A Production Model of Service Quality at An Post[1]

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Abstract

Postal operators face regulatory constraints on both their pricing and resource allocation policies. Given fixed prices and obligations to serve demand, a natural concern of postal regulatory policy becomes quality of service. Quality of service regulations have been implemented at the EU and Member State levels. The postal regulatory body in Ireland (ComReg) has recently asked An Post, Ireland's universal service provider, for information on the cost of service quality improvements. This paper is based on the research of London Economics on this subject. Service quality in Ireland is defined by ComReg to be a percentage of mail items hitting the service quality standard of next day delivery in Ireland. Ireland's service quality standard is next day delivery for all standard mail items, with only one mail class. To measure service quality, we adopt a production function approach. We develop an econometric model of production with service quality as the dependent variable and levels of inputs, volumes, and capacities, as well as test mail item characteristics (size, weight, shape, etc,) as explanatory variables. The one-day cycle of Ireland's mail system makes each day a convenient production cycle. Estimation is operationalised as a Probit model, with each day having a probability of a test mail item hitting the service quality standard. We utilise a unique dataset with about 200,000 observations, based on An Post's test mail system and management information systems for inputs, volumes, and other variables. We estimate relationships between input levels and service quality, independent of other factors such as volume/capacity. Prices are applied to incremental input levels to obtain estimates of the costs of service quality improvement. The results show holiday peak capacity constraints are a major driver of service quality failures and labor input increases are predicted to be most costly.

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1 INTRODUCTION

Universal Service Obligations (USOs) create special difficulties for liberalisation, as they can impose potentially unsustainable cross subsidies. Postal operators and regulators thus face a range of issues in terms of regulation, which include regulation of both price and quantity, as well as entry. Given fixed prices and obligations to serve demand, quality of service targets are a natural concern of postal regulatory policy.

When regulating quantity under a USO, it is of course imperative that output be measured on a constant quality basis. Ignoring quality could allow output, or cross subsidies, to be implicitly reduced. Quite naturally then, USOs for a number of EU countries have included service quality agreements and standards. Typically, the most important facet of service quality is hitting a delivery time standard for 1st and 2nd class post. Other facets of quality usually focus on what defines "residential" delivery. In general, postal regulatory authorities have been charged with overseeing whether the USPs are fulfilling their obligations for service quality under their USO or other license or legislative requirements.

The postal regulatory body in Ireland (ComReg) has recently consulted An Post on the cost of service quality improvements.[3] Service quality in Ireland is defined by ComReg to be the percentage of mail items hitting the service quality standard of next day delivery in Ireland. Ireland's service quality standard is next day delivery for all standard mail items, with only one mail class.

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3 Ideally, the fullest analysis of service quality at a USP would include demand-side estimation as well. A marginal analysis of the benefits verses the costs would have been preferable from a pure public policy perspective. However, we have not addressed this issue, principally because it was outside the scope of the question posed by the regulator. We also believe, however, that a regulator should attempt to allocate its scarce resources optimally. Focusing on the cost side only might be expected to yield more concrete results and avoid potentially allowing the process to go on too long. Work on the theory of quality improvement in terms of willingness to pay has been studied previously by Ian Reay at Royal Mail (1993). While Reay's study looked at a few particular measures, such as missorts in OCRs, to our knowledge comprehensive empirical work has not attempted to measure marginal costs and benefits of current levels of service quality.

Postal universal service providers (USPs) face a variety of constraints, both on their operations and their pricing. They face pricing and product choice constraints on the output side, while they often face wage and labor constraints and capital spending constraints on the inputs side. Quality of service, therefore, becomes a natural choice as an endogenous output variable when attempting to model the production process of a USP.

In this paper we describe a model of quality developed by London Economics. More specifically, we posit a model of a production function for a USP. The model takes as exogenous inputs levels of labor, capital, and letter volumes. The model takes as its endogenous variable the level of service quality for mail items in the system. The model is applied using test mail and other management information systems data from An Post. The model is operationalised as a Probit model, with each test mail item representing an observation on the probability of hitting the target. We then estimated relationships between key variables and service quality, and then "cost" service quality improvements by applying known factor prices to input increases needed to provide a predicted increment of service quality.[4]

1.1 Why Some Items Do Not Get Next Day Delivery

There are many reasons why an item may fail to receive next day delivery. Some of these have to do with process failures, e.g. where a tray of post from a sorting office is sent to the wrong delivery office. Others relate to mismatches between volume and capacity; there may simply be too much post to process in a given time window for the staff and equipment available to sort and deliver. Within this latter category, mismatches may arise

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4 While ComReg had asked for cost of service improvement estimates, we took a production function approach rather than a cost function approach because we believed that an explicit cost model would have proved difficult for a number of reasons. First, the normal assumption of cost minimisation might not be valid. While in some cases, such as productivity growth measurement, this is not as problematic, we felt it might create exceptional difficulties here. The second reason we decided against the cost function approach is that the nature of data necessary for cost function estimation would have been rather sparse in the case of An Post. Wage rates, capital, and other input prices do not change very regularly, while quality of service is known to fluctuate significantly throughout the year. Thus we suspected that at a fundamental level a cost model would not be able to capture the details of what is driving service quality.

because of unanticipated fluctuations in volume or capacity[5] or they may involve systematic deviations between volume and required capacity.

An Post's quality control department tracks and quantifies reasons for failures to deliver next day in terms of their production process.[6] An Post attributes quality failures based on a mixture of direct measurement (e.g. location of transponder-equipped mail items) and sampling exercises designed to identify more detailed reasons for failures. An Post's estimates suggest that few failures arise in the collection function, with a higher proportion arising in outward processing (e.g. mis-sorts and mis-directed bags and trays), and lesser shares in inward processing and delivery.

Basic data on failures presented in Table 1.1.1 suggest some areas for further empirical investigation. For example, it is interesting note the divergence between estimated full-year performance (88.9%) and performance in "normal" months – i.e. excluding the Christmas period (90.9%). Sources at An Post have suggested that this divergence could be purely volume related, as Christmas volumes are significantly higher than volumes at other times of the year, but this is something that will empirically examined by our modelling. This perhaps highlights some of the benefits of multivariate analysis, because as it turns out, we found a significant seasonal effect, even when controlling for volumes.

Table 1.1.1: Attribution of failure to deliver next day to a range of causes

90.9%	Service performance at baseline level of volume (ex. December)
88.9%	Service performance full year (incl. December)
9.1%	Failures – baseline months
11.1%	Failures - Full year

Source: An Post estimates

5 Fluctuations in capacity may, in turn, be caused by internal or external factors.

6 The data informing this analysis is drawn mainly from the latter half of 2001 and first quarter of 2002.

The rest of the paper is organised as follows. Section 2 presents the initial model. The next section, section 3, describes the data. Section 4 discusses the estimation, while section 5 presents and discusses results. Conclusions and final remarks are in section 6.

2 MODEL

This section describes the production-based model of service quality for a regulated USP used by LE. The model assumes that a functional relationship exists between levels of service quality, inputs, mail volumes, capacity, and other characteristic variables. The model assumes that levels of inputs are exogenous and that service quality become endogenous. We write the model in the following general form:

Equation 2.1: $$Q = F(L, K, V, \mathbf{D}, \mathbf{C}, t)$$

Here, Q is quality of service, F is a production function, L is labor input, K is capital input, V is mail volumes. **D**, is a matrix of dummy variables that are assumed to shift the production function and **C** is a matrix of continuous characteristics data, while t is a time index.[7]

Equation 2.1 is the most general form of the preferred model. It imposes no particular[8] *a priori* restrictions on the data. Due to a number of difficulties, we were led to posit a slightly different model. First, we allow for different types of labor input. This is by now standard practice in production modelling.[9] Due to the inherent difficulties of measuring capital input, along with particular difficulties in measuring cost of capital for some of An Post's capital stock,[10] we posited the following alternative model.

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7 While there may be other inputs to the process, such as materials and intermediate input, by excluding them, we have implicitly assumed that their impacts on quality of service are zero.

8 Other than the assumption that the relationship is a function.

9 See for example, Jorgenson, Gollop and Fraumeni, US Economic Growth: Harvard University Press, 1987.

10 For example, some buildings are rented from the government at nominal cost.

Equation 2.2: $$Q = F(L_1, L_2, ...L_n, v, \mathbf{D}, \mathbf{C}, t) \quad \text{with } v = V / K$$

The model as rewritten is akin to restricting the coefficients on the capital stock to be the inverse of the coefficients for volumes. In creating this variable, we have a capacity variable in place of volumes and capital. Notice also that if the quality function were constant returns to scale in labor, capital, and volumes, then this restriction would still be consistent with that condition.

Next we must operationalised the model by choosing a functional form. While we considered the translog and a number of forms, we settled on a quadratic form. The model can then be written:

Equation 2.3:

$$Q = \alpha_0 + \sum_i \alpha_i D_i + \sum_j \beta_j L_j + \beta_v v + \sum_k \beta_{C_k} C_k + \sum_j \delta_j L_j^2 + \delta_v v^2 + \beta_t t$$

Here the Greek letters are parameters to be estimated. We will discuss more regarding the functional form as well as assumptions about the addition of an error term later in the estimation section. First, we turn now to a description of the data.

3 DATA

3.1 Test mail data

The first building block of the data set on quality of service is An Post's test mail data. We take as our measure of service quality, Q above, to be based on test mail data.

Since 1998, An Post has been keeping track of service quality using a test-mail system from an independent accounting firm. The system mails 1000 test items weekly at random. The process continues throughout the year and the distribution of items and locations is consistent with a distribution survey and occasional sampling done throughout the year. Due to timing, overlap, and some missing observations, 2000 was the first full year of data, however. Data for 2002 were for the first three months only. Therefore, the sample consisted of about half a year 1998 data, and observations for all of 2000 and 2001, as well as the first three months of 2002.

For each test mail item, we have a detailed record of where and when it is dropped off and where and when it arrives. Each test mail item also contains details about the type of mail item being mailed, e.g., whether it is a flat, packet, hand-written envelope, etc. The list of characteristics data collected for each test mail item is as follows:

Where "factors" are variables associated with each observation, such as:

- mail item type (size, weight, letter, flat, packet, address type, etc),
- location of origin (county)
- destination (county)
- letter forwarding office
- day of week originated
- day of the week delivered
- time of day dropped off
- last pick-up time at drop off
- induction method
- delivery method
- drop off date (day/month/year)
- drop role
- receiver role
- proximity to last drop-off time

Since we know how long each item took to be delivered, we can convert each test mail observation into a zero-one variable: hit the standard; failed the to hit the standard, that is then associated with each variable listed above. An Post thus has detailed service quality data cross classified by locations (inbound and outbound), type of product, and mailing date, etc.

3.2 Other input data

Labor data are on hours worked per day. We were able to obtain labor data for a number types and categories of worker. An Post provided labor data on hours worked cross-classified by a number of types. Labor types were split into three categories, Provincial; Dublin Delivery; Dublin mails centre. In addition, the provincial and Dublin delivery office data are split into management and nonmanagerial. We also had data on hours missed due to absenteeism and overtime hours. The labor data are in general available on a daily or weekly basis for the full time period of the sample. Some data such as provincial hours are on a weekly basis, with only daily variations reflected by absenteeism and overtime.

3.3 Volumes and capacity data

Data on daily volumes for the Dublin mails sorting centre as well as for the provincial sorting offices were also used for the full sample period. Volumes data were therefore numbers of items sorted for each day in either the provinces or the Dublin mails sorting centre. We also obtained data on the sorting capacity of the Dublin mails centre. This was obtained from An Post's own engineering estimates. In addition, during the sample period, additional capacity was brought online at the Dublin mails centre, so that the impact of capacity additions should be reflected in the data. It was assumed that there were no changes in non labor capacity in the provincial sorting/forwarding offices during the sample period.

4 ESTIMATION

Estimating can proceed after recognition of the assumptions needed to operationalised **Equation 2.3** with the data described in the previous section. The first assumption is that each test mail item is fundamentally subjected to the same production process, shifted by the exogenous variables, but with some degree of random error for any one particular test mail item. The zero-one test mail observation is then viewed as having been drawn from some probability distribution. By making additional assumptions about the distribution and the error term, we can operationalised the model for estimation purposes.

We assume that the normal probabilistic or Probit[11] model, along with a standard error term is an appropriate model for the test mail observations. The probit model can be written as:

Equation 4.1 Prob(Q=1) = $\Phi(\mathbf{X}\beta)+\varepsilon$

Where:

- a success is defined as a test mail item being delivered within the standard;
- Φ is the cumulative normal distribution function;[12]

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11 See Greene (1993), Econometric Analysis, Macmillan: New York.

- **X** is an array (or matrix) of observations on factors representing the 100+ explanatory variables
- β is a vector of parameter coefficients to be estimated;
- ε is a random error term;

5 Results

The results of the estimated (preferred) model(s) are presented in Table 5.1 below. Results for dummy variables for model 1 and two additional models are in the annex in Table 6.2 and Table 6.3.[13] Each set of parameters presented in these tables corresponds to results from the full sample period with slight variations in each model. Model 1 imposes a restriction that quality must converge to 100% as volumes fall or capacity is increased. Model 2 relaxes this assumption. Model 3 allows an instrumental variable for labor absences in the provinces.

Some of the column headings in Table 5.1 need explanation. The leftmost column is the variable name. dF/dx indicates the coefficient estimate converted to a rate of change in probability of a success; X-bar is the mean of the explanatory variable. The statistical results are all standard outputs from Probit regressions run in the statistical software package, STATA.

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12 This function returns a value between 0 and 1 for a given number, call it z, which is interpreted as the probability that a random variable, call it Z, will be less than z.

13 We present here the estimation results for the continuous (i.e., not the dummy variables) variables only, as these are the most important to our analysis. The full tables with dummy variables are presented in the Annexes.

Table 5.1: Econometric results Model 1							
Variable	dF/dx	Std. Err.	z	P>|z|	x-bar	[95%	C.I.]
volcap2	-7.02E-15	1.35E-15	-5.21	0.00	2.80E+12	-9.70E-15	-4.40E-15
vprov2	-2.84E-15	4.05E-16	-7.02	0.00	1.90E+12	-3.60E-15	-2.00E-15
pctpacs	-1.84E-01	5.71E-02	-3.22	0.00	7.53E-02	-2.96E-01	-7.22E-02
pctflats	-1.05E-01	4.96E-02	-2.12	0.03	1.02E-01	-2.02E-01	-7.87E-03
labbasic	1.10E-05	4.65E-06	2.35	0.02	3.07E+03	1.80E-06	2.00E-05
labbas2	2.27E-09	9.73E-10	2.33	0.02	1.00E+07	3.60E-10	4.20E-09
lababs	-3.17E-05	6.03E-06	-5.26	0.00	9.77E+02	-4.40E-05	-2.00E-05
labprov	-1.12E-05	1.31E-06	-8.52	0.00	1.70E+05	-1.40E-05	-8.60E-06
labprov2	2.91E-11	3.54E-12	8.22	0.00	2.90E+10	2.20E-11	3.60E-11
lababspr	8.69E-06	2.75E-06	3.16	0.00	1.00E+04	3.30E-06	1.40E-05
labdd	5.73E-06	1.28E-06	4.49	0.00	8.72E+04	3.20E-06	8.20E-06
labdd2	-3.57E-11	6.87E-12	-5.20	0.00	7.70E+09	-4.90E-11	-2.20E-11
labsdd	-3.67E-06	2.00E-06	-1.83	0.07	4.67E+03	-7.60E-06	2.60E-07
indu_tim	-3.87E-03	9.04E-04	-4.28	0.00	1.36E+01	-5.64E-03	-2.10E-03
proximit	-8.78E-04	1.01E-03	-0.87	0.39	4.16E+00	-2.86E-03	1.10E-03
proxsq	-1.43E-04	3.98E-05	-3.59	0.00	3.51E+01	-2.21E-04	-6.50E-05

The results in Table 5.1 above, and in the tables in the annex, Table 6.2 and Table 6.3, show the estimated impact of a change in each variable on quality—the probability of success. More precisely, each coefficient estimate shows the rate of change (dF/dx) on the probability that an average item will meet the next day delivery standard, *ceteris paribus.*[14] It is worth discussing the estimated coefficients on each of the variables in turn in terms of type. We start with the impact of volumes on quality.

5.1 Volumes/Capacity

The estimated coefficients on volumes/capacity from the models are statistically significant and of the expected signs. Increased volumes/capacity tend to decrease quality. The volumes/capacity variables included in the models, volcap2 and vprov2, represent the volumes divided by capacities squared for the Dublin mails centre and provinces, respectively. Including linear terms (Model 2 results in annex), volcap and vprov, allows us to relax the assumption that quality must converge to 100% as volumes decrease or capacity increases. We see that these coefficients in Model 2, Table 6.2, are statistically insignificant, so the data as modelled support the hypothesis that quality must converge to 100% as volumes/capacity falls.

We also included variables, pctflats and pctpacs, to account for the percentage of flats and packets in the mail. The hypothesis is that these items are particularly difficult to sort and handle. These were the daily percentages from the Dublin mails centre. These estimates are also statistically significant and, as might be expected, have a negative impact on quality, as they are more bulky and more difficult to handle.

5.2 Timing

One of the underlying questions in the consultation process was how much quality should be expected from initiatives such as early presentation discounts for bulk mailers and large customers. To evaluate the effects of timing, we included several variables from the test mail database. First, we included a variable "last induction time, ("indu_tim" in the tables). This indicates the time of day that the test mail item was introduced into the system. The expectation is that later induction times cause additional failures. This is for at least two reasons. One is that later in the day simply means less time to get the item there the next day. The other is that later

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14 For dummy (zero/one) variables, the estimates represent the impact of going from the dummy variable to its complement, i.e., from say "delivered in Dublin" to "not delivered in Dublin". See the Chapter on "Probit", Stata 6 Reference Manual, Stata Corporation: College Station, TX, 2000.

almost necessarily means that the item will be showing up at a sortation centre later in the evening/early morning, when peak volumes and difficulties are most likely to arise. The coefficients estimated in Models 1, 2 and 3 were all statistically significant.

However, as our variable captures the time of day, and test mail items mailed after the last collection time would not be expected to get there the next day under the standard we control for this with the and additional variable, proximity. To do this we created a continuous measure of proximity to the last pickup with the variable proximity (proximit), defined as induction time less last pickup time.[15] We also introduced a proximity-squared term (proxsq). This allows the impact of proximity on quality to be non-linear. In the case of the proximity variable, in general the proximity-squared variable was statistically significant whereas the proximity variable was not significantly different from zero in any of the models 1-3. This simply indicates that the impact of proximity on quality is constrained to have no impact when proximity is zero.

We had originally included time trend variables but found them to be insignificant and so did not include them in the final models presented. Models were run instead using yearly dummy variables; the 2002 yearly dummy was significant and positive. This is not to say that there is not a time trend in quality; merely that increases in inputs and other factors accounted for the major changes in quality over the sample period (outside of 2002).

5.3 Labor

Changes in labor inputs likely affect the quality of service of An Post. We included several labor variables, one for each of the Dublin mails centre, the Provinces, and Dublin delivery (named in the tables, labbasic, labprov, labdd, respectively). The variables were in units of hours worked per day. We also included a squared term to allow the impacts of labor to be non-linear (labbas2, labprov2, labdd2, respectively in the tables). Labor units at the Dublin mails centre consisted of basic hours. This was to account for potential endogeneity bias[16] in the OT variable, since the simple correlation

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15 In a very few cases, the last pick-up time was not defined due to the mail type. In these cases we used the typical (based on An Post's input) last pickup time of 17:30.

16 A potential problem is the possibility of joint causality, or endogeneity of the explanatory (right hand side) variables. This could occur, for example here, if

between overtime hours and quality was negative. The coefficients on the labor variables were in general statistically significant across all the models and of the expected signs. Basic labor (labbasic) at the Dublin mails centre tended to increase quality at an increasing rate (+ sign on labbas2). This is somewhat surprising, as one might suspect it to increase quality at a decreasing rate. We suspect that this might be the case over a range of higher labor values. One possible cause of this result is that as the Dublin mails centre added operational capability over the sample period in question, labor was added. There may have also been some "learning by doing". This potentially caused quality to go up more than it might have otherwise (i.e., without learning by doing).

Other labor coefficients were statistically significant and of plausible sign over the range of relevant values for the sample. The labor variable on the Provinces labor variable was increasing after the average level of labor input, although at low levels of labor we found it to have a negative impact. In addition, we find Dublin delivery labor levels to be increasing at a decreasing rate over the relevant ranges of the data; exactly what we would expect. Other labor variables that we included were data on labor absences. Managerial labor variables were not significant and were dropped from the analysis. Absences variables were defined over Dublin mails centre, Provinces, and Dublin delivery, similarly to the labor inputs data, and were in hours missed units (named in the tables, lababs, lababspr, labsdd, respectively). Absences outside the Dublin mails centre were tracked on a weekly basis in the Provinces and Dublin delivery until end June 2001, while the Dublin mails centre data are on a daily basis. In general, labor absences have a statistically significant and negative impact on service quality. In relation to labor absences in the Provinces, we used a predicted value[17] or instrument from managerial Provinces absences (labmpro), which

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managers tended to respond to difficulties (and hence low quality) by adding more hours. We suspected that this was likely the case as our "overtime" hours variables were showing consistently negative signs, i.e., overtime hours seemed to decrease quality. We attempted to correct for this by using IV variables techniques and tried a number of instruments, including various lags as well as predicted values from regression on other exogenous variables in the system—all to no avail; the coefficients remained negative. We concluded to drop the overtime variables.

[17] More precisely regressed absences on managerial absences and then used the resulting predicted value. The suspicion of simultaneity can be described as somehow "poor quality" in the provinces is causing absences, which might be true if high volume times were particularly stressful, for example. The hypothesis is that the managerial absences

returned the expected negative sign in Model 3. This was the only difference between Model 2 and Model 3.

5.4 Daily and seasonal dummy variables

We also included a full range of day-of-week daily dummy variables and monthly dummy variables to account for day-of-week effects and seasonal effects, and yearly dummies to account for shifts across years (see annex). Some interesting results emerged. In spite of the possibility that a "weekend" effect is present in An Post's operations, the Monday dummy is not statistically significant in any of the models. The likely explanation is that the "Monday" effect is wholly accounted for by variations in the other variables; such as labor absences, volumes, and labor inputs. Other day of week variables did not seem to have a large impact or were not statistically significant.

In contrast, the seasonal impact, measured by monthly dummies, was significant in some months. In spite of accounting for variations in volumes, capacity, labor, etc, there is a large seasonal effect on quality that shows up at the Christmas holiday season. The impact of Christmas (December) relative to the average quality is to reduce quality by about 16%. This December effect is independent of the volume changes in December, as they are accounted for elsewhere by volumes and capacity variables. The December effect includes the impacts of all other unspecific seasonal factors that occur in December and are uncorrelated with other included variables such as volumes and capacities, drop-off timing, etc. These effects could include changes in the likely address quality;[18] changes in the size and shape of packages, weather related effects, etc. The December specific effect is estimated to be around 16%. That is to say, that the rate of increase in quality from going from December to "not December" is about 16%, over all test mail items. It is important to note that this is independent of volumes, and so suggests that other non-volume impacts are likely around the holiday season. We also included a range of dummy variables for the products as defined by An Post's test mail system (pr1-33). The product codes vary in

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would not be subjected to this bias, and thus would form an appropriate instrument.

18 While it is noteworthy that average address quality does not change over the year for the test-mail, it is of course very possible that the address quality of live mail imposes an externality on the test mail (i.e. having poor quality non-test mail in the system may have the side-effect of reducing actual performance of test mail).

weight, size class, hand addressed/machine, letter/flat/packet, envelope type (brown, plain, etc) and payment method (stamped, meter, ceadunas[19]). In general, the product specific dummies did not seem to have statistically significant effects across the three models.

5.5 Locations

Other dummy variables were included for letter forwarding office location from both the received letter forwarding to the drop letter forwarding office. In general, the effects of location do not seem to have much statistically significant impact on the quality variable. However, from the received letter forwarding office, there appears to be a significant negative effect for two offices. At the other end, the drop letter forwarding offices also seem to have little significant statistical impact. In the case of the drop letter forwarding offices, only one location had a significant (and negative).

5.6 Other operational variables

Other operational variables were also included in all the models. These were drop role category (ddrole) and received role category (drecrole), delivery method (ddelmeth) and induction methods# 1-6[20] (dinmeth1-6). Drop role, received role refers to business vs public (private). Private mail seems to have a significant negative impact on both the drop role and received role. An important factor to remember in regulatory assessment is the network attributes of mail delivery, i.e., it is both the sender and the receiver who are customers. Delivery method (ddelmeth) refers to postman, verses post-office, where in the latter the customer calls in to the post office to pick up mail. This has an insignificant impact on quality. Induction method (dinmeth1-6) methods 2,3, and 5 are predicted to have significant positive impacts on quality according to Model 1. These refer to pick-up (dinmeth2) and post office mailbox (dinmeth3), and sorting office drop off (dinmeth5). Rationale for these effects seems intuitively evident, as the more direct the induction method the more likely the smooth transition into the sorting phase of the network, and thus the lower the likelihood of quality failures.

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19 Ceadunas is a type of pre-paid meter mail at An Post.

20 One dummy variable must always be dropped to avoid the "dummy variable trap", i.e., the estimation problem of perfect multicollinearity of the explanatory data.

5.7 Cost of quality improvement

A final part of the paper is to present cost estimates in order to get cost estimates for incremental quality improvements at An Post. To do this, what was done was to take a number of scenarios of input quantity additions, such as adding labor or adding capacity, and then obtaining price estimates for each scenario from An Post. We do not go into details of these for commercial sensitivity and space reasons. Each input scenario for additional inputs was then assigned a cost based on the price estimates from An Post. The quantity of additional input was then associated with a particular quality improvement using the model of service quality estimated. The results are presented in Table 5.7.1 below.

Table 5.7.1: Summary of Potential Quality Improvements and Costs

Scenario	Actions	Quality impact	Capital costs €index[21]	Annualised Cost est. €index
1. Scale up Capacity 50%	Add automation equipment, sorting capacity, and some labor	2.9%	3.76	1.00
2. Improve early presentation	Additional network, tariff discounts, some labor	1.6%	0.0	0.01 + 0.945 revenue losses
3. Increase labor 10%-25%	Add labor at key points	1.3-3.3%	0.0	0.851 – 2.133
4. Decrease labor absences 10-25%	Programme underway	0.5 – 1.3%	0.0	0.0

21 An index of these costs was created to protect commercial sensitivity of cost information.

6 SUMARRY AND CONCLUSIONS

In this paper we have presented London Economics' model that estimates the impact of a variety of variables on service quality at An Post. This was done by positing a production function relationship between service quality, volumes and capacity, input levels, and mail item characteristics. The model implemented detailed data using An Post's test mail dataset and other management information system variables and was estimated as a probit model. The model is very general and could be applied to any USP collecting detailed data on service quality.

The model results showed statistically significant relationships between quality and a number of key variables, including volumes/capacity, labor hours, daily and seasonal dummy variables, and well as variables relating to the timing of items and when they were dropped off or presented to the mails centre.

These results enable us to estimate costs of a variety of scenarios for improving service quality at An Post. The results showed that adding more labor was likely to be the most costly. Incrementally, decreasing labor absences is seen as the cheapest source of initial quality improvement. The next least expensive improvements could come from giving incentives to bulk mailers and large customers to work with An Post to "time" their drop-offs of mails. Capacity additions would have the most significant impacts, but would be considerably expensive.

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Annex 1 Additional details of results

Table A6.1: Econometric results Model 1 – all coefficients							
Variable	dF/dx	Std. Err.	z	P>|z|	x-bar	[95%	C.I.]
volcap2	-7.02E-15	1.35E-15	-5.21	0.00	2.80E+12	-9.70E-15	-4.40E-15
vprov2	-2.84E-15	4.05E-16	-7.02	0.00	1.90E+12	-3.60E-15	-2.00E-15
pctpacs	-1.84E-01	5.71E-02	-3.22	0.00	7.53E-02	-2.96E-01	-7.22E-02
pctflats	-1.05E-01	4.96E-02	-2.12	0.03	1.02E-01	-2.02E-01	-7.87E-03
labbasic	1.10E-05	4.65E-06	2.35	0.02	3.07E+03	1.80E-06	2.00E-05
labbas2	2.27E-09	9.73E-10	2.33	0.02	1.00E+07	3.60E-10	4.20E-09
lababs	-3.17E-05	6.03E-06	-5.26	0.00	9.77E+02	-4.40E-05	-2.00E-05
labprov	-1.12E-05	1.31E-06	-8.52	0.00	1.70E+05	-1.40E-05	-8.60E-06
labprov2	2.91E-11	3.54E-12	8.22	0.00	2.90E+10	2.20E-11	3.60E-11
lababspr	8.69E-06	2.75E-06	3.16	0.00	1.00E+04	3.30E-06	1.40E-05
labdd	5.73E-06	1.28E-06	4.49	0.00	8.72E+04	3.20E-06	8.20E-06
labdd2	-3.57E-11	6.87E-12	-5.20	0.00	7.70E+09	-4.90E-11	-2.20E-11
labsdd	-3.67E-06	2.00E-06	-1.83	0.07	4.67E+03	-7.60E-06	2.60E-07
indu_tim	-3.87E-03	9.04E-04	-4.28	0.00	1.36E+01	-5.64E-03	-2.10E-03
proximit	-8.78E-04	1.01E-03	-0.87	0.39	4.16E+00	-2.86E-03	1.10E-03
proxsq	-1.43E-04	3.98E-05	-3.59	0.00	3.51E+01	-2.21E-04	-6.50E-05
mon*	-3.80E-02	3.60E-02	-1.13	0.26	1.76E-01	-1.09E-01	3.26E-02
tue*	-5.33E-02	3.75E-02	-1.54	0.12	1.97E-01	-1.27E-01	2.02E-02
wed*	-5.01E-02	3.72E-02	-1.46	0.15	1.95E-01	-1.23E-01	2.29E-02
thu*	-3.88E-02	3.59E-02	-1.15	0.25	2.05E-01	-1.09E-01	3.16E-02

Table A6.1: Econometric results Model 1 – all coefficients							
Variable	dF/dx	Std. Err.	z	P>|z|	x-bar	[95%	C.I.]
fri*	1.80E-02	2.95E-02	0.59	0.56	2.25E-01	-3.99E-02	7.59E-02
jan*	-2.20E-02	7.10E-03	-3.25	0.00	1.19E-01	-3.59E-02	-8.09E-03
feb*	-5.01E-02	7.48E-03	-7.37	0.00	1.10E-01	-6.48E-02	-3.54E-02
mar*	-6.49E-02	7.70E-03	-9.50	0.00	9.30E-02	-8.00E-02	-4.98E-02
apr*	-1.87E-02	7.25E-03	-2.69	0.01	7.36E-02	-3.29E-02	-4.46E-03
may*	-2.91E-02	7.00E-03	-4.43	0.00	8.43E-02	-4.28E-02	-1.54E-02
jun*	-4.64E-02	7.28E-03	-7.02	0.00	7.78E-02	-6.07E-02	-3.21E-02
jul*	-7.68E-03	7.06E-03	-1.11	0.27	7.27E-02	-2.15E-02	6.16E-03
aug*	2.15E-02	6.08E-03	3.31	0.00	7.96E-02	9.54E-03	3.34E-02
sep*	5.67E-03	5.81E-03	0.96	0.34	7.51E-02	-5.71E-03	1.71E-02
nov*	-3.02E-02	6.78E-03	-4.77	0.00	8.16E-02	-4.35E-02	-1.69E-02
dec*	-1.63E-01	1.59E-02	-12.70	0.00	5.85E-02	-1.94E-01	-1.32E-01
yr01*	2.06E-03	4.29E-03	0.48	0.63	4.59E-01	-6.35E-03	1.05E-02
yr02*	2.27E-02	6.36E-03	3.33	0.00	7.90E-02	1.02E-02	3.51E-02
cork*	-2.70E-03	6.62E-03	-0.41	0.68	1.15E-01	-1.57E-02	1.03E-02
dub*	-5.27E-02	5.74E-03	-9.17	0.00	5.06E-01	-6.40E-02	-4.14E-02
gal*	-5.64E-03	7.32E-03	-0.78	0.43	5.90E-02	-2.00E-02	8.71E-03
lim*	-6.42E-03	6.81E-03	-0.96	0.34	1.05E-01	-1.98E-02	6.93E-03
mull*	-4.27E-03	7.00E-03	-0.62	0.54	6.76E-02	-1.80E-02	9.46E-03
naas*	-1.66E-02	6.99E-03	-2.47	0.01	9.87E-02	-3.03E-02	-2.94E-03
pr1*	6.82E-02	4.76E-02	1.01	0.31	2.25E-02	-2.51E-02	1.62E-01
pr2*	8.27E-03	7.09E-03	1.14	0.25	6.79E-02	-5.62E-03	2.22E-02

Table A6.1: Econometric results Model 1 – all coefficients							
Variable	dF/dx	Std. Err.	z	P>|z|	x-bar	[95%	C.I.]
pr4*	8.68E-02	5.21E-02	1.25	0.21	1.48E-01	-1.54E-02	1.89E-01
pr5*	9.31E-03	6.94E-03	1.31	0.19	7.77E-02	-4.28E-03	2.29E-02
pr6*	7.04E-02	5.32E-02	1.00	0.32	8.62E-02	-3.38E-02	1.75E-01
pr7*	7.89E-02	4.07E-02	1.24	0.21	2.99E-02	-8.60E-04	1.59E-01
pr8*	4.14E-03	8.71E-03	0.47	0.64	2.55E-02	-1.29E-02	2.12E-02
pr9*	7.15E-02	4.54E-02	1.08	0.28	2.37E-02	-1.74E-02	1.60E-01
pr10*	4.86E-03	6.97E-03	0.69	0.49	9.05E-02	-8.80E-03	1.85E-02
pr12*	6.94E-02	5.31E-02	0.98	0.33	8.03E-02	-3.47E-02	1.74E-01
pr13*	7.67E-02	4.23E-02	1.19	0.23	2.99E-02	-6.23E-03	1.60E-01
pr14*	5.01E-03	8.55E-03	0.58	0.56	2.71E-02	-1.17E-02	2.18E-02
pr15*	7.48E-02	4.36E-02	1.15	0.25	2.93E-02	-1.07E-02	1.60E-01
pr16*	2.34E-02	7.56E-03	2.86	0.00	2.95E-02	8.64E-03	3.83E-02
pr19*	7.70E-02	4.53E-02	1.17	0.24	5.35E-02	-1.17E-02	1.66E-01
pr20*	1.64E-02	7.36E-03	2.12	0.03	4.08E-02	2.01E-03	3.09E-02
pr22*	6.52E-02	5.00E-02	0.95	0.34	2.45E-02	-3.28E-02	1.63E-01
pr23*	-8.62E-03	8.66E-03	-1.02	0.31	3.40E-02	-2.56E-02	8.35E-03
pr25*	7.15E-02	4.48E-02	1.08	0.28	1.88E-02	-1.63E-02	1.59E-01
pr26*	6.58E-02	4.79E-02	0.97	0.33	5.95E-03	-2.80E-02	1.60E-01
pr27*	7.64E-02	3.95E-02	1.21	0.23	3.90E-03	-1.09E-03	1.54E-01
pr29*	7.44E-02	4.12E-02	1.15	0.25	3.06E-03	-6.42E-03	1.55E-01
pr30*	6.64E-02	4.89E-02	0.97	0.33	2.19E-02	-2.94E-02	1.62E-01
dcork*	1.09E-03	5.57E-03	0.20	0.85	1.52E-01	-9.83E-03	1.20E-02

Table A6.1: Econometric results Model 1 – all coefficients							
Variable	dF/dx	Std. Err.	z	P>|z|	x-bar	[95%	C.I.]
ddub*	7.07E-03	4.96E-03	1.42	0.16	3.53E-01	-2.66E-03	1.68E-02
dgal*	3.05E-03	6.15E-03	0.49	0.62	7.17E-02	-9.00E-03	1.51E-02
dlim*	5.60E-03	5.52E-03	1.00	0.32	1.32E-01	-5.22E-03	1.64E-02
dmull*	-1.30E-02	6.08E-03	-2.20	0.03	1.03E-01	-2.49E-02	-1.08E-03
dnaas*	1.32E-03	5.56E-03	0.24	0.81	1.31E-01	-9.58E-03	1.22E-02
ddrole*	-7.01E-03	3.50E-03	-1.98	0.05	7.77E-01	-1.39E-02	-1.57E-04
drecrole*	-5.36E-03	2.10E-03	-2.56	0.01	4.64E-01	-9.47E-03	-1.25E-03
ddelmeth*	4.79E-03	4.29E-03	1.13	0.26	9.33E-01	-3.62E-03	1.32E-02
dinmeth1*	1.08E-01	5.86E-02	1.48	0.14	2.47E-01	-6.63E-03	2.23E-01
dinmeth2*	4.06E-02	1.19E-02	2.89	0.00	5.00E-03	1.73E-02	6.38E-02
dinmeth3*	4.38E-02	8.45E-03	4.72	0.00	2.05E-01	2.72E-02	6.04E-02
dinmeth4*	1.05E-01	4.77E-02	1.57	0.12	1.71E-01	1.19E-02	1.99E-01
dinmeth5*	6.67E-02	8.78E-03	7.17	0.00	3.64E-01	4.94E-02	8.39E-02
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obs. P	0.8763308						

The results for Model 2 are presented in Table 6.2.

Table 6.2: Estimation results; Model 2							
Variable	dF/dx	Std. Err.	z	P>z	x-bar	[95%	C.I.]
volcap	0.000	1.9200E-08	1.420	0.155	1.6000E+06	-1.0000E-08	6.5000E-08
volcap2	0.000	5.1100E-15	-2.760	0.006	2.8000E+12	-2.4000E-14	-4.1000E-15
vprov	0.000	4.2100E-09	-1.510	0.131	1.1000E+06	-1.5000E-08	1.9000E-09
vprov2	0.000	8.1500E-16	-2.150	0.032	1.9000E+12	-3.3000E-15	-1.5000E-16
pctpacs	-0.193	5.7302E-02	-3.370	0.001	7.5257E-02	-3.0527E-01	-8.0645E-02
pctflats	-0.103	4.9630E-02	-2.070	0.039	1.0209E-01	-1.9996E-01	-5.4150E-03
labbasic	0.000	4.7100E-06	2.070	0.038	3.0679E+03	5.3000E-07	1.9000E-05
labbas2	0.000	9.8600E-10	2.600	0.009	1.0000E+07	6.3000E-10	4.5000E-09
lababs	0.000	6.1300E-06	-5.120	0.000	9.7686E+02	-4.3000E-05	-1.9000E-05
labprov	0.000	1.3200E-06	-8.680	0.000	1.6987E+05	-1.4000E-05	-8.9000E-06
labprov2	0.000	3.5800E-12	8.380	0.000	2.9000E+10	2.3000E-11	3.7000E-11
lababspr	0.000	2.7500E-06	3.210	0.001	1.0017E+04	3.4000E-06	1.4000E-05
Labdd	0.000	1.2900E-06	4.600	0.000	8.7169E+04	3.4000E-06	8.5000E-06
labdd2	0.000	6.9400E-12	-5.300	0.000	7.7000E+09	-5.0000E-11	-2.3000E-11
labsdd	0.000	2.0000E-06	-1.710	0.088	4.6740E+03	-7.4000E-06	5.1000E-07
Indu_tim	-0.004	9.0390E-04	-4.280	0.000	1.3613E+01	-5.6390E-03	-2.0960E-03
proximit	-0.001	1.0112E-03	-0.860	0.389	4.1644E+00	-2.8530E-03	1.1110E-03
proxsq	0.000	3.9800E-05	-3.610	0.000	3.5092E+01	-2.2200E-04	-6.6000E-05

The estimation results for Model 3 are presented in Table 6.3.

Table 6.3: Estimation results; Model 3							
Variable	dF/dx	Std. Err.	z	P>z	x-bar	[95%	C.I.]
volcap2	-9.960E-15	1.330E-15	-7.470	0.000	2.800E+12	-1.300E-14	-7.300E-15
vprov2	-3.170E-15	3.970E-16	-8.000	0.000	1.900E+12	-3.900E-15	-2.400E-15
Pctpacs	-2.467E-01	5.772E-02	-4.270	0.000	7.526E-02	-3.599E-01	-1.336E-01
pctflats	-1.521E-01	4.905E-02	-3.100	0.002	1.021E-01	-2.483E-01	-5.599E-02
Labbasic	5.820E-06	4.860E-06	1.200	0.231	3.068E+03	-3.700E-06	1.500E-05
labbas2	2.040E-09	9.830E-10	2.080	0.037	1.000E+07	1.200E-10	4.000E-09
lababs	-1.810E-05	5.810E-06	-3.120	0.002	9.769E+02	-3.000E-05	-6.800E-06
labsprov	4.230E-05	3.580E-06	11.800	0.000	8.779E+03	3.500E-05	4.900E-05
Labprov2	-6.040E-12	6.770E-13	-8.920	0.000	2.900E+10	-7.400E-12	-4.700E-12
labsmpro	-3.180E-05	5.580E-05	-0.570	0.568	8.129E+01	-1.410E-04	7.800E-05
labdd	-3.450E-08	1.060E-06	-0.030	0.974	8.717E+04	-2.100E-06	2.000E-06
labdd2	-4.210E-12	5.740E-12	-0.730	0.463	7.700E+09	-1.500E-11	7.000E-12
labsdd	-2.950E-06	1.960E-06	-1.500	0.132	4.674E+03	-6.800E-06	8.900E-07
indu_tim	-3.743E-03	9.027E-04	-4.150	0.000	1.361E+01	-5.512E-03	-1.973E-03
proximit	-7.844E-04	1.010E-03	-0.780	0.437	4.164E+00	-2.764E-03	1.195E-03
proxsq	-1.422E-04	3.970E-05	-3.580	0.000	3.509E+01	-2.200E-04	-6.400E-05