Estimation of Cost Efficiency without Cost Data

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Abstract

One of the advantages of conduct parameter games is that they enable estimation of market power without total cost data. In line with this, we develop a conduct parameter based model to estimate the firm specific “implied cost efficiency” and conduct without using total cost data. We use our methodology to estimate the conducts and marginal cost efficiencies of U.S. airlines.

Keywords: Market power; Conduct parameter; Efficiency; Stochastic frontier analysis; Airlines

JEL classification: C13, L13, L93

1 Introduction

A widely used market power measure is the Lerner index (1934), which is the ratio of price-marginal cost mark-up and price. One potential difficulty for calculating the Lerner index is that the total cost data may not be available, which makes estimation of the marginal cost difficult. A potential solution to this problem is estimating a conduct parameter (or conjectural variations) game in which the firm form a conjecture about the variation in the other firms’ strategies (e.g., output) in response to a change in its

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†See Perloff, Karp, and Golan (2007) and Bresnahan (1989) for more details on conduct parameter approach.
own strategy. For given demand and cost conditions, the conjecture corresponding to the observed price-cost margins can be estimated "as-if" the firms are playing a conduct parameter game. In this setting the "implied marginal cost" can be estimated via a supply-demand system.

Stochastic frontier analysis (SFA) literature relaxes the full efficiency assumption of neoclassical production theory by allowing firms to act suboptimally. Among others, one potential reason for inefficiency is the principle agent problem that the objectives of shareholders and manager are not fully aligned. For example, the manager may use extra staff to reduce manager workloads at expense of higher costs. In SFA literature, cost efficiency is defined as the ratio of minimum cost to actual cost. A standard stochastic frontier model estimates cost inefficiency from a (log-transformed) cost function, which treats the cost inefficiency as an unobserved non-negative error term. The resulting model would have a composed error term consisting of a one-sided error term, which captures cost inefficiency, and a conventional two-sided error term. Hence, the SFA literature\(^2\) suffers from the same problem that market power literature suffers. That is, it requires the total cost data in order to estimate the cost efficiencies of firms. We overcome this issue by introducing a conduct parameter game, which enables us to estimate "implied cost efficiencies" and conduct parameters jointly without using the total cost data. Hence, in contrast to the SFA literature, which infers the cost efficiency from a cost function, we estimate the cost efficiency from a supply-demand system, which is derived from a conduct parameter game. To the best of our knowledge, this is the first study that enables estimation of cost efficiency that doesn’t require the total cost data.

The Quiet Life Hypothesis” (QLH) by Hicks (1935) and “the Efficient Structure Hypothesis” (ESH) by Demsetz (1973) are two well-known hypotheses that relate market power to efficiency. The former claims that higher competitive pressure is likely to force management work harder, which in turn increases efficiencies of firms. The latter states that the firms with superior efficiency levels use their competitive advantages to gain larger market shares, which leads to higher market concentration and thus higher market power. The findings of Berger and Hannan (1998) and Kutlu and Sickles (2012) support

\(^2\)See Kumbhakar and Lovell (2000) for a book-length survey on SFA and Sickles (2005) for a simulation study examining the performances of some estimators in the SFA literature.
the QLH for the banking and airline industries, respectively. However, Maudos and Fernández de Guevara (2007) show evidence for ESH for the banking industry. Moreover, Delis and Tsionas (2009) are in favor of the QLH on average but they also mention that for the highly efficient banks the relationship reverses in favor of the ESH. Hence, the relationship between market power and efficiency has long been acknowledged by economists. However, the market power and SFA literatures largely ignore this relationship.\textsuperscript{3} This can potentially cause inconsistent parameter estimates for both conduct parameter and SFA models. For example, consider a market in which the true efficiency levels of the firms are the same but the researcher does not control for firm specific market power when estimating efficiencies of the firms. The differences in market powers would lead to different firm behavior and this can be confused with the firm level cost inefficiency. Generally, efficiencies are measured by closeness of production units to the best-practice units observed in the market. If the firm level conducts affect the performance of the best-practice units, then the efficiency estimates which do not take this into account would not be accurate. For example, in a market facing a Cournot competition the best practicing firm may not really be fully efficient. Lee and Johnson (2012) show that, in the Cournot environment, inefficiency may in fact be a result of endogenous prices and the effect of output production on price. Similarly, ignoring inefficiencies of firms in a conduct parameter model can lead to an omitted variable bias. Our methodology aims to overcome these difficulties by explicitly and simultaneously modeling a conduct parameter game in an environment where firms are allowed to be inefficient.

Another estimation problem is related to calculation of dead-weight-loss (DWL). Ignoring the inefficiencies of productive units may invalidate standard DWL calculations since DWL from collusive behavior depends on inefficiency levels.\textsuperscript{4} If the productive units exhibit inefficiency that is misinterpreted as firm heterogeneity, then the standard calculations of DWL may not be valid. In such cases, Kutlu and Sickles (2012) recommend using what they call the efficient full marginal cost (EFMC) for the markup calculation.\textsuperscript{5}

\textsuperscript{3}Koetter, Kolari, and Spierdijk (2012), Delis and Tsionas (2009), Koetter and Poghosyan (2009), and Kutlu and Sickles (2012) exemplify some studies that attempt to estimate market powers of firms in a framework where firms are allowed to be inefficient. Except for Delis and Tsionas (2009) the market power estimates in these studies are conditional on efficiency estimates.

\textsuperscript{4}See Comanor and Leibenstein (1969) and Kutlu and Sickles (2012) for more details about calculation of DWL when firms are inefficient.

\textsuperscript{5}They define EFMC as the sum of a shadow cost and efficient marginal cost calculated from stochastic
Hence, the simultaneous estimation of conduct and efficiency may provide us more precise estimates for DWL.

A common problem is that of measuring inefficiencies and market powers of firms when the firms face optimization constraints. For example, a firm which is seemingly inefficient may actually be relatively more efficient if we take the optimization constraints (e.g., capacity constraints) into account. Standard stochastic frontier models do not explicitly model such optimization constraints which may result in inaccurate efficiency estimates. In order to overcome this difficulty, we present an extension of our model which makes it possible to get efficiency and market power estimates jointly in the presence of capacity constraints.

We apply our methodology to estimate the firm-route-quarter specific conducts and marginal cost efficiencies of the U.S. airlines for routes that originate from Chicago. The time period that our data set covers is 1999I-2009IV. One of the difficulties that empirical researchers face is that the available cost data set is for the entire U.S. system. So, route level total cost data is not available. Kutlu and Sickles (2012) try to overcome this problem by incorporating a specific number of enplanements for each airline, a specific distance of each city-pair, and airline fixed effects when estimating the cost function. This enables them to calculate the route specific marginal costs from the cost function estimation. However, their efficiency estimates are still firm-quarter specific. Moreover, their conduct estimates are conditional on efficiency estimates. That is, they first estimate the efficiencies using the standard stochastic frontier models; and use these efficiency estimates when estimating the supply relation. In contrast to their study, we jointly estimate the firm-route-quarter specific conducts and efficiencies of the U.S. airlines; and when doing so we do not need route specific total cost data. Our results suggest that concentration ratio (measured by $CR_4$) and market share of airlines are negatively related
to the marginal cost efficiency. In contrast to this, the concentration ratio and market share of airlines are positively related to the conduct.

The rest of the paper is structured as follows. In Section 2, we build up our theoretical model. In Section 3, we describe our data set. In Section 4, we present our empirical model. In Section 5, we present and discuss our results. In the final section, we make our concluding remarks.

2 Theoretical Model

In this section we describe our theoretical framework, which enables us to estimate marginal cost efficiencies and conducts of firms without total cost data. The stochastic frontier literature relaxes full efficiency assumption of neoclassical production theory by allowing the firms to be inefficient. The inefficiency is treated as an unobserved component which is captured by a one-sided error term. The total cost of firm \( i \) at time \( t \) is given by:

\[
C(q_{it}; X_{c,it}) = C^*(q_{it}; X_{c,it}) \exp(u_{it} + v_{it})
\]

(1)

where \( q_{it} \) is the quantity of firm \( i \) at time \( t \); \( X_{c,it} \) is a row vector of variables related to cost; \( u_{it} \geq 0 \) is a term which is capturing the inefficiency; \( v_{it} \) is the conventional two-sided error term; and \( C^* \) is the deterministic component of cost when firms achieve full efficiency. In the conventional stochastic frontier framework the cost efficiencies of firms would be estimated by using the following model:

\[
\ln C(q_{it}; X_{c,it}) = \ln C^*(q_{it}; X_{c,it}) + u_{it} + v_{it}.
\]

(2)

Figure 1 shows a 2-input and 1-output example. The inputs in the figure are labeled as \( x_1 \) and \( x_2 \). The points in this figure represent input bundles. The curve labelled \( y^0g^0 \) is the efficient frontier of the input requirement set for producing output \( y^0 \). In this curve any further equi-proportionate reduction of inputs would make the output \( y^0 \) infeasible. The point \( P \) represents the actual input and the \( AB \) line is its corresponding iso-cost line. The points below this line are less expensive than input bundle \( P \). The point \( Q \) is
the cost-minimizing bundle and the CD line is its corresponding iso-cost line. The cost efficiency is defined as $|OR| / |OP|$. 

![Figure 1. Cost efficiency](image)

A variety of distributions is proposed for $u_{it}$ including the half normal (Aigner, et al., 1977), exponential (Meeusen and van den Broeck, 1977), truncated normal (Stevenson, 1980), and gamma (Greene, 1980a, 1980b, 2003) distributions. The cost efficiency of a firm, $EFF_{it}$, is estimated by:

$$EFF_{it} = \exp(-\hat{u}_{it})$$

$$\hat{u}_{it} = E[u_{it} | u_{it} + v_{it}].$$

The stochastic frontier approach that we presented above requires a detailed cost data set which many times is not available. We utilize the conduct parameter approach in order to overcome this issue. For this purpose, instead of modelling total cost as in the conventional SFA models, we directly model marginal cost, $c$, as follows:

$$\ln c(q_{it}; X_{c, it}) = \ln c^* (q_{it}; X_{c, it}) + u_{it} + v_{it}.$$ 

Here, rather than estimating a cost function, we estimate a supply-demand system, which enables us to calculate the implied cost efficiency. We call $c^*$ efficient marginal cost (EMC), which is equal to the marginal cost when firms achieve full efficiency. Under constant
marginal cost assumption. Equation (4) can directly be derived from Equation (1). Hence, in this case the theoretical efficiency values for these two approaches coincide. When the marginal cost is not constant, we directly model marginal cost efficiency through Equation (4) and remain silent about the way in which the inefficiency is modelled in the cost function. Therefore, the constant marginal cost assumption is not required in our theoretical model. Nevertheless, from the antitrust point of view, which is concerned with market power and DWL estimations, the marginal cost efficiency seems to be a more relevant efficiency concept.

Let \( P_t = P(Q_t; X_{d,t}) \) be the inverse demand function, \( Q_t \) be the total quantity, and \( X'_{d,t} \) is a row vector of demand related variables at time \( t \). The perceived marginal revenue (PMR) is given by:

\[
PMR(\theta_{it}) = P_t + \frac{\partial P_t}{\partial Q_t} \frac{\partial Q_t}{\partial q_{it}} q_{it} = P_t \left( 1 - \frac{s_{it}}{E_{it}} \right)
\]

where \( s_{it} = \frac{q_{it}}{Q_t} \) is the market share of firm \( i \) at time \( t \); \( E_{it} = \frac{\partial Q_t}{\partial P_t} \) is the (absolute value of) elasticity of demand; \( \theta_{it} = \frac{\partial Q_t}{\partial q_{it}} \) is the conduct parameter. Three benchmark values for \( \theta_{it} = \{0, 1, \frac{1}{s_{it}}\} \) correspond to perfect competition, Cournot competition, and joint profit maximization, respectively. The supply relation is:

\[
P_t \left( 1 - \frac{s_{it}}{E_{it}} \right) = c_{it} \Leftrightarrow \ln P_t + \ln \left( 1 - \frac{s_{it}}{E_{it}} \right) = \ln c_{it}
\]

where \( c_{it} = c(q_{it}; X_{c,it}) \). After including the econometric error terms, the supply relation

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9 Whenever we refer to constant marginal costs we also assume that \( \frac{\partial(u_{it} + v_{it})}{\partial q} = 0 \), which would be consistent with the constant marginal cost assumption.

10 The reason may be clearer when we introduce Figure 2 later on in this section.

11 Note that perceived marginal revenue must be positive so that the equilibrium makes sense. Hence, we assume that \( 1 - \frac{s_{it}}{E_{it}} \theta_{it} > 0 \). So, we have \( \ln \left( 1 - \frac{s_{it}}{E_{it}} \theta_{it} \right) \leq 0 \).
becomes: \(^{12}\)

\[
\ln P_{it} = -\ln \left(1 - \frac{s_{it}}{E_t} \theta_{it}\right) + \ln c_{it} + \varepsilon_{it}^s
\]

\[
= g\left(\theta_{it}, s_{it}, E_t\right) + \ln c_{it} + \varepsilon_{it}^s.
\]

\[
= \ln c_{it}^s + g_{it} + u_{it} + \varepsilon_{it}^s
\]

where \(g_{it} = -\ln \left(1 - \frac{s_{it}}{E_t} \theta_{it}\right) \geq 0\) is the market power term and \(u_{it} \geq 0\) is the inefficiency term.\(^{13}\) The \(E_t\) term is identified through the demand equation. We assume that the demand function and marginal cost functions are so that the conduct parameter and marginal cost can be separately identified.\(^{14}\) Intuitively, Equation 5 suggests that if \(c_{it}\) and \(q_{it}\) are highly collinear, then the conduct parameter maybe identified through the variation in \(\frac{\partial P}{\partial Q}\). A common approach to achieve identification is assuming a constant marginal cost.\(^{15}\) Our model is different from the standard market power models due to the additional \(u_{it}\) term. This inefficiency term is identified by utilizing the asymmetric distribution of the variations of \(u_{it}\). Intuitively, \(u_{it}\) is identified if the signal-to-noise ratio (the variance ratio of the inefficiency component to the composite error) is not small.

Hence, the identification of model parameters requires the standard conduct parameter model and SFA identification assumptions. A standard conduct parameter model ignores \(u_{it}\), which would likely be correlated with \(g_{it}\). Hence, any conduct parameter model that is ignoring \(u_{it}\) risks getting inaccurate market power estimates.

Figure 2 aims to illustrate the underlying mechanism of our model and consequences of ignoring inefficiency when calculating DWL. The figure includes inverse demand function, perceived marginal revenue (PMR), marginal revenue (MR) that is corresponding to monopoly scenario, marginal cost (MC), and efficient marginal cost (EMC). For illustrative purposes we consider the same constant marginal costs, conduct, and efficiencies for each firm. \(P_0\) and \(Q_0\) are the equilibrium price and quantity at conduct level \(\theta\). Similarly, \(P_C\) and \(Q_C\) are price and quantity for the perfect competition scenario, in which conduct

\(^{12}\)The introduction of the error term enables us to deviate from a single market price. Also, the price may be considered to be a function of firm specific variables, \(X_{d, it}\).

\(^{13}\)Note that \(g_{it}\) is an increasing function of \(\theta_{it}\).

\(^{14}\)For details about the identification conditions for conduct parameter models, we direct the reader to Bresnahan (1982), Lau (1982), Perloff, Karp, and Golan (2007), and Perloff and Shen (2012).

\(^{15}\)A constant marginal cost function does not depend on quantity but it may still depend on variables other than the quantity.
equals 0. In the figure it is assumed that under perfect competition there would be no inefficiency and thus the efficient marginal cost and marginal cost coincide for this case. If QLH holds, then as the market power, measured by $\theta$, increases $MC$ diverges from $EMC$. In our framework, the marginal cost efficiency is defined as $EMC/MC$. The social welfare loss at conduct level $\theta$ would be equal to the shaded area (sum of dark and light shaded regions). In Figure 2, the efficiency is roughly 60%, which is relatively low. As a consequence the social welfare loss due to inefficiency is substantial. The conventional DWL value, which is ignoring inefficiency, is given by the dark shaded triangular area; and is much smaller than the overall social welfare loss. In general, when both conduct and marginal cost efficiency are low, the conventional DWL values would be much lower than overall social welfare losses.

![Figure 2: Conduct, marginal cost efficiency, and social welfare](image-url)

Now, we describe how this conduct parameter game would be estimated. We assume that the conduct parameter $\theta_{it}$ is a function of variables, $X_{g,it}$, that affect firm specific market power such as market shares and concentration ratios. Modeling $\theta_{it}$ through this function may lead to computational difficulties. An arguably better way, which we prefer to follow, would be directly modeling $g_{it}$ as a function of $X_{g,it}$ and solving for $\theta_{it}$ after getting the parameter estimates. That is:

$$\hat{\theta}_{it} = \frac{E_{it}}{s_{it}} (1 - \exp (-\hat{g}_{it}))$$  \hspace{1cm} (8)
where $\hat{E}_t$ and $\hat{g}_{it}$ are the estimates for $E_t$ and $g_{it}$, respectively. The market power term, $g_{it}$, is bounded by 0 and $B_{it} = -\ln \left( 1 - \frac{1}{E_t} \right)$. Hence, the choice of functional form should be so that $g_{it} \in [0, B_{it}]$. In this study we use:

$$
\begin{align*}
g_{it} &= \frac{B_{it} \exp \left( X_{g,it}^{'} \beta_g \right)}{1 + \exp \left( X_{g,it}^{'} \beta_g \right)},
\end{align*}
$$

(9)

One of the drawbacks of the standard stochastic frontier models is that if the regressors are correlated with $v_{it}$ or $u_{it}$, then the parameter and efficiency estimates are inconsistent. Moreover, in this setting, $v_{it}$ and $u_{it}$ terms are assumed to be independent, which can be a questionable assumption in a variety of settings. We use a control function approach to handle the endogeneity issue that occurs when the $v_{it}$ is correlated with the regressors or $u_{it}$. For example, $u_{it}$ can be a function of regressors (e.g., market shares of firms or concentration ratios) that are correlated with $v_{it}$ term.\(^{16}\) The idea is including a bias correction term in the model. Consider the following supply relation model with endogenous explanatory variables:

$$
\begin{align*}
\ln P_{it} &= \ln c_{it} + g_{it} + u_{it} + \varepsilon_{it}^s \\
X_{en,it} &= \zeta_{it}^{'} \delta + v_{it} \\
\begin{bmatrix}
\tilde{v}_{it} \\
\varepsilon_{it}^s \\
u_{it}
\end{bmatrix} &= \begin{bmatrix}
\Sigma^{-1/2} v_{it} \\
\varepsilon_{it}^s \\
u_{it}
\end{bmatrix} \sim \mathcal{N} \left( \begin{bmatrix} 0 \\
I_m & \rho \sigma_{\varepsilon} \\
\rho' \sigma_{\varepsilon} & \sigma_{\varepsilon}^2 \end{bmatrix} \right) \\
h_{it} &\geq 0 \\
u_{it} &\sim \mathcal{N}^+ (\mu_u, \sigma_u^2)
\end{align*}
$$

(10)

where $P_{it}$ is the price; $X_{en,it}$ is an $m \times 1$ vector of all endogenous variables used in modelling $c_{it}^s$, $g_{it}$, and $u_{it}$; $\zeta_{it} = I_m \otimes Z_{it}$ where $Z_{it}$ is a $l \times 1$ (with $l \geq m$) vector of all exogenous variables. The irregular term $\varepsilon_{it}^s$ is correlated with the regressors but conditionally independent from the inefficiency term $u_{it}$ given $X_{en,it}$ and $Z_{it}$.\(^{17}\) Note that

\(^{16}\)See Kutlu (2010) and Karakaplan and Kutlu (2015) for control function solutions to the endogeneity problem. Also see Guan et al. (2009) and Tran and Tsionas (2013) for GMM based stochastic frontier approaches that aim to handle endogeneity.

\(^{17}\)We may replace $u_{it} = h_{it} \tilde{u}_{it}$ assumption by $u_{it} = h_{it} \tilde{u}_{i}$ so that $\tilde{u}_{i}$ is a firm specific term. This would be in line with the panel data frameworks.
and \( u_{it} \) may still be correlated unconditionally. By applying a Cholesky decomposition of the variance-covariance matrix of \( \begin{bmatrix} \tilde{\varepsilon}'_{it} & \varepsilon^s_{it} \end{bmatrix}' \), we can rewrite the supply equation as follows:

\[
\ln P_{it} = \ln c^*_it + g_{it} + \sigma_{e} \rho' \tilde{\varepsilon}_{it} + \tilde{\varepsilon}^s_{it} + u_{it}
\]

(11)

where \( \tilde{\varepsilon}^s_{it} \sim N(0, (1 - \rho' \rho) \sigma^2_e) \) and \( \eta = \sigma_{x} \rho' \Sigma_u^{-1/2} \). The parameters of this supply relation can be estimated in one stage using the maximum likelihood estimation method. However, sometimes it is simpler to get the consistent parameter estimates in two stages by first estimating the bias correction term \( \eta'(X_{en,it} - \zeta'_i) \); then including the estimate of bias correction term in the second stage in which we apply traditional SFA methods.

For the two-stage approach the standard errors need to be corrected, e.g., by a bootstrap procedure. In our empirical section we use the limited information maximum likelihood estimator that we presented in this section, i.e., the one stage method.

The model that we introduced can be extended to a setting in which firms have capacity constraints. This extension of our model is inspired by the conduct parameter model proposed by Puller (2007). In the presence of capacity constraints the optimization problem for firm \( i \) becomes:

\[
\max P_{it} q_{it} - C_{it} \text{ s.t. } q_{it} \leq K_{it}
\]

(12)

where \( K_{it} \) is the capacity constraint that firm \( i \) is facing at time \( t \). Then, the corresponding supply relation becomes:

\[
\ln P_{it} = \ln c^*_it + g_{it} + \lambda_{it} + u_{it} + \varepsilon^s_{it}
\]

(13)

where \( \lambda_{it} \geq 0 \) is the shadow cost of capacity which can be estimated by including variables capturing extent of capacity constraints. For example, Puller (2007) uses a dummy variable which is equal to one when the constraint is binding.

Finally, a formal treatment of conduct parameter games in which the strategic interactions of the firms are dynamic is beyond the scope of this study. Following Puller
(2009), we recommend including time fixed-effects which may condition out the dynamic effects in firms’ optimization problems.\textsuperscript{18} Note, however, that even though the estimates of parameters (including parameters of the conduct and efficiency) are consistent in this dynamic game scenario, we cannot separately identify the efficient marginal costs, $c_{it}^*$, and dynamic correction terms. The reason is that the time dummies not only capture cost related unobserved factors that change over time but also the dynamic correction terms.\textsuperscript{19} Nevertheless, except the portion of time fixed-effects that contribute to $c_{it}^*$, the other parameters of $c_{it}^*$ are identified. Moreover, many times $c_{it}^*$ is not the main interest. In what follows we assume a static model.

3 The Data

In order to testify our theoretical framework, we use the U.S. domestic airline data. One of the main data sources that we use is the Passenger Origin-Destination Survey of the U.S. Department of Transportation (DB1B data set). This data set is a 10\% random sample of all tickets that originate in the U.S. on domestic flights. In our data set a market is defined as a directional city-pair (route). Calculation of prices and quantities are based on the tickets that have no more than three segments in each direction. About $1\%$ of tickets are eliminated during the elimination of tickets with more than 3 segments. We only focus on coach class tickets due to the differences in demand elasticities and other characteristics between coach class and high-end classes (first class and business class).

Our data set covers the time period from the first quarter of 1999 to fourth quarter of 2009. During this time period, the U.S. airlines face serious financial problems. As pointed out by Duygun, Kutlu, and Sickles (2014), the financial losses for the domestic passenger airline operations in this time period is substantially higher than their losses between 1979 and 1999. Increase in taxes and jet fuel prices, relatively low fares, and sharp decrease in demand are some of the challenging properties of this period for the U.S.

\textsuperscript{18}See Puller (2009) for further details about his model and restrictions. One particular assumption that Puller (2009) makes is that the firms play an efficient super-game equilibrium when they cooperate. That is, they maximize the joint profit subject to incentive compatibility constraints. Hence, the corresponding efficient super-game equilibrium values are benchmark for the full market power case.

\textsuperscript{19}Of course, in the static setting we don't have this identification issue as the dynamic correction terms are zero.
airlines. In this time period, we observe dramatic increases in load factors. Borenstein (2011) argue that such an increase might be attributed to improved yield management techniques.

Now, we provide the details about data construction process. First, all multi-destination tickets are dropped as it is difficult to identify the ticket’s origin and destination without knowing the exact purpose of the trip. Second, any itinerary that involves international flights is eliminated. Third, we adjust the fare class for high-end carrier. That is, for some airlines, due to marketing strategies, only first class and business class (high-end) tickets are provided to consumers on all routes. However, the quality should be taken as coach class. So, we consider all tickets as coach class tickets if there is no coach class tickets from certain carrier in given quarter. In different time periods, due to changes in the pricing strategy, sometimes high-end-only carrier switches to a regular carrier which sells both coach class tickets and high-end tickets. For instance, Sun Country Airlines does not provide coach class tickets in 2001 but provides coach tickets in 2005 and years after. So, we treat the tickets in each quarter separately when considering this adjustment. That is, we treat high-end tickets from Sun Country Airlines as coach class tickets in 2001, not in year 2005. Fourth, tickets that have high-end segments and unknown fare classes are dropped.

We followed Borenstein (1989) and Brueckner, Dyer, and Spiller (1992) by using ticketing carrier as our airline as an observation unit. After further elimination of multi-ticketing-carrier tickets, firm specific average segment numbers (SE\(G\)) and average stage length (SL) on a given route are calculated as indicators of quality and costs. Moreover, our data set includes a distance variable which is the shortest directional flight distance (DIST). A ticket is online when one-way ticket does not involve change of airplanes. The online variable is the percentage of online tickets.

For the price variable, we use the average price of all tickets for a given airline on a given route in given quarter. All tickets with incredible prices are dropped from our data set. Following Borenstein (1989) and Ito and Lee (2007), we eliminate the open-jaw tickets since it would be difficult to distribute the ticket price into outbound and inbound segment for open jaw tickets. We drop the tickets that have a price less than 25 dollars or higher than 99 percentile or more than 2.5 times standard deviation from the mean for
each airline within a route. The tickets that have price less than 25 dollars are considered as frequent flyer program tickets and the tickets that have prices higher than 99 percentile are considered to be input (key punch) errors for the data set. For the round trip tickets, we divided the total price by two to get the one-way price.

The cost data set is constructed from the firm level data of DOT’s airline production data set (based on Form 41 and T100). We control for three types of important costs: labor price (LP), energy price (EP), and capital price (KP). The salaries and benefits for five main types of personnel are provided in Form 41/P6. Annual employee number is given in Form 41, P10. We interpolated the annual employee data to get the quarterly values. For energy price, we only capture the cost based on aircraft fuel. The energy input is developed by combining information on aircraft fuel gallons used with expense data per period. Flight capital is described by the average size (measured in number of seats) of the fleet. The number of aircraft that a carrier operated from each different model of aircraft in airline’s fleet is collected from DOT Form 41. For each quarter, the average number of aircraft in service is calculated by dividing the total number of aircraft days for all aircraft types by the number of days in the quarter. This serves as an approximate measure of the size of fleet.

In order to estimate the demand, we also include the city specific demographic variables: per capita income (PCI) and population (POP). We get the city level per capita income and population data from Bureau of Labor Statistics. We interpolate the annual data to get the quarterly PCI and population variables for each city. For each origin-destination city-pair, we use the population weighted PCI as the route-specific PCI measure. Similarly, city-pair population is the average population of origination and destination cities. In order to get the real prices, we deflated the nominal prices by Consumer Price Index (CPI) and use the first quarter of 1999 as the base time period. Since only the metropolitan areas have the demographic information but some airports are located in small cities, the number of the city-pairs is further reduced in our final database.

We apply our theoretical method on the routes that originate from Chicago, which is a popular choice because of its relatively large airport and wide selection of airline firms. For instance, Brander and Zhang (1990) use 33 Chicago-based routes in their studies.
In our final data set, we further eliminate the small firms and small routes. On a given route, firms with market shares less than 0.01 are eliminated. For a given quarter, any route with enplanements less than 1800, i.e., 20 passengers per day, is dropped. Also, we eliminate routes with less than 30 observations. Table 1 presents the summary statistics for Chicago-based routes.

Table 1. Summary for Chicago Originating Routes

<table>
<thead>
<tr>
<th>Variables: Name in Estimation</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Cost Carrier Dummy: LCC</td>
<td>0.11225</td>
<td>0.31569</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>ln(Population): ln(POP)</td>
<td>15.50922</td>
<td>0.18392</td>
<td>15.33637</td>
<td>16.46417</td>
</tr>
<tr>
<td>ln(Per Capita Income): ln(PCI)</td>
<td>10.4226</td>
<td>0.03828</td>
<td>10.33827</td>
<td>10.61397</td>
</tr>
<tr>
<td>ln(Stage Length): ln(SL)</td>
<td>6.40837</td>
<td>0.59661</td>
<td>4.69135</td>
<td>8.34378</td>
</tr>
<tr>
<td>ln(Distance): ln(DIST)</td>
<td>6.63774</td>
<td>0.59661</td>
<td>4.69135</td>
<td>8.35303</td>
</tr>
<tr>
<td>ln(Average Fleet Size): ln(SIZE)</td>
<td>4.97262</td>
<td>0.08467</td>
<td>4.80562</td>
<td>5.33165</td>
</tr>
<tr>
<td>ln(Labor Price): ln(LP)</td>
<td>9.23198</td>
<td>0.73460</td>
<td>5.58453</td>
<td>10.00725</td>
</tr>
<tr>
<td>ln(Capital Price): ln(KP)</td>
<td>7.27984</td>
<td>0.76111</td>
<td>3.6658</td>
<td>8.1754</td>
</tr>
<tr>
<td>ln(Fuel Price): ln(FP)</td>
<td>3.87272</td>
<td>0.33975</td>
<td>3.72431</td>
<td>4.83215</td>
</tr>
<tr>
<td>ln(Average Number of Segments): ln(SEG)</td>
<td>0.3698</td>
<td>0.32171</td>
<td>0</td>
<td>1.09861</td>
</tr>
</tbody>
</table>

Number of Observations: 18209

Low cost carrier is a dummy variable that equals 1 if the ticketing carrier is a low cost carrier, otherwise it is 0. Number of firms represents the total number of firms that operate on the route. Total number of passengers is the total tickets sold on a given route by all airlines together in a given quarter. Total number of passengers for other routes (OQOTH) variable is the total number of tickets that are sold on the other routes that share the same origination city. We use the geometric market share (GEOS) variable of Gerardi and Shapiro (2009) as an instrument. Another instrumental variable that we use is GEONF. This variable is the product of GEOS and \( n_f^* = \sqrt{n_o \times n_d} \), where \( n_o \) denotes to the mean value of number of firms for all routes that share the same origination.

\( ^{20} \)GEOS is the GENSP variable that is used in Gerardi and Shapiro (2009). GENSP is similar to the GEOSHARE variable of Borenstein and Rose (1994). The difference is that Borenstein and Rose (1994) use average daily enplanements while we use average quarterly enplanements.
as route of interest while the \( n_d \) refers to the mean value of number of firms for all routes that share the same destination city.

The final data set contains 108 routes that originate from Chicago and 14 carriers. The low cost carriers are Frontier Airlines, JetBlue Airways, Southwest Airlines, and Spirit Airlines. The rest of the carriers are: Alaska Airlines, American Airlines, Continental Airlines, Delta Airlines, Northwest Airlines, United Airlines, US Airways, America West Airlines, ATA Airlines and Trans World Airways.

4 Empirical Model

In this section, we want to shed some light on the market powers and efficiencies of the U.S. airlines. Moreover, we aim to illustrate our methodology using this empirical example. In particular, we estimate time-varying firm-route-specific conducts and marginal cost efficiencies of the U.S. airlines. Similar to Brander and Zhang (1990) and Oun, Zhang, and Zhang (1993), we only consider coach class tickets. Our city-pair markets consist of one-way or round-trip directional trips in each direction for three-segment (up to three segments in each direction) data set. We divide the total ticket price by 2 to get the one-way fare for round-trip tickets. The demand and supply equations are estimated separately. The demand equation is given by:

\[
\ln P_{itr} = \beta_0 + \beta_1 \ln Q_{tr} + \beta_2 \ln PCI_{tr} \ln Q_{tr} + f_d (X_{d,itr}) + \varepsilon^d_{itr} \tag{14}
\]

where \( f_d \) is a function of demand related variables, \( Q_{tr} \) is the total quantity at time \( t \) for route \( r \), \( X'_{d,itr} \) is a row vector of demand related variables, and \( \varepsilon^d_{itr} \) is the conventional two-sided error term. We assume that \( \ln Q_{tr} \) and \( \ln PCI_{tr} \ln Q_{tr} \) are endogenous. Along with the exogenous variables included in the demand model, our instrumental variables are \( GEOS_{itr}, GEONF_{itr}, \ln OQOTH_{rt} \), logarithm of labor price (\( \ln LP_{it} \)), logarithm of capital price (\( \ln KP_{it} \)), and logarithm of energy price (\( \ln EP_{it} \)).

The supply equation is given by:

\[
\ln P_{itr} = \ln c^s_{itr} + g_{itr} + u_{itr} + \varepsilon^s_{itr} \tag{15}
\]
where $c_{itr}$ is the marginal cost when firms achieve full efficiency, $g_{itr} = -\ln \left(1 - \frac{\theta_{itr}}{E_{itr}}\right)$ is the market power term, $u_{itr} \geq 0$ is the inefficiency term, and $\varepsilon_{itr}$ is the conventional two sided error term. The parameters of the $E_{itr}$ term is identified through the demand equation. We assume that the efficient marginal cost, $c_{itr}$, is constant, i.e., it is not a function of quantity but maybe a function of exogenous cost shifters. Hence, as we described in the theoretical model section, the theoretical values for cost and marginal cost efficiencies coincide in this model. While constant marginal cost is a relatively strong assumption, it is commonly used in the conduct parameter models. Iwata (1974), Genesove and Mullin (1998), Corts (1999), and Puller (2007) exemplify some papers that use this assumption in a variety of conduct parameter settings. We use this simplifying assumption to illustrate our methodology. Nevertheless, we approximate the efficient marginal cost function by a fairly flexible function of input prices and other cost related exogenous variables. These cost related variables include year, quarter, and firm dummy variables, which capture time-firm-specific unobserved factors.\footnote{If the airlines are playing a version of dynamic conduct parameters game that is suggested by Puller (2009), route-specific time dummy variables would capture dynamic factors that enter the airlines’ optimization problems as well. In this case, the parameter estimates of the model would still be consistent including the conduct parameters and efficiencies. However, the marginal cost estimates may be biased (downwards) as the prediction of marginal costs include these dynamic factors.} We model $g_{itr}$ as in the theoretical model section and assume that $X_{g,itr}' = [s_{itr}, CR_{4,itr}, \ln DIST_r, t, E_{itr}, 1]$ where $CR_{4,itr}$ is the concentration ratio for largest four firms on route $r$ at time $t$. We assume that $u_{itr} = h_{itr} \tilde{u}_{itr}$ and $\tilde{u}_{itr} \sim N^+ (0, \sigma_u^2)$ where $\sigma_u^2 = \exp \left(X_{g,itr}' \beta_u\right)$; and $\varepsilon_{itr} \sim N (0, \sigma_e^2)$ where $\sigma_e^2 = \exp (\beta_e)$. For the supply side, $s_{itr}$ and $CR_{4,itr}$ are assumed to be endogenous. Our instrumental variables are $GEOS_{itr}, GEONF_{itr}$, $\ln POP_{itr}$, and $\ln PCI_{itr}$. The estimations of the supply relations are done by using the one-stage version of the control function approach that we described in our theoretical model section.

5 Results

In this section, we present our estimation results. The demand parameter estimates for the routes originating from Chicago are given in Table 2.\footnote{The estimation includes a constant term.} We estimated the (inverse) demand equation by 2SLS. Our demand model controls for year, quarter, and firm dummies.
The demand elasticities are negative at each observation, i.e., $E_{tr} > 0$.

<table>
<thead>
<tr>
<th>Table 2. Estimation for Demand Function</th>
<th>Estimates</th>
<th>Std. Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(Q)</td>
<td>2.91356***</td>
<td>(0.50629)</td>
</tr>
<tr>
<td>ln(Q)*ln(PCI)</td>
<td>-0.29270***</td>
<td>(0.04861)</td>
</tr>
<tr>
<td>ONLINE</td>
<td>0.01940*</td>
<td>(0.00880)</td>
</tr>
<tr>
<td>ln(DIST)</td>
<td>7.47912***</td>
<td>(0.95064)</td>
</tr>
<tr>
<td>ln(SEG)</td>
<td>-10.03281***</td>
<td>(0.97631)</td>
</tr>
<tr>
<td>ln(SIZE)</td>
<td>-15.81152***</td>
<td>(2.31769)</td>
</tr>
<tr>
<td>ln(SL)</td>
<td>-8.24091***</td>
<td>(0.97745)</td>
</tr>
<tr>
<td>ln(DIST) Square</td>
<td>-0.22445**</td>
<td>(0.07828)</td>
</tr>
<tr>
<td>ln(SEG) Square</td>
<td>0.53698***</td>
<td>(0.11695)</td>
</tr>
<tr>
<td>ln(SIZE) Square</td>
<td>1.50167***</td>
<td>(0.22554)</td>
</tr>
<tr>
<td>ln(SL) Square</td>
<td>-0.62278***</td>
<td>(0.08377)</td>
</tr>
<tr>
<td>ln(DIST)* SEG</td>
<td>-0.65458**</td>
<td>(0.19646)</td>
</tr>
<tr>
<td>ln(DIST)* ln(SIZE)</td>
<td>-1.93435***</td>
<td>(0.18417)</td>
</tr>
<tr>
<td>ln(DIST)* ln(SL)</td>
<td>0.90929***</td>
<td>(0.15754)</td>
</tr>
<tr>
<td>ln(SEG)* ln(SIZE)</td>
<td>2.44755***</td>
<td>(0.19223)</td>
</tr>
<tr>
<td>ln(SEG)* ln(SL)</td>
<td>0.24996</td>
<td>(0.19551)</td>
</tr>
<tr>
<td>ln(SIZE)* ln(SL)</td>
<td>1.98114***</td>
<td>(0.18886)</td>
</tr>
<tr>
<td>ln(POP)</td>
<td>0.30783***</td>
<td>(0.01673)</td>
</tr>
<tr>
<td>ln(PCP)</td>
<td>4.19634***</td>
<td>(0.56805)</td>
</tr>
<tr>
<td>LCC</td>
<td>-0.21325**</td>
<td>(0.00862)</td>
</tr>
<tr>
<td>Quarter Dummies</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Year Dummies</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Firm Dummies</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Centered R Square</td>
<td>0.4976</td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>18209</td>
<td></td>
</tr>
</tbody>
</table>

Note: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.
Robust standard errors are given in bracket.

For the supply function, as we described earlier, we use the one-stage control function approach to deal with endogeneity. We estimated two supply models: the first one allows inefficiency (Benchmark model) and the second one assumes full efficiency so that $u_{it} = 0$ (Full efficiency model). The full efficiency model is a standard conduct parameter model, which helps us to compare our benchmark estimates with the standard models. Table 3 shows the estimation results.

The bias correction terms ($\eta$) are jointly significant at any conventional significance level, which is an indication of endogeneity. The median of conduct estimates is 0.63. This value is lower than the theoretical conduct value for Cournot competition, which equals...
Hence, at the median, the extent of competition lies somewhere between perfect competition and Cournot competition. The median of conduct estimates from the full-efficiency model is somewhat lower and suggests a competitive market. Low cost carriers, due to their special operating style\textsuperscript{24}, tend to have lower marginal costs compared to other airlines, which helps them to reduce price. Hence, it is worthwhile to examine the decomposition of conducts based on LCCs and non-LCCs. We observe that the conduct estimates for LCC and non-LCC carriers are 0.24 and 0.74, respectively. Therefore, while the conducts of LCCs are closer to perfectly competitive values, the conducts of non-LCCs are closer to Cournot competition values. Finally, the median of the conduct estimates from the full efficiency model is 0.22, which is somewhat lower than that of the benchmark model.

<table>
<thead>
<tr>
<th>Table 3. Estimation for Supply Function</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Supply Function:</strong></td>
</tr>
<tr>
<td>Inefficiency Allowed</td>
</tr>
<tr>
<td>Full Efficiency</td>
</tr>
<tr>
<td>Price</td>
</tr>
<tr>
<td>ln(KP)</td>
</tr>
<tr>
<td>Estimates: -0.72825***</td>
</tr>
<tr>
<td>(0.13523)</td>
</tr>
<tr>
<td>ln(KP)</td>
</tr>
<tr>
<td>Std. Err.: -0.63778***</td>
</tr>
<tr>
<td>(0.15070)</td>
</tr>
<tr>
<td>ln(FP)</td>
</tr>
<tr>
<td>Estimates: 0.02501</td>
</tr>
<tr>
<td>(0.11625)</td>
</tr>
<tr>
<td>ln(FP)</td>
</tr>
<tr>
<td>Std. Err.: 0.02449</td>
</tr>
<tr>
<td>(0.02310)</td>
</tr>
<tr>
<td>ln(LP)</td>
</tr>
<tr>
<td>Estimates: 0.01010</td>
</tr>
<tr>
<td>(0.01061)</td>
</tr>
<tr>
<td>ln(LP)</td>
</tr>
<tr>
<td>Std. Err.: 0.02082</td>
</tr>
<tr>
<td>(0.01929)</td>
</tr>
<tr>
<td>ln(KP)* ln(FP)</td>
</tr>
<tr>
<td>Estimates: 0.02793+</td>
</tr>
<tr>
<td>(0.01550)</td>
</tr>
<tr>
<td>ln(KP)* ln(LP)</td>
</tr>
<tr>
<td>Estimates: 0.02922</td>
</tr>
<tr>
<td>(0.04268)</td>
</tr>
<tr>
<td>ln(KP)</td>
</tr>
<tr>
<td>Std. Err.: -0.76658***</td>
</tr>
<tr>
<td>(0.07363)</td>
</tr>
<tr>
<td>ln(KP)</td>
</tr>
<tr>
<td>Std. Err.: -0.76248***</td>
</tr>
<tr>
<td>(0.08575)</td>
</tr>
<tr>
<td>Quarter Dummies</td>
</tr>
<tr>
<td>Yes</td>
</tr>
<tr>
<td>Year Dummies</td>
</tr>
<tr>
<td>Yes</td>
</tr>
<tr>
<td>Firm Dummies</td>
</tr>
<tr>
<td>Yes</td>
</tr>
</tbody>
</table>

\textsuperscript{23}The median of theoretical conduct values for joint profit maximization scenario is 6.77, which is the median of \(\frac{1}{s_{itr}}\).

\textsuperscript{24}For example, some of them operate only on certain routes in order to reduce costs.
The conduct parameter estimates show that an airline with higher market share tends to have higher market power. In markets with high $CR_4$ values, it may be easier for airlines (those with higher market share) to cooperate. The positive coefficient of $CR_4$ in conduct verifies this. For the time period that we examine, the U.S. airlines seem to be losing market power over time. For longer flight distances the alternative transportation means (e.g., bus or car) are likely to become less attractive to the consumers. This reduction in outside competition suggests a positive relationship between market power and distance. The positive sign of distance variable for the market power term is in line with this intuition.

In our benchmark estimates, the medians of efficiency estimates for the whole sample and non-LCC carriers are 82.6% and 84.4%, respectively. Hence, the efficiencies of LCCs and non-LCCs are similar. The parameter estimates for inefficiency term show that an airline with higher market share, tends to have higher inefficiency. Similarly, higher $CR_4$ values lead to higher inefficiency. This is in line with the QLH that more market power

<table>
<thead>
<tr>
<th>Nonlinear Function: $g$</th>
<th>Inefficiency Allowed</th>
<th>Full Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>s</td>
<td>17.62885***</td>
<td>(1.77711)</td>
</tr>
<tr>
<td>CR4</td>
<td>8.82176***</td>
<td>(2.35791)</td>
</tr>
<tr>
<td>ln(DIST)</td>
<td>0.38011</td>
<td>(0.33349)</td>
</tr>
<tr>
<td>t</td>
<td>-0.22842***</td>
<td>(0.02998)</td>
</tr>
<tr>
<td>Elasticity of Demand</td>
<td>-0.13075</td>
<td>(0.28139)</td>
</tr>
<tr>
<td>Constant</td>
<td>-10.53598*</td>
<td>(5.06577)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$\sigma_\omega$</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-3.46254***</td>
<td>(0.03206)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$\sigma_u$</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>s</td>
<td>0.41774***</td>
<td>(0.08396)</td>
</tr>
<tr>
<td>CR4</td>
<td>3.95924***</td>
<td>(0.28411)</td>
</tr>
<tr>
<td>ln(DIST)</td>
<td>-0.94727***</td>
<td>(0.04206)</td>
</tr>
<tr>
<td>t</td>
<td>-0.03700***</td>
<td>(0.00233)</td>
</tr>
<tr>
<td>Elasticity of Demand</td>
<td>-0.15413***</td>
<td>(0.04344)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.94036***</td>
<td>(0.53855)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$\eta$ (bias correction term)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>s</td>
<td>-0.33883***</td>
<td>(0.02233)</td>
</tr>
<tr>
<td>CR4</td>
<td>0.09003**</td>
<td>(0.02838)</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>30772.7323</td>
<td>30033.13415</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>18209</td>
<td>18209</td>
</tr>
</tbody>
</table>

Note: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.
leads to lower efficiency levels.\textsuperscript{25} The medians of price-marginal cost markups, price-efficient marginal cost markups, and prices are $4.63$, $30.30$, and $142.70$, respectively. Historically, the airlines are known to complain about not being able to make much money. These markup values indicate that the airlines may partially be responsible for the financial difficulties that they face. Hence, the airlines can achieve reasonable profit levels if they work harder to improve their efficiency levels.

In Table 4, we decompose the sample into two regions based on market shares of airlines: 1) Airlines with market shares smaller than $s^*$ and 2) Airlines with market shares greater than $s^*$. We consider three different values for $s^* = \{0.05, 0.25, 0.50\}$. The values in the table are the medians of conduct and efficiency estimates from the benchmark model, which correspond to these subsamples. Based on this decomposition, it seems that the airlines with market shares greater than 0.05 act similar to Cournot competitors. On the other hand, the airlines with market shares smaller than 0.05, act more like perfectly competitive firms. We also observe that the airlines with high market shares are much less efficient compared to airlines with smaller market shares. For instance, in the third column the medians of efficiencies are 83.92\% and 68.46\% for small market share and large market share groups, respectively.

<table>
<thead>
<tr>
<th>Table 4. Conduct and Efficiency by Market Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conduct Parameter</td>
</tr>
<tr>
<td>Market Share</td>
</tr>
<tr>
<td>Smaller</td>
</tr>
<tr>
<td>Greater</td>
</tr>
</tbody>
</table>

6 Summary and Concluding Remarks

In this paper, we provided a conduct parameter based framework to estimate market powers and efficiencies of firms simultaneously. Our methodology enables us to relax the total cost data requirement for the stochastic frontier models. The total cost data may

\textsuperscript{25} Note that since $u$ has a half normal distribution its mean depends on $\sigma_u^2$. In particular, the mean of $u$ is an increasing function of $\sigma_u^2$. 

21
not be available for a variety of reasons. For example, firms might not want to reveal such a strategic information whenever it is possible. Even when some form of total cost data is available, the data may not reflect the total cost of the relevant unit that we want to examine. For instance, for the U.S. airlines only firm specific total cost data is available for the whole U.S. airline system. Hence, the conventional stochastic frontier models cannot estimate route specific efficiencies as this would require route-specific total cost data.

Besides relaxing a vital data requirement, our methodology aims to overcome some estimation issues. Efficiencies are generally measured by the distance between the units of production and the best practice units observed in the market. If the performance of the best-practice units depends on their market powers, then the efficiency estimates not taking this into account would not be accurate. We overcome this difficulty by explicitly modeling a conduct parameter game in an environment where firms are allowed to be inefficient. Moreover, we provided a simple extension of our model which allows the firms to have capacity constraints.

Researchers may be interested in estimating the market powers and efficiencies of firms in an environment where firms interact repeatedly so that they play a dynamic game. While we did not provide an explicit solution to this problem, it is possible to extend our model to a dynamic setting in which firms play an efficient supergame equilibrium as in Puller (2009). Finally, an extension of our conduct parameter model so that the firms price discriminate is not complicated. Such an extension would enable us to understand the connection between price discrimination, market power, and efficiency better. Hence, our theoretical model serves as a guideline as to how conduct parameter and efficiency can be estimated simultaneously without requiring total cost data; and this guideline can be applied to a variety of conduct parameter settings.

The U.S. airline industry is a good example to apply our methodology due to the unavailability of route specific total cost data. Hence, we applied our methodology to estimate the conducts and marginal cost efficiencies of the U.S. airlines for the time period

\[ \text{26} \text{See Corts (1999) for a simulation study examining the performance of the static version of conduct parameter method in a dynamic environment.} \]

\[ \text{27} \text{See Borenstein and Rose (1994), Stavins (2001), Gerardi and Shapiro (2009), and Chakrabarty and Kutlu (2014) for works examining the relationship between market power and price discrimination.} \]
1999I-2009IV. We found that the market concentration and market share of airlines are negatively related to the marginal cost efficiency, which is in line with the quiet life hypothesis.

7 References


Tran, K.C., and Tsionas, E.G. (2013), GMM Estimation of Stochastic Frontier Model