Capturing the impact of fuel price on jet aircraft operating costs with Leontief technology and econometric models

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ABSTRACT

Investigation of the airline response to a fuel price increase is in effect an investigation of the role of variable interactions in aircraft cost models. We examine the impact of fuel price on aircraft costs and airline operational strategies by developing two classes of operating cost models for jet aircraft and comparing the results. The translog operating cost model is a flexible functional form that provides a detailed representation of the empirical relationship between fuel cost and operating cost, allowing for substitution, scale, aircraft age, and variable interactions to be captured. The simpler Leontief model assumes that inputs of a cost model must be used in fixed proportions regardless of their prices. While it does not capture variable interactions, the Leontief model is more transparent, requires fewer inputs, and allows the contribution of a single factor, such as fuel price, to operating cost to be more easily isolated. An analysis of the translog operating cost model reveals that as fuel price increases, airlines will take steps to use fuel more efficiently by leveraging other inputs; a comparison of the translog and the Leontief technology models, however, show that the potential for this supplier input substitution for fuel is rather modest. By building the two operating cost models and comparing their predictions, we illustrate a method to determine the prediction potential of a Leontief technology model and assess the importance of input substitution at the vehicle level.

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1. Introduction

As 2008 jet fuel prices reached levels more than three times those of 2004, airlines responded in a number of ways to control costs. Airlines reportedly flew slower to reduce fuel consumption and decreased the common practice of tankering fuel.[1] Additionally, there were reports of airlines ceasing operations on older, less fuel efficient fleet and upgauging where possible (United States Government Accountability Office, 2009). While 2009–2010 fuel prices fell from their 2007–2008 highs, the spike demonstrated uncertainty in the magnitude of future fuel prices. Furthermore, the scope and timeline of a future climate change policy threatens the stability of fuel prices. As a result, the impact of fuel price on aircraft costs and airline operational strategies remains a question of great practical importance. This question is, in effect, a methodological question as to how aviation costs should be modeled: are aircraft operating costs best captured with complex models that allow for input substitution or by simpler models that assume inputs are independent?

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[1] Given an airport routing of A–B–C, if the price of fuel at airport B is greater than that at airport A, it may be more economical to refuel to the maximum level at airport A to avoid purchasing fuel at airport B.

We address the aviation cost modeling tradeoff while examining the impact of fuel price on aircraft costs and airline operational strategies by developing two classes of operating cost models for jet aircraft and comparing the results. Using published airline data we develop the translog and the Leontief technology operating cost models. In developing the translog model, we seek to both update and improve upon the translog econometric operating cost model for jet aircraft developed by Wei and Hansen (2003) and to consider in more detail the effect of fuel price. In improving on the model, we use econometric methods that account for correlation across airlines, aircraft, and time. We also estimate on a larger and more up-to-date data set, which includes a broader range of aircraft types and explanatory variables. The translog model developed in this study provides the most complete representation of the empirical relationship between fuel cost and operating cost, allowing for substitution, scale, aircraft age, and other effects – including interactions – to be captured. It can also be used to model the impact of fuel price on the aircraft size that minimizes operating cost; however, the detailed nature of the translog model (hereafter, TM) makes it challenging to gain immediate insights and to predict future operating costs.

The simpler Leontief model is more transparent, requires fewer inputs, and allows the contribution of a single factor, such as fuel price, to operating cost to be more easily isolated. The Leontief technology cost models (hereafter, LM) developed in Ryerson and Hansen (2010) assume that inputs of a cost model, such as labor, fuel, and materials, must be used in fixed proportions regardless of their prices. Because the inputs are assumed to be in fixed proportions, these models are specific to an aircraft type. This produces a set of models rather than a single, generalized model. The development of the TM and LM and comparison of their predictions allows us to investigate the importance of the interaction effects the translog uniquely captures. The results of this investigation will inform the tradeoff between a complicated but flexible cost model and a simpler but highly restrictive one as well as shed light on airline behavior due to a fuel price increase.

The remainder of this paper is organized as follows: The following sections review the modeling approach (Section 2) and the data collected for the development of the translog model (Section 3). Regularity conditions of the estimated TM are explored in Section 4, and coefficient estimates are presented and interpreted based on the objective of the study. In Section 5, predictions from the translog model and LM are compared, and conclusions are drawn in Section 6.

2. Translog operating cost model

The operating cost per operation (O) function has the form:

$$O = f(p, z, q, c, g) \tag{1}$$

where p is a vector of input prices including fuel price; z is a vector of airline–aircraft outputs – specifically average seat capacity and segment length; q is the value capturing the time in year-quarter; c is the vector of airline designations; and g is the vector of aircraft age variables. Along with the fuel price, the vector p includes measures for pilot cost and materials cost. The vector z includes the seat capacity per operation and average stage length per operation. While p and z are essential arguments of the operating cost function, this study will focus on the variation of operating cost with fuel price ($fuel$) and seats per operation ($seat$). The vector g includes variables to measure the age of the aircraft, the length of time an airline has been operating a certain aircraft model, and the number of hours operated in a quarter per airline per aircraft. The value q is one of a set of ordinal values signifying year-quarter values. We denote airlines by c and aircraft by n, such that each observation has a unique combination of c, n, and q. We capture airline fixed effects with c, where $c = 1$ if the observation is for airline i, 0 otherwise.

The model specification used is a translog model to estimate the operating cost per departure (O_{cnq}). The translog model is widely used in cost modeling (for example, Wei and Hansen, 2003; Caves et al., 1984; Hansen et al., 2001); as a second order Taylor series expansion, it is able to approximate many different model specifications.

$$\ln O_{cnq} = \alpha q_{cnq} + \sum_c \phi_c + \sum_i \omega_i \ln p^i_{cnq} + \sum_i \delta_i \ln z^i_{cnq} + \sum_i \varphi_i g^i_{cnq} + \sum_i \sum_{j \geqslant i} \beta_{ij} \ln p^i_{cnq} \ln p^j_{cnq} + \sum_i \sum_{j \geqslant i} \pi_{ij} \ln z^i_{cnq}$$
$$\times \ln z^j_{cnq} + \sum_i \sum_{j \geqslant i} \gamma_{ij} g^i_{cnq} g^j_{cnq} + \sum_i \sum_j \rho_{ij} \ln p^i_{cnq} \ln z^j_{cnq} + \sum_i \sum_j \theta_{ij} \ln p^i_{cnq} g^j_{cnq} + \sum_i \sum_j \tau_{ij} \ln z^i_{cnq} g^j_{cnq} + \varepsilon_{cnq} \tag{2}$$

where i, j are the index elements in p, z, g and α, ϕ_c, ω_i, δ_i, φ_i, β_{ij}, π_{ij}, γ_{ij}, ρ_{ij}, θ_{ij}, τ_{ij} are the coefficients to be estimated.

3. Data for operating cost model

To estimate the operating cost model in (2), data from the US Department of Transportation (DOT) Form 41 are collected. Form 41 provides quarterly cost data and operating statistics per airline and per aircraft type. The dataset includes a large set of explanatory variables and a date range from 1996 to 2006 inclusive. Data for 26 airlines (c) (network, regional, and low cost) that operated jet aircraft during the study period were collected (Appendix A). Across the airlines there were 23 unique jet aircraft types (n) operated (Appendix A) in this period. The panel data used in this model has airline–aircraft designators in vector k over a set of year-quarters (q). Because the set of k values represented in the data vary across q, the panel is unbalanced. The total number of observations is 1657 covering 66 unique aircraft–airline combinations. The dependent and independent variables are presented in Table 1, and procedures for calculating these variables are discussed below.