1.53%	-0.58%	2.24%	9.38%	7.28%
2004	0.8606	0.8551	0.8805	7.02%	1.55%	7.78%	-1.52%	-0.85%	1.63%	8.44%	2.33%	6.08%
2005	0.8808	0.8942	0.9124	4.30%	0.22%	2.28%	2.24%	7.52%	6.42%	2.36%	-6.70%	-3.60%
2006	0.8511	0.9158	0.9474	4.54%	7.78%	11.56%	-5.14%	2.99%	3.38%	11.34%	4.07%	8.06%
2007	0.7993	0.9095	0.9200	3.70%	3.31%	1.48%	-3.84%	-1.13%	-2.64%	9.06%	4.55%	4.24%
Number of units observed	n = 5	n = 12	n = 5	n = 5	n = 12	n = 5	n = 5	n = 12	n = 5	n = 5	n = 12	n = 5
Average change rate	-1.74%	-0.17%	2.49%	1.15%	6.93%	7.17%	-1.26%	6.14%	5.67%	2.81%	1.12%	1.70%

SFA estimates	**Technical efficiency**			**TFP change**			**Efficiency change (catch-up effect)**			**Technical change (innovation)**		
	East-Asia	Europe	North-America	East-Asia	Europe	North-America	East-Asia	Europe	North-America	East-Asia	Europe	North-America
1998	0.8716	0.8434	0.7943									
1999	0.8382	0.8875	0.7424	-5.23%	-5.06%	-0.61%	-3.52%	-4.03%	-0.83%	-1.87%	-1.08%	0.21%
2000	0.8516	0.8595	0.7438	0.84%	3.81%	1.25%	1.45%	4.60%	0.22%	-0.62%	-0.75%	1.03%
2001	0.8891	0.8347	0.7496	4.80%	-0.89%	3.96%	4.45%	-1.33%	1.84%	0.44%	0.45%	2.05%
2002	0.8706	0.9145	0.8228	-0.63%	11.23%	13.46%	-1.92%	8.98%	10.60%	1.28%	2.00%	2.68%
2003	0.8733	0.9273	0.8706	3.07%	3.68%	10.19%	0.84%	1.58%	7.10%	2.14%	2.08%	2.92%
2004	0.8592	0.9316	0.8765	1.00%	2.75%	4.61%	-1.66%	0.63%	0.94%	2.74%	2.11%	3.61%
2005	0.8701	0.9200	0.9047	4.36%	1.65%	7.72%	0.91%	-1.09%	3.35%	3.49%	2.76%	4.28%
2006	0.8597	0.9253	0.9226	2.97%	4.50%	6.75%	-1.09%	0.83%	2.01%	4.08%	3.63%	4.67%
2007	0.8204	0.9211	0.9013	0.14%	3.82%	2.59%	-4.21%	-0.41%	-2.45%	4.41%	4.25%	5.16%
Number of units observed	n = 5	n = 12	n = 5	n = 5	n = 12	n = 5	n = 5	n = 12	n = 5	n = 5	n = 12	n = 5
Average change rate	-0.64%	1.05%	1.51%	1.26%	3.69%	5.66%	-0.53%	1.19%	2.47%	1.79%	2.48%	3.14%

Note: change indices are measured over a pair of adjacent periods.

Table 5: Panel-data FGLS regression results of reform effects on the DEA and SFA TE estimates

Dependent Variable	DEA estimates	SFA estimates
Competition effects:		
NoF	0.246***	0.184***
	5.91	*6.65*
sqNoF	-0.028***	-0.020***
	-5.73	*-6.43*
Privatization effects:		
Private	-0.061*	0.018
	-1.61	*0.71*
Independent regulator effects:		
IndReg	0.391***	0.464***
	4.29	*7.35*
Other control effects:		
Time trend	0.010***	0.009***
	2.66	*4.10*
GDP_growth	0.0001	0.0001
	0.08	*0.08*
Europe	-0.061***	-0.035**
	-2.43	*-1.91*
N-America	-0.079**	-0.080***
	-1.97	*-3.23*
	n = 178	n = 178
FGLS	Wald chi2(8) = 13124.81	Wald chi2(8) = 26034.09

Note: East-Asia is the base case used for the regional comparison.
Z-statistics are reported below each coefficient in *italic* type. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table 6: Panel-data FGLS regression results of reform effects on the DEA and SFA TFP change, efficiency change and technical change indices

Dependent variable	TFP change		Efficiency change (catch-up)		Technical change (innovation)	
	DEA	SFA	DEA	SFA	DEA	SFA
Competition effects:						
NoF	0.472***	0.491***	0.467***	0.493***	0.357***	0.455***
	9.94	*15.41*	*10.03*	*15.43*	*8.96*	*17.27*
sqNoF	-0.047***	-0.050***	-0.046***	-0.051	-0.036***	-0.045
	-9.21	*-14.37*	*-9.24*	*-14.68*	*-8.74*	*-16.24*
Privatization effects:						
Private	0.291***	0.232***	0.253***	0.220***	0.256***	0.240***
	4.47	*5.19*	*4.23*	*5.22*	*4.84*	*6.15*
Independent regulator effects:						
IndReg	-0.320***	-0.371***	-0.274***	-0.305***	-0.189***	-0.344***
	-4.16	*-7.00*	*-3.66*	*-5.86*	*-2.86*	*-7.83*
Other control effects:						
Time trend	-0.003	-0.0003	-0.010**	-0.007**	0.009***	0.004*
	-0.59	*-0.11*	*-2.15*	*-2.20*	*2.71*	*1.49*
GDP_growth	0.026***	0.027***	0.029***	0.027***	0.037***	0.029***
	3.60	*5.25*	*4.26*	*5.32*	*6.35*	*6.85*
Europe	-0.072*	-0.025	-0.014	-0.040	-0.065*	-0.041*
	-1.46	*-0.72*	*-0.31*	*-1.20*	*-1.59*	*-1.42*
N-America	-0.087*	0.013	-0.045	-0.006	-0.050	-0.050*
	-1.48	*0.29*	*-0.81*	*-0.14*	*-1.11*	*-1.57*
FGLS	n = 156 Wald chi2(8) = 12486.13	n = 156 Wald chi2(8) = 28404.23	n = 156 Wald chi2(8) = 11769.17	n = 156 Wald chi2(8) = 26332.29	n = 156 Wald chi2(8) = 22461.01	n = 156 Wald chi2(8) = 41836.20

Note: East-Asia is the base case used for the regional comparison.
Z-statistics are reported below each coefficient in *italic* type. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

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Appendix 1

Färe *et al*. (1994) proposed a three-part decomposition form, given that the VRS is assumed, in which the $EFFCH_c$ can be further decomposed into two more components: pure technical efficiency change ($PEFFCH_v$) and scale efficiency change (*SECH*) (The subscript 'v' denotes these distance measures are under the VRS assumption). It can be expressed as,

$$\underset{(EFFCH_c)}{\frac{d_c^{t+1}(x^{t+1}, y^{t+1})}{d_c^t(x^t, y^t)}} = \underset{(PEFFCH_v)}{\frac{d_v^{t+1}(x^{t+1}, y^{t+1})}{d_v^t(x^t, y^t)}} \times \underset{(SECH)}{\frac{SE^{t+1}(x^{t+1}, y^{t+1})}{SE^t(x^t, y^t)}}.$$

Färe *et al*.'s (1994) Malmquist TFP index is thus decomposed into three components as:

$$M_o(y^{t+1}, x^{t+1}, y^t, x^t) = PEFFCH_v \times SECH \times TECHCH_c.$$

However, a problem of internal inconsistency appears in this three-part decomposition posed above, as pointed out by Ray and Desli (1997). They strongly argued that Färe *et al*.'s measure of technical change, defined in Equation (2), is correct only when CRS is assumed. However, if this is the case, then under CRS no scale inefficiency exists by definition. In other terms, if scale inefficiency does exist and leads to the VRS assumption, then Färe *et al*.'s measure of technical change is flawed because it does not measure the shift in the VRS frontier. Ray and Desli (1997) then proposed their decomposition of the Malmquist TFP index based on VRS frontiers. However, Ray and Desli's decomposition is not without problems. Firstly, as Färe *et al*. (1997) pointed out, although Ray and Desli provided different specifications for the *TECHCH* and *SECH* components based on VRS reference technology, their overall Malmquist TFP index was still computed in terms of a CRS benchmark. Therefore, Ray and Desli's overall measure of Malmquist TFP is in essence identical to Färe *et al*.'s. Secondly, Ray and Desli (1997) also recognized that highest average productivity could only be achieved at the tangent point of VRS and CRS frontiers. The problem then becomes whether or not one believes that the VRS frontier can represent best practice in the industry. If not, then there is no ground to use the shift of VRS frontier to represent technical change correspondingly. Thirdly, Grifell-Tatje and Lovell (1995) pointed out that when VRS is assumed, the Malmquist TFP index defined in Equations (1 & 2) provides an inaccurate measure of TFP change. This inaccuracy is systematic and depends on the magnitude of scale economies. All these observations question the rationality of using the VRS frontier as a benchmarking technology for calculating the Malmquist TFP indices. Therefore, this paper adopts the CRS frontier as a benchmarking technology; meanwhile, in recognition of Ray and Desli's inconsistency argument against Färe *et al*.'s decomposition, the two-part decomposition is applied in this study.

Appendix 2: Likelihood ratio tests for SFPF

Stochastic frontier production functions, as defined in Equation (6), are estimated using the data described in the data section. A number of hypothesis tests are conducted, regarding (A) the functional form; (B) the existence of technical change (time effects); and (C) the distribution form of *in*efficiency term. The results of these three LR tests and the estimation results for the finally decided model are presented in Table below.

Hypotheses tests for parameters of the SFPF models and final model estimation results

Null hypothesis	$LogL_{H1}$ (unrestricted model)	$LogL_{H0}$ (restricted model)	LR statistics	Critical value	Decision
A. H_0: Cobb-Douglas model is preferred ($\beta_{kj} = \beta_{k\tau} = \beta_{\tau\tau} = 0$, $k, j = 1, 2, 3$)	-19.137	-32.115	25.96	18.31	Reject H_0, in favour of translog model
B. H_0: no technical change (time effects) ($\beta_{\tau} = \beta_{k\tau} = \beta_{\tau\tau} = 0$, $k = 1, 2, 3$)	-19.137	-28.351	18.43	11.07	Reject H_0, significant technical change exists
C. H_0: normal-half normal model is preferred (μ=0)	43.483	25.634	35.69	3.84	Reject H_0, normal-truncated normal model is preferred

Maximum-likelihood estimates of translog normal-truncated normal model

β_l	0.068	*(0.107)*	$\beta_{\tau\tau}$	0.003	*(0.002)*
β_m	0.770	*(0.179)*	β_{lm}	-0.316	*(0.095)*
β_k	0.054	*(0.079)*	β_{lk}	0.138	*(0.054)*
β_τ	-0.030	*(0.038)*	β_{mk}	-0.018	*(0.056)*
β_{ll}	0.045	*(0.039)*	$\beta_{l\tau}$	0.018	*(0.012)*
β_{mm}	0.220	*(0.074)*	$\beta_{m\tau}$	-0.023	*(0.020)*
β_{kk}	-0.091	*(0.022)*	$\beta_{k\tau}$	0.012	*(0.009)*
λ	6.231	*(1.714)*			
σ	0.568	*(0.119)*			

Note: standard errors are presented in the parentheses next to the coefficients. The first-order coefficient estimates may be interpreted as production elasticities at the sample mean because the data was mean-corrected prior to estimation.

The first LR test in Table above is a test of the Cobb-Douglas functional form versus the translog functional form. The test result indicates that the more flexible translog form is favoured in this empirical analysis. The following LR test is related to the test for the existence of technical change (time effects). The result indicates significant technical change in the period being studied. The last LR test is a test to see if the *in*efficiency error term has a half-normal distribution or a truncated-normal distribution allowing heterogeneity to enter the mean of the *in*efficiency distribution. The test result indicates that the normal truncated-normal model was preferred to control over the cross-unit heterogeneity absorbed by the *in*efficiency term. Thus, the finally preferred SFA model used in the entire empirical analysis is a translog (including time effects) normal truncated-normal model, approached by the true fixed effects procedure.

Appendix 3

For each DMU, four distance functions must be calculated to measure the TFP change between two periods, *t* and *t+1*. This requires solving four LP problems. The required LPs are specified as follows:

$$\left[d_c^t\left(y^t, x^t\right)\right]^{-1} = \max_{\phi,\lambda} \phi, \quad s.t. \; -\phi y_{i,t} + \sum_s \lambda_s y_{s,t} \geq 0, \quad x_{i,t} - \sum_s \lambda_s x_{s,t} \geq 0, \lambda_s \geq 0, s = 1, ..., N; \tag{11}$$

$$\left[d_c^{t+1}\left(y^{t+1}, x^{t+1}\right)\right]^{-1} = \max_{\phi,\lambda} \phi, \quad s.t. \; -\phi y_{i,t+1} + \sum_s \lambda_s y_{s,t+1} \geq 0, \quad x_{i,t+1} - \sum_s \lambda_s x_{s,t+1} \geq 0, \lambda_s \geq 0, s = 1, ..., N; \tag{12}$$

$$\left[d_c^t\left(y^{t+1}, x^{t+1}\right)\right]^{-1} = \max_{\phi,\lambda} \phi, \quad s.t. \; -\phi y_{i,t+1} + \sum_s \lambda_s y_{s,t} \geq 0, \quad x_{i,t+1} - \sum_s \lambda_s x_{s,t} \geq 0, \lambda_s \geq 0, s = 1, ..., N; \tag{13}$$

$$\left[d_c^{t+1}\left(y^t, x^t\right)\right]^{-1} = \max_{\phi,\lambda} \phi, \quad s.t. \; -\phi y_{i,t} + \sum_s \lambda_s y_{s,t+1} \geq 0, \quad x_{i,t} - \sum_s \lambda_s x_{s,t+1} \geq 0, \lambda_s \geq 0, s = 1, ..., N. \tag{14}$$

where y_{it} is the single-output quantity for the *i*-th DMU in the *t*-th year; x_{it} is a vector of three input quantities for the *i*-th DMU in the *t*-th year; λ_s is a vector of optimal weights defined by optimization LP problem (with a constraint $\beta' x_i = 1$ to avoid the problem of infinite solutions), such that the efficiency measure of the *i*-th DMU is maximized subject to the restriction that the efficiencies of all DMUs must be less than or equal to 1, and that all weights are non-negative; and ϕ is a scalar, reflecting the degree to which the output can be expanded (or contracted). In the solution, $1 \prec \phi_i \prec \infty$, and the value of $\phi_i - 1$ measures the extent to which outputs could conceivably be increased using the same inputs – relative to other DMUs in the sample. The value of $1/\phi_i$ is the *output-oriented* TE score for the *i*-th DMU.[32] It satisfies

[32] An alternative view of the optimization process is to consider the *input-oriented* efficiency measure, i.e. measuring the extent to which the DMU could reduce inputs to obtain the same output – again relative to the standard of other DMUs in the sample. The LP problem for *input-oriented* efficiency measure is specified as: Min. w.r.t. θ_i, λ: θ_i

Subject to
$$\sum_s \lambda_s y_s - y_i \geq 0, s = 1, 2, ..., N$$
$$\theta_i x_i - \sum_s \lambda_s x_s \geq 0,$$
$$\lambda_s \geq 0,$$

where the scalar θ_i is the *input-oriented* TE score for the *i*-th DMU, satisfying $\theta_i \leq 1$, with a value of 1 indicating a point on the frontier and thus a technically efficient DMU. However, the *input-oriented* efficiency measure provides the same value as the *output-oriented* efficiency measure under the CRS. In addition, it should be emphasized that the *output*- and *input*-oriented models will estimate exactly the same frontier and therefore, by definition, identify the same set of DMUs as being efficient. It is only the efficiency measures associated with the *in*efficient DMUs that may differ between the two methods if the VRS is assumed. Although the two measures are unequal under the VRS, nevertheless, the influences upon the efficiency scores obtained are only minor (Coelli and Perelman, 1996). This point is also confirmed by my data. Hence, in this study, in order to consist with Färe *et al*.'s (1994) CRS (*output-oriented*) Malmquist TFP measure (also used in this study), the *output-oriented* efficiency measure is chosen.

$0 \prec 1/\phi_i \leq 1$, where a value which equals 1 indicates a point on the frontier and hence a technically efficient DMU, referring to the Farrell (1957) definition.

The above four LPs must be solved for each DMU, for each pair of adjacent periods to calculate the TFP change index. Thus, for example, with 22 DMUs and 10 years of annual data, this equates to 22 × (3 × 10 − 2) = 616 LPs. The DEAP Version 2.0 computer program (Coelli, 1996) was used to carry out these calculations in this study.

Appendix 4

Summary of TE scores across units by year from DEA and SFA models

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Mean
DEA approach											
CM	0.99	1.00	1.00	1.00	1.00	0.97	0.88	0.91	0.77	0.83	0.94
CU	0.72	0.85	0.90	0.87	0.81	0.68	0.64	0.61	0.55	0.55	0.72
VodafoneUK	.	1.00	1.00	0.96	0.97	0.89	0.83	0.86	0.81	0.79	0.90
O2UK	.	0.91	0.92	0.94	0.80	0.80	0.80	0.84	0.97	0.84	0.87
OrangeUK	.	.	.	.	0.87	0.89	0.83	1.00	1.00	1.00	0.93
OrangeFT	.	0.90	0.86	0.94	0.89	0.93	0.92	0.93	0.82	0.88	0.90
T-mobile	.	.	.	0.59	0.71	0.91	0.92	0.87	0.89	0.85	0.82
T-mobileEurope	.	.	.	.	.	.	.	0.84	0.90	0.85	0.86
T-mobileUSA	.	.	.	.	.	.	.	0.87	0.86	0.82	0.85
O2Germany	.	.	0.14	0.56	0.60	0.68	0.68	0.74	1.00	1.00	0.68
VodafoneGermany	.	.	.	.	1.00	1.00	1.00	1.00	0.98	1.00	0.99
E-plus	.	.	.	.	0.73	0.69	0.78	0.83	0.89	0.98	0.82
OrangeFrance	.	.	.	.	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Bouygues Telecom	.	.	.	1.00	0.87	0.80	0.79	0.87	0.76	0.75	0.84
SFR	0.95	0.84	0.84	0.83	0.85	0.87	0.85	0.96	0.98	0.97	0.89
SK Telecom	1.00	0.91	1.00	1.00	1.00	1.00	0.85	1.00	0.94	0.80	0.95
KTF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
LG Telecom	1.00	0.91	0.99	1.00	0.97	0.77	0.94	0.88	1.00	0.81	0.93
Sprint Nextel	0.30	0.45	0.58	0.72	0.78	0.70	0.75	0.81	0.88	0.79	0.67
Verizon Wireless	1.00	1.00	0.93	0.91	1.00	1.00	1.00	1.00	1.00	1.00	0.98
Rogers wireless	0.93	0.85	0.83	0.83	0.82	0.76	0.78	0.88	1.00	1.00	0.87
Telus (Mobility)	.	0.75	0.67	0.63	0.87	0.98	1.00	1.00	1.00	0.99	0.88
Mean	0.88	0.88	0.83	0.86	0.88	0.87	0.86	0.90	0.91	0.89	0.88
SFA approach											
CM	0.93	0.93	0.94	0.97	0.94	0.94	0.90	0.91	0.91	0.92	0.93
CU	0.59	0.59	0.59	0.59	0.59	0.64	0.62	0.59	0.59	0.59	0.60
VodafoneUK	.	0.97	0.97	0.95	0.96	0.96	0.95	0.93	0.90	0.88	0.94
O2UK	.	0.91	0.94	0.91	0.90	0.93	0.93	0.91	0.94	0.91	0.92
OrangeUK	.	.	.	.	0.93	0.96	0.94	0.95	0.93	0.93	0.94
OrangeFT	.	0.86	0.92	0.93	0.94	0.96	0.96	0.95	0.89	0.92	0.93
T-mobile	.	.	.	0.72	0.94	0.94	0.90	0.92	0.93	0.91	0.90
T-mobileEurope	.	.	.	.	.	.	.	0.90	0.93	0.91	0.91
T-mobileUSA	.	.	.	.	.	.	.	0.91	0.91	0.90	0.90
O2Germany	.	.	0.59	0.59	0.73	0.81	0.82	0.79	0.94	0.90	0.77
VodafoneGermany	.	.	.	.	0.98	0.98	0.98	0.98	0.98	0.97	0.98
E-plus	.	.	.	.	0.89	0.82	0.92	0.90	0.93	0.95	0.90
OrangeFrance	.	.	.	.	0.98	0.98	0.98	0.97	0.97	0.97	0.98
Bouygues Telecom	.	.	.	0.89	0.89	0.90	0.92	0.90	0.82	0.84	0.88
SFR	0.84	0.81	0.88	0.85	0.91	0.95	0.95	0.95	0.95	0.94	0.90
SK Telecom	0.93	0.89	0.97	0.98	0.97	0.97	0.96	0.97	0.95	0.90	0.95
KTF	0.95	0.91	0.94	0.95	0.93	0.94	0.93	0.96	0.93	0.84	0.93
LG Telecom	0.95	0.87	0.82	0.97	0.92	0.88	0.88	0.92	0.91	0.85	0.90
Sprint Nextel	0.59	0.59	0.61	0.72	0.81	0.80	0.83	0.84	0.86	0.78	0.74
Verizon Wireless	0.98	0.98	0.98	0.97	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Rogers wireless	0.81	0.80	0.80	0.71	0.85	0.89	0.81	0.90	0.96	0.97	0.85
Telus (Mobility)	.	0.61	0.59	0.59	0.65	0.81	0.89	0.90	0.90	0.88	0.76
Mean	0.84	0.82	0.82	0.83	0.89	0.90	0.90	0.91	0.91	0.89	0.88

Summary of SFA & DEA results of efficiency change, technical change and TFP change

	Obs.	SFA model			DEA model		
		EFFCH	TECHCH	TFPCH	EFFCH	TECHCH	TFPCH
1998-1999	9	0.9732	0.9891	0.9633	1.0788	0.9599	1.0364
1999-2000	13	1.0204	0.9985	1.0188	1.0229	1.0089	1.0341
2000-2001	14	1.0164	1.0090	1.0253	1.2197	0.9918	1.1939
2001-2002	16	1.0598	1.0194	1.0808	1.0847	0.9264	1.0066
2002-2003	20	1.0250	1.0226	1.0483	0.9867	1.0718	1.0575
2003-2004	20	1.0012	1.0257	1.0268	0.9948	1.0461	1.0416
2004-2005	20	1.0030	1.0325	1.0354	1.0598	0.9619	1.0165
2005-2006	22	1.0066	1.0397	1.0466	1.0123	1.0663	1.0790
2006-2007	22	0.9826	1.0450	1.0270	0.9791	1.0550	1.0298
1998-2007	**156**	**1.0099**	**1.0243**	**1.0346**	**1.0389**	**1.0175**	**1.0532**
China Mobile	9	0.9991	1.0580	1.0570	0.9821	1.0268	0.9994
China Unicom	9	1.0005	1.0483	1.0488	0.9747	1.0250	0.9969
Vodafone UK	8	0.9876	1.0215	1.0087	0.9754	1.0031	0.9775
O2UK	8	1.0008	1.0202	1.0209	0.9979	0.9993	0.9973
Orange UK	5	1.0001	1.0284	1.0284	1.0320	1.0390	1.0682
Orange FT	8	1.0090	1.0271	1.0360	1.0120	1.0076	1.0174
T-mobile	6	1.0462	1.0428	1.0908	1.0858	0.9988	1.0810
T-mobile Europe	2	1.0030	1.0458	1.0488	1.0015	1.0465	1.0475
T-mobile USA	2	0.9932	1.0508	1.0436	0.9665	1.0790	1.0425
O2Germany	7	1.0674	1.0242	1.0935	1.5181	0.9966	1.4913
Vodafone Germany	5	0.9989	1.0352	1.0341	1.0002	1.0164	1.0164
E-plus	5	1.0163	1.0245	1.0410	1.0622	1.0230	1.0864
Orange France	5	0.9991	1.0130	1.0121	1.0000	1.0566	1.0566
Bouygues Telecom	6	0.9923	1.0219	1.0140	0.9765	0.9813	0.9547
SFR	9	1.0133	1.0141	1.0275	1.0207	1.0141	1.0336
SK Telecom	9	0.9971	1.0140	1.0107	0.9888	1.0283	1.0163
KTF	9	0.9865	0.9862	0.9727	1.0000	1.0239	1.0239
LG Telecom	9	0.9904	0.9829	0.9736	0.9916	1.0364	1.0210
Sprint Nextel	9	1.0344	1.0263	1.0612	1.1606	1.0066	1.1637
Verizon Wireless	9	1.0001	1.0552	1.0554	1.0031	1.0187	1.0222
Rogers wireless	9	1.0237	1.0107	1.0349	1.0300	1.0044	1.0330
Telus (Mobility)	8	1.0506	1.0286	1.0805	1.0526	1.0254	1.0746

EFFCH: technical efficiency change; TECHCH: technical change; TFPCH: Malmquist total factor productivity change. Note that all Malmquist index averages are geometric means.