LETTER TRAFFIC DEMAND IN THE UK: AN ANALYSIS BY PRODUCT AND ENVELOPE CONTENT TYPE*

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1. INTRODUCTION AND BACKGROUND

Addressed inland letter traffic volumes in the UK have been in decline for a number of years. Until around 2002 UK mail volumes tended to move in line with economic and demographic growth[1]. However, since then first growth rates and then mail volumes have declined despite the UK economy exhibiting robust rates of economic growth until 2007. The sharp contraction in economic activity after 2008 exacerbated this decline. The extent to which letter traffic volumes are likely to continue to decline and the degree to which this may be offset by an improvement in the economic environment or factors within postal operators' control (such as prices and quality of service), are important questions facing postal policy makers.

In order to better inform evidence based analysis of the postal industry in the UK this paper uses econometric time series techniques to shed light on the main drivers of letter demand. In particular, the paper updates the Nankervis et al (2002) study of the demand for letters disaggregated by high level product streams and also provides new insights to the literature by examining the demand for UK letters by analysing trends in the content of mail envelopes.

The impact on letter volumes from developments related to the economy, electronic substitution and price changes are likely to vary across different postal service products and types of mail. This paper identifies and provides quantitative estimates of the key factors that influence the demand for letter in the UK using two data sets. The first analyses the demand for total letter traffic volumes using information on three Royal Mail Group product streams (First Class non-presort, Second Class non-presort and Other (mainly presort traffic)). The second examines the demand for letters by three content types (Social, Commercial (mainly transactional) and Direct Mail).

There is a long tradition of modelling letter traffic demand using time series data. Previous studies in the UK, France and Finland have concentrated on total letter demand or the demand for services differentiated by their expected time of delivery

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* The analysis contained in this chapter reflects the views of the authors and not necessarily those of Royal Mail Group.

[1] The analysis in this paper refers solely to addressed inland mail volumes and does not consider developments in unaddressed mail volumes.

(First and Second Class services) or single piece versus bulk mail services[2]. In the USA much of the differentiation in mail is by content type and single piece versus bulk or worksharing specifications[3]. The current study by utilising two segmentations of the same traffic data series provides updated estimates of UK demand elasticities for products differentiated by service specification and also, for the first time, demand elasticities by letter content.

Section 2 describes the time series data for the product and content traffic streams used to model the demand for letters in the UK. Section 3 sets out the estimation methodology and reports the results of the modelling of letter product streams. Section 4 reports the results of modelling letter demand by content type. Section 5 compares the two sets of results and highlights new insights into the demand for UK letter demand using this dual data lens approach. Finally, section 6 provides a summary and conclusions.

2. ADDRESSED INLAND LETTER TRAFFIC TRENDS IN THE UK

Using data from 1976Q4 to 1999Q1, Nankervis et al. (2002) modelled the demand for UK addressed inland letter traffic as a function of economic activity, the number of households, prices, quality of service and time trends to account for electronic substitution. Two notable features of the results of this study were: firstly, the total traffic unit long run elasticities for the number of households and economic activity; and secondly a low total traffic price elasticity underpinned by larger own and cross price letter product elasticities reflecting substitution between the product streams.

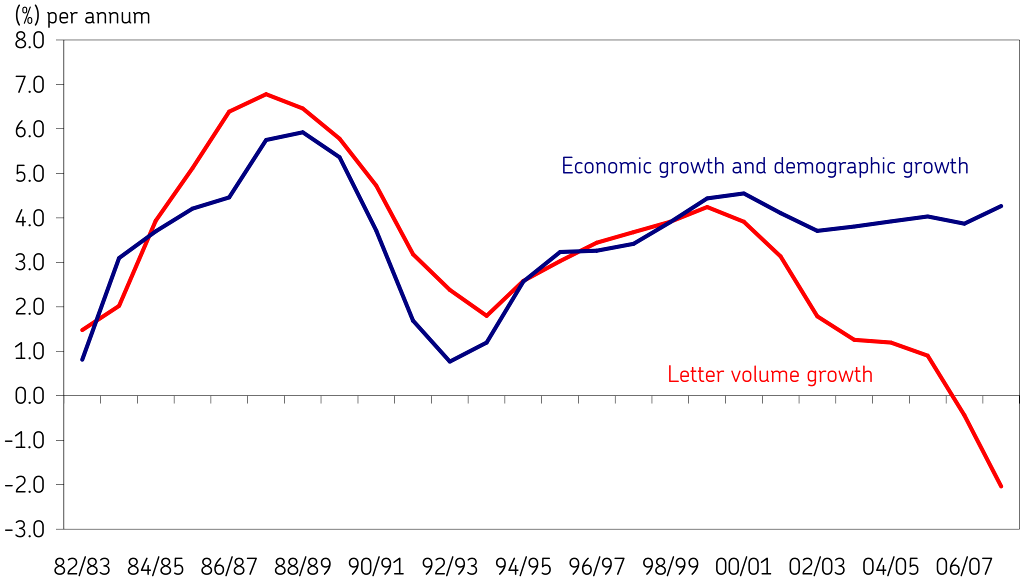
Figure 1 displays a time series for UK total addressed inland letter traffic growth. This shows that historically addressed inland letter traffic in the UK has tended to move in line with the economy and demographic trends. It should be noted that while Nankervis et al. (2002) found other factors, such as mail prices and the price of substitute products to have statistically significant effects on UK mail volumes, their impact on letter volumes have historically been of relatively less importance. However, after around 2002 this pattern no longer appears to have held. This has led to a debate amongst postal administrations and by postal regulators and policy makers as to whether a relationship with economic activity and demographic trends continues to exist or, alternatively, whether this relationship has become more complex and multi-dimensional in nature and so more difficult to detect using simple graphics.

The communication industry is changing rapidly in response to technological advances. The increasing speed and declining cost of electronic forms of communication is leading to the replacement of paper based communications. But to what extent is this driving down mail volumes and what type of mail will be

[2] See Boldron et al. (2009), Florens et al. (2002), Nankervis et al. (2002), Nikali (2002), and Soteri et al. (2009)
[3] See Thress (2006).

affected to a greater or lesser degree? Furthermore, from a business and policy perspective, are there factors within the control of postal operators and policy makers to counter such substitution? This paper uses time series econometric techniques to shed some light on these questions.

Figure 1: UK Addressed Inland Mail Traffic Trends Versus Economic and Demographic Growth Trends, 1982/83 to 2007/08



Source: Data from National Statistics, Experian, Royal Mail Group.

Note: (1) Letter traffic growth rates adjusted for number of working days. (2) Economic growth refers to GDP growth weighted by letter demand (GVA(L)). (3) Data in chart refer to three year moving averages.

Following Nankervis et al. (2002) the current paper models the demand for total addressed inland letter traffic by traffic streams. In particular, total Royal Mail delivered traffic data is disaggregated into three high level product categories of mail: First Class non-presort mail; Second Class non-presort mail; and Other (mainly presort traffic)[4]. These three streams of traffic also broadly align to those used in previous UK econometric studies[5]. The main difference between the definition of product streams in this paper and previous studies relates to the treatment of downstream access volumes. For example, in the data set used in Soteri et al. (2009) access volumes in 2004/05 were negligible and in 2005/06, the final year of the time series, accounted for only 6% of total addressed inland letter traffic. This small amount of access traffic was assumed to have almost all switched

[4] The First and Second Class non-presort traffic streams have a next working day and within three working days delivery specification respectively. They include the following single-piece priced addressed inland Royal Mail products: Stamp, Meter, PPI, Cleanmail and estimates for non customer presorted downstream access traffic. Other (mainly presort) traffic includes the following addressed inland Royal Mail products: Mailsort, Walksort, Packetpost, Presstream, Response Services, USO Parcels, Large Mail Order Returns (LMOR), Tracked, Heavyweight and estimates for customer presorted downstream access traffic.

[5] See Nankervis et al. (2002), Cazals et al. (2008) and Soteri et al. (2009).

from Royal Mail's bulk end-to-end products and therefore included in the Other (mainly presort) category.

The data period used to undertake the econometric analysis in the current study extends to 2008Q1 and covers UK data up to and including the UK financial year 2007/08. Downstream access volumes delivered by Royal Mail amounted to over 4bn items and accounted for around one-fifth of total letter traffic in 2007/08. Ideally, it would have been better to model access traffic as a separate traffic stream. However, while competition in the UK mail market is still evolving and the number of time series data points for access are limited (only 13 quarterly data points were available up to 2008Q1), it is not possible to estimate a robust econometric time series model for access traffic.

The methodology adopted to handle access traffic in this paper was to include access traffic that mail senders presort prior to handing it to a Royal Mail competitor (or in some cases handed back directly to Royal Mail to deliver[6]) in the Other (mainly presort) category, and traffic that is not presorted in the non-presort categories. Estimates by Royal Mail were used to quantify the non-presort and presort categorisation of access traffic. In these estimates a negligible quantity of First Class mail senders had switched to downstream access; a considerable proportion of presorted volumes had switched to access traffic (the vast majority of which is estimated to originate from the Royal Mail Mailsort product range); and a considerably smaller proportion of Second Class non-presort volumes had switched to access[7]. This approach is consistent with using external information to better inform the econometric modelling and is consistent with the approach to updating model parameter estimates in Fève et al. (2010).

Figure 2 shows that there has been a long-term trend away from using both First and Second Class non-bulk letter services towards using bulk presorted services. Proportionately, discounts earned for presorting mail remained broadly unchanged for much of the period reported in figure 2. Following the introduction of work-sharing discounts in the UK in the late 1970s and more extensively in the 1980s, the migration of non-presort traffic would, in general, have reflected one-off changes in relative prices. The main beneficiaries of these services in the early years would have been very large mailers. However, over time smaller scale senders will also have benefited as a result of advances in technology that have lowered the cost of presorting letters.

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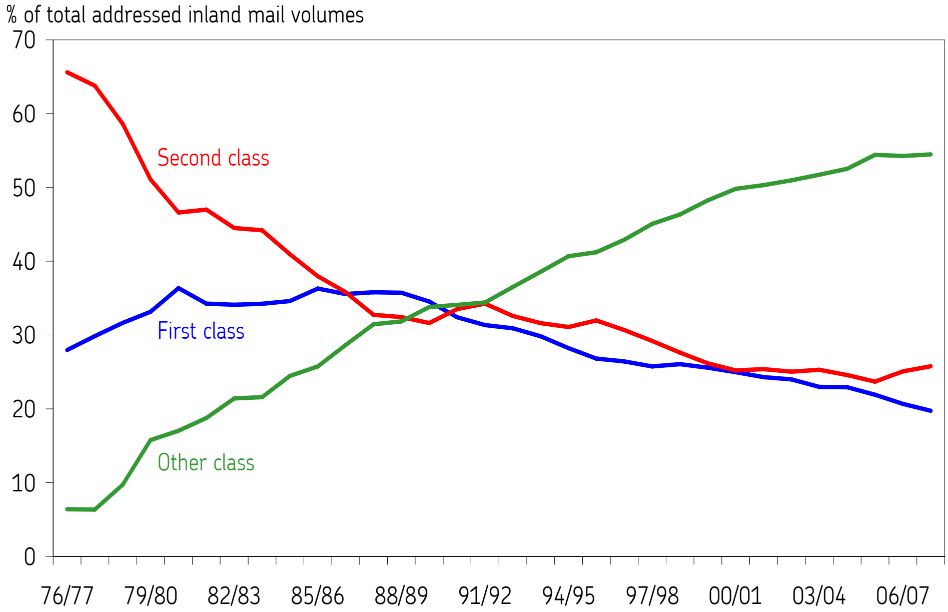
[6] A number of customers have access contracts directly with Royal Mail ("customer direct access").
[7] In particular, it is estimated that almost all access traffic in 2004/05 and 2005/06 was presorted traffic. For 2006/07 this figure was estimated to be over 80% and in 2007/08 around 80%.

Figure 2: Addressed Inland Letter Volume Product Category Shares



Source Royal Mail Group

The impact of new technology is likely to have had a markedly different impact on each of the three traffic streams. The introduction of bulk mail discounts for presorted traffic and declining costs of sorting letters due to advances in technology is likely to have encouraged mailers to switch away from non-presort traffic from the late 1970s. Public tariff First Class mail volumes, where customers pay more for speed of delivery, are likely to have a higher exposure to electronic forms of communication than the slower Second Class service with any negative impact being felt from the late 1980s onwards when fax, and then email and internet usage, developed. Conversely, presort traffic levels should have benefited initially from switching from public tariff service, but, over time, this benefit should have dissipated as the relative magnitude of non-presort traffic declined. In addition, advances in technology which helped to reduce the cost of acquiring and interrogating marketing databases for direct mail campaigns in the 1980s initially boosted bulk letter volumes. However, two decades later, advances in technology have created an alternative and relatively lower cost direct marketing medium in the form of internet "paid-for-search" advertising[8] that is competing with direct mail letter communications and other advertising media for business advertising budgets[9].

In order to obtain further insights into the demand drivers for addressed inland letter traffic, and, in particular, factors underpinning the impact of esubstitution, an examination of letter volume trends by content type was also undertaken. The

[8] That is, adverts triggered by key "searchwords".

[9] See Soteri et al. (2009).

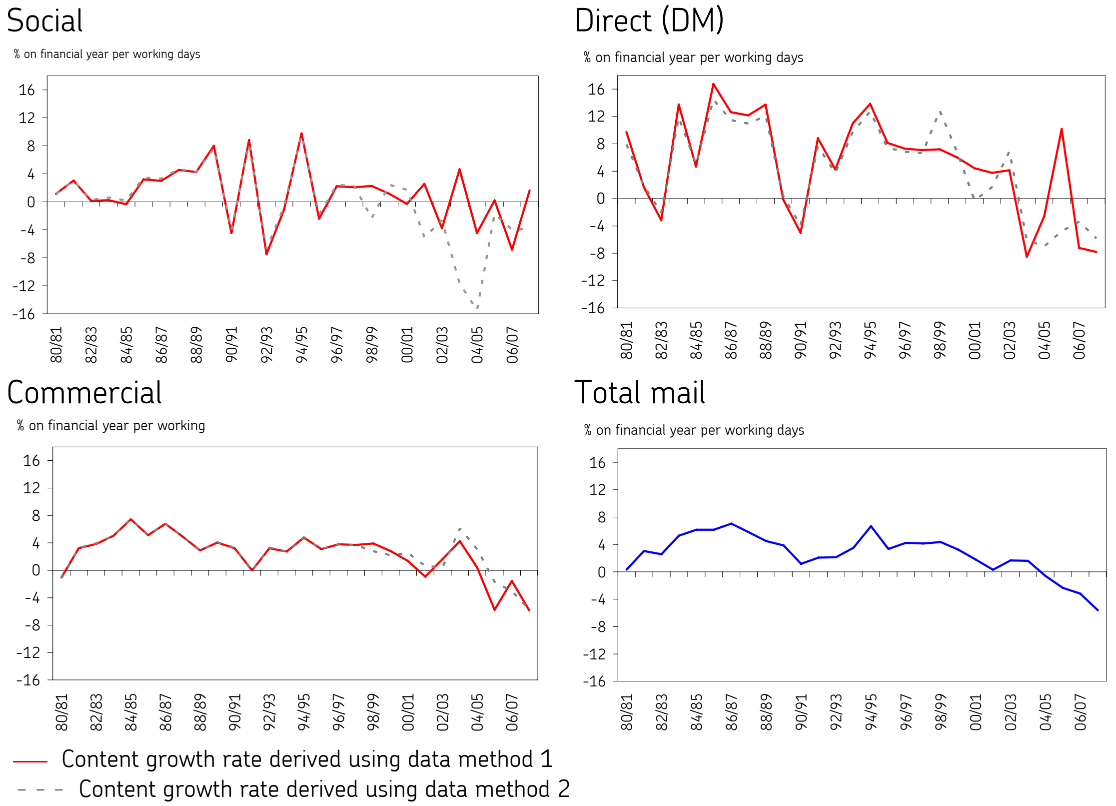
absence of sales data by content type led to the use instead of two Royal Mail surveys: the Mail Characteristics Survey (MCS) and the Consumer Panel Survey (CPS). However, neither of these sources provided a comprehensive survey of total letter traffic and information from both was required to derive time series data for addressed inland mail. In particular, although available from 1980/81 the MCS did not cover the recent development of access traffic and the CPS was available only from 2001/02 and did not cover business-to-business (B2B) mail. Given the information gaps of both surveys, two data methods were adopted to derive estimates of content based traffic volumes. Data method 1 focussed firstly on the MCS and used the CPS to inform elements of traffic not covered by the MCS. In contrast, data method 2 started with the CPS and used the MCS to inform gaps in its survey coverage. Given the shorter time period for which CPS content data was available, it was not possible to use method 2 alone to derive content time series that are long enough to undertake robust time series econometrics. However, a continuous time series data set going back to 1980/81 was derived by splicing this data series to MCS content share estimates.

The estimated shares of addressed inland letter traffic by content type using the two data methods yielded broadly similar results. For example, in 2007/08 both methodologies estimate that: Direct Mail (DM) accounted for around 20% of total letter traffic; Commercial mail for a little over 70%; and Social mail for between 6% and 8%. Figure 3 shows the estimated content volume annual growth rates per working day for the period 1981/82 to 2007/08. Note that, prior to 2001/02 data method 2 used the method 1 share estimates to derive long run time series data (as outlined above) and therefore the annual growth rates reported in figure 3 prior to this time period are almost identical.

In terms of directional trends, figure 3 shows that for Commercial mail both data methods estimated the trend rate of growth to have declined from around 2004/05 onwards. Similarly, both data methods estimated that the trend rate of Social letter volume growth declined somewhat from around 2002/03 onwards. Data method 2 suggests a more accentuated decline in the Social mail volume trend during the period between 2003/04 and 2007/08 in comparison to data method 1. However, this is more likely to be related to changes in the definition of Social traffic in the CPS than changes in the actual trend of Social mail volumes.

In the case of DM traffic, figure 3 shows that both data methods estimated that the trend rate of volume growth slowed down from 2000/01 onwards. Furthermore, both data methods indicated that DM volumes exhibited considerable declines in individual years from 2004/05 onwards. However, it should be noted, that while some clear changes in the DM letter content trend can be discerned from the two time series data, there is considerable variation in individual year-on-year growth rates. This is to be expected, given the reliance on survey data, which contains elements of sampling error, random noise and differences in the nature of the surveys themselves. The large difference between the method 1 and 2 DM growth rates in 2006/07 is likely to be due to such factors. For example, method 1 suggests that DM increased in 2006/07 by around 10% while Method 2 suggested a decline of around 5%. In such circumstances other external information can be used to assess the appropriateness of these estimates. For example, estimates of DM expenditure provided to Royal Mail from external market research suggest that it was more likely that DM volumes declined in 2006/07 than increased.

Figure 3: Mail Volume Growth Rates by Content Type Using Data Method 1 and 2



Note: Data in figure 3 refers to year-on-year growth in UK Financial years (FY). For example, UK FY 2007/08 refers to the data period April 2007 to March 2008.

The time series data for volume trends by content type suggest a number of important points should be borne in mind when using and interpreting content volume data. Three points to note in particular are: survey data can be used to derive reasonable estimates of the magnitude of the relative share of letter traffic by content type; high level trend estimates of content shares can be used to derive time series estimates of content volumes, and there is a high level of statistical noise associated with content traffic growth rates in individual years.

Bearing in mind the above and concentrating on directional trends, a number of important points emerge from the series reported in figure 3. First, during the early 1980s, Social mail volumes grew by around 2% to 3% annually and then declined on average, but fluctuated considerably, in the early 1990s. Subsequently, Social mail volumes tended to display mainly positive rates of growth, until around 2003/04 when Social mail volumes started to decline. Second, DM volume growth appears to be highly cyclical and its trend rate of growth has declined over time. For example, DM volumes increased by double digit growth rates during the 1980s when the UK economy was growing strongly and DM was a relatively new advertising medium. But it exhibited a sharp contraction around the time of the recession of the early 1990s. As the economy recovered from this, so did the demand for DM but the rate of growth was somewhat lower than in the previous decade. From around 2000 onwards, despite robust levels of economic growth, DM volume growth rates slowed considerably and were, on average, negative from 2005/06 to 2007/08. Third, Commercial mail volumes grew strongly in the mid 1980s, and between 1982/83 to 1989/90 averaged around 5%. It is clear that Commercial traffic volumes have been somewhat cyclical, as the low or negative growth rates in the early 1980s and 1990s show. A further feature of the Commercial traffic growth rate data is the clear downward trend that has emerged since about 2004/05.

3. AN ECONOMETRIC ANALYSIS OF UK LETTER TRAFFIC DEMAND USING ROYAL MAIL DELIVERED PRODUCT DATA

3.1 Estimation methodology

The modelling of demand for addressed inland letter traffic volumes by product stream in the current study followed a similar estimation methodology to Nankervis et al. (2002). In summary, the modelling for addressed inland letter traffic by product type comprised of three relationships, one for each of the following product categories: First Class non-presort traffic; Second Class non-presort traffic; and Other (mainly presort) traffic[10]. The demand relationships were estimated using single equation econometric time series error correction models and the long run coefficients entering the error correction models for each of the three traffic streams were estimated using Dynamic OLS (DOLS) models of the following form[11]:

$$q_{it} = A_i^{'} D_{it} + \Pi_i^{'} x_{it} + \sum_{k=-m_i}^{k=m_i} C_{ik}^{'} \Delta x_{i,t-k}^{I} + \sum_{k=0}^{k=m_i} F_{ik}^{'} x_{i,t-1-k}^{0} + \eta_{it} \qquad (1)$$

where lower case letters for Q_{it} and X_{it} denote logarithms of variables in time period t. X^{I}_{it} is a subset of X_{it} variables integrated of order 1 (that is, are I(1)) and X^{0}_{it} is a subset of X_{it} variables integrated of order 0 (that is, are I(0))[12]. The Δ represents time series change terms (e.g. $\Delta x_{it} = x_{it} - x_{it-1}$). The variable Q_i denotes the volume of traffic per working day for stream i (i=1,2,3); where i=1 refers to First Class non-presort traffic; i=2 to Second Class non-presort; i=3 to Other (mainly presort) traffic. The variable X_{it} denotes a vector of explanatory variables

[10] The model was estimated using the econometric package EVIEWS5.

[11] See Stock and Watson (1993) and Saikkonen (1991).

[12] In particular, X^{0} contains real mail tariff price indices (that is mail prices deflated by the UK Retail Prices Index) which were estimated to be I(0). Since mail prices in the UK have been subject to an RPI-X price control formula since 2003 and previous to this prices were periodically updated roughly in line with inflationary pressures, it is perhaps not surprising that the mail tariff indices deflated by the RPI were found to be I(0).

corresponding to each traffic stream *i*. The vector of explanatory variables X_{it} included the number of households (*H*), economic activity weighted by letter demand (*Y*), real letter tariff price indices for product *i* (P_i), the quality of letter service delivery (*QoS*), the real price of traditional non-mail advertising media substitutes (*PA*), the proportion of internet advertising expenditure relative to total advertising expenditure (*PIA*). Also, initially included in X_t were a number of variables linked to technology trends, such as the proportion of households with access to the internet and broadband and real telecommunication prices. D_{it} is a vector of deterministic variables which includes a constant, seasonal dummies and a number of time trends. Π_i is a vector of long-run coefficients and A_i, C_{ik} and F_{ik} are vectors of estimated coefficients for each of the sub-product models.

The time series nature of the Q_i variables and most of the variables included in X_i exhibit non-stationarity and a single cointegrating vector was found to exist for each of the three DOLS models estimated using (1). The values of m_i were chosen on the basis of AIC and SBC information criteria[13]. The resulting estimators for the long-run coefficients Π are therefore said to be superconsistent and these estimates were incorporated into general error correction models for each of the three broad product categories. The individual product models were then estimated using a general to specific product modelling methodology, where the general error correction models were of the following form:

$$\Delta q_{it} = \alpha_i' D_{it} + \theta_i (q_{i,t-1} - \hat{\Pi}_i' x_{i,t-1}^I) + \lambda_i x_{i,t-1}^0 + \sum_{k=1}^{n_i} \theta_{ik} \Delta q_{i,t-k} + \sum_{k=0}^{n_i} \varphi_{ik} \Delta x_{i,t-k} + \varepsilon_{it} \quad (2)$$

where α, θ, λ and Φ are estimated coefficients and lower case variables are in natural logarithmic form.

3.2 Addressed inland letter traffic model by product stream econometric estimates

The estimated equations for the addressed inland letter traffic model by broad product stream (ILTMP), after deleting insignificant variables and setting the long run elasticities for the number of households to unity[14], are reported in table 1. The estimated parameters have reasonably high t-statistics and the reported diagnostic tests suggest that the ILTMP is statistically sound[15]. Furthermore, the error correction terms, which include I(1) variables, have high t-statistics in each of the three models from which it is concluded that these variables cointegrate[16]. This conclusion is also supported by Johansen cointegration tests.

[13] Akaike's Information Criterion and Schwarz's Bayesian Criterion.

[14] A unit long-run elasticity hypothesis could not be rejected in the first stage of the estimation process.

[15] In addition, plots of the recursive estimates of the key variables in each of the product sub-models and cusum and cusumq-squared tests suggest that the estimated coefficients in ILTMP are relatively stable and do not exhibit parameter instability. These tests, along with the Chow tests for predictive failure reported in table 1 indicate that parameter values are relatively stable and the estimated coefficients in ILTMP are statistically robust.

[16] See Ericsson and MacKinnon (2002).

Table 1. Addressed Inland Letter Traffic Model by Product Stream: (ILTMP)

Estimated Coefficients and Diagnostic Tests

First Class [(a)]			**Second Class [(a)]**			**Other class [(a)]**		
Dependent variable dq1-h			Dependent variable dq2-h			Dependent variable dq3-h		
Estimation method least squares			Estimation method least squares			Estimation method least squares		
	Estimated coefficients	**T-value**		**Estimated coeffecients**	**T-value**		**Estimated coeffecients**	**T-value**
ECT1(-1)*	-0.30	-4.7	ECT2(-1)*	-0.49	-8.2	ECT3(-1)*	-0.87	-8.9
T87	-0.003	-3.8	T75	-0.007	-7.7	pia(-1)	-1.52	-6.4
T02	-0.005	-4.3	T87	0.004	6.3	T83	0.011	8.9
p1(-1)	-0.23	-2.7	p1(-1) [(b)]	0.15		T97	-0.010	-7.6
p2(-1)	0.10	1.9	p2(-1) [(b)]	-0.15				
			qos(-1)	0.25	4.3			
dy	0.91	2.4	dy	1.03	2.8	dy	1.06	2.0
			dqos	0.22	5.0			
Rsq adjusted	0.83		Rsq adjusted	0.94		Rsq adjusted	0.80	
Reg. SE	0.030		Reg. SE	0.032		Reg. SE	0.031	
DW	2.1		DW	2.2		DW	2.1	
Estimation Period 1975 Q4 - 2008 Q1			Estimation Period 1975 Q3 - 2008 Q1			Estimation Period 1983 Q1 - 2008 Q1		
*ECT1=q1 -h-1.65*y			* ECT2 = q2 -h-0.65*y			* ECT3=q3-h-1.10*y -0.44*(pa-p3)		
Diagnostic Tests [(c)]			**Diagnostic Tests [(c)]**			**Diagnostic Tests [(c)]**		
	P values			**P values**			**P values**	
Serial correlation	0.28		Serial correlation	0.33		Serial correlation	0.24	
Heteroskedasticity	0.89		Heteroskedasticity	0.08		Heteroskedasticity	0.35	
Normality	0.45		Normality	0.81		Normality	0.38	
Reset	0.32		Reset	0.80		Reset	0.69	
Chow	0.68		Chow	0.97		Chow	0.20	

(a) The estimated models also included deterministic variables such as constant, seasonal dummy and time trends, which were statistically significant at the 5% level.

(b) The Slutsky-Schultz symmetry constraint between First and Second Class traffic was tested using a simultaneous cross equation Wald-test restriction. The Wald test statistic indicated that this restriction was statistically valid and imposed in the model. In addition, the own and cross price elasticities in the Second Class equation were tested to be equal and opposite in magnitude. Again this restriction could not be rejected via statistical tests and was imposed in the model.

(c) The reported diagnostic tests refer to the estimated models prior to the imposition of the cross equation restrictions between First and Second Class models noted in (a):

The Serial Correlation test is an LM test of up to 4th order autocorrelation.
The Normality test is based on a test of skewness and kurtosis of residuals.
The Heteroskedasticity is based on the regression of squared residuals on fitted values.
The Reset test used one fitted term
The predictive failure test is Chow 's test with a breakpoint set at 2004Q2

The econometric results reported in table 1 were used to derive the estimated long run elasticities and time trend effects reported in table 2 for ILTMP [17]. The long run elasticities for total addressed inland letter traffic volumes were calculated by aggregating each of the three product stream long run parameters by their respective share of total traffic[18]. The magnitudes of the estimated long run

[17] For variables contained in the error correction term the long run elasticities are their imposed coefficients multiplied by -1. For variables not contained in the error correction term, their long run estimated coefficients are obtained by dividing a particular variables' regression coefficient by the error correction term contained within the same regression and then multiplying by -1. In order to express the long run time trend impacts from the quarterly model in percentage terms per annum, their estimated coefficients have been multiplied by 400.

[18] The parameters for total traffic were obtained by weighting each of the individual product stream parameter estimates by their volume weights in 2007/08. In theory, it would be more appropriate to use volume weight averages over the estimation period. However, from a business perspective, model parameters tend to be used to assess recent outturns and forecast volumes around the latest within sample data point that is available (that is 2007/08). An alternative and strictly more accurate methodology to derive total traffic elasticities would be to use Monte Carlo simulation techniques to aggregate the results of the three models. The adoption of this much simpler technique provides results which are approximately consistent with such an approach.

elasticities are, in general, broadly consistent with the results reported in Nankervis et al (2002) despite extending the estimation period to include an additional 36 quarters of data.

Table 2: Addressed Inland Letter Traffic per Household Product Model (ILTMP) Long Run Elasticities and Time Trend Impacts

	Long-Run Elasticities ILTMP			
	Total traffic[1]	First Class non-presort	Second Class non-presort	Other traffic (mainly presort)
Economic activity (Y)	1.09	1.65	0.65	1.10
First Class non-presort price[2] (P1)	-0.07	-0.77	0.31	ns
Second Class non-presort price[2] (P2)	-0.01	0.33	-0.31	ns
Other (mainly presort) price[2] (P3)	-0.24	ns	ns	-0.44
Quality of Service[3]	0.13	ns	0.52	ns
Price of non-mail advertising[2] (PA)	0.24	ns	ns	0.44
Proportion of internet advertising spend (PIA)	-0.95	na	na	-1.75
Net impact of "unexplained" time trends (% p.a.)	Pre 02 0.7%	87-02 -3.8%	75-87 -5.4%	83-97 5.2%
	Post 02 -2.4%	Post 02 -10.9%	Post 87 -2.5%	Post 97 0.7%

Note:
1. Total traffic estimated elasticities and time trend effects were calculated by weighting the estimated coefficients in each of the traffic streams by their by their respective traffic volume share in 2007/08.
2. Deflated by the All Items Retail Prices Index
3. Refers to Royal Mail First Class quality of service for Stamp and Meter traffic
na denotes not applicable
ns denotes not statistically significant at 5% level

Similarly, the addition of a further eight quarters of data to the Other traffic model produced results that were similar to Soteri et al (2009). The elasticity of demand for total letter traffic with respect to economic activity is again estimated to be close to unity and again varies considerably across streams. In particular, similar to previous results, First Class non-presort traffic is estimated to have a relatively high long run economic activity elasticity of around 1.7 while the estimate for Other (mainly presort) traffic is a little over unity and again, economic activity is estimated to have the weakest impact on Second Class non-presort letter traffic.

The estimated impact of First and Second Class prices on mail volumes exhibit similar properties to those reported in Nankervis et al (2002). In particular, the results suggest that First Class non-presort traffic has a relatively high own price long run elasticity of around -0.8 and a cross price elasticity with respect to Second Class traffic of around 0.3. Since the respective shares of these traffic streams is broadly equal, these results suggest that a 1% rise in the price of First Class will lead to a loss in First Class traffic of about 0.8%, of which 0.3% will switch to Second Class traffic, implying that the overall loss to First Class traffic will be about 0.5%. The estimated long run own price elasticity for Second Class traffic is lower than that for First Class, but in this case it is estimated that all this traffic would switch to the First Class stream and the net loss in First and Second Class traffic jointly would be close to zero. Note that a simultaneous equal percentage increase in First and Second Class prices would imply that these switching effects would largely cancel each other out and yield an overall long run price elasticity for First and Second Class traffic jointly of about -0.2.

The estimated long run price elasticity for Other (mainly presort) traffic is around -0.4. There are no cross-price elasticities estimated for this stream and hence this represents the overall impact on the demand for Other (mainly presort) traffic of changing prices[19]. However, note that it is the price of Other (mainly presort mail) relative to the price of competing modes of advertising that matters (in particular, publishing and TV media) rather than letter prices alone.

The estimated long run quality of service (QoS) elasticity for total letter demand was estimated to be about 0.1. Note that the impact of QoS is found only to be statistically significant in the Second Class stream. This is consistent with an interpretation of "trading up". That is, movements in First Class and Second Class QoS tend to be highly correlated. Hence declines in First Class QoS (and hence of Second Class as well) reduce Second Class mail volumes as some mailers trade up to First Class services to lower the overall effect on them of declining performance. At the same time, some First class traffic is lost in response to the decline in First Class QoS so that the net impact is that the overall decline in mail volumes is accompanied by First Class volumes remaining more or less unchanged but Second Class volumes falling.

The impact of the time trends are perhaps best considered as primarily reflecting the impacts of technology on the demand for mail. The effect of technology on the erosion of mail volumes was explored in a number of ways. For example, model specifications including the proportion of households with internet and broadband access yielded broadly similar results to those reported in table 2. However, statistical criteria (for example, diagnostic test statistics, AIC and SBC information criteria and the standard error of regression) preferred models with time trend break terms. This could reflect the fact that changes in technology are dynamic in nature and unlikely to be reflected within the properties of a single variable or group of variables. For example, it could be the case that, potentially, time trend terms may be a better proxy for the combined and evolving impacts of different technologies, which individually can be modelled as being logistic in their effect on the demand for mail, but over time cumulate to yield "corrugated S-shaped"

[19] The estimated coefficients for the First and Second Class tariff indices were found to be not statistically significant different from zero in the Other traffic equation. The absence of a statistically significant estimated coefficient with respect to First Class prices is likely to reflect a genuine lack of direct substitution between First Class non-presort mail and Other mainly presort traffic. However, in the case of substitution with respect to Second Class mail this is less clear. The large majority of Other traffic is related directly, or indirectly, via discounts to the price of products contained in the Second Class category. Hence, it is not clear whether the lack of statistically significant terms is due to the absence of a relationship or due to the non-identification of a statistically significant coefficient arising from the correlation of the Second Class and Other (mainly presort) price indices.

impacts[20] that are better reflected by time trend terms and/ or time trend break terms[21].

The time trend in the First Class traffic stream reported in table 2 suggests that from around 1987 factors other than those explicitly contained in the model reduced First Class traffic volumes by around 4% per annum, consistent with key developments in communication technology. The negative time trend effect from the late 1980s coincides with the widespread adoption of fax machines, the introduction of bill payments by direct debit and the development of electronic communication and ebusiness services in the 1990s. Furthermore, the increasingly negative trend term after 2002 is consistent with the rapid increase in internet and other electronic technologies substituting for traditional mail communications to the scale of around 11% per annum of the First Class stream.

The net impact of the 'unexplained' time trend in the Second Class model has been to reduce Second Class traffic volumes, although the extent of this reduction has slowed down from 5% per annum up to 1987 to a decline of 3% per annum thereafter. The key driving force accounting for the earlier trend is likely to have been the offering of worksharing discounts and advances in technology over time that have reduced the cost of switching from Second Class non-presort products into Other (mainly presort) mail products. The decline in the negative time trend impact to 3% per annum after 1987 suggests that the pace of such switching has slowed and/ or esubstitution effects have been taking place. It is likely that both factors have been at work but their relative magnitude is uncertain.

In contrast to the First and Second class time trends, the net impact of the time trend variable on Other (mainly presort) traffic has been positive throughout the sample period. Two key factors that are likely to have driven this are the impact of switching from Second Class, as discussed above, and until fairly recently high rates of growth in Direct mail (DM) traffic. The results reported in table 2 suggest that up to 1997 the time trend impacts accounted for about 5% of growth in presort volumes per annum over and above other factors in the presort model (that is, economic activity, letter prices and non-mail advertising prices), but after 1997 this slowed to less than 1% per annum. The slowdown in the presort time trend is consistent with the rapid advance of electronic billing and banking services which relate to non-DM bulk services. However, it is also consistent with a slow down in the Second Class time trend effect, as, over time, the volume of Second Class non-presort traffic switching into the Other (mainly presort) traffic stream must eventually decline as a proportion of the latter.

[20] See Nikali (2008)

[21] The technology variables tested in the econometric modelling included measures of the number of connections and subscribers to the internet in the UK; the index of broadband internet connections in the UK; the proportion of adults with access to electronic banking; and the proportion of UK households with access to the internet.

The internet advertising variable (PIA) included in the model can also be considered to be reflecting the impact of substitution on Other traffic volumes. In particular, as noted in section 2, advertising budgets are increasingly moving online and in particular towards "paid-for-search" advertising[22]. The impact of this variable is estimated to have a statistically significant and large negative effect on Other (mainly presort) traffic mail volumes. Over the three year period 2005/06 to 2007/08 the rapid growth in internet advertising expenditure is estimated to have reduced this stream by almost 7 per cent per annum[23]. If the impact of esubstitution in the Other traffic model is assumed to be approximately equal to the sum of the impacts of the estimated time trends and the proportion of internet advertising, then esubstitution is estimated to have been reducing Other traffic volumes by around 6 per cent per annum. This suggests that similar to the results in Soteri et al. (2009), technology developments in alternative media communications (in particular, the internet) have been exerting substantial downward pressure on bulk mail traffic, and in particular DM advertising volumes[24]. However, it is not certain to what extent the internet advertising variable can be assessed to be impacting solely on DM if, as is likely to be the case, the profile of this variable is correlated with that for other technologies that are substituting for traditional letter mail.

4. AN ECONOMETRIC ANALYSIS OF UK LETTER TRAFFIC DEMAND BY CONTENT TYPE

4.1 Estimation methodology

To estimate the demand for letters by content type, a similar econometric methodology was used to that in the product model as specified in equation (1). The main difference to the product model estimation methodology was that the coefficients associated with lagged terms of the different explanatory variables corresponding to each traffic content type, in vector C_{jk}, were statistically not significant. The use of annual data is likely to be a key reason for the absence of lagged terms. The estimated models were therefore of the following form:

$$q_{jt} = A_j^{'} D_{jt} + \Pi_j^{'} x_{jt} + \eta_{jt} \qquad (3)$$

The variable Q_j denotes the volume of traffic per working day for content j (j =1,2,3); where j=1 refers to Social mail; j=2 refers to DM traffic and j=3 refers to Commercial mail. As before, the X_j vector represents a vector of explanatory variables for each traffic content type j. One difference in the explanatory variables is the use of GDP instead of GVA sectors weighted by letter demand (GVA(L)) to

[22] For example, WARC(2008) reports that in the five year period up to 2007 internet advertising expenditure is estimated to have increased fourteen fold to almost £3bn and account for around 17% of total UK advertising expenditure. Paid-for-search advertising refers to internet adverts triggered by key "searchwords".

[23] This is estimated by multiplying the average change in PIA over the period 2005/06 to 2007/08 (4 per cent per annum) by the long-run coefficient reported in table 1.

[24] See Soteri et al (2009)

estimate the impacts of economic growth on content traffic volumes[25]. The estimated coefficients of the parameters in the vector Π_j provide direct estimates for the long run elasticities and parameters for traffic by content type.

4.2 ILTM Content Model Long Run Elasticities and Time Trends

Table 3 reports the estimated long run estimated elasticities and time trends for the addressed inland letter traffic model by content type (ILTMC) using data methods 1 and 2. As in the product model, the estimated long run elasticities and time trends for total addressed inland letter traffic volumes were calculated by weighting the long-run parameters for each of the three content types by their respective share of total traffic.

In the majority of cases the estimated parameters reported in table 3 have reasonably high t-statistics (reported in brackets). The only exception was the estimated t-statistic for the estimated price elasticity for Commercial mail which is statistically significant using a critical region of around 20%. Given the use of survey data in constructing the data series it is likely that a higher degree of noise is associated with individual parameter estimates and the usual 5% to 10% critical values for comparing t-statistics was relaxed in this case and, given the price variable was correctly signed, was not deleted from the model.

The same diagnostic tests reported for the product model in table 1 are reported for the content model in table 3. In general, similar to the product model, these diagnostic tests suggest the content model is also statistically sound. However, it should be noted that a number of these tests, in particular the Heteroskedasticity and Reset tests, are strictly not valid when I(1) variables (such as economic activity) are included in regression models of this type.

The estimated models using the two data sets yield broadly similar results although with some exceptions. In particular, the estimated coefficients yielded very similar results for economic activity, quality of service and telephone price impacts and Commercial letter tariff prices. By contrast, the estimated coefficients for internet advertising, the time trend estimates and the DM price elasticity were somewhat different.

The models estimated using the two data sets generated by methods 1 and 2 suggest that price elasticities vary substantially across content type. While the DM price elasticities estimated using data generated by methods 1 and 2 differ in absolute size, their relative order of magnitude is similar. The estimated price elasticity for Commercial traffic (mainly transactional mail) has the lowest value in absolute terms (around -0.2) while Social mail is estimated to have a slightly higher

[25] The generation of mail volumes by content type using survey data includes a high level of noise for individual year estimates. The benefits of using GVA(L) to explain historic behaviour and project mail volumes into the future was therefore considered to be low relative to adopting GDP which is the standard and publicly available indicator of economic activity .

price elasticity of demand (around -0.3 to -0.4). DM traffic is considered to possess the highest price elasticity of demand (somewhere in the range of -0.7 to -1.4).

Table 3: Addressed Inland Letter Content Traffic Per Household Model[1]

	Social	Commercial	Direct	Total Traffic
	Method 1 Data Set: Long-Run Elasticities ILTMC			
Economic activity[2] (Y')	ns	0.97 (7.5)	1.87 (4.1)	1.07
Tariff index own price (P)	-0.43 (-3.7)	-0.19 (-1.2)	-1.35 (-2.8)	-0.44
Quality of service (QoS)	0.43 (5.5)	0.34 (5.4)	ns	0.28
Price of telecommunications index (TP)	na	0.10 (2.0)	ns	0.07
Proportion of internet adv. Spend (PIA)	na	na	-1.79 (-4.6)	-0.36
Net impact of “unexplained” time trends	ns	ns	Pre 1997 2.5% (2.5)	Pre 1997 0.5%
	T03 -1.7% (-3.9)	T02 -2.9% (-9.4)	T97 -5.2% (-4.9)	Post 2003 -2.8%
Rsq adjusted	0.853	0.995	0.992	na
Reg. SE	0.027	0.014	0.025	na
DW	1.83	1.52	2.04	na
Diagnostic tests (p-values)				
Serial Correlation	0.683	0.417	0.771	na
Heteroscedasticity	0.322	0.291	0.039	na
Normality	0.583	0.967	0.692	na
Reset	0.105	0.545	0.633	na
	Method 2 Data Set: Long-Run Elasticities ILTMC			
Economic activity (Y')	ns	0.96 (7.7)	2.04 (4.5)	1.11
Tariff index own price (P)	-0.29 (-2.0)	-0.19 (-1.3)	-0.74 (-1.5)	-0.31
Quality of service (QoS)	0.49 (5.1)	0.36 (6.0)	ns	0.29
Price of telecommunications index (TP)	na	0.12 (2.4)	ns	0.09
Proportion of internet adv. Spend (PIA)	na	na	-3.31 (-8.8)	-0.66
Net impact of “unexplained” time trends	ns	ns	Pre 1997 1.5% (1.5)	Pre 1997 0.3%
	T03 -2.8% (-1.5)	T02 -1.7% (-6.3)	T97 -2.5% (-2.5)	Post 2003 -1.6%
Rsq adjusted	0.941	0.995	0.990	na
Reg. SE	0.032	0.014	0.025	na
DW	1.57	1.65	2.25	na
Diagnostic tests (p-values)				
Serial Correlation	0.308	0.544	0.563	na
Heteroscedasticity	0.429	0.043	0.080	na
Normality	0.474	0.768	0.886	na
Reset	0.117	0.720	0.569	na

Note:
1. T-statistics are reported in brackets
2. Y' refers to Gross Domestic Product (GDP)

The relatively low price elasticity of demand for Commercial (mainly transactional) letter mail may, to some extent, reflect the lower degree of choice open to the large majority of sender-to-receiver channels for such communications. The low price elasticity could reflect the fact that this type of mail (which includes bills, statements and invoices) is usually sent to a specific named individual or business and, in general, cannot be substituted without additional information about the receiver (such as their email address or mobile telephone number) which in most cases may not be readily available. Furthermore, even if such information were available, the substitution of letter transactions via an electronic alternative would, in most cases, require the prior agreement of the receiver.

In contrast, the low estimated price elasticity of demand for Social mail (in the range -0.3 to -0.4) is, in general, more likely to reflect the value that Social letter mailers obtain from sending mail such as birthday and Christmas cards rather than factors relating to sender-to-receiver information.

The relatively high price elasticity estimates for DM traffic, which are estimated to be in the range -0.7 to -1.4, is likely to reflect the higher degree of choice that senders of DM have with respect to the use of mail and wider range of substitutes in the advertising market. The considerably higher DM price elasticities estimated relative to other types of mail are broadly consistent with the findings of other econometric studies. For example, Thress (2006) reports estimated price elasticities for United States Postal Services (USPS) Standard Mail Regular traffic and Standard Mail Enhanced Carrier Route traffic that primarily consists of DM traffic, that lie in the range -0.3 to -1.1. In addition, estimates of DM price elasticities in Santos and Lagao (2001) range from -0.8 to -2.8, although this study concluded that the lower estimates were likely to be a better approximation of the demand behaviour of firms.

The estimated parameters of ILTMC reported in table 3 suggest that there was a decline in the trend rate of Social and Commercial traffic around 2003/04 and 2002/03 respectively and that this slowdown was of the scale of about 2% to 3% per annum. While the estimated decline in the trend rate of growth is a little different when using data methods 1 and 2, they are of a similar order of magnitude and the slowdown in the trend rates of growth is estimated to occur around the same time[26]. The timing coincides with the sharp increase in the number of firms and individuals with broadband connections in the UK. It is likely that this combined with advances in internet enabled technology has resulted in continuing substitution of Social and Commercial letter traffic.

The estimated impact of electronic substitution on DM resulting from the emergence of the internet, and in particular "paid-for-search" advertising can be estimated using the estimated coefficients of the PIA variable reported in table 3. For example, multiplying the average change in PIA over the period 2005/06 to 2007/08 (4% per annum) by the long run coefficient reported in table 3 suggests that internet related esubstitution could have reduced DM traffic volumes by between 7% to 13% per annum during this period. However, independent of the

[26] A number of time trends were tested around this time period. The adoption of starting dates for the time trends was informed by the Akaike information criterion (AIC) and the Schwarz criterion (SC).

impact of internet advertising, it is likely that the high rates of technology driven DM growth experienced in the 1980s and 1990s would have eventually slowed down in order to stabilise the share of DM advertising spend within overall marketing budgets. The decline in the post 1997 DM time trend term effects reported in table 3 is consistent with such a hypothesis.

A point to note about the data method 1 and 2 estimates for the share of internet advertising expenditure variable and time trends is the considerable difference in their relative importance. For example, the content model results using data method 1 estimate lower esubstitution impacts for PIA but higher negative time trend estimates post 1997 in comparison with those using data method 2. This perhaps suggests that the econometric estimates may be unable to identify fully the impact of each of these two effects separately but a greater degree certainty can be attached to their combined impact.

5. PERSPECTIVES ON TOTAL ADDRESSED INLAND LETTER TRAFFIC FROM THE PRODUCT AND CONTENT MODELS

Table 4 presents the estimated time trend impacts and long run elasticities contained in the addressed inland letter traffic model using product stream data (ILTMP) and contents data (ILTMC) using data methods 1 and 2.

The estimated economic activity elasticities for total traffic in the product and the content models are broadly similar and around unity. The estimated total traffic letter price elasticities are also similar in the two models and lie in the range -0.3 to -0.4, while the quality of service elasticity in the product model is a little smaller compared to those obtained in the content models. However, there are a number of differences between the models. First, the price of non-mail advertising did not appear to be statistically significant in the content model while the price of telecommunication was statistically significant in the content model but did not appear in the product model. Both of these variables have a relatively small effect in their respective models. Second, the impact of the PIA variable, the ratio of internet advertising spend to total advertising expenditure, on mail volumes is somewhat higher in the product model. Third, the net impacts of the unexplained time trends are similar in the product and content models using the data method 1, although this impact is somewhat smaller using data method 2.

The econometric results reported in table 4 can be used to provide some general insights into the recent behaviour of letter traffic volumes and potentially the behaviour of UK total traffic in the future. The econometric analysis of UK total letter traffic using Royal Mail product streams and letter content types suggests that the relationship between total traffic growth rates and economic factors remains important. However, their impact has become more complex to identify as other factors appear to have become significant drivers of letter traffic growth and these are driving a wedge between economic activity and letter traffic growth rates.

Table 4: Long Run Elasticities and Time Trends for Total Traffic Per Household: Comparison of Product and Content models

	Estimated models		
	ILTMP	ILTMC using data method 1	ILTMC using data method 2
Economic activity	1.09	1.07	1.11
Letter price[1]	-0.33	-0.44	-0.31
Quality of Service	0.13	0.28	0.29
Price of non-mail advertising[1]	0.24	ns	ns
Proportion of internet advertising spend	-0.95	-0.36	-0.66
Price of telecommunication[1]	n.s.	0.07	0.09
Net impact of "unexplained" time trends post 2002 (% p.a.)	-2.4	-2.7	-1.0

[1.] Deflated by the all items Retail Prices Index.

The long run estimated elasticities reported in table 4 can be used to estimate the scale of this wedge effect, which can perhaps be best ascribed to technology impacts. A quantitative analysis of the impact of esubstitution using the results reported in table 4 suggests the estimated impact of this "technology wedge" reduced total UK letter traffic growth rates by around 5% to 6% per annum[27] on average during the period 2005/06 to 2007/08. This suggests that the declines in UK letter traffic growth rates that took place after 2002 are the outcome of two quite large and offsetting factors. On the one hand economic growth and demographic trends continued to raise the demand for letter traffic but this was more than offset by powerful esubstitution factors that reduced the demand for mail.

6. SUMMARY AND CONCLUSIONS

This paper has applied econometric modelling techniques using time series data to quantify the impact of key factors affecting UK letter traffic. The econometric methodology followed is based on a previous study by Nankervis et al (2002) and has updated the high level product stream estimates in the paper using nine years of additional quarterly data. Furthermore, the paper provides new insights to the literature by examining the demand for UK letters by the contents of mail items using two survey based sources of data. The updated product models produced broadly similar results to those reported in Nankervis et al (2002) and also Soteri et al (2009). In particular, with regard to the estimated long run elasticities for

[27] The technology wedge estimate was derived as follows: multiply the parameter estimates for the internet share variable by its average change over the past 3 years; plus the average rate of growth of real telecommunication prices multiplied by its parameter estimate; plus the impact of the time trends.

economic activity in the product model, these were close to unity and the number of households' elasticity was estimated to be equal to unity. Similar results were found in the content models. The results of adopting this dual lens approach to modelling letter traffic were, in this case, mutually reinforcing. Furthermore, in addition to obtaining updated results in the differences in economic activity by broad product streams, the content models provided new insights into the different impacts of economic activity by letter content type. For example, DM traffic was estimated to be around twice as sensitive to changes in economic conditions than Commercial (mainly transactional) traffic.

The effect of technology on the erosion of mail volumes was explored in a number of ways but most satisfactorily through the share of internet advertising variable and the use of time trends. The product model results suggest that the adverse impact of esubstitution has been on First Class traffic and Other (mainly presort) traffic. The content traffic models provide further insights into the impact of esubstitution and, in general, are consistent with the product model. For example, the impact of the time trend variables and the share of internet advertising variable in the DM models is considerably higher than that for the other content categories and consistent with the large negative impacts estimated for the Other (mainly presort) traffic product model which contains a substantial proportion of DM traffic. There are some differences between the individual variables used to proxy esubstitution when applying the two data sets in the content models and also between the product and content models. However, the combined impact of the esubstitution variables on total UK letter traffic are similar, and suggest that such factors exerted downward pressure on total letter traffic growth of around 5% to 6% per annum on average over the period 2005/06 to 2007/08.

The estimated long run price elasticity for total traffic using both the product and content models was estimated to be around -0.3 to -0.4. The product model estimates a considerably higher own price elasticity for First Class non-presort traffic of about -0.8. However, due to switching between First and Second Class non-presort products their combined own-price elasticity is estimated to be around -0.2. The own-price elasticity for Other (mainly presort) traffic was estimated to be about -0.4. The long-run price elasticities estimated using the content model provided a number of new insights. In particular, the estimated price elasticity for Social mail was estimated to be about -0.3 to -0.4 and for Commercial (mainly transactional) mail to be around -0.2. By contrast, the DM price elasticity was estimated to be considerably higher and lie somewhere in the range -0.7 to -1.4.

The difference between the estimated DM price elasticity estimates using the two data sources in the content model reflects, at least in part, data issues associated with allocating UK traffic volumes to content types using survey data. It should be noted that while survey data was used to derive reasonable estimates of directional trends for content traffic, there is some statistical noise associated with movements for individual years. Consequently, this is likely to lead to wider confidence intervals for estimated elasticities. In future research, it may be possible to combine the information available from each survey using statistical techniques to obtain more robust content share estimates. Furthermore, it may be possible to combine such data with product time series data to jointly estimate letter demand elasticities. Given the importance of price elasticities to inform business strategies this could be an avenue for future research.

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APPENDIX: USING MCS AND CPS SURVEY DATA

The Mail Characteristics Survey (MCS) is a large random survey that obtains information on content types by information from mail receivers via a response card. The response rate for the card is high for surveys of this type (around one in six as is the survey sample size (around 0.7 million)). The MCS covers Royal Mail end-to-end (E2E) traffic (except for Response Mail, Special Delivery and Cleanmail Advance which accounted for around 3% of E2E traffic in 2007/08). The survey excluded downstream access. The Consumer Panel Survey (CPS) is a weekly household survey diary and covered a panel of around 1000 households. This survey therefore excluded business-to-business (B2B) traffic.

Since neither of the two surveys provided a comprehensive survey of total letter traffic, information from both was used to derive letter content time series data for addressed inland mail volumes. Information from the MCS was available on a quarterly basis going back to 1999 and for UK financial years to 1980/81. In contrast, the CPS contained information on a quarterly basis only from 2000. Due to the longer time span of data available from the MCS its content category definitions were adopted to derive content shares for total UK letter traffic.

The MCS survey recorded up to five different content types for a specific envelope and allocated a prioritisation routine to identify the “primary” content. This eliminated the double counting of contents within the envelope. Since there were no access volumes prior to 2004/05 the MCS covered the large majority of Royal Mail addressed inland mail up to that point in time. However, access volumes increased from a negligible level in 2004/05 to account for around one-fifth of total letter traffic by 2007/08. The MCS therefore excluded an increasing proportion of mail volumes from 2004/05 onwards. In contrast, the CPS which did not include information on B2B mail excluded around a quarter of total inland mail (based on MCS estimates).

Given the substantial information gaps contained in both surveys two different data methods were adopted to derive estimates of content based traffic volumes. Data method 1 used MCS content shares and Royal Mail E2E volumes to derive a content volume time series for Royal Mail E2E traffic and from 2004/05 onwards used CPS to derive estimates for content shares and access volumes. These time series were then aggregated together to provide a single content based traffic volumes series for total addressed inland letter traffic.

Data method 2 derived estimates of content based traffic data by primarily focussing on the CPS and using MCS B2B information to derive content share estimates for 2001/02 onwards. Given the shorter time period for which CPS content data is available, it was not possible to use method 2 alone to derive content time series that is long enough to undertake robust time series econometrics. However, a continuous time series data set going back to 1980/81 was derived by splicing this data series to MCS content share estimates. While data method 2 does not provide a full time series data set for econometric analysis, it generates an alternative set of data that can be used for comparison purposes.