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# EXPLAINING VARIABILITY IN AIR TRAFFIC CONTROL COSTS IN THE DOMESTIC U.S.

David Gillen

Institute for Transportation Studies

University of California

Berkeley CA

## INTRODUCTION

This report provides a summary of empirical research that sought to explain the variability in costs across designated ATC zones in the domestic U.S. Differences in costs can be attributed to a number of factors. These can be categorized into three general categories; structural, environmental and managerial. The structural factors would include the level and technology of capital equipment, external rules or requirements imposed on the particular ATC unit and combination of services offered by the ATC unit. We would include such things as externally designated salary scales, factor prices and the like in this category as well. Environmental factors refer for the most part to locational influences. An ATC unit in the middle of Kansas has different weather conditions to contend with than one located in Southern California. Other factors to consider would be geographic location in the US and the adjacency of other ATC units. If there were major hub airports located in your jurisdiction you would expect a different traffic pressure than if there were none. Similarly, hubs located in an adjacent ATC jurisdiction would have a spillover effect since it would generate more through movements. This category was a central focus of our efforts; that is, distinguishing own from adjacency (or externality) affects.

The final category of factors would be those managerial decision variables that offer some discretion to the local ATC management team. In this group we would include quality or performance measures. It is certainly true that some failures (or successes) may be due to a failure to invest on the part of a central authority but it makes more sense to include them in this category since ultimately local management will be responsible and must provide a solution. There is also an issue of adjacency associated with performance. A failure, error or outage in one ATC unit can have downstream effects. Similarly, a decision rule, such as flow control, to slow aircraft down before they approach a congested area such as the northeast US, will be reflected in the local ATC units' performance. In our view it is important to understand the cost drivers not just explain costs, so management decisions can be made to improve efficiency as well as service quality.

This report can be considered as a ‘work-in-progress’ as the data sets are continually evolving. In section 1 we describe our approach to the problem. Organizing our efforts along the lines of cost, production and service quality models. Section 2 describes the model experiments we carried out looking at the use of dummy variables, defining output measures and service quality. In section 3 we describe the difference between productivity and efficiency and include a explanation of an alternative approach to measuring performance and productivity, namely TFP, Malmquist and Data Envelopment Analysis (DEA). The summary and conclusions are contained in section 4.

## MODELING ATC COST VARIATION: COST, PRODUCTION AND SERVICE QUALITY

The materials provided by GRA prior to the August report can generally be classified as cost allocation/attribution exercises.  GRA was attempting to classify costs into different categories such as fixed versus variable and direct versus indirect and this was carried out across products or service categories such as Air Traffic Operations (ATO) and Air Facility Operations (AFO).  The best way to visualize this problem is in the form of either a two or three-dimensional matrix.  In the two-dimensional case one can think of cost categories such as direct labour, indirect labour, capital etc. along one dimension and products or services such as ATO and AFO along the other dimension.  GRA was attempting to fill in the boxes in the matrix.

| **Cost Allocation** | | | |
|---|---|---|---|
| | Labour | Capital | Materials |
| ATO | ? | ? | ? |
| AFO | ? | ? | ? |

If this matrix is viewed as three dimensional then along the third dimension there would be cost attributes such as fixed, variable, direct and indirect etc.  Simple regression analysis or bivariate regressions were used to determine which costs varied with which output or service.

Some of the cost items were accounting type costs where FAA overhead was allocated to different divisions.

Our approach was to use economic theory as a guide to the extent possible. Thus we started by classifying the data provided to us by GRA into the following categories. We constructed adjacency variables to capture externality effects or interdependence between ATC centers.

Our goal was to model costs as a function of output, size measures and characteristics:

| | |
|---|---|
| Output Measures | Total operations |
| | Operations disaggregated into categories such as scheduled carrier, general aviation, air taxi, and military |
| | Number of over flights |
| Size measures | Employment or workers by category |
| | Total annual flight hours in SDP |
| | Total annual flight miles in SDP |
| | Square miles or area of SDP |
| Characteristics | Traffic density |
| | Number of units of specialized equipment such as radars and VORs |
| | Measures of delay and operating errors |
| | Hubs or gateways in SDP |
| Adjacency Variables (External Effects) | Number of adjacent SDPs |
| | Hubs or gateways in adjacent SDPs |
| | Delay and operating errors in adjacent SDPs |

Our methods included both single equation and systems models. In other words we used ordinary least squares (OLS) and iterative three stage least squares (I3SLS). I3SLS produces asymptotically efficient estimates and allows us to take care of endogeniety issues. For example one might specify a cost model, which includes the level of capital equipment and the number of errors (or outages) experienced by the ATC unit. However, the number of errors or outages could be related to the amount of capital investment. This second relationship needs to be specified separately to ensure we are able to distinguish the direct impacts of capital on cost differences and how it may influence the number of errors (or other service quality measures) and the separate contribution of errors to cost variability across units.

Regardless of the type of models we estimate we had a few choices to make at the beginning of the process. The first issue was to determine if should estimate a cost function or a production function. A general cost function for any time period *n* can be written as:

$$C = g(y, w, t) \tag{1}$$

where *C* is total cost, *y* is a vector of outputs, *w* is a vector of input prices and *t* is a scalar measure of technical change. Under certain restrictive conditions, a cost function is the dual of a production function. In other words, it is an equally fundamental representation of the production technology and all the information contained in the production function can also be extracted from the cost function. The cost function is the preferred specification if outputs and factor prices are exogenous. A second reason for preferring cost functions is they reflect 'optimizing' behaviour on the part of the firm or economic agent. Input prices are included so the trade-off between productivity and input prices is reflected in the cost function.

A related issue is that of hedonic cost functions, which are generally used when there is, an output and various output characteristics or service attributes. The following is a quality separable hedonic cost function:

$$C = f(Q(y; z); w, t) \tag{2}$$

here *Q(.)* is an aggregated output index that depends on output (*y*) and service attributes (*z*). It can be written as:

$$Q(\,) = y \cdot f(z) \tag{3}$$

Clearly incorporating service attributes increases the number of parameters to be estimated even though we specify a quality separable output aggregator.

At the very outset it was clear that we would not be able to estimate a ‘proper’ cost function using the data provided to us because we were missing input prices for the various factors of production. Estimating a cost function requires data on outputs, output prices, inputs and input prices. In addition it is best to have this information at a disaggregated level. For example labour data can usually be classified into different categories such as administrative and technical, or unionized and non-unionized. If detailed data are available for each category in the form of hours worked, or person years or persons; this along with benefits loaded wage data allows us to construct a consistent aggregate of labour input using the following Törnqvist index:

$$\ln\left(\frac{L_t}{L_{t-1}}\right) = \sum_{j=1}^{m}\left(\frac{s_{jt} + s_{jt-1}}{2}\right)\cdot\ln\left(\frac{L_{jt}}{L_{jt-1}}\right) \tag{4}$$

where $s_{jt}$ is the share in total compensation of labour category *j* at time *t* and $L_{jt}$ is the quantity of labour input of type *j* at time *t*. If there are zero observations in the labour data, let us say due to the addition of 'new' labour categories, then the Törnqvist index cannot be constructed since the natural logarithm of zero is not defined. In this case one can use the Fisher Ideal index to aggregate labour input. The index can be constructed using the equation below where $w_{jt}^{L}$ is the price of labour input of type *j* at time *t* :

$$\ln\left(\frac{L_t}{L_{t-1}}\right) = \frac{1}{2}\cdot\ln\left(\frac{\sum_{j=1}^{n} w_{jt}^{L} L_{jt}}{\sum_{j=1}^{n} w_{jt}^{L} L_{jt-1}}\right) + \frac{1}{2}\cdot\ln\left(\frac{\sum_{j=1}^{n} w_{jt-1}^{L} L_{jt}}{\sum_{j=1}^{n} w_{jt-1}^{L} L_{jt-1}}\right) \tag{5}$$

The data requirements for both measures are the same and both are superlative index numbers that provide for consistency in aggregation. Loosely speaking, this means that the Fisher aggregate of many Fisher aggregates is approximately a Fisher aggregate and the Törnqvist aggregate of many Fisher aggregates is also approximately a Fisher aggregate index. These are chain-linked weighted index numbers. The weights allow us to capture changes in labour quality over time. For example if over the years the number of technical workers has increased, this quality change in the composition of the workforce will be captured by the above index numbers. The above examples are for time-series data, but it is also possible to calculate such measures across cross-sections using multilateral versions of these index numbers.

The economic approach to calculating capital stocks or the quantity of capital input is to use the perpetual inventory method as follows:

$$K_{it+1} = I_{it} + (1-\delta_i)\cdot K_{it} \qquad (6)$$

where $K_{it}$ is the capital stock of type *i* in year *t*, $I_{it}$ is gross real investment and $\delta_i$ is the economic decay rate applicable to capital of type *i*. The price of capital or the user cost of capital is calculated as follows:

$$\left(\frac{1-u\cdot z}{(1-u)\cdot(1-t_p)}\right)\cdot\left(r+\delta_i-\left[\frac{q_{it}-q_{it-1}}{q_{it-i}}\right]\right) \qquad (7)$$

In the above equation:

| | |
|---|---|
| $u$ | is the corporate income tax rate |
| $t_P$ | is the property tax rate and applicable to buildings and structures. It is assumed that property taxes are deductible from income |
| $r$ | is the marginal opportunity cost of capital |
| $\delta_i$ | is the depreciation rate for capital type *i* |
| $q_i$ | is the price of new capital goods, or the investment price deflator for capital type *i* |
| z | is the present value of capital consumption allowance (CCA) deductions on a dollar's worth of investment |

Indices for materials, energy and other inputs would be constructed in a similar fashion. In some cases where detailed information is available on labour, capital and energy use, the residual is lumped together as 'other' inputs or materials. Because of the importance of contract services this is not an approach we would recommend here. Rather, contract services should be included as a separate factor input.

In its present form, the GRA database does not allow for the implementation of most of the above models, so we started with something more modest. For example, our estimated cost function does not include factor prices as explanatory variables.

Prior to estimation, we had to choose the functional form, or the mathematical parametric form of the cost function. Here again if the dataset permits, it is preferable to use flexible functional forms. Flexible functional forms do not impose any a-priori restrictions on the production technology and can provide a second order approximation to any arbitrary production technology. There are many ways to think about the concept of flexibility, but the simplest, is to use a parameter count. Typically researchers are interested in a number of economic effects. The number of economic effects depends on the dimensionality of the model, or, the number of inputs and the number of outputs. The following example is for the case where there is one output and N factor inputs. The table below shows that if there is one output and two inputs, there are 6 distinct economic effects.

| **Flexibility and Parameter Count** | | |
|---|---|---|
| **Economic Effects** | **Number of Parameters** | |
| | ***N inputs*** | ***N=2*** |
| Cost level | 1 | 1 |
| Returns to scale | 1` | 1 |
| Input Shares | N-1 | 1 |
| Price elasticities of input demand | N | 2 |
| Elasticities of factor substitution | N(N-1)/2 | 1 |
| Total | (N+1)(N+2)/2 | 6 |

Next consider the following Cobb-Douglas type cost function.

$$\ln C = \alpha + \beta \ln w_L + \gamma \ln w_K \qquad (8)$$

The above cost function is not flexible as it contains three parameters whereas we are interested in six economic effects. Thus it has less than the number of parameters required for flexibility. The above cost function therefore imposes a priori restrictions on the production technology. Since flexibility requires more parameters, and more parameters require more observations, flexible functional forms cannot be estimated using small datasets. Examples of flexible functional forms include the Translog, Generalized Leontiev, Symmetric Generalized McFadden, and Symmetric Generalized Barnett.[1] In our work we use simple Cobb-Douglas type cost functions.

[1] Flexibility comes at a cost; often, flexible functional forms do not satisfy theoretical consistence requirements.

Since the data do not allow us to consider flexible functional forms, we had to choose between the simple linear and the log-linear form. The former is sometimes referred to as a constant slope – varying elasticity model and the latter is referred to as a varying slope-constant elasticity model. These properties come from mathematics and not from economics. We prefer to use the log-linear version because the resulting parameters are the elasticity estimates and these have a simple yet useful intuitive interpretation. Thus we have a ready answer to questions such as: What happens to costs if the number of flights increases by one percent?

This choice may also be resolved using more defensible econometric methods and though we did not implement this; the appropriate way is to use the Box-Cox transformation of the regression model. Using this approach both the linear and log-linear models are nested in the Box-Cox regression, so the choice of functional form is dictated by the outcome of the appropriate statistical test. Suppose we were trying to choose between two commonly considered linear relationships:

$$y_t = \beta_1 + \beta_2 x_t + \varepsilon_t \tag{9}$$

$$\ln y_t = \alpha_1 + \alpha_2 \ln x_t + \varepsilon_t \tag{10}$$

The Box-Cox transformation of a variable *z* is:

$$\begin{aligned} z^{(\lambda)} &= \frac{z^{\lambda} - 1}{1} \quad \lambda \neq 0 \\ z^{(\lambda)} &= \ln z \qquad \lambda = 0 \end{aligned} \tag{11}$$

The estimated value of λ determines the functional form. If λ=0 then we have the log-linear form as the correct form and if λ=1 then as we see below, the correct from is linear:

$$\begin{aligned} & y_t^{(\lambda)} = \beta_1 + \beta_2 x_t^{(\lambda)} + \varepsilon_t \\ \lambda = 1 \Rightarrow\ & y_t - 1 = \beta_1 + \beta_2 (x_t - 1) + \varepsilon_t \\ \Leftrightarrow\ & y_t = (\beta_1 - \beta_2 + 1) + \beta_2 x_t + \varepsilon_t \\ \Leftrightarrow\ & y_t = \beta_1^* + \beta_2 x_t + \varepsilon_t \end{aligned} \tag{12}$$

**EMPIRICAL RESULTS OF MODEL SPECIFICATION**

Regardless of model specification, one of the issues we faced was the treatment of dummy variables. Rather than including a dummy variable for Alaska, we excluded the Alaska observation from the dataset because it is an outlier in many respects. There are three ways to incorporate dummy variables in regression models. The first is to include shift dummies that affect the constant term in the regression; the second is to include interactive or slope dummies; and the third is to include both shift and interactive dummies. The following three regressions provide an example.[2]

| | | |
|---|---|---|
| ***Dependent variable*** | | |
| ***All regressions*** | l_tc | Natural logarithm (ln) of Total Cost |
| | | |
| ***Independent Variables*** | | |
| ***Regression 1*** | l_flthrs | ln of Flight Hours |
| | y2d | Year 2000 Dummy (1 in year 2000, 0 otherwise) |
| | l12 | Level 12 Dummy (1 for level 12, 0 otherwise) |
| | | |
| ***Regression 2*** | l_flthrs | ln of Flight Hours |
| | flt2 | Year 2000 Dummy * ln of Flight Hours |
| | flt12 | Level 12 Dummy * ln of Flight Hours |
| | | |
| ***Regression 3*** | l_flthrs | ln of Flight Hours |
| | flt2 | Year 2000 Dummy * ln of Flight Hours |
| | flt12 | Level 12 Dummy * ln of Flight Hours |
| | y2d | Year 2000 Dummy |
| | l12 | Level 12 Dummy |

The results are shown on the next page and as is evident, it is difficult to choose between regressions 1 and 2. If both shift and interactive dummies are included as in regression 3,

[2] Note that ideally total cost data should be corrected for inflation.

they are all statistically insignificant. Interactive dummies generally provide richer information. For example from regression 2 we can calculate the percentage change in total cost due to a 1% increase in total flight hours and due to the use of interactive dummies, this measure varies both across years and levels.

| Output cost elasticity of flight hours | Year and Level |
|---|---|
| 0.370 | 1999 and all levels other than 12 |
| 0.378 | 1999 and level 12 |
| 0.376 | 2000 and all levels other than 12 |
| 0.384 | 2000 and level 12 |

The differences though small in magnitude, are statistically significant. In comparison using shift dummies only (as in regression 1) provides one value (0.376) of the output cost elasticity of flight hours. In what we report later we only use shift dummies primarily because using interactive dummies leads to identification problems in our simultaneous equation model. In the single equation context, we would not rely on shift dummies alone.

An important issue we had to deal with was choosing between different output measures. Our results show that one has to choose an appropriate measure of output from the following three alternatives:

1. Total operations (defined as over flights + (departures*2))
2. Total Flight Hours
3. Two outputs – departures and over flights

Using permutations and combinations of the above three alternatives either produces estimates that are not statistically significant or estimates that are biased, or have the wrong signs. The results of the three alternatives are shown above in regressions 4 through 6. All three regressions are log-linear and total cost is the independent variable.

## Interactive vs. Shift Dummy Variables

### Regression 1: ols l_tc l_flthrs y2d l12

```
 R-SQUARE =   0.6942     R-SQUARE ADJUSTED =   0.6687
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.74203E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.86141E-01
SUM OF SQUARED ERRORS-SSE=  0.26713
MEAN OF DEPENDENT VARIABLE =   18.462
LOG OF THE LIKELIHOOD FUNCTION =  43.4205
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 36 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_FLTHRS | 0.37630 | 0.7626E-01 | 4.935 | 0.000 | 0.635 | 0.5300 | 0.2836 |
| Y2D | 0.76402E-01 | 0.2776E-01 | 2.752 | 0.009 | 0.417 | 0.2585 | 0.0021 |
| L12 | 0.10504 | 0.3194E-01 | 3.289 | 0.002 | 0.481 | 0.3482 | 0.0023 |
| CONSTANT | 13.146 | 1.052 | 12.49 | 0.000 | 0.901 | 0.0000 | 0.7121 |

### Regression 2: ols l_tc l_flthrs flt2 flt12

```
 R-SQUARE =   0.6945     R-SQUARE ADJUSTED =   0.6690
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.74146E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.86108E-01
SUM OF SQUARED ERRORS-SSE=  0.26692
MEAN OF DEPENDENT VARIABLE =   18.462
LOG OF THE LIKELIHOOD FUNCTION =  43.4358
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 36 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_FLTHRS | 0.37065 | 0.7683E-01 | 4.824 | 0.000 | 0.627 | 0.5221 | 0.2793 |
| FLT2 | 0.54899E-02 | 0.1994E-02 | 2.753 | 0.009 | 0.417 | 0.2591 | 0.0021 |
| FLT12 | 0.75344E-02 | 0.2286E-02 | 3.296 | 0.002 | 0.481 | 0.3507 | 0.0023 |
| CONSTANT | 13.224 | 1.060 | 12.48 | 0.000 | 0.901 | 0.0000 | 0.7163 |

### Regression 3: ols l_tc l_flthrs flt2 flt12 y2d l12

```
 R-SQUARE =   0.6954     R-SQUARE ADJUSTED =   0.6506
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.78260E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.88465E-01
SUM OF SQUARED ERRORS-SSE=  0.26608
MEAN OF DEPENDENT VARIABLE =   18.462
LOG OF THE LIKELIHOOD FUNCTION =  43.4989
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 34 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_FLTHRS | 0.36088 | 0.1162 | 3.106 | 0.004 | 0.470 | 0.5083 | 0.2720 |
| FLT2 | -0.10743E-01 | 0.1372 | -0.7829E-01 | 0.938 | -0.013 | -0.5071 | -0.0041 |
| FLT12 | 0.58679E-01 | 0.1614 | 0.3635 | 0.718 | 0.062 | 2.7309 | 0.0178 |
| Y2D | 0.22590 | 1.909 | 0.1183 | 0.907 | 0.020 | 0.7643 | 0.0061 |
| L12 | -0.71444 | 2.255 | -0.3169 | 0.753 | -0.054 | -2.3683 | -0.0155 |
| CONSTANT | 13.359 | 1.607 | 8.313 | 0.000 | 0.819 | 0.0000 | 0.7236 |

## Choice of Output Variable

### REGRESSION 4: OLS L_TC L_OPS Y2D L12

```
 R-SQUARE =   0.6396     R-SQUARE ADJUSTED =   0.6095
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.87467E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.93524E-01
SUM OF SQUARED ERRORS-SSE=  0.31488
MEAN OF DEPENDENT VARIABLE =   18.462
LOG OF THE LIKELIHOOD FUNCTION =  40.1312
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 36 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_OPS | 0.39192 | 0.1005 | 3.899 | 0.000 | 0.545 | 0.6082 | 0.3093 |
| Y2D | 0.90904E-01 | 0.2973E-01 | 3.057 | 0.004 | 0.454 | 0.3076 | 0.0025 |
| L12 | 0.42332E-01 | 0.4696E-01 | 0.9014 | 0.373 | 0.149 | 0.1403 | 0.0009 |
| CONSTANT | 12.690 | 1.449 | 8.759 | 0.000 | 0.825 | 0.0000 | 0.6874 |

### REGRESSION 5: OLS L_TC L_FLTHRS Y2D L12

```
 R-SQUARE =   0.6942     R-SQUARE ADJUSTED =   0.6687
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.74203E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.86141E-01
SUM OF SQUARED ERRORS-SSE=  0.26713
MEAN OF DEPENDENT VARIABLE =   18.462
LOG OF THE LIKELIHOOD FUNCTION =  43.4205
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 36 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_FLTHRS | 0.37630 | 0.7626E-01 | 4.935 | 0.000 | 0.635 | 0.5300 | 0.2836 |
| Y2D | 0.76402E-01 | 0.2776E-01 | 2.752 | 0.009 | 0.417 | 0.2585 | 0.0021 |
| L12 | 0.10504 | 0.3194E-01 | 3.289 | 0.002 | 0.481 | 0.3482 | 0.0023 |
| CONSTANT | 13.146 | 1.052 | 12.49 | 0.000 | 0.901 | 0.0000 | 0.7121 |

### REGRESSION 6: OLS L_TC L_OVR L_DEP Y2D L12

```
 R-SQUARE =   0.6781     R-SQUARE ADJUSTED =   0.6413
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.80341E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.89633E-01
SUM OF SQUARED ERRORS-SSE=  0.28119
MEAN OF DEPENDENT VARIABLE =   18.462
LOG OF THE LIKELIHOOD FUNCTION =  42.3944
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 35 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_OVR | 0.71670E-01 | 0.2560E-01 | 2.800 | 0.008 | 0.428 | 0.3582 | 0.0505 |
| L_DEP | 0.29358 | 0.6607E-01 | 4.443 | 0.000 | 0.601 | 0.5356 | 0.2158 |
| Y2D | 0.93190E-01 | 0.2844E-01 | 3.276 | 0.002 | 0.484 | 0.3153 | 0.0025 |
| L12 | 0.45684E-01 | 0.4376E-01 | 1.044 | 0.304 | 0.174 | 0.1514 | 0.0010 |
| CONSTANT | 13.481 | 1.068 | 12.62 | 0.000 | 0.905 | 0.0000 | 0.7302 |

We have no defensible method of choosing one measure of output over another. One might use non-nested statistical tests but there should be some underlying model or at least intuition. It may also be that for some purposes one measure provides a better indicator for the underlying drivers. Finally, we could argue this provides a motivation for moving to multivariate statistical techniques in which multiple outputs can be considered simultaneously. In an ideal framework perhaps the use of hedonics to model output characteristics would take care of this problem. However we offer all three as workable alternatives. We continue to work with the flight hours model because in our view this represents a reasonable measure of en-route output.

In the interim, we retain flight hours as a measure of output and consider systems estimation. Regressions 7 through 9 are single equation estimates whereas regressions 10 through 12 are iterative three stage least squares results (I3SLS). The variables are explained below:

***Regressions 7 (and 10) – Cost Function***

Dependent variable is l_tc or ln of Total Cost

Independent Variables

| | |
|---|---|
| l_flthrs | ln of Flight Hours |
| l_mdel | ln of Total minutes of delay of all flights |
| y2d | Year 2000 Dummy (1 in year 2000, 0 otherwise) |
| l12 | Level 12 Dummy (1 for level 12, 0 otherwise) |

***Regressions 8 (and 11) – Production Function***

Dependent variable is l_flthrs or ln of Flight Hours

Independent Variables

| | |
|---|---|
| L | ln Labour input (ATCS_ADJ) |
| K2 | ln of Capital input (Equipment count or NAPRS) |

## Single Equation Models – Total Cost

### Regression 7: ols l_tc l_flthrs l_mdel y2d l12

```
R-SQUARE =   0.7641     R-SQUARE ADJUSTED =   0.7371
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.58889E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.76739E-01
SUM OF SQUARED ERRORS-SSE=  0.20611
MEAN OF DEPENDENT VARIABLE =   18.462
LOG OF THE LIKELIHOOD FUNCTION =  48.6069
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 35 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_FLTHRS | 0.35770 | 0.6818E-01 | 5.246 | 0.000 | 0.663 | 0.5038 | 0.2696 |
| L_MDEL | 0.30714E-01 | 0.9542E-02 | 3.219 | 0.003 | 0.478 | 0.2842 | 0.0215 |
| Y2D | 0.74660E-01 | 0.2474E-01 | 3.018 | 0.005 | 0.454 | 0.2526 | 0.0020 |
| L12 | 0.78247E-01 | 0.2964E-01 | 2.640 | 0.012 | 0.407 | 0.2594 | 0.0017 |
| CONSTANT | 13.019 | 0.9383 | 13.88 | 0.000 | 0.920 | 0.0000 | 0.7052 |

### Regression 8: ols l_flthrs L K2

```
R-SQUARE =   0.7906     R-SQUARE ADJUSTED =   0.7793
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.98090E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.99040E-01
SUM OF SQUARED ERRORS-SSE=  0.36293
MEAN OF DEPENDENT VARIABLE =   13.914
LOG OF THE LIKELIHOOD FUNCTION =  37.2908
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 37 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L | 0.78332 | 0.6753E-01 | 11.60 | 0.000 | 0.886 | 0.8785 | 0.3219 |
| K2 | 0.58879E-01 | 0.6392E-01 | 0.9212 | 0.363 | 0.150 | 0.0698 | 0.0237 |
| CONSTANT | 9.1043 | 0.4962 | 18.35 | 0.000 | 0.949 | 0.0000 | 0.6543 |

### Regression 9: ols l_mdel l_hub l_err

```
R-SQUARE =   0.4538     R-SQUARE ADJUSTED =   0.4243
VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.1041
STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.0508
SUM OF SQUARED ERRORS-SSE=   40.853
MEAN OF DEPENDENT VARIABLE =   12.938
LOG OF THE LIKELIHOOD FUNCTION = -57.1795
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 37 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_HUB | 1.4516 | 0.3763 | 3.858 | 0.000 | 0.536 | 0.5036 | 0.1989 |
| L_ERR | 0.59457 | 0.2590 | 2.295 | 0.027 | 0.353 | 0.2996 | 0.1477 |
| CONSTANT | 8.4536 | 0.8716 | 9.699 | 0.000 | 0.847 | 0.0000 | 0.6534 |

## I3SLS – Simultaneous Equation Models – Total Cost, Production and Delay Functions

```
SYSTEM R-SQUARE =  0.9539 ... CHI-SQUARE =   123.08     WITH   8 D.F.
```

### Regression 10: ols l_tc  l_flthrs  l_mdel  y2d  l12

```
R-SQUARE =   0.6624
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.73735E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.85869E-01
SUM OF SQUARED ERRORS-SSE=  0.29494
MEAN OF DEPENDENT VARIABLE =   18.462
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | ASYMPTOTIC T-RATIO -------- | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_FLTHRS | 0.57845 | 0.7395E-01 | 7.823 | 0.000 | 0.798 | 0.8148 | 0.4360 |
| L_MDEL | 0.22803E-01 | 0.1044E-01 | 2.183 | 0.029 | 0.346 | 0.2110 | 0.0160 |
| Y2D | 0.10518 | 0.1791E-01 | 5.872 | 0.000 | 0.704 | 0.3558 | 0.0028 |
| L12 | 0.18286E-01 | 0.2384E-01 | 0.7669 | 0.443 | 0.129 | 0.0606 | 0.0004 |
| CONSTANT | 10.059 | 0.9985 | 10.07 | 0.000 | 0.862 | 0.0000 | 0.5448 |

### Regression 11: ols l_flthrs L  K2

```
R-SQUARE =   0.7881
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.91833E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.95830E-01
SUM OF SQUARED ERRORS-SSE=  0.36733
MEAN OF DEPENDENT VARIABLE =   13.914
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | ASYMPTOTIC T-RATIO -------- | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L | 0.76430 | 0.6415E-01 | 11.91 | 0.000 | 0.891 | 0.8571 | 0.3141 |
| K2 | 0.99516E-01 | 0.4418E-01 | 2.253 | 0.024 | 0.347 | 0.1179 | 0.0401 |
| CONSTANT | 8.9851 | 0.4188 | 21.46 | 0.000 | 0.962 | 0.0000 | 0.6458 |

### Regression 12: ols l_mdel  l_hub  l_err

```
R-SQUARE =   0.4509
VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.0267
STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.0133
SUM OF SQUARED ERRORS-SSE=   41.069
MEAN OF DEPENDENT VARIABLE =   12.938
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | ASYMPTOTIC T-RATIO -------- | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_HUB | 1.5092 | 0.3458 | 4.364 | 0.000 | 0.583 | 0.5236 | 0.2068 |
| L_ERR | 0.68016 | 0.2431 | 2.797 | 0.005 | 0.418 | 0.3428 | 0.1690 |
| CONSTANT | 8.0763 | 0.8254 | 9.784 | 0.000 | 0.849 | 0.0000 | 0.6242 |

***Regressions 9 (and 12) – Delay Function***

Dependent variable is ln of Total minutes of delay of all flights

Independent Variables

L_hub ln of Total number of hubs in SDP

L_err ln of Operational errors

We also estimated specifications of the cost function that included the ln of the total number of adjacent zones and the ln of the ratio of actual route nautical miles to greater circle distance (ACTNM/GCR). Though both variables have a positive impact on total costs the estimates are not statistically significant.

In principle we should not be estimating both a cost and a production function as a system since one is the dual of the other and we only need estimate one or the other since all the information contained in one is also in the other. Clearly, the approach used is not theoretically defensible, however given the data constraints, in this case our interpretation of the equations is different. The single equation estimates (regressions 7 through 9) treat all independent variables as exogenous whereas in the simultaneous equation model we are essentially treating the output variable (flight hours) and the delay variable as endogenous. Indeed, the theoretical inconsistency of our approach can be demonstrated by examining returns to scale. Using the cost function, the scale elasticity is the inverse of the output cost elasticity, or 1.728 (Regression 10) indicating very large increasing returns to scale, if the cost function is interpreted as a long run cost function. If it is interpreted as a short run cost function it indicates significant cost economies with capacity use or sizable density economies. The production function however indicates returns to scale are 0.864 (regression 11) that is; there are decreasing returns to scale. We would tend to consider the latter estimate more reliable because at least our production function is theoretically correct (output is a function of factor inputs) even though it is simple and may not capture the complexity of the production technology. The cost function on the other hand does not include prices of factors of production. The correct measure of returns to scale would use the output cost elasticity assuming factor prices are constant – in this case our estimate does not control for factor prices.

Nonetheless our models, though parsimonious in parameters have the correct signs. So for example, a higher number of hubs and higher operational errors lead to more minutes of delay, which in turn increase total costs. Similarly, using more capital and labour enable producing more flight hours, which in turn lead to higher costs. Note however that the coefficient of capital in regression 8 is not significant but it becomes significant in regression 11 where we use I3SLS estimation.

Next, we specifically estimate a variable cost function and, a production function and a delay function, both of which are specified exactly as before. Before proceeding to discuss the results we discuss the theoretical framework. The choice between estimating a variable (or short-run) cost function and a total (or long-run) cost function is dictated by fixity of factors of production. If some factors of production are quasi-fixed in the short run then the variable cost function is the appropriate specification; alternatively if firms can adjust on all margins then the appropriate specification is the long run cost function. Properties of both can be examined if the focus is on whether or not there is excess capacity and on capacity utilization issues. Further, dynamic models can be estimated if one is interested in adjustment costs. However, the first step in the process is to derive variable costs from data on prices and quantities of factors of production, as follows:

$$\begin{gathered} C = w_L \cdot L + w_K \cdot K \\ VC = C - w_K \cdot K = w_L \cdot L \end{gathered} \tag{13}$$

We assume for simplicity that there are only two factors of production; capital and labour, thus variable costs are identical to the wage bill. This is the procedure for deriving the value of the independent variable (variable cost) in the variable cost function regression. Here of course we are assuming that the user cost of capital and the capital stocks (quantities) have been constructed as described earlier. A general variable cost function for any time period *n* can be written as:

$$VC = h(y, w', \overline{K}, t) \tag{14}$$

where $VC$ is variable cost, $y$ is a vector of outputs, $w'$ is a vector of prices of variable factors of production, $\overline{K}$ is a scalar or vector representing one or more quasi-fixed factors of production and $t$ is a scalar measure of technical change. Of course we cannot implement this because of data constraints and so the values of variable cost we use are those provided by GRA, which we assume have been derived using accounting type cost allocation constructs. In such applications one may wish to distinguish between direct and indirect variable costs. From an economic theory perspective we cannot make such distinctions – costs are either fixed or variable and indeed though it is easier to identify with capital as being a fixed factor of production, unionized labour can also be treated as quasi-fixed if the collective bargaining agreement prevents a firm from adjusting the labour force in response to changes in demand.

In estimating the variable cost model we encountered issues similar to those in estimating the total cost model. Again, for example, dummy variables can be either interactive or shift dummies. Further, it is possible to use various definitions of output – operations, flight hours etc. Some alternatives are shown below. Regression 13 uses the ln of disaggregated flight operations, which include Air Taxi and Commuter (L_TOPS); Air Carrier Flights (L_COPS); general Aviation (L_GOPS) and Military (L_MOPS). In addition, the dummy for level 11 is significant in all variable cost function regressions. We also experimented with including measures of density, hubs, size, delay, errors etc. in this equation but these were not significant. Regression 14 is similar to the total cost regression in that it only uses flight hours as an output; the difference lies in using a measure of density instead of delay as an additional explanatory variable. The density measure (L_DEN) is the ln of departures per square mile. The density measure is an alternative to the delay measure we used earlier. Regression 15 is the same model we used for total costs. Again, we have no particular preference for a particular model. We retain two models for further investigation.

## Single Equation Models – Variable Cost Function and Choice of Output Variable

### Regression 13: ols l_vc l_tops l_cops l_gops l_mops y2d l12 l11

```
 R-SQUARE =   0.8829     R-SQUARE ADJUSTED =   0.8573
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.70736E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.84105E-01
SUM OF SQUARED ERRORS-SSE=  0.22636
MEAN OF DEPENDENT VARIABLE =   17.820
LOG OF THE LIKELIHOOD FUNCTION =  46.7330
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 32 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_TOPS | 0.27282 | 0.7456E-01 | 3.659 | 0.001 | 0.543 | 0.3359 | 0.2133 |
| L_COPS | 0.14199 | 0.3391E-01 | 4.188 | 0.000 | 0.595 | 0.3051 | 0.1016 |
| L_GOPS | 0.15153 | 0.5788E-01 | 2.618 | 0.013 | 0.420 | 0.2556 | 0.1097 |
| L_MOPS | 0.39853E-01 | 0.2528E-01 | 1.577 | 0.125 | 0.268 | 0.1006 | 0.0270 |
| Y2D | 0.97080E-01 | 0.2682E-01 | 3.620 | 0.001 | 0.539 | 0.2208 | 0.0027 |
| L12 | 0.17089 | 0.6125E-01 | 2.790 | 0.009 | 0.442 | 0.3809 | 0.0038 |
| L11 | 0.10216 | 0.4679E-01 | 2.184 | 0.036 | 0.360 | 0.2277 | 0.0023 |
| CONSTANT | 9.6148 | 1.253 | 7.675 | 0.000 | 0.805 | 0.0000 | 0.5395 |

### Regression 14: ols l_vc l_flthrs y2d l12 l11 l_den

```
 R-SQUARE =   0.9103     R-SQUARE ADJUSTED =   0.8971
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.50985E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.71404E-01
SUM OF SQUARED ERRORS-SSE=  0.17335
MEAN OF DEPENDENT VARIABLE =   17.820
LOG OF THE LIKELIHOOD FUNCTION =  52.0689
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 34 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_FLTHRS | 0.56380 | 0.6641E-01 | 8.490 | 0.000 | 0.824 | 0.5339 | 0.4402 |
| Y2D | 0.70122E-01 | 0.2306E-01 | 3.041 | 0.005 | 0.462 | 0.1595 | 0.0020 |
| L12 | 0.19533 | 0.5530E-01 | 3.532 | 0.001 | 0.518 | 0.4353 | 0.0044 |
| L11 | 0.69490E-01 | 0.3939E-01 | 1.764 | 0.087 | 0.290 | 0.1549 | 0.0016 |
| L_DEN | 0.68941E-01 | 0.3001E-01 | 2.297 | 0.028 | 0.367 | 0.1981 | 0.0059 |
| CONSTANT | 9.7291 | 0.9102 | 10.69 | 0.000 | 0.878 | 0.0000 | 0.5460 |

### Regression 15: ols l_vc l_flthrs y2d l12 l11 l_mdel

```
 R-SQUARE =   0.9204     R-SQUARE ADJUSTED =   0.9087
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.45257E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.67274E-01
SUM OF SQUARED ERRORS-SSE=  0.15387
MEAN OF DEPENDENT VARIABLE =   17.820
LOG OF THE LIKELIHOOD FUNCTION =  54.4524
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | T-RATIO 34 DF | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_FLTHRS | 0.57369 | 0.6264E-01 | 9.159 | 0.000 | 0.844 | 0.5432 | 0.4479 |
| Y2D | 0.67681E-01 | 0.2175E-01 | 3.111 | 0.004 | 0.471 | 0.1539 | 0.0019 |
| L12 | 0.22925 | 0.3965E-01 | 5.782 | 0.000 | 0.704 | 0.5109 | 0.0051 |
| L11 | 0.76832E-01 | 0.3353E-01 | 2.292 | 0.028 | 0.366 | 0.1712 | 0.0017 |
| L_MDEL | 0.29339E-01 | 0.9164E-02 | 3.201 | 0.003 | 0.481 | 0.1825 | 0.0213 |
| CONSTANT | 9.3020 | 0.8699 | 10.69 | 0.000 | 0.878 | 0.0000 | 0.5220 |

## I3SLS – Simultaneous Equation Models – Variable Cost and Production Function (with density measure)

SYSTEM R-SQUARE = 0.9725 ... CHI-SQUARE = 143.72 WITH 7 D.F.

## Regression 16: ols l_vc l_flthrs y2d l12 l11 l_den

R-SQUARE = 0.8687
VARIANCE OF THE ESTIMATE-SIGMA**2 = 0.63442E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA = 0.79650E-01
SUM OF SQUARED ERRORS-SSE= 0.25377
MEAN OF DEPENDENT VARIABLE = 17.820

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | ASYMPTOTIC T-RATIO | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_FLTHRS | 0.76008 | 0.6736E-01 | 11.28 | 0.000 | 0.888 | 0.7197 | 0.5935 |
| L_DEN | 0.73213E-01 | 0.2063E-01 | 3.549 | 0.000 | 0.520 | 0.2104 | 0.0063 |
| Y2D | 0.10391 | 0.1434E-01 | 7.247 | 0.000 | 0.779 | 0.2364 | 0.0029 |
| L11 | 0.70736E-01 | 0.2395E-01 | 2.953 | 0.003 | 0.452 | 0.1576 | 0.0016 |
| L12 | 0.12507 | 0.3418E-01 | 3.659 | 0.000 | 0.532 | 0.2787 | 0.0028 |
| CONSTANT | 7.0021 | 0.9271 | 7.552 | 0.000 | 0.792 | 0.0000 | 0.3929 |

## Regression 17: ols l_flthrs L K2

R-SQUARE = 0.7878
VARIANCE OF THE ESTIMATE-SIGMA**2 = 0.91947E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA = 0.95889E-01
SUM OF SQUARED ERRORS-SSE= 0.36779
MEAN OF DEPENDENT VARIABLE = 13.914

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | ASYMPTOTIC T-RATIO | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L | 0.78508 | 0.6536E-01 | 12.01 | 0.000 | 0.892 | 0.8804 | 0.3227 |
| K2 | 0.10333 | 0.4538E-01 | 2.277 | 0.023 | 0.351 | 0.1224 | 0.0417 |
| CONSTANT | 8.8449 | 0.4129 | 21.42 | 0.000 | 0.962 | 0.0000 | 0.6357 |

## I3SLS – Simultaneous Equation Models – Variable Cost, Production and Delay Functions

```
SYSTEM R-SQUARE =  0.9813 ... CHI-SQUARE =   159.12     WITH   9 D.F.
```

### Regression 18: ols l_vc l_flthrs y2d l12 l11 l_mdel

```
R-SQUARE =   0.8193
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.87303E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.93436E-01
SUM OF SQUARED ERRORS-SSE=  0.34921
MEAN OF DEPENDENT VARIABLE =   17.820
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | ASYMPTOTIC T-RATIO | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_FLTHRS | 0.89538 | 0.7316E-01 | 12.24 | 0.000 | 0.903 | 0.8479 | 0.6991 |
| L_MDEL | 0.13261E-01 | 0.8886E-02 | 1.492 | 0.136 | 0.248 | 0.0825 | 0.0096 |
| Y2D | 0.10369 | 0.1327E-01 | 7.812 | 0.000 | 0.801 | 0.2358 | 0.0029 |
| L11 | 0.83250E-01 | 0.2282E-01 | 3.647 | 0.000 | 0.530 | 0.1855 | 0.0019 |
| L12 | 0.13762 | 0.3085E-01 | 4.461 | 0.000 | 0.608 | 0.3067 | 0.0031 |
| CONSTANT | 5.0500 | 1.007 | 5.015 | 0.000 | 0.652 | 0.0000 | 0.2834 |

### Regression 19: ols l_flthrs  L  K2

```
R-SQUARE =   0.7856
VARIANCE OF THE ESTIMATE-SIGMA**2 =  0.92900E-02
STANDARD ERROR OF THE ESTIMATE-SIGMA =  0.96385E-01
SUM OF SQUARED ERRORS-SSE=  0.37160
MEAN OF DEPENDENT VARIABLE =   13.914
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | ASYMPTOTIC T-RATIO | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L | 0.77808 | 0.6452E-01 | 12.06 | 0.000 | 0.893 | 0.8726 | 0.3198 |
| K2 | -0.39960E-04 | 0.3336E-01 | -0.1198E-02 | 0.999 | 0.000 | 0.0000 | 0.0000 |
| CONSTANT | 9.4647 | 0.3954 | 23.94 | 0.000 | 0.969 | 0.0000 | 0.6802 |

### Regression 20: ols l_mdel  l_hub  l_err

```
R-SQUARE =   0.4531
VARIANCE OF THE ESTIMATE-SIGMA**2 =   1.0225
STANDARD ERROR OF THE ESTIMATE-SIGMA =   1.0112
SUM OF SQUARED ERRORS-SSE=   40.901
MEAN OF DEPENDENT VARIABLE =   12.938
```

| VARIABLE NAME | ESTIMATED COEFFICIENT | STANDARD ERROR | ASYMPTOTIC T-RATIO | P-VALUE | PARTIAL CORR. | STANDARDIZED COEFFICIENT | ELASTICITY AT MEANS |
|---|---|---|---|---|---|---|---|
| L_HUB | 1.4426 | 0.3419 | 4.219 | 0.000 | 0.570 | 0.5005 | 0.1976 |
| L_ERR | 0.64667 | 0.2392 | 2.703 | 0.007 | 0.406 | 0.3259 | 0.1607 |
| CONSTANT | 8.3022 | 0.8218 | 10.10 | 0.000 | 0.857 | 0.0000 | 0.6417 |

For the I3SLS estimation we have two alternative specifications. The first has two equations, which include Regression 14 and a production function. The second has three equations, which include Regression 15, a production function and a delay function. These results are shown above in Regressions 16 through 20. We should note though that in our two-equation model that uses density (regressions 16 and 17) the coefficient of capital in equation 17 has the correct sign and is statistically significant. In the three-equation model, which uses delay (regressions 18 through 20) the coefficient of capital in equation 19 has the wrong sign and is not statistically significant.

The value of variable cost, or, the observations for the dependent variable in the above regression equations is a 'constructed' variable from cost allocation and bivariate regression analysis conducted by GRA. We therefore prefer to work further with the total cost model. We also do not pursue the systems models further and we restrict our specification to log-linear models. In the following table we provide results for three models that we consider promising. All three models have some common variables. These include the two shift dummies for the year 2000 and for level 12. In all models these variables have positive and statistically significant coefficients. The two other variables that are common to all three models are average miles flown per operation and average hours per operation. The former has a negative sign in all three models and the latter has a positive sign. Both variables are significant in all three models. Thus all three models indicate that it is cheaper to control longer distance flights and costs increase as more hours are flown in an SDP. Indeed, in the first model this may be capturing the effect of speed. Holding total miles flown and average miles per operation constant, average hours may increase due to slower speed, which increases costs.

All externality effects increase costs. In model 1, equipment downtime in adjacent centers and in models 2 and 3 the number of adjacent zones create negative externality effects since they result in higher costs. Model 2 excludes total miles flown and instead includes the number of domestic sectors. The latter also has a positive impact on costs.

| SOME PROMISING SINGLE EQUATION MODELS | | |
|---|---|---|
| Dependent Variable: Total SDP Cost | | |
| 40 observations (excluding Alaska) - Log-Linear Regression | | |
| | | |
| ***Model 1: Adjusted R-square: 0.7405*** | ***Coefficient*** | ***T-stat*** |
| Total miles flown by all aircraft | 0.243 | 2.41 |
| Average miles per operation | -0.267 | -2.53 |
| Average hours per operation | 0.444 | 3.18 |
| Total minutes of delay for all flights | 0.042 | 3.66 |
| Total amount of equipment downtime in adjacent centers | 0.029 | 1.67 |
| Year 2000 Dummy | 0.091 | 3.23 |
| Level 12 Dummy | 0.108 | 2.58 |
| Constant | 14.573 | 9.10 |
| | | |
| ***Model 2: Adjusted R-square: 0.7971*** | ***Coefficient*** | ***T-stat*** |
| Average miles per operation | -0.132 | -1.91 |
| Average hours per operation | 0.381 | 2.99 |
| Total minutes of delay for all flights | 0.032 | 3.01 |
| Number of Domestic Sectors | 0.334 | 3.48 |
| Total number of adjacent centers | 0.044 | 1.41 |
| Year 2000 Dummy | 0.076 | 3.29 |
| Level 12 Dummy | 0.105 | 3.23 |
| Constant | 17.632 | 35.04 |
| | | |
| ***Model 3: Adjusted R-square: 0.6913*** | ***Coefficient*** | ***T-stat*** |
| Total miles flown by all aircraft | 0.377 | 3.37 |
| Average miles per operation | -0.346 | -3.10 |
| Average hours per operation | 0.388 | 2.59 |
| Share of over flights in total operations | -0.080 | -2.49 |
| Total number of adjacent centers | 0.075 | 1.59 |
| Year 2000 Dummy | 0.081 | 2.87 |
| Level 12 Dummy | 0.129 | 2.65 |
| Constant | 12.742 | 6.79 |

Model 3 excludes the number of domestic sectors but includes both total miles flown and the proportion of over flights in total operations. A higher share of over flights reduces costs. Given that total miles flown, average miles per operation and average hours per operation are constant, this is likely capturing the impact of the pure replacement effect – replacing over flights with arrivals and departures reduces costs.

## PRODUCTIVITY, EFFICIENCY AND DEA

Productivity and efficiency are often interpreted as being as being synonymous. Though the concepts are related, in general, productivity is a broader concept than efficiency. Both concepts can be related to a production function, which is the primitive (in the single output case) representing the transformation of inputs to output.[3] From a conceptual viewpoint, productivity and efficiency measurement can be classified into the frontier and non-frontier approaches and from an implementation viewpoint, into parametric and non-parametric. These are discussed below.

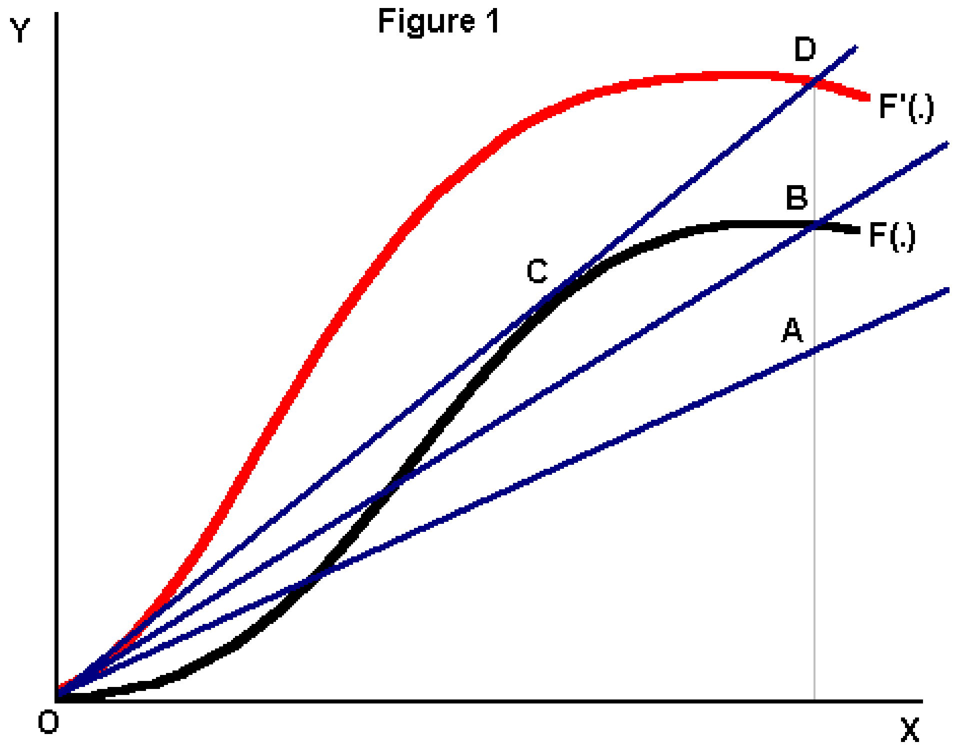
Consider the simple case of one output, one fixed factor of production – capital and one variable factor of production – labour. A measure of partial productivity could be labour productivity, which is output per unit of labour input, or, the average product of labour. An increase in the average product of labour would represent an increase in productivity however, as discussed below, this could come from a variety of sources.

Figure 1 illustrates a production function F(.); output is measured on the vertical axis and input on the horizontal axis. Consider a firm operating at the point A. This firm is operating at a point below the production function. Its productivity is the slope of the ray through the origin OA. Some researchers interpret the production function as a *frontier*, which represents the best practice.[4] Though all firms may have access to the same technology, some may be

[3] In the case of multiple outputs the primitive is a Transformation Function

[4] The frontier is generally assumed to a stochastic frontier and in the production context the frontier can only move in one direction, which is up. This is due to improvements in best practice or technical progress.

better at using the technology than others. Firms that operate on the production function are obviously more efficient than those that do not. Thus, a firm operating at the point B is more efficient than one operating at point A. Moving from A to B increases productivity, but this increase is coming from *catch-up* or reducing *technical inefficiency*. Similarly, there could be another firm operating at point C. This firm is technically efficient, just like firm B, but it is utilizing the optimal scale of production and therefore has higher productivity than B. The source of higher productivity in this case is *economies of scale*. Thus Figure 1 shows that productivity improvements can come from different sources.




Now consider the addition of another production function to Figure 1. The new production function, F'(.), lies above the old one. This represents *innovation*, *technical change* or *technical progress*. The production function is also sometimes interpreted as a *stochastic frontier*, which moves out over time due to advances in technology. Thus, firm B could move to a new position D; doing so will increase productivity, but the source of the productivity improvement is not a reduction in technical inefficiency or as a result of exploiting scale economies, but due to technical change or innovation. Conventional or *non-frontier* approaches to productivity measurement, such as labour productivity or total factor

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productivity (TFP) ignore technical efficiency. Implicitly these measures assume either that all firms are on the frontier or that their distance from the frontier does not change over time.

From an implementation viewpoint, methods of measuring efficiency can be broadly classified into non-parametric and parametric. Non-parametric methods include indexes of partial and total factor productivity, and data envelopment analysis. The latter is essentially a linear programming based method. Parametric methods involve the estimation of neo-classical and stochastic cost or production functions.

The data requirements for the various methods differ, as do their ability to inform managerial decisions. The use of partial productivity measures is pervasive and though these measures are easy to understand and compute, they can be quite misleading, because they do not reflect differences in factor prices and do they take account of differences in productivity of the other factor inputs used in production. Partial productivity measures are also unable to handle multiple outputs. Multiple outputs have to be aggregated into a single measure and often this is difficult to do if the output has service or quality characteristics or attributes.

One alternative to partial productivity measures is to use a more complete multi-factor measure such as a Törnqvist index of total factor productivity (TFP). This measure does not suffer from the shortcomings of partial productivity measure, but taken alone it is not very informative for evaluating management strategies. Extracting more information from measures of total factor productivity typically requires estimation of parametric neo-classical cost or production functions. In addition to data on physical inputs and outputs, this approach also requires information on prices, which is used to aggregate inputs and outputs.

***Data Envelopment Analysis***

Data Envelopment Analysis (DEA) is a frontier method and an alternative that has found favor in applications where the behavioural objective of the firm or decision-making unit under study is neither minimization of costs, nor maximization of profit; or where outputs are not easily or clearly defined. For example, DEA has been used in measuring efficiency of schools, hospitals and government institutions. It is also useful in determining the efficiency of firms that consume or produce inputs or outputs, which lack natural prices. DEA is a linear programming based technique and the basic model only requires information on inputs and outputs, though if prices are available then DEA can be used to study cost efficiency. DEA can incorporate multiple outputs and inputs; in fact, inputs and outputs can be defined in a very general manner without getting into problems of aggregation. If more of a measure is desirable it can be modeled as output and if less of something is better, it can be interpreted as input. This is an attractive feature as in many service industries such as banking; it is difficult to determine whether deposits, for example, are an output or an input, which produce loans. DEA can also make use of proxy outputs including output combinations that would not be used with other efficiency measures.

DEA provides a scalar measure of relative efficiency by comparing the efficiency achieved by a decision-making unit (DMU) with the efficiency obtained by similar (or peer) DMUs. The method allows us to obtain a well-defined relation between outputs and inputs. In the case of a single output this relation corresponds to a production function in which the output is maximal for the indicated inputs. In the more general case of multiple outputs this relation can be defined as an efficient production possibility surface or frontier. As this production possibility surface or frontier is derived from empirical observations, it measures the relative efficiency of DMUs that can be obtained with the existing technology or management strategy. Technological or managerial change can be evaluated by considering each set of values for different time periods for the same DMU as separate entities (each set of values as a different DMU). If there is a significant change in technology or management strategies this will be reflected in a change in the production possibility surface.

To summarize: DEA is a non-parametric technique that can be used to model production and efficiency of non-profit organizations. Inputs and outputs can be defined in a very general manner in that if more of something is better then it is an output and if less of something is better it is an input. DEA can handle multiple inputs and outputs and can be used to study cost or productive efficiency of a firm or a division or department within a firm. It basically compares a DMU to (efficient) peers thus it is somewhat similar to benchmarking. It can also predict how inputs and outputs should be adjusted for an inefficient unit to become efficient. Further, the efficiency scores can also be used in a second stage regression analysis, which allows for examining the impact of managerial variables on efficiency.

DEA methods can also be used to construct distance functions, which can be used to construct the Malmquist index of productivity change. This can then be decomposed into various components such as scale efficiency change and technical efficiency change.

The Malmquist index of productivity change can be written as follows, where *y* represents outputs, *x* represents inputs, *t* indexes time periods and *D(.)* represents distance functions:

$$M_{t,t+1} = \left[ \frac{D_t(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)} \frac{D_{t+1}(x_{t+1}, y_{t+1})}{D_{t+1}(x_t, y_t)} \right]^{1/2} \qquad (15)$$

The above measure can also be expressed as:

$$M_{t,t+1} = \frac{D_{t+1}(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)} * \left[ \frac{D_t(x_{t+1}, y_{t+1})}{D_{t+1}(x_{t+1}, y_{t+1})} \frac{D_t(x_t, y_t)}{D_{t+1}(x_t, y_t)} \right]^{1/2} \qquad (16)$$

In the above equation, the first term measures efficiency change and the second term (in square brackets) measures technical change. Calculating the Malmquist index and its components requires the calculation of four distances: $D_t(x_t, y_t)$, $D_{t+1}(x_{t+1}, y_{t+1})$, $D_t(x_{t+1}, y_{t+1})$ and $D_{t+1}(x_t, y_t)$. This is accomplished by solving four (constant returns to scale) linear programming (DEA) problems, thus making use of the fact that output distance function is the inverse of the Farrell output oriented measure of technical efficiency. For each firm *k*, $D_t(x_t, y_t)$ can be computed as follows, as can $D_{t+1}(x_{t+1}, y_{t+1})$ by substituting *t+1* for *t*:

$$
\begin{aligned}
&((D_t(x_t, y_t))^{-1} = \max_{\theta_k, \lambda_k} \theta_k \\
&s.t. \\
&\theta_k\, y_{t,m}^k \le \sum_{k=1}^{K} \lambda_{k,t}\, y_{t,m}^k \quad m = 1, \dots, M \\
&\sum_{k=1}^{K} \lambda_{k,t}\, x_{t,n}^k \le x_{t,n}^k \quad n = 1, \dots, N \\
&\lambda_{k,t} \ge 0 \quad k = 1, \dots, K
\end{aligned}
\tag{17}
$$

Similarly, $D_t(x_{t+1}, y_{t+1})$ can be computed as follows, as can $D_{t+1}(x_t, y_t)$ by interchanging *t+1* and *t*:

$$
\begin{aligned}
&((D_t(x_{t+1}, y_{t+1}))^{-1} = \max_{\theta_k, \lambda_k} \theta_k \\
&s.t. \\
&\theta_k\, y_{t+1,m}^k \le \sum_{k=1}^{K} \lambda_{k,t}\, y_{t,m}^k \quad m = 1, \dots, M \\
&\sum_{k=1}^{K} \lambda_{k,t}\, x_{t,n}^k \le x_{t+1,n}^k \quad n = 1, \dots, N \\
&\lambda_{k,t} \ge 0 \quad k = 1, \dots, K
\end{aligned}
\tag{18}
$$

Both the efficiency change and technical change measures in (16) can be decomposed further. The output oriented measure of scale efficiency can be defined as the ratio of an output oriented distance function for a variable returns to scale technology to that for a constant returns to scale technology or:

$$
S_t(x_t, y_t) = \frac{D_t(x_t, y_t | V)}{D_t(x_t, y_t | C)} \tag{19}
$$

Calculating this requires solving the LP in (17) with the following additional restriction for variable returns to scale:

$$\sum_{k=1}^{K} \lambda_{k,t} = 1 \tag{20}$$

Thus, the efficiency change component in (16) can be decomposed into scale efficiency change and pure efficiency change as:

$$EFFCH = \frac{S_t(x_t, y_t)}{S_{t+1}(x_{t+1}, y_{t+1})} \frac{D_{t+1}(x_{t+1}, y_{t+1}|V)}{D_t(x_t, y_t|V)} \tag{21}$$

The technical change component in (16) can also be decomposed as the product of the magnitude of technical change and (input and output) bias, where magnitude is defined as follows:

$$MTECH = \frac{D_t(x_t, y_t)}{D_{t+1}(x_{t+1}, y_{t+1})} \tag{22}$$

To summarize: the Malmquist index of productivity change can be represented as the product of efficiency change and technical change. Efficiency change can be further decomposed as the product of scale efficiency change and pure efficiency change, whereas technical change can be decomposed as the product of the change in the magnitude of technical change and bias.

DEA offers advantages because it can employ physical measures of inputs and outputs but it also has some disadvantages. It is sensitive to outliers and there will invariably be more than 'most efficient' firm. This is equivalent to having more than one benchmark. Another major criticisms of non-parametric methods of measuring productivity such as those described above is that one has no sense of statistical significance. Increasingly this is becoming less of a problem, since bootstrap techniques can be used to derive confidence intervals for both DEA efficiency scores and the Malmquist index of productivity change.

**SUMMARY AND CONCLUSIONS**

The numerous statistical cost equations estimated by GRA attempt to identify cost drivers, service quality and productivity. Our approach is designed to complement this work and in some sense provide a check. For example, where GRA's estimate would provide a measure of average variable cost of a particular activity. Our approach would provide a measure of marginal costs. These two values serve as a check on the robustness of the cost estimates and to some degree on measures of returns to scale.[5]

When it comes to strategy or to issues such as what can management do? one has to be very clear about what management can control and what it cannot. ATC is affected by technology issues, capital investment and by regulatory issues – these aspects are 'exogenous' in the sense that they are external but they affect ATC. Exogenous factors should not be used to study efficiency or performance of ATC controllers, because they represent constraints within which ATC controllers must operate. However, they also provide information for senior management and policy makers at the FAA as to how future investments might be made to ease such constraints.

In order to perform a sensible analysis we need to identify these variables. For example if an ATC controller cannot really force aircraft to stick to a particular route then any errors due to separation violations may affect the productivity of the ATC controller, but separation errors cannot be used as an endogenous variable or a variable under the control of management. Similarly when it comes to performance measurement, the number of errors should be held constant – so given the extent/number of separation errors (which are outside the control of ATC controllers) how have they performed? This is the correct question.

DEA may be used as a benchmarking tool for SDPs, but we have to be very careful in the specification of what is discretionary and what is not. It is also critical to check the

[5] The cost elasticity can be defined as the ratio of marginal to average cost. A cost elasticity $<1$ implies increasing returns to scale.

distribution of all variables, as DEA is highly susceptible to outliers. The Malmquist index can be used to study performance over time.

Any subsequent analysis must carefully identify key variables such as institutional and regulatory technology. Institutional technology would reflect the sets of rules that govern input and output ratios in operations and are established by the FAA. Such rules as numbers of controllers for a given traffic level affect costs but do not reflect a flexible production structure. Regulatory technology would reflect rules concerning separations of aircraft, aircraft spacing and operational rules in conditions of congestion. Such rules result in ceilings being imposed on the output of an ATC center. These are exogenous and must be controlled for in any model.

Externalities between ATC centers must also be accounted for. This was a major theme of our work. Neither TFP nor DEA are able to handle such effects directly in their calculation. Indeed, one would expect the 'gross' measures of either TFP or DEA to include such externality effects and identification would require a second stage estimation such as a Tobit regression on a set of characteristic or exogenous variables to net out these influences.

Perhaps the most important effort in the next step is to develop or construct a model or theory of ATC management. At present we have a set of operations and these operations reflect past decisions and investments. But operations take place in a context of firm objectives, a production technology and a market setting. By having a model of the ATC plant or firm we would better be able to judge or assess the signs and significance of variable relationships.