ECONOMIC INSIGHTS Pty Ltd

Memorandum

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To: Mark Pollock, Australia Post
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Subject: Australia Post's Mail and Delivery Centre Cost Elasticities

Australia Post has requested Economic Insights to undertake an econometric analysis of the likely effects of declining mail volumes and declining mail density on Australia Post's future costs. We do this by estimating total cost and variable cost functions for panel data on Australia Post's key mail centres (MCs) and for panel data on its delivery centres (DCs). From these cost functions we derive cost output elasticities which show the percentage change in costs in response to a one per cent change in output. A cost elasticity of one would indicate that costs change by exactly the same percentage as output while a cost elasticity of zero would indicate that costs are totally independent of output changes.

Background

In reviewing Australia Post's mail volume and cost forecasts submitted with its previous draft changes to the domestic reserved letter service, the Australian Competition and Consumer Commission's (ACCC's) consultant, Frontier Economics (2010), noted that there was no reviewable information supplied to support the relationship between output and costs postulated. It also noted that the implied elasticities appeared low in comparison to those derived from a number of international studies. Frontier calculated Australia Post's overall implied cost elasticity to be 0.14 and compared that to a number of international studies which estimated postal cost elasticities to be between 0.60 and 0.70. These studies included Moriarty et al (2006) prepared for PostComm using Royal Mail network data, NERA (2004) using data from the ten original European Union countries and Bozzo (2009) using USPS data.

In response, Australia Post (2011) noted that these studies were of limited relevance to Australia because, among other things, they were all undertaken in an environment of increasing volumes and for countries with higher population densities than Australia. Australia Post argued there was likely to be an asymmetry in the cost/volume relationship between situations of increasing volumes versus declining volumes with a more inelastic relationship applying for declining volumes, ie it is harder to reduce costs in response to volume reductions as more costs then become akin to fixed costs.

Australia Post also argued that a higher population density implies that delivery costs are a smaller proportion of total costs and, since delivery costs are less variable when volume falls, the total cost elasticity in high density countries is likely to be higher.

This study aims to provide information on postal cost elasticities specifically for Australia and using recent data from the period of secularly declining mail volumes. It also uses flexible functional forms for the estimated cost function and covers all inputs whereas earlier studies have tended to use simple functional forms and only cover labour data.

Australia Post mail centre data

Australia Post provided detailed monthly output and cost data and annual asset data on its six major metropolitan MCs for the period July 2006 to October 2013. The six MCs included are:

- Adelaide Mail Centre (SA)
- Dandenong Letters Centre (Vic)
- Northgate Mail Centre (Qld)
- Perth Mail Facility (WA)
- Sydney West Letters Facility (NSW), and
- Underwood Mail Centre (Qld).

In 2012–13 these six MCs accounted for over 80 per cent of overall mail processing costs. Around 80 per cent of articles processed in these six MCs were reserved services. The results from the analysis will thus be representative of reserved service processing costs. Processing costs account for just under 20 per cent of overall reserved service operational costs.

Volume data for the six MCs were extracted from Australia Post's Mail and Delivery Centre Statistics (MDCS) database which is updated daily while financial and asset data were extracted from Australia Post's SAP financial system. The MC data started to be recorded in its current format in 2007–08. As with any database there were some early changes to the way items were recorded and increasing automation of recording with progressively less reliance on manual data entry has improved the accuracy of data over time. Some anomalous observations (mainly found in 2007–08 and 2008–09) have been interpolated, based largely on relative movements of the item between months in subsequent years.

Data are included for the 76 months from July 2006 to October 2013 for all MCs except Underwood which is included only up to June 2012 due to its increasing focus on parcels and subsequent reclassification as a parcels centre rather than an MC. This leads to a total of 440 observations for the MC analysis.

Mail centre outputs

Australia Post's MCs undertake four key stages of mail processing being:

- culling, franking and cancelling (CFC)
- optical character reading (OCR)
- bar code sorting (BCS), and
- manual sorting (MS)

Data on a total of 81 individual MC processes were provided by Australia Post. These processes were allocated to one of the four key stages with assistance from Australia Post operational experts. These individual processes are further associated with one of four broad types of mail being:

- Standard letters (SL)
- Large letters (LL)
- Small parcels (SP), and
- Large parcels (LP).

The four different types of mail listed above have progressively increasing resource requirements. Since the shares of these mail types will differ between MCs and between months, it is important to allow for these differences in resource requirements across the 440 MC observations. We do this by converting the number of articles handled in each of the four key MC processing stages into numbers of 'standard letter equivalents'. Conversion factors were derived from data on volumes and costs of around 30 different types of mail supplied by Australia Post. Since MC activities could not be consistently separated within these data, overall unit cost relativities were used to derive the conversion factors for forming the number of standard letter equivalents. Relative to a standard letter unit cost of one, the unit cost of large letters is taken to be 1.8, of small parcels to be 8.9 and of large parcels to be 15.

The allocation and conversion factor matrix used to form the number of standard letter equivalents handled in each of the four key MC processing stages is presented in appendix A.

Mail centre non–capital inputs

Australia Post provided detailed monthly operating cost data on each of the six included MCs. These data were divided into labour costs and other (non–labour and non–capital) costs for the analysis. Labour costs comprised directly employed staff labour costs (including on–costs), contract labour and staff–associated costs. An Australia Post–specific labour price index was formed based on scheduled wage increases included in Australia Post's Enterprise Bargaining Agreements (EBAs).

The other costs category includes the remaining non–capital costs making up trading expenditure (excluding notional expenses) with the exception of air transport. Air transport costs are excluded as they are not a facility cost and disproportionately impact Perth MC costs. Notional expenses are excluded to avoid double counting with our explicitly included capital costs. In the absence of more specific price information, the consumer price index (CPI) is used as the price index associated with other costs.

In the first half of the time period examined there were a number of cost reallocations for some of the MCs and, in some cases, creation of additional cost centres. In most cases these reallocations were subsequently reversed by Australia Post. To ensure consistency of treatment we have aggregated relevant cost centre accounts for each MC and, where necessary, interpolated items that were temporarily transferred to product rather than facility reporting.

Mail centre capital inputs

Australia Post provided detailed MC asset data separately covering Plant and equipment and Buildings. Plant and equipment data supplied included:

- Asset code (eg ZP14)
- Acquisition value

- Accumulated depreciation, and
- Book value

These data were supplied for each of the six MCs for the 13 years from 2000–01 to 2012–13 and covered some 6,500 items each year across the six MCs in up to 300 asset categories. It is important to note that each reported item could relate to multiple physical items, such as 2 or more PCs, but in our calculations we implicitly treat the data as if each reported item only contains one physical item (or, alternatively, a number of similarly classified physical items purchased at the same point in time). Australia Post separately supplied detailed information on the expected asset life for each asset category.

Our calculations (for each asset category in each year in each MC) proceeded as follows:

- Use the asset code (eg ZP14) to allocate an assumed asset life (eg 5 years)
- Estimate the approximate average age of assets in the asset category by the formula:

  Asset age = accumulated depreciation / acquisition value × asset life

- Use the asset age information to convert the (nominal) acquisition value into a real acquisition value (in 2013 dollars) by the formula:

  Real acquisition value = Nominal acquisition value × CPI index,

  where the CPI index has a base of 1 in 2012–13. We used the ABS March quarter CPI index in these calculations. Note that the CPI index used depends on the asset age AND the year involved (eg an asset age of 6 years in 2010–11 equates to a period lag of 6+2=8 years which means that the 2004–05 CPI index would be used in this case).

- Calculate a real annuity using three pieces of information:
  - Real acquisition value
  - Asset life, and
  - Real interest rate of 7 per cent per annum.

These annuities are then added together to obtain an aggregate Plant and equipment estimate for each MC in each year until the end of the asset's expected life has been reached. These annual values are then divided by 12 to obtain monthly values. Real annuities for the four included months of 2013–14 (for which no annual data is currently available) were formed by extrapolating the change in monthly real annuities between 2011–12 and 2012–13.

For Buildings data, in addition to the same book value information as supplied for Plant and equipment, Australia Post also supplied us with data on current cost asset valuations or 'fair values' for the 13 year period 2000–01 to 2012–13. Australia Post uses an external valuer to revalue its MC buildings on a 3 year rotational basis and the assets that are not individually valued in a particular year are adjusted by use of a property index. As this additional information is available, we use a different approach to forming the Buildings real annuity.

Our calculations (for each year in each MC) proceeded as follows:

- Convert the (nominal) current cost values into real values (in 2013 dollars) by the formula:

Real fair value = Nominal fair value × CPI index,

where the CPI index has a base of 1 in 2012–13. We used the ABS March quarter CPI index in these calculations. Note that the CPI index used depends only on the year involved because the fair value is already in "current cost" terms.

- Calculate a real annuity using three pieces of information:
  - Real asset valuation
  - Asset life of 40 years
  - Real interest rate of 7 per cent per annum.

These annual values are then divided by 12 to obtain monthly values.

Econometric estimation of a total cost function for MCs

We begin by defining the following notation:

TC = nominal total cost;

$Y = (Y_1, Y_2, ..., Y_M)$ = an M×1 vector of output quantities; and

$W = (W_1, W_2, ..., W_M)$ = a K×1 vector of input prices.

We use lower case notation to define the natural logarithms of variables. For example, $y_1 = \log(Y_1)$.

The two most commonly used functional forms in econometric estimation of cost functions are the Cobb–Douglas and translog functional forms. These functions are linear in logs and quadratic in logs, respectively.

The Cobb–Douglas cost function may be written as:

$$tc_{ijt} = \alpha_0 + \sum_{k=1}^{K} \alpha_k w_{kijt} + \sum_{m=1}^{M} \beta_m y_{mijt} + \lambda_1 t + v_{ijt}, \tag{1}$$

while the translog cost frontier may be specified as:

$$\begin{aligned} tc_{ijt} = {} & \alpha_0 + \sum_{k=1}^{K} \alpha_k w_{kijt} + 0.5 \sum_{k=1}^{K} \sum_{l=1}^{K} \alpha_{kj} w_{kijt} w_{lijt} + \sum_{m=1}^{M} \beta_m y_{mijt} + 0.5 \sum_{m=1}^{M} \sum_{n=1}^{M} \beta_{mn} y_{mijt} y_{nijt} \\ & + \sum_{k=1}^{K} \sum_{m=1}^{M} \gamma_{km} w_{kijt} y_{mijt} + \sum_{k=1}^{K} \delta_k w_{kijt} t + \sum_{m=1}^{M} \phi_m y_{mijt} t + \lambda_1 t + 0.5 \lambda_{11} t^2 + v_{ijt}, \end{aligned} \tag{2}$$

where subscripts i, j and t denote MC, month and year, respectively. Furthermore, the regressor variable "t" is a time trend variable used to capture the effects of year to year technical change, v_{ijt} is a random disturbance term and the Greek letters denote the unknown parameters that are to be estimated.

A cost function should be homogenous of degree one in input prices, which means that the multiplication of all input prices by any constant value multiplies the costs by the same constant. The required homogeneity restrictions for the Cobb–Douglas are

$$\sum_{k=1}^{K}\alpha_k = 1, \tag{3}$$

while for the translog they are

$$\sum_{k=1}^{K}\alpha_k = 1, \quad \sum_{k=1}^{K}\alpha_{kl} = 0 \;\; (l = 1,2,...,K), \quad \sum_{k=1}^{K}\gamma_{kl} = 0 \;\; (l = 1,2,...,M), \quad \sum_{k=1}^{K}\delta_k = 0\,. \tag{4}$$

In our analysis of MCs, we have identified a set of K=4 input variables:

1. labour
2. plant and equipment (P&E)
3. buildings
4. other,

and a set of M=4 output variables:

1. CFC = culling, franking and cancelling
2. OCR = optical character reading
3. BCS = bar code sorting
4. MS = manual sorting.

In our assessment these input and output categories represent the key aspects of production in Australia Post MCs.

These variables would imply the need to estimate $M + K + 2$ parameters for the Cobb–Douglas function and $M + K + 2 + (M + K)(M + K + 1)/2$ for the translog function. It is tempting to choose the Cobb–Douglas functional form because it involves the estimation of fewer parameters. However, given that it only provides a first–order approximation to the true unknown functional form, it has a number of shortcomings. For example, it assumes that elasticities remain constant over all data points, and hence that scale economies and technical change must also be constant over time. Furthermore, it has particular shortcomings in multi–output settings, because it cannot accommodate a production possibility curve that is concave to the origin (ie one which incorporates the fundamental property of diminishing returns). Hence, we will use the translog model as our first choice, and then conduct a formal statistical test to see if the restrictions implicit in the Cobb–Douglas apply in our data.

In our discussion above we noted that four input variables have been identified and measured. However, in identifying possible price variables associated with these four input categories, we concluded that a wage price index was appropriate for the labour category, while the Australian Bureau of Statistics (ABS) Consumer Price Index (CPI) was the best available price measure for the remaining three categories of inputs. As a result, the number of price variables in our model reduces from K=4 to K=2.

Furthermore, when we attempted to estimate an econometric model with K=2 input price variables and the homogeneity restrictions imposed, we found that the price coefficients were not well estimated in some models, producing own price elasticities outside of the theoretical

0–1 range. This is perhaps not unexpected, given that our EBA–based labour price index only involves eight unique values. As a consequence, we decided to impose the restriction that the input price elasticities are equal to the mean input cost shares for the sample. This implies an assumption of cost minimising behaviour at the sample mean data point.

In practical terms, this involved the construction of an aggregate input price index using a Tornqvist index formula (using the sample mean input cost share weights of 79 per cent and 21 per cent for the wage index and CPI, respectively), and then using this aggregate input price index to deflate the nominal total cost measure. We then use a real (as opposed to nominal) total cost measure as the dependent variable and omit input price variables from the regressor list.[1]

Given that our data set involves data on a number of units (MCs) observed over a number of years and months (ie monthly panel data), we have chosen to include dummy variables to capture differences in production activities across MCs and across months. We define six dummy variables for MCs 1 to 6:

$$DMC_{hijt} = 1 \text{ when } h = i, \text{ and is 0 otherwise, } (h = 1,...,6).$$

And 12 dummy variables for months 1 to 12:

$$DMO_{gijt} = 1 \text{ when } g = \mathrm{j}, \text{ and is 0 otherwise, } (g = 1,...,12).$$

With these additions, our translog cost function becomes:

$$\begin{aligned} rtc_{ijt} = {} & \alpha_0 + \sum_{m=1}^{4} \beta_m y_{mijt} + 0.5 \sum_{m=1}^{4} \sum_{n=1}^{4} \beta_{mn} y_{mijt} y_{nijt} + \sum_{m=1}^{4} \phi_m y_{mijt} t + \lambda_1 t + 0.5 \lambda_{11} t^2 \\ & + \sum_{h=2}^{6} \eta_h DMC_{hijt} + \sum_{g=1}^{11} \theta_g DMO_{gijt} + v_{ijt}, \end{aligned} \tag{5}$$

where *rtc* refers to real total cost.

Note that one dummy variable is omitted from each group to avoid perfect multicollinearity in the econometric model. Hence, the "base category" in our model becomes MC1 in month 12 (December).

With these changes, we obtain a final *fixed effects panel data model* where there are 38 unknown parameters to be estimated from a sample size of 440 observations.

Econometric results for the mail centre total cost function

The model in equation (5) is estimated using a variant of *ordinary least squares* (OLS) regression, where OLS is applied to data that has been transformed to correct for serial correlation (assuming a common autoregressive parameter across the MCs)[2]. We have also chosen to report *panel–corrected standard errors*, where the standard errors have been corrected for cross–sectional heteroskedasticity. The estimation methods used follow those described in Beck and Katz (1995) and Greene (2000, Ch15) and have been calculated using the POOL command in Shazam Version 10 Software (Northwest Econometrics 2007).

[1] The imposition of this restriction had very minimal effects of the output elasticities obtained.
[2] As recommended by Beck and Katz (1995).

The econometric results are reported in table 1, where we observe that the majority of estimated coefficients have t–ratios in excess of 1.96, indicating that they are statistically different from zero at the five per cent level of significance, and the R–Square is a healthy 98.8 per cent.

Table 1: Econometric results for the mail centre panel data total cost function

VARIABLE	COEFFICIENT	ST-ERROR	T-RATIO
CFC	0.102	0.029	3.550
OCR	0.080	0.039	2.044
BCS	0.151	0.045	3.361
MS	0.106	0.034	3.165
YEAR	-0.014	0.003	-4.841
MO1	-0.129	0.025	-5.196
MO2	-0.153	0.022	-6.978
MO3	-0.125	0.021	-6.062
MO4	-0.100	0.022	-4.454
MO5	-0.128	0.021	-6.043
MO6	-0.148	0.022	-6.779
MO7	-0.153	0.021	-7.443
MO8	-0.134	0.020	-6.569
MO9	-0.157	0.021	-7.592
MO10	-0.133	0.019	-6.871
MO11	-0.140	0.019	-7.404
MC2	0.799	0.042	19.100
MC3	0.049	0.016	3.054
MC4	0.043	0.015	2.840
MC5	0.857	0.047	18.190
MC6	0.135	0.115	1.174
CFC*CFC	0.148	0.078	1.896
CFC*OCR	-0.171	0.047	-3.636
CFC*BCS	0.017	0.124	0.134
CFC*MS	-0.048	0.032	-1.509
OCR*OCR	0.226	0.105	2.151
OCR*BCS	-0.122	0.106	-1.154
OCR*MS	0.021	0.058	0.371
BCS*BCS	0.236	0.292	0.810
BCS*MS	-0.068	0.065	-1.051
MS*MS	0.084	0.050	1.687
YEAR*YEAR	0.006	0.002	3.294
YEAR*CFC	-0.014	0.008	-1.780
YEAR*OCR	-0.012	0.007	-1.618
YEAR*BCS	0.023	0.012	1.928
YEAR*MS	0.005	0.006	0.863
CONSTANT	14.870	0.017	886.300
BUSE R-SQUARE			*0.988*

It is important to note that the regressor variables (except for the dummy variables) have been mean–corrected prior to estimation (in all the econometric models in this report). This does not change the substance of the empirical results in any way, but has the advantage that it allows one to interpret the first order coefficients as elasticities at the sample means, which saves considerable secondary calculations.

We first discuss the first–order coefficients of the four output variables. All four output coefficients have the expected positive signs, implying that extra output incurs extra costs. The estimated coefficient of the CFC output is 0.102, implying that a 1 per cent increase in CFC will lead to a 0.102 per cent increase in costs (all else held constant), at the sample mean. The corresponding coefficients of OCR, BCS and MS, are 0.080, 0.151 and 0.106, respectively, implying elasticities at the sample means of 0.080 per cent, 0.151 per cent and 0.106 per cent, respectively.

When added together, these four output elasticity estimates provide a total elasticity measure of 0.102+0.080+0.151+0.106=0.440, implying that a 1 per cent increase in all outputs will lead to a 0.44 per cent increase in total MC costs. Equivalently, it implies that a 1 per cent *decrease* in all outputs should correspond to a 0.44 per cent *decrease* in total MC costs, which is of particular interest in this study. This linear combination estimate (0.440) has an estimated standard error of 0.041, producing a 95 per cent confidence interval of (0.360, 0.520).

The first order coefficient of the YEAR (time trend) variable is negative as expected (and statistically significant).[3] The value of –0.014 implies that that costs decrease at a rate of 1.4 per cent per year (all else held constant), at the sample mean. This estimate of technical change of 1.4 per cent can be compared to rates of 1 to 2 per cent that are generally found in empirical studies of various industries.

The estimated coefficients of the 11 monthly dummy variables are all negative. This is as expected, given that the base month of comparison is December. We expected that costs would be higher in December because of the extra overtime expenditure used in dealing with the Christmas rush. For example, the estimated coefficient of MO3 (March) is –0.125, implying that costs in March are 12.5 per cent below those in December (all else held constant), at the sample mean. The other ten monthly dummy variable coefficients are interpreted in a similar manner.

The estimated coefficients of the 5 MC dummy variables are interpreted in a similar manner. Recalling that the base MC is MC1, the estimated coefficient of MC4 is 0.043, which implies that costs in MC4 are 4.3 per cent higher than those in MC1 (all else held constant), at the sample mean, and so on.

The estimated coefficients of the other (second order) coefficients are difficult to interpret directly. Their main use is in allowing one to estimate elasticities at points other than the sample means (after some calculations).

A number of hypothesis tests were also conducted to see if a more parsimonious model could be used to describe these data. We conducted a hypothesis test to see if a Cobb–Douglas functional form was appropriate for these data. The parameter restrictions involved setting

[3] All references to statistical insignificance are at the 5 per cent level, unless otherwise stated.

the 15 second order coefficients in equation (5) to zero producing a Cobb–Douglas cost function of the form:

$$rtc_{ijt} = \alpha_0 + \sum_{m=1}^{4} \beta_m y_{mijt} + \lambda_1 t + \sum_{h=2}^{6} \eta_h DMC_{hijt} + \sum_{g=1}^{11} \theta_g DMO_{gijt} + v_{ijt}, \qquad (6)$$

The F–test statistic with 15 and 403 degrees of freedom was 4.989 with a p–value of 0.000, indicating that the null hypothesis of a Cobb–Douglas model cannot be accepted at a 5 per cent level of significance, implying that the translog form is the preferred model.

We conducted a second hypothesis test to see if the 11 monthly dummy variables were a significant addition to the model. The F–test statistic with 11 and 403 degrees of freedom was 9.660 with a p–value of 0.000, indicating that the null hypothesis of these 11 coefficients being zero could not be accepted at a 5 per cent level of significance, implying that the 11 monthly dummy variables were a significant addition to the model.

We conducted a third hypothesis test to see if the 5 MC dummy variables were a significant addition to the model. The F–test statistic with 5 and 403 degrees of freedom was 98.615 with a p–value of 0.000, indicating that the null hypothesis of these 5 coefficients being zero could not be accepted at a 5 per cent level of significance, implying that the 5 MC dummy variables were a significant addition to the model.

To summarise, we illustrate the pricing implications of our MC total cost function findings using the changes observed in relevant variables across the first five MCs as a whole between 2011–12 and 2012–13 in the following calculations. The total standard letter equivalents processed in the four MC processing stages decreased by 3.32 per cent over this period. The wage rate index increased by 1.49 per cent while the CPI increased by 2.27 per cent between the two years. Combining these changes with their relevant cost elasticities and including the estimated impact of technical change, we obtain the following estimated change in total costs:

0.440 x (–0.0332) + 0.790 x 0.0149 + (1 – 0.790) x 0.0227 + (–0.014) = –0.0121

That is, the combined effects of the 3.32 per cent reduction in output, the 1.49 per cent increase in the wage rate, the 2.27 per cent increase in the price of other inputs and capital and ongoing technical change would have been an overall MC cost reduction of 1.2 per cent between 2011–12 and 2012–13. The effect on MC total costs of the output reduction in isolation would have been a reduction in total MC costs of 1.5 per cent (from the first term above).

Econometric estimation of a mail centre variable cost function

The above estimates for a total cost function provide elasticity estimates that assume that all costs (including capital costs) can be varied when output varies. Hence they provide an estimate of how costs can be varied in the long run, when there is sufficient time to adjust quantities of capital.

In the short run, one is unable to easily adjust capital inputs, and hence it is of interest to also estimate a variable cost function, where the dependant variable is variable costs (total costs minus capital costs). This function will allow us to estimate the degree to which variable costs respond to output changes (with capital quantity held fixed).

To define our new model we define the additional notation:

RVC = real variable costs (labour plus other costs deflated by an aggregate input price index),

CAP = capital quantity (real P&E and building costs).

and once again we use lower case notation to define the natural logarithms of variables. For example, $rvc = \log(RVC)$.

Note that the real variable cost measure is obtained by deflating nominal variable cost by an aggregate input price index, where the sample mean input cost share weights are 91 per cent and 9 per cent for the wage index and CPI, respectively.

Our translog variable cost function is then defined as:

$$\begin{aligned} rvc_{ijt} &= \alpha_0 + \sum_{m=1}^{4} \beta_m y_{mijt} + 0.5 \sum_{m=1}^{4} \sum_{n=1}^{4} \beta_{mn} y_{mijt} y_{nijt} + \sum_{m=1}^{4} \phi_m y_{mijt} t + \lambda_1 t + 0.5 \lambda_{11} t^2 \\ &+ \rho_1 cap_{ijt} + 0.5 \rho_{11} cap_{ijt} cap_{ijt} + \sum_{m=1}^{4} \psi_{1m} cap_{ijt} y_{mijt} + \tau_1 cap_{ijt} t \\ &+ \sum_{h=2}^{6} \eta_h DMC_{hijt} + \sum_{g=1}^{11} \theta_g DMO_{gijt} + v_{ijt}, \end{aligned} \tag{7}$$

and the Cobb–Douglas becomes:

$$rvc_{ijt} = \alpha_0 + \rho_1 cap_{ijt} + \sum_{m=1}^{4} \beta_m y_{mijt} + \lambda_1 t + \sum_{h=2}^{6} \eta_h DMC_{hijt} + \sum_{g=1}^{11} \theta_g DMO_{gijt} + v_{ijt} \tag{8}$$

Econometric results for the mail centre variable cost function

The model in equation (7) is estimated using the same econometric methods used in the previous section. That is, we correct for serial correlation and have chosen to report *panel–corrected standard errors*, where the standard errors have been corrected for cross–sectional heteroskedasticity.

The econometric results are reported in table 2, where we again observe that the majority of estimated coefficients have t–ratios in excess of 1.96, indicating that they are statistically different from zero at the five percent level of significance, and the R–Square is an impressive 98.5 per cent.

We first discuss the first–order coefficients of the four output variables. All four output coefficients have the expected positive signs, implying that extra output incurs extra variable costs. The estimated coefficient of the CFC output is 0.130, implying that a 1 per cent increase in CFC will lead to a 0.130 per cent increase in variable costs (all else held constant), at the sample mean. The corresponding coefficients of OCR, BCS and MS, are 0.071, 0.213 and 0.148, respectively, implying elasticities at the sample means of 0.071 per cent, 0.213 per cent and 0.148 per cent, respectively.

When added together, these four output elasticity estimates provide a total elasticity measure of 0.130+0.071+0.213+0.148=0.562, implying that a 1 per cent increase in all outputs will lead to a 0.562 per cent increase in variable costs. Equivalently, it implies that a 1 per cent *decrease* in all outputs should correspond to a 0.562 per cent *decrease* in variable costs, which is of particular interest in this study. This linear combination estimate (0.562) has an estimated standard error of 0.050, producing a 95 per cent confidence interval of (0.463, 0.660).

The total elasticity measure in the variable cost function (0.562) is larger than that obtained in the total cost function (0.440). This is as expected, given that variable costs are expected to be more “flexible” over the short time frame considered in these data.

The first order coefficient of the YEAR (time trend) variable is negative as expected (although statistically insignificant). The value of –0.014 implies that variable costs decrease at a rate of 1.4 per cent per year (all else held constant), at the sample mean. This estimate of technical change is the same as that found in the total cost function.

The first order coefficient of the CAP variable is negative as expected (implying input substitution). It has a value of –0.096 implying that a 1 per cent increase in capital will lead to a 0.096 per cent decrease in variable costs (all else held constant), at the sample mean. However, we note that this measure is small and statistically insignificant. This may be a consequence of the fact that capital does not vary substantially during the sample period.

The estimated coefficients of the monthly dummy variables and MC dummy variables are similar to those seen in the total cost function, and are interpreted in a similar manner.

Once again, a number of hypothesis tests were also conducted to see if a more parsimonious model could be used to describe these data. We conducted a hypothesis test to see if a Cobb–Douglas functional form was appropriate for these data. The parameter restrictions involved setting the 28 second order coefficients in equation (7) to zero producing the Cobb–Douglas variable cost function reported in equation (8).

The F–test statistic with 21 and 396 degrees of freedom was 4.376 with a p–value of 0.000, indicating that the null hypothesis of a Cobb–Douglas model cannot be accepted at a 5 per cent level of significance, implying that the translog form is the preferred model.

We conducted a second hypothesis test to see if the 11 monthly dummy variables were a significant addition to the model. The F–test statistic with 11 and 396 degrees of freedom was 9.075 with a p–value of 0.000, indicating that the null hypothesis of these 11 coefficients being zero could not be accepted at a 5 per cent level of significance, implying that the 11 monthly dummy variables were a significant addition to the model.

We conducted a third hypothesis test to see if the 5 MC dummy variables were a significant addition to the model. The F–test statistic with 5 and 388 degrees of freedom was 9.601 with a p–value of 0.000, indicating that the null hypothesis of these 5 coefficients being zero could not be accepted at a 5 per cent level of significance, implying that the 5 MC dummy variables were a significant addition to the model.

Table 2: Econometric results for the mail centre panel data variable cost function

VARIABLE	COEFFICIENT	ST-ERROR	T-RATIO
CFC	0.130	0.033	3.928
OCR	0.071	0.049	1.439
BCS	0.213	0.052	4.114
MS	0.148	0.038	3.880
YEAR	-0.014	0.004	-3.109
CAP	-0.096	0.102	-0.936
MO1	-0.140	0.030	-4.727
MO2	-0.180	0.027	-6.744
MO3	-0.154	0.025	-6.055
MO4	-0.118	0.027	-4.339
MO5	-0.159	0.026	-6.121
MO6	-0.176	0.027	-6.640
MO7	-0.183	0.025	-7.247
MO8	-0.164	0.025	-6.571
MO9	-0.189	0.025	-7.460
MO10	-0.161	0.024	-6.716
MO11	-0.169	0.023	-7.210
MC2	0.876	0.178	4.926
MC3	0.050	0.033	1.520
MC4	0.061	0.043	1.422
MC5	0.838	0.220	3.803
MC6	0.124	0.123	1.004
CFC*CFC	0.109	0.089	1.233
CFC*OCR	-0.146	0.096	-1.519
CFC*BCS	0.002	0.138	0.017
CFC*MS	-0.072	0.040	-1.825
OCR*OCR	0.125	0.182	0.684
OCR*BCS	-0.203	0.098	-2.085
OCR*MS	-0.273	0.183	-1.491
BCS*BCS	0.262	0.319	0.822
BCS*MS	-0.058	0.078	-0.747
MS*MS	0.154	0.061	2.504
YEAR*YEAR	0.007	0.003	2.416
YEAR*CFC	-0.012	0.010	-1.243
YEAR*OCR	-0.020	0.017	-1.124
YEAR*BCS	0.027	0.015	1.838
YEAR*MS	0.012	0.008	1.552
CAP*CAP	-0.009	0.154	-0.058
CAP*CFC	-0.008	0.068	-0.119
CAP*OCR	0.025	0.124	0.203
CAP*BCS	0.173	0.114	1.516
CAP*MS	0.251	0.065	3.870
CAP*YEAR	0.003	0.012	0.264
CONSTANT	14.704	0.071	207.600
BUSE R-SQUARE			*0.985*

To summarise, we illustrate the implications of our MC variable cost function findings using the changes observed in output variables across the first five MCs as a whole between 2011–12 and 2012–13 in the following calculations. As noted above, the total standard letter equivalents processed in the four MC processing stages decreased by 3.32 per cent while the wage rate index increased by 1.49 per cent and the CPI increased by 2.27 per cent between the two years. Combining these changes with their relevant variable cost elasticities and including the estimated impact of technical change, we obtain the following estimated change in variable costs:

$$0.562 \times (-0.0332) + 0.910 \times 0.0149 + (1 - 0.910) \times 0.0227 + (-0.014) = -0.0171$$

That is, the combined effects of the 3.32 per cent reduction in output, the 1.49 per cent increase in the wage rate, the 2.27 per cent increase in the price of other inputs and capital and ongoing technical change would have been an MC variable cost reduction of 1.7 per cent between 2011–12 and 2012–13. The effect on MC variable costs of the output reduction in isolation would have been a reduction in variable MC costs of 1.9 per cent.

Australia Post delivery centre data

Australia Post provided detailed monthly output and cost data and annual asset data on its 125 urban DCs for the period July 2012 to October 2013. DC data are available for a shorter period than MC data because they have only recently been integrated into the nationally consistent MDCS and SAP databases. Before this DC records were maintained at a state and territory level using different reporting conventions between state offices. Australia Post's output reporting is generally on an average per work day basis. We convert this to monthly totals based on the number of working days per month for our analysis.

Rural and remote DCs were excluded from the analysis because they tend to have quite different characteristics to urban DCs. Rural and remote DCs are typically smaller, are often run in conjunction with post offices and make greater use of contractors. Articles delivered are generally less than for urban DCs but distances covered per route are considerably longer. The urban DCs included in the analysis generally cover over 85 per cent of delivery activity nationally.

The output and cost data used in the analysis excludes parcel delivery by contractors. Instead it focuses on mail delivery on daily rounds, generally undertaken by motorbike, cycle or on foot. Small parcels delivered on normal rounds are included in the analysis. The results from the analysis will thus be representative of reserved service delivery costs. Delivery costs account for just over 60 per cent of overall reserved service operational costs.

Volume data for the 125 DCs were extracted from Australia Post's Mail and Delivery Centre Statistics (MDCS) database which is updated daily while financial and asset data were extracted from Australia Post's SAP financial system. The DC data runs for 16 months from July 2012. Some points and distance observations for September and October 2013 were incomplete and were extrapolated from preceding observations. This leads to a total of 2,000 observations for the DC analysis.

Delivery centre outputs

We include three outputs for Australia Post's DCs being:

- Number of articles delivered
- Number of delivery points served, and
- Distance covered on rounds.

While Australia Post is not paid per delivery point or per kilometre of rounds, the inclusion of the number of delivery points and distance covered as output variables captures an important function that Australia Post is required to perform. There are many precedents in econometric analyses of other network industries, such as electricity, gas and water distribution, where volume supplied, number of customers and distance covered are often the first three output variables specified to capture the range of functional outputs and also differences in density across firms (or data points). In this case differences in density relate to both mail density (ie articles per customer) and customer density (ie customers per round kilometre). The Australian Energy Regulator (2013) has recently proposed a broadly analogous output specification to measure electricity distribution performance.

Delivery centre non–capital inputs

Australia Post provided detailed monthly operating cost data on each of the 125 included DCs. These data were divided into labour costs and other (non–labour and non–capital) costs for the analysis. Labour costs comprised directly employed staff labour costs (including on–costs), contract labour and staff–associated costs. An Australia Post–specific labour price index was formed based on scheduled wage increases included in Australia Post's Enterprise Bargaining Agreements.

The other costs category includes the remaining non–capital costs making up trading expenditure (excluding notional expenses). Notional expenses are excluded to avoid double counting with our explicitly included capital costs. In the absence of more specific price information, the consumer price index (CPI) is used as the price index associated with other costs.

Delivery centre capital inputs

Australia Post provided detailed DC asset data covering Plant and equipment and Buildings. Asset data supplied included:

- Asset code
- Acquisition value
- Accumulated depreciation, and
- Book value

These data were supplied for each of the 125 included DCs for 2012–13 and covered numerous items in up to 13 broad asset categories. In the interests of keeping the calculations manageable, we proceeded by forming real annuities at this broad asset category level. In our calculations we implicitly treat the data as if each broad asset category only contains one physical item (or, alternatively, a number of similarly classified physical items with the same average age). Australia Post separately supplied detailed information on the expected asset life for each asset type and, from this, we formed a representative weighted average asset life for each broad asset category.

Our calculations (for each broad asset category for each DC) proceeded as follows:

- Estimate the approximate average age of assets in the asset category by the formula:

  Asset age = accumulated depreciation / acquisition value × asset life

- Use the asset age information to convert the (nominal) acquisition value into a real acquisition value (in 2013 dollars) by the formula:

  Real acquisition value = Nominal acquisition value × CPI index,

  where the CPI index has a base of 1 in 2012–13. We used the ABS March quarter CPI index in these calculations. Note that the CPI index used depends on the asset age AND the year involved (eg an asset age of 6 years in 2010–11 equates to a period lag of 6+2=8 years which means that the 2004–05 CPI index would be used in this case).

- Calculate a real annuity using three pieces of information:
  - Real acquisition value
  - Asset life, and
  - Real interest rate of 7 per cent per annum.

These annuities are then added together to obtain an aggregate capital input estimate for each DC in 2012–13. These annual values are then divided by 12 to obtain monthly values. Real annuities for the four included months of 2013–14 (for which no annual data is currently available) were formed by assuming the same real monthly annuity applied as in 2012–13.

Unlike MCs, no separate fair value or current cost data are available for DC buildings and so buildings are included as one of the broad asset categories above.

Econometric estimation of a total cost function for DCs

We use similar notation to that used above for the MC analysis:

RTC = real total cost;

$Y = (Y_1, Y_2, ..., Y_M)$ = an M×1 vector of output quantities (and related measures); and

$W = (W_1, W_2, ..., W_M)$ = a K×1 vector of input prices.

We again use lower case notation to define the natural logarithms of variables. For example, $y_1 = \log(Y_1)$.

Furthermore, we again consider the Cobb–Douglas and translog functional forms.

In this analysis of DCs, we have identified a set of K=3 input variables:

1. labour
2. capital
3. other

and a set of M=3 output variables:

1. ART = articles delivered

2. PTS = points delivered to
3. DIS = distance covered on delivery round.

In our assessment these input and output categories represent the key aspects of production in Australia Post DCs.

As noted in our econometric analysis of MCs (see above) we excluded input price variables from the list of regressors in the econometric model because we had only eight unique price values in our eight years of MC EBA–based labour price data. Given that we have only 16 months of data (over a two year period) in this DC analysis we have only two unique EBA–based labour price index values. As a result, it is not feasible to include input price variables as regressors in the DC econometric model either. We thus construct an aggregate input price index using a Tornqvist index formula (using sample mean share weights), and then use this price index to deflate the cost measure that is used as the dependant variable. Hence we also use real (as opposed to nominal) cost measures in the DC analysis. Our aggregate input price index uses sample mean input cost share weights of 60 per cent and 40 per cent for the wage index and CPI, respectively.

We have again chosen to include dummy variables to capture differences in production activities across months. We define 12 dummy variables for months 1 to 12:

$DMO_{gijt} = 1$ when g = j, and is 0 otherwise, (g = 1,...,12).

However, we have decided to not include dummy variables for the 125 DCs in our econometric model. This is because the data on distance (DIS) and points (PTS) varies little from month to month in each DC over the 16 month time period (as one would expect). If these 125 dummies are included, they are almost exactly correlated with these two variables and hence would make it impossible for one to obtain reliable elasticity estimates.

Given the above discussion, our translog total cost function for DCs is defined as:

$$rtc_{ijt} = \alpha_0 + \sum_{m=1}^{3} \beta_m y_{mijt} + 0.5 \sum_{m=1}^{3} \sum_{n=1}^{3} \beta_{mn} y_{mijt} y_{nijt} + \sum_{g=1}^{11} \theta_g DMO_{gijt} + v_{ijt}, \tag{9}$$

where $rtc = \log(RTC)$ relates to real total cost and all other notation is as previously defined. Note that the technical change time trend has been omitted (since it is near impossible for one to identify technical change over a 16 month period).

Thus we have a *fixed effects panel data model* where there are 21 unknown parameters to be estimated from a sample size of 2,000 observations.

Econometric results for the total cost function for DCs

The model in equation (9) is estimated using similar econometric methods to those used in the previous section. That is, we correct for serial correlation and have chosen to report *panel–corrected standard errors*, where the standard errors have been corrected for cross–sectional heteroskedasticity.

The econometric results are reported in table 3, where we observe that the majority of estimated coefficients have t–ratios in excess of 1.96, indicating that they are statistically different from zero at the five percent level of significance. The R–Square is 57.3 per cent, which is lower that obtained in the MC analysis. This is as expected, given the larger variability across DCs and the omission of cross–sectional dummy variables in the DC model.

We now discuss the first–order coefficients of the three output variables. All three output coefficients have the expected positive signs, implying that extra output incurs extra costs. The estimated coefficient of the ART output is 0.062, implying that a 1 per cent increase in articles delivered will lead to a 0.062 per cent increase in costs (all else held constant), at the sample mean. That is, DC costs are not particularly sensitive to changes in the number of articles with both increases in and decreases in the number of articles having only very modest impacts on DC costs. The corresponding coefficients of PTS and DIS, are 0.616 and 0.077, respectively, implying elasticities at the sample means of 0.616 per cent and 0.077 per cent, respectively. This means the primary driver of DC costs is the number of points the DC has to cover or provide deliveries to. On the other hand, distance – like the number of articles – is only a very modest driver of DC costs.

When added together, these three output elasticity estimates provide a total elasticity measure of 0.062+0.616+0.077=0.756, implying that a 1 per cent increase in all outputs will lead to a 0.756 per cent increase in costs. Equivalently, it implies that a 1 per cent *decrease* in all outputs should correspond to a 0.756 per cent *decrease* in costs, which is of interest in this study. This linear combination estimate (0.756) has an estimated standard error of 0.021, producing a 95 per cent confidence interval of (0.715, 0.796).

The above total elasticity measure is of most use when <u>all</u> output measures increase proportionally. Thus, this measure would have been of some interest 10 years ago, prior to the recent substantial impact of emails and similar technologies upon postal volumes. However, given that in recent years the volume of articles are decreasing while the number of delivery points is increasing, the three output elasticities need to be considered individually.

The number of articles delivered by Australia Post peaked in 2007–08 at 5.6 billion articles (Australia Post 2010, p.113) and has since declined by 18 per cent to 4.6 billion articles in 2012–13 (Australia Post 2013, p.131). This translates to an average annual decline of around 4 per cent. Combining this with the articles cost elasticity of 0.062, the impact on Australia Post's annual real delivery costs would have been –0.25 per cent.

Over this same 6 year period, however, the number of delivery points Australia Post is required to serve have increased by 6.7 per cent from 10.5 million in 2007–08 to 11.2 million in 2012–13. This translates to an average annual increase of around 1.3 per cent. Combining this with the points cost elasticity of 0.616, the impact on Australia Post's annual real delivery costs would have been 0.8 per cent.

Only limited information is available on changes in the distance Australia Post delivery officers travel on their rounds. For the 125 DCs included in our analysis, the total distance travelled on rounds increased marginally by 0.14 per cent over the course of 2012–13. Taking this as being representative of the average annual increase over the last 6 years – something which is reasonable given the ongoing growth over this period in the number of delivery points that had to be covered – and combining it with the distance cost elasticity of 0.077, the impact on Australia Post's annual real delivery costs would have been 0.01 per cent.

Combining the impacts of actual average annual changes in articles delivered, delivery points and distance travelled over the last 6 years, the impact on Australia Post's annual real delivery costs is an *increase* of 0.55 per cent (=0.062 x (–0.041) + 0.616 x 0.013 + 0.077 x 0.001).

Table 3: Econometric results for the panel data total cost function for DCs

VARIABLE	COEFFICIENT	ST-ERROR	T-RATIO
ART	0.062	0.015	4.186
PTS	0.616	0.033	18.945
DIS	0.077	0.026	3.036
MO1	-0.034	0.006	-5.689
MO2	-0.096	0.007	-13.492
MO3	-0.058	0.008	-7.228
MO4	-0.042	0.009	-4.739
MO5	-0.015	0.010	-1.517
MO6	-0.076	0.009	-8.527
MO7	-0.013	0.010	-1.341
MO8	-0.010	0.009	-1.110
MO9	-0.054	0.008	-6.876
MO10	-0.001	0.008	-0.066
MO11	-0.027	0.006	-4.303
ART*ART	0.129	0.076	1.692
ART*PTS	-0.073	0.074	-0.988
ART*DIS	-0.072	0.036	-1.960
PTS*PTS	0.080	0.096	0.836
PTS*DIS	0.046	0.044	1.051
DIS*DIS	0.107	0.042	2.519
CONSTANT	12.967	0.024	547.200
BUSE R-SQUARE			*0.573*

If we look at the actual changes in the latest year, we find that some of the changes observed over the last 6 years tend to have accelerated. For example, between 2011–12 and 2012–13 the number of articles delivered fell by 5.4 per cent while the number of delivery points Australia Post is required to serve increased by 1.8 per cent. Combining these annual changes with the estimated real cost elasticities, the impact on Australia Post's annual real delivery costs is an *increase* of 0.79 per cent (=0.062 x (–0.054) + 0.616 x 0.018 + 0.077 x 0.001).

Adding the effect of input price changes using an analogous method to that for MCs, the change in Australia Post's annual nominal delivery costs is an *increase* of 2.6 per cent (=0.0079 + 0.60 x 0.0149 + (1 – 0.6) x 0.0227).

Returning to the estimated coefficients in table 3, we see the 11 monthly dummy variables are all negative. This is as expected, given that the base month of comparison is December. We expected that costs would be higher in December because of the extra overtime expenditure used in dealing with the Christmas rush. For example, the estimated coefficient of MO3 (March) is –0.058, implying that costs in March are 5.8 per cent below those in December (all else held constant), at the sample mean. The other ten monthly dummy variable coefficients are interpreted in a similar manner.

A number of hypothesis tests were also conducted to see if a more parsimonious model could be used to describe these data. We conducted a hypothesis test to see if a Cobb–Douglas functional form was appropriate for these data. The parameter restrictions involved setting the 6 second order coefficients in equation (9) to zero producing a Cobb–Douglas total cost function of the form:

$$rtc_{ijt} = \alpha_0 + \sum_{m=1}^{3} \beta_m y_{mijt} + \sum_{g=1}^{11} \theta_g DMO_{gijt} + v_{ijt}, \tag{10}$$

The F–test statistic with 6 and 1979 degrees of freedom was 5.110 with a p–value of 0.000, indicating that the null hypothesis of a Cobb–Douglas model cannot be accepted at a 5 per cent level of significance, implying that the translog form is the preferred model.

We conducted a second hypothesis test to see if the 11 monthly dummy variables were a significant addition to the model. The F–test statistic with 11 and 1979 degrees of freedom was 51.445 with a p–value of 0.000, indicating that the null hypothesis of these 11 coefficients being zero could not be accepted at a 5 per cent level of significance, implying that the 11 monthly dummy variables were a significant addition to the model.

Econometric estimation of a variable cost function for DCs

The above estimates for a total cost function provide elasticity estimates that assume that all costs (including capital costs) can be varied when output varies. Hence, they provide an estimate of how costs can be varied in the long run, when there is sufficient time to adjust quantities of capital.

In the short run, one is unable to easily adjust capital inputs, and hence it is of interest to also estimate a variable cost function, where the dependant variable is variable costs (total costs minus capital costs). This function will allow us to estimate the degree to which variable costs respond to output changes (with capital quantity held fixed).

To define our new model we define the additional notation:

RVC = real variable costs (measured using real labour and other costs),

CAP = capital quantity (measured using real capital costs).

and once again we use lower case notation to define the natural logarithms of variables. For example, $rvc = \log(RVC)$.

Our translog variable cost function is then defined as:

$$\begin{aligned} rvc_{ijt} = {} & \alpha_0 + \sum_{m=1}^{3} \beta_m y_{mijt} + \rho_1 cap_{ijt} + 0.5 \sum_{m=1}^{3} \sum_{n=1}^{3} \beta_{mn} y_{mijt} y_{nijt} + 0.5 \rho_{11} cap_{ijt} cap_{ijt} \\ & + \sum_{m=1}^{3} \psi_{1m} cap_{ijt} y_{mijt} + \sum_{g=1}^{11} \theta_g DMO_{gijt} + v_{ijt}, \end{aligned} \tag{11}$$

and the Cobb–Douglas becomes:

$$rvc_{ijt} = \alpha_0 + \sum_{m=1}^{3} \beta_m y_{mijt} + \rho_1 cap_{ijt} + \sum_{g=1}^{11} \theta_g DMO_{gijt} + v_{ijt}. \tag{12}$$

Econometric results for the variable cost function for DCs

The model in equation (11) is estimated using the same econometric methods used in the previous section. That is, we correct for serial correlation and have chosen to report *panel–corrected standard errors,* where the standard errors have been corrected for cross–sectional heteroskedasticity.

The econometric results are reported in table 4, where we again observe that the majority of estimated coefficients have t–ratios in excess of 1.96, indicating that they are statistically different from zero at the five percent level of significance, and the R–Square is an acceptable 59.3 per cent.

We now discuss the first–order coefficients of the three output variables. All three output coefficients have the expected positive signs, implying that extra output incurs extra costs. The estimated coefficient of the ART output is 0.065, implying that a 1 per cent increase in articles delivered will lead to a 0.065 per cent increase in costs (all else held constant), at the sample mean. The corresponding coefficients of PTS and DIS are 0.417 and 0.101, respectively, implying elasticities at the sample means of 0.417 per cent and 0.101 per cent for the number of delivery points and the total distance travelled on rounds, respectively. Again we see the number of points being the primary driver of variable costs with the number of articles delivered and the distance travelled being much more modest drivers.

When added together, these three output elasticity estimates provide a total elasticity measure of 0.065+0.417+0.101=0.583, implying that a 1 per cent increase in all outputs will lead to a 0.583 per cent increase in variable costs. Equivalently, it implies that a 1 per cent *decrease* in all outputs should correspond to a 0.583 per cent *decrease* in variable costs, which is of interest in this study. This linear combination estimate (0.583) has an estimated standard error of 0.046, producing a 95 per cent confidence interval of (0.492, 0.673).

The total elasticity measure in the variable cost function (0.583) is smaller than that obtained in the total cost function (0.756). This is not as expected, given that variable costs are expected to be more “flexible” over the short time frame considered in these data.

However, as discussed above, the total elasticity measure is of most use when <u>all</u> output measures increase proportionally. However, given that in recent years the volume of articles are decreasing while the number of delivery points is increasing, the three output elasticities need to be considered individually. The distance elasticity is larger in the variable cost model, while the points elasticity is somewhat smaller. This latter estimate appears to imply that servicing points is relatively capital intensive (eg extra motorbikes are needed). The articles elasticity is only marginally larger in the variable cost function model as expected (provided delivery officers have not reached full capacity in their sacks).

The first order coefficient of the CAP variable has a value of 0.246 implying that a 1 per cent increase in capital will lead to a 0.246 per cent increase in variable costs (all else held constant), at the sample mean. This positive coefficient is not as one would expect if input substitution between capital and variable inputs was possible. One explanation could be that CBD DCs use less capital because their rounds are either walk rounds or bicycle rounds and also have lower unit costs because they have higher volumes per point. Hence low capital is associated with low costs. This warrants further investigation.

Table 4: Econometric results for the panel data variable cost function for DCs

VARIABLE	COEFFICIENT	ST-ERROR	T-RATIO
ART	0.065	0.018	3.501
PTS	0.417	0.057	7.356
DIS	0.101	0.034	3.027
CAP	0.246	0.049	4.997
MO1	-0.047	0.008	-6.030
MO2	-0.128	0.009	-13.814
MO3	-0.076	0.011	-7.187
MO4	-0.054	0.011	-4.742
MO5	-0.019	0.013	-1.440
MO6	-0.101	0.012	-8.664
MO7	-0.017	0.012	-1.330
MO8	-0.012	0.012	-0.972
MO9	-0.071	0.010	-6.969
MO10	0.003	0.011	0.245
MO11	-0.036	0.008	-4.312
ART*ART	0.100	0.096	1.046
ART*PTS	-0.040	0.099	-0.399
ART*DIS	-0.120	0.047	-2.577
PTS*PTS	0.253	0.177	1.432
PTS*DIS	0.151	0.070	2.165
DIS*DIS	0.172	0.055	3.131
CAP*CAP	0.251	0.148	1.694
CAP*ART	0.056	0.049	1.145
CAP*PTS	-0.318	0.136	-2.342
CAP*DIS	-0.091	0.044	-2.072
CONSTANT	12.690	0.024	532.110
BUSE R-SQUARE			*0.593*

The estimated coefficients of the monthly dummy variables are similar to those seen in the total cost function, and are interpreted in a similar manner.

Once again, a number of hypothesis tests were also conducted to see if a more parsimonious model could be used to describe these data. We conducted a hypothesis test to see if a Cobb–Douglas functional form was appropriate for these data. The parameter restrictions involved setting the 10 second order coefficients in equation (11) to zero producing the Cobb–Douglas variable cost function reported in equation (12).

The F–test statistic with 10 and 1974 degrees of freedom was 5.219 with a p–value of 0.000, indicating that the null hypothesis of a Cobb–Douglas model cannot be accepted at a 5 per cent level of significance, implying that the translog form is the preferred model.

We conducted a second hypothesis test to see if the 11 monthly dummy variables were a significant addition to the model. The F–test statistic with 11 and 388 degrees of freedom was 54.705 with a p–value of 0.000, indicating that the null hypothesis of these 11 coefficients being zero could not be accepted at a 5 per cent level of significance, implying that the 11 monthly dummy variables were a significant addition to the model.

To summarise, we illustrate the implications of our DC variable cost function findings using the changes observed in output variables between 2011–12 and 2012–13 in the following calculations. Recall that the number of articles delivered fell by 5.4 per cent while the number of delivery points increased by 1.8 per cent and distance travelled increased marginally by 0.14 per cent in the last year. We assumed that the quantity of capital used by each DC did not change between 2011–12 and 2012–13. The effect on DC real variable costs of these changes was an *increase* in real variable DC costs of 0.42 per cent (=0.065 x (–0.054) + 0.417 x 0.018 + 0.101 x 0.001 + 0.246 x 0).

Adding the effect of input price changes using an analogous method to that for MCs, the change in Australia Post’s annual nominal variable delivery costs is an *increase* of 2.1 per cent (=0.0042 + 0.85 x 0.0149 + (1 – 0.85) x 0.0227).

Conclusions

The current study provides the first set of cost elasticity estimates for the conditions Australia Post currently faces. The econometric results reported use flexible functional forms, data reflecting the secular decline in postal volumes now occurring and Australia’s actual population density, and use comprehensive cost measures covering all postal service inputs. This contrasts with most previous studies which have used simple functional forms, have used data from periods of increasing postal volumes and countries with much higher population densities than Australia, and have often only concentrated on labour costs.

Looking at the effects of the actual output changes observed between 2011–12 and 2012–13 on MC and DC costs, we find that the estimated MC cost elasticities imply that MC real costs would have reduced by 1.5 per cent while DC real costs would have increased by 0.8 per cent. While the fall in postal article numbers appears to have accelerated in the last year, the increase in the number of points Australia Post is required to serve has continued to increase steadily. Consequently, while MC real costs – which are driven by articles numbers – have fallen, DC real costs have increased because the impact on increased delivery points has outweighed the effects of declining articles numbers.

Using data supplied by Australia Post on its reserved service operational costs taken from its SAP accounting system, delivery accounts for 62 per cent of reserved service costs, processing (ie MCs) accounts for 19 per cent and other costs such as acceptance and transport also account for 19 per cent. Using this information and assuming that the cost elasticities of other inputs such as acceptance and transport are zero, we conclude that the output changes observed between 2011–12 and 2012–13 in isolation would have *increased* Australia Post’s reserved service real costs by 0.2 per cent (=0.62 x 0.008 + 0.19 x (–0.015) + 0.19 x 0).

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Appendix A: MC output items allocation and conversion factor matrix

Process	CFC	OCR	BCS	MS
AEG OCR - Metro		1		
AEG OCR - Regional		1		
EMS Despatch				8.9
EMS Inbound Opening				8.9
EMS Outbound				8.9
BCS			1	
Cancellation - Face Up Large Letters	1.8			
Cancellation - Face Up Small Letter Bundles	1			
Cancellation - TSC42	1			
Cancellation - TSC81	1			
Cancellation - TSC85	1			
Cancellation - Handstamping Small Letters	1			
Cancellation - Handstamping Small Parcels	8.9			
Cancellation - GG	1			
Cancellation - RAP17 Automatic Tipper	1			
Cancellation - RAP17 Manual Tipper	1			
Competition Mail			1	
Express Post				8.9
FMOCR - With Manual Feeder		1.8		
FMOCR - Without Manual Feeder		1.8		
Flicksort - LL				1.8
Flicksort - SL				1
LL Spectrum 10 - 12 Coding Stations				1.8
LL Spectrum 10 - 15 Coding Stations				1.8
MLOCR		1		
Manual Sort Bullrings				1.8
Manual Sort LL Domestic				1.8
Manual Sort LL Overseas				1.8
Manual Sort LP Domestic (ULD array)				15
Manual Sort SL Domestic (MMF)				1
Manual Sort SL Domestic (VSD/VSF)				1
Manual Sort SL Overseas				1
Manual Sort SP Domestic				8.9
Manual Sort SP Overseas				8.9
SP Spectrum 10 - 15 Coding Stations				8.9
Video Coding LL				1.8
Video Coding SL				1
Dock - Airmail Receipt And Despatch				1
Dock - Empty ULD And Tray Management				1

Process	CFC	OCR	BCS	MS
Dock - General				1
Mail Movement - Express Post				8.9
Mail Movement - Large Letters		1.8		
Mail Movement - Large Parcels				15
Mail Movement - Small Letters			1	
Mail Movement - Small Parcels				8.9
Mail Preparation - Large Letters		1.8		
Mail Preparation - Large Parcels				15
Mail Preparation - Small Letters		1		
Mail Preparation - Small Parcels				8.9
Cancellation - Handstamping Large Letters	1.8			
Non-Processing Hours				1
Mail Movement - TMS Induction			1	
BCS Sequence Two Pass Sorting			1	
BSP Bullring				1
Cancellation - Handstamping Large Parcels	15			
Despatch Consolidation Bullring				1
Dock - Airmail Despatch				1
Dock - Airmail Receipt				1
Dock - Load/Unload Transportation Vehicles				1
Dock Movement				1
Mail Movement - TCS Induction			1	
Manual Sort LP Domestic				15
Manual Sort SL Domestic				1
Print Post Bullring				1
Receipt Streaming Bullring				1
UMS Bullring				1
PSHS - Face Up				15
PSHS - Manual Coding				15
PSHS - Take Off				15
Manual Sort LP Domestic Non Machinable				15
EMS Processing (free) Interstate				8.9
Manual Sort ECI/EPI to Overseas				8.9
Manual Sort EMS Domestic				8.9
Manual Sort Packets Overseas				8.9
BCS Sequence Sorting			1	
TMS		1		
Despatch LC/AO Overseas				8.9
Registered Insured & EPI Documents				8.9
Network Assistance				1
MARS Sequence Sorting			1	
Manual Sort XL Parcels Domestic				15