USPS-T-7

BEFORE THE
POSTAL RATE COMMISSION
WASHINGTON, D.C. 20268-0001

POSTAL RATE AND FEE CHANGES, 2000

Docket No. R2000-1

DIRECT TESTIMONY
OF
THOMAS E. THRESS
ON BEHALF OF THE
UNITED STATES POSTAL SERVICE

Table of Contents

DIRECT TESTIMONY
OF
THOMAS E. THRESS

AUTOBIOGRAPHICAL SKETCH

My name is Thomas E. Thress. I am a Vice-President at RCF Economic and Financial Consulting, Inc., where I have been employed since 1992. As Vice President at RCF, I have major responsibilities in RCF's forecasting, econometric, and quantitative analysis activities. I have had primary responsibility for the econometric analysis underlying Dr. George Tolley's volume forecasting testimony since Docket No. R94-1. In addition, I was responsible for the development of the share equation methodology used by the Postal Service since MC95-1, as well as the classification shift matrix construction used in Dr. Tolley's volume forecasting testimony in MC95-1 and MC96-2 to shift mail into the new categories proposed under classification reform.

I testified regarding the demand equations underlying the Postal Service's volume forecasts for all mail categories except for Priority and Express Mail in Docket No. R97-1. Prior to that, I appeared as a rebuttal witness for the Postal Service in Docket No. MC95-1, and submitted written testimony for the Postal Service in Docket No. MC97-2.

I completed my Master's Degree in Economics in 1992 at the University of Chicago. I received a B.A. in Economics and a B.S. in Mathematics from Valparaiso University in 1990.

PURPOSE AND SCOPE OF TESTIMONY

The purpose of this testimony is to model the demand for mail volume for domestic subclasses and services (except for Priority and Express Mail, which are addressed by Dr. Gerald Musgrave, USPS-T-8), and to provide forecasts of the worksharing categories of First-Class and Standard A mail. The demand equations developed in this testimony provide demand elasticity estimates which are used by Dr. George Tolley in making volume forecasts in support of this case (USPS-T-6).

I. Introduction

A. General Outline of Testimony and Supporting Material

In this testimony, demand equations are modeled for mail, which provide demand elasticities and share forecasts which are used by Dr. George Tolley in making volume forecasts, as described in USPS-T-6. This work builds upon the testimony of Dr. Tolley and me in R97-1, as well as Dr. Tolley's work in earlier rate cases, going back to R80-1. As in R97-1, Dr. Tolley played an integral role in the development of the results presented here.

Demand equations for the categories of mail forecasted by Dr. Tolley are presented and discussed in section II below. The general econometric methodology used in modeling these demand equations is outlined in section III below. Shares of the presortation and automation rate categories of First-Class and Standard A mail are forecasted in section IV of my testimony below.

My direct testimony is supported by four workpapers. The first of these presents the data used in my econometric work as well as the econometric results presented here. This workpaper is accompanied by Library Reference LR-I-122, which provides electronic versions of the data and programs necessary to replicate these results. My second workpaper presents the estimation of permanent income elasticities from Household Diary Study data. Library Reference LR-I-123 provides electronic versions of the data and programs necessary to replicate the results in Workpaper 2. Workpaper 3 presents some intermediate econometric results which were used in the development of my testimony. Finally, Workpaper 4 forecasts the number of additional ounces associated with single-piece First-Class letters in the Test Year. The spreadsheets used for this calculation are filed as part of Library Reference LR-I-122. In addition, Library Reference LR-I-119, which presents before-rates fixed-weight price indices, was used by me to develop the price variables used in my testimony. The actual price variables used by me are presented in Workpaper 1 and Library Reference LR-I-122, described above.

B. Demand Equation Estimation

The basic approach to modeling demand equations taken here is to model mail volume as a function of explanatory variables suggested by economic theory. A separate demand equation is generally modeled for each subclass of mail, except for First-Class letters, where separate equations are modeled for workshared and single-piece mail, First-Class cards, where separate equations are modeled for postal and private cards, and for Standard bulk nonprofit mail, where a single equation is modeled for Nonprofit and Nonprofit Enhanced Carrier Route mail. The coefficients estimated from these equations are used as an input in the Postal Service's forecasting model to forecast future mail volumes for each subclass of mail. Volume forecasts are performed by Dr. George Tolley in USPS-T-6.

The final demand equations are presented in section II below on a class-by-class basis. First-Class Mail is discussed in section II.B.; Periodical Mail is discussed in section II.C.; Standard A mail is discussed in section II.D.; Standard B mail is discussed in section II.E.; finally, other mail categories and special services are presented and discussed in section II.F. The econometric methodology used to develop these demand equations is outlined in section III below.

C. Share Equation Estimation

The shares of First-Class and Standard A mail that have taken advantage of Postal Service presort and automation discounts are modeled as a function of the level of the discounts offered by the Postal Service as well as the costs to mailers of doing the work necessary to receive these discounts. The methodology for modeling worksharing shares in this way was originally presented in Dr. Tolley's testimony in MC95-1 (USPS-T-16). This methodology is developed in section IV.A. of this testimony below.

Information on the distribution of mailers' user costs historically is forecasted and combined with information on Postal Service discounts to forecast the use of Postal Service worksharing categories of First-Class and Standard A mail. The econometric analysis of historical worksharing usage is described in section IV.B. of my testimony below. This information in then used to project the shares of these categories of mail in the forecast period in section IV.C. below. Forecasted shares, both before- and after-rates, are presented in section IV.D. at the conclusion of my testimony.

II. Demand Equation Estimation

A. General Overview

1. General Approach to Demand Equation Estimation

The economic demand for a product can be defined as "the quantity of an economic good that will be bought at a given price at a particular time" (A Dictionary of Economics, by Harold S. Sloan & Arnold J. Zurcher, 1959). A demand equation relates the quantity demanded of a particular good to factors which affect this quantity. That is, a demand equation takes the general form,

$$Q_t = f(Y_t, P_t, ...) \tag{II.1}$$

where Q_t is the quantity of the particular good consumed at time t, f(.) indicates that Q_t is a function of the variables within the parentheses, Y_t refers to income of consumers in the particular market at time t, P_t is the price of the good at time t, and the ... is included to reflect the fact that factors other than income and price may affect demand for the product being modeled. The factors affecting the demand of a product, as well as the magnitude of the impact of these factors, may be expected to differ across consumers and across products. Within the context of the Postal Service, therefore, a separate demand equation along the lines of equation (II.1) ought to be specified for each unique product provided by the Postal Service and/or for each specific group of users of a particular Postal product.

2. Division of Mail for Estimation Purposes

The demand for mail is not limited to a single demand based upon a single purpose. Rather, mail demand is expected to differ across mailers, due, at least in part, to differences in the purpose of the mail. Mail serves a purpose in many economic markets, in the sense that it satisfies a number of unique roles and purposes. For example, mail can be used for personal correspondence, for bill-sending and bill-paying, for advertising, for delivery of newspapers and magazines, and for delivery of other types of goods.

Mail can be divided into four broad categories, based on the purpose of the mail:

(i) Correspondence & Transactions

(ii) Periodicals

(iii) Direct-mail advertising

and (iv) Delivery Services

Correspondence & Transactions mail is mail sent for the purpose of establishing or maintaining a relationship. This mail may be sent between households (e.g., letters, greeting cards), between households and nonhouseholds (e.g., orders, bills, bill-payments, financial statements), or between nonhouseholds (e.g., invoices, bill-payments). For the purposes of my testimony, Correspondence & Transactions are equated to First-Class Mail. Not all First-Class Mail would properly be considered Correspondence & Transactions based on this breakdown of mail. For example, there is a significant amount of direct-mail advertising that is sent First-Class. Data limitations effectively prevent us from separating out this portion of First-Class Mail, however. Hence, this mail is combined with the rest of First-Class Mail. The distinctions made within First-Class Mail and the final demand equations associated with this type of mail are developed and presented in section B. below.

Periodicals are magazines, newspapers, journals, and newsletters sent on a periodic basis through the mail. This corresponds to the Postal Service's Periodical class. As with Correspondence & Transactions mail and First-Class Mail, the correspondence between the Periodical mail market and the Periodical mail class may not be exact. For purposes of estimating demand equations, given the data limitations imposed by the RPW system, however, this distinction is useful and sufficient. The distinctions within Periodical Mail and the final demand equations associated with this type of mail are developed and presented in section C. below.

Direct-mail advertising is mail sent by businesses or other organizations for the purpose of advertising goods or services. Over 90 percent of Standard A mail (mail formerly classified as third-class bulk regular and third-class bulk nonprofit mail) falls within this category. As noted above, some portion of First-Class Mail is also direct-mail advertising. It is difficult, if not impossible, however, to develop a useable time series of First-Class advertising mail volume given available data sources. Hence, this category of mail is included with the rest of First-Class Mail for modeling purposes. Standard A mail volume is modeled in section D. below using a model of direct-mail advertising.

Delivery services refer to the use of the Postal Service to deliver goods which would not fall into one of the earlier categories (e.g., mail-order deliveries, books). This corresponds roughly to Standard B mail. This type of mail is modeled and discussed in section E. below.

Other categories of mail are discussed in section F. below, including Mailgrams, Postal Penalty mail, Free-for-the-Blind mail, and special services.

3. Changes since R97-1

There have been several improvements to the econometric demand equations since R97-1. These include the following:

- Simultaneous estimation of coefficients, autocorrelation parameters, and Shiller k^2 parameters
- Relaxation of Price Lag restrictions used in earlier rate cases, allowing the number of price lags included in the equations to differ across

equation, and to ease the Shiller restriction to only require that all price coefficients have the expected sign, with no restrictions on the shape of the price distribution

- Correction of significant fourth-order autocorrelation
- Later starting periods for some econometric demand equations, including Periodical nonprofit, Standard library rate, and registered mail
- Inclusion of time trends in some demand equations, most notably Periodical Mail
- Use of the wholesale price of newspaper advertising as reported by the Bureau of Labor Statistics instead of McCann-Erickson CPM data in Standard A equations
- Significant changes to Parcel Post equation, and
- Estimation of a separate demand equation for return receipts

These changes are discussed in more detail in the appropriate sections below.

4. Sources of Information used in Modeling Demand Equations

The primary source of information on mail volumes is the Postal Service's quarterly RPW reports. These data serve as the dependent variable in the demand equations developed and described in my testimony.

In general, variables which are believed to influence the demand for mail volume are introduced into an econometric equation as a quarterly time series in which an elasticity of mail volume with respect to the particular variable is estimated, using a Generalized Least Squares estimation procedure that is described more fully in section III below.

The estimation of elasticities with respect to certain variables may be problematic, however, in an isolated quarterly time series regression. Even if quarterly time series data exists on this information, additional data may be brought into the regression process, including the results of independent regression procedures. The Household Diary Study provides an alternate source for modeling the relationship of mail volume with other factors. The Household Diary Study data provides cross-sectional, rather than time series, data. For certain mail relationships (e.g., modeling the effect of income on mail volume received by consumers), cross-sectional data lends itself more easily to evaluation and estimation than does time series data. In addition, the Household Diary Study provides a means of dividing mail within a particular subclass or rate category by content, sender, or recipient, in a way that is not possible with RPW data (e.g., distinguishing First-Class advertising mail from First-Class non-advertising mail). In selective instances, information was obtained from the Household Diary Study, and was then introduced into the quarterly time series equations. This information was introduced in such a way as to continue to gather the maximum possible amount of information from the time series data themselves.

When appropriate, Dr. Tolley may introduce additional non-econometric information in making volume forecasts. This is a necessary and prudent thing to do, particularly when this information is not available in the form of a quarterly time series amenable to introducing into an econometric demand equation. The demand equations presented and discussed in my testimony should be viewed therefore as providing a starting point for Dr. Tolley in making volume forecasts, but should not be viewed as the end-all and the be-all in understanding mail volume behavior in the future.

B. First-Class Mail

1. General Overview

First-Class Mail is the largest class of mail delivered by the Postal Service, accounting for more than 50 percent of all mail and generating more than 55 percent of Postal Service revenue. First-Class Mail is divided into two subclasses on the basis of the shape of the mail: First-Class letters, flats, and IPPs (often referred to simply as First-Class letters); and First-Class cards. First-Class Mail is used for a variety of purposes, which can be summarized as Correspondence and Transactions.

2. First-Class Letters

a. Breakdowns of First-Class Letters Used in This Case

The First-Class letters subclass includes a wide variety of mail sent by a wide variety of mailers for a wide variety of purposes. This mail can be divided into various substreams of mail based on several possible criteria, including the content of the mail-piece (e.g., bills, statements, advertising, and personal correspondence), the sender of the mail-piece (e.g., households versus businesses versus government), or the recipient of the mail-piece (e.g., households versus business versus government). While the above-mentioned distinctions may be useful from a theoretical standpoint, the Postal Service's quarterly volume data do not distinguish between these various types of mail. Instead, the Postal Service's volumes only distinguish between First-Class letters on the basis of postage received by the Postal Service.

Looking at other sources, most notably the Household Diary Study, it is clear that different subsets of First-Class letters volume have grown at different rates in recent years.

For example, household-generated mail has actually fallen over the past ten years, while nonhousehold-generated mail has grown faster than total First-Class letters over this time period.

The Household Diary Study data is not sufficiently inclusive (e.g., nonhousehold-to-nonhousehold data can only be inferred) nor is there a sufficiently long time period to break First-Class letters down based on content. Instead, First-Class letters can only be divided into distinct rate categories.

All household-generated mail is single-piece letters. This type of mail has declined considerably over time. On the other hand, a large portion of nonhousehold-generated mail is workshared, and this type of mail has grown more rapidly than household-generated mail.

This leads to a general approximation that may be useful in determining how best to model the demand for First-Class letters. First-Class letters can be broadly divided into two categories of mail: Individual Correspondence, consisting of household-generated mail, and nonhousehold-generated mail sent a few pieces at a time; and Bulk Transactions, consisting of nonhousehold-generated mail sent in bulk. Relating these two categories of First-Class letters to rate categories, Individual Correspondence mail may be thought of as being approximately equivalent to single-piece First-Class letters, while Bulk Transactions mail could be viewed as comparable to workshared First-Class letters.

Based on an understanding of the content of mail, it therefore appears worthwhile to attempt to distinguish between single-piece and workshared First-Class letters. Within workshared First-Class letters, however, it seems unlikely that any meaningful demand differences could be distinguished between the volumes of specific worksharing categories of First-Class Mail. Thus, separate demand equations are estimated for single-piece and workshared First-Class letters.

b. Choice of Starting Date for First-Class Letters Regressions

The single-piece and workshared First-Class letters regressions are estimated over a sample period of 1983Q1 through 1999Q4. This encompasses 68 observations and spans seven rate regimes, including classification reform (MC95-1).

The starting period of 1983Q1 was chosen based on experimentation with the starting period in the workshared First-Class letters equation prior to R97-1.

In R97-1, the regressions were ended in 1996Q3 to avoid potentially confounding the results with the impact of classification reform, which was implemented in 1996Q4. For this case, the First-Class letters equations have been extended through 1999Q4, the ending period for all of the econometric equations presented here. The effect of classification reform on First-Class letters volumes is modeled by including a dummy variable for MC95-1 in the single-piece and workshared letters equations.

c. Modeling Shifts between Single-Piece and Worksharing Letters

One of the most obvious trends evident through even casual observation of First-Class letters volumes is that the share of total First-Class letters that are workshared has grown considerably over time. For example, in 1983 21.7 percent of First-Class letters were workshared. By 1991, this share grew to 34.2 percent and by 1996, the share of First-Class letters that were workshared was 41.4 percent, an increase of nearly 100 percent in thirteen years. Classification reform caused this share to remain nearly stagnant at 41.5 percent in 1997, but it has since resumed its upward trend, reaching 44.4 percent in 1999.

While some of this growth has been due to differences in demand characteristics between single-piece and workshared First-Class letters and differences in changes in the prices of single-piece and workshared First-Class letters over this time period, another important reason for this phenomenon has been the substitution of mail from single-piece First-Class letters into workshared First-Class letters.

Any demand equations that purport to accurately model the demands for single-piece and workshared First-Class letters must therefore take into account shifts between these two categories. A mailer will choose whether or not to workshare by comparing the costs to the mailer of worksharing vis-a-vis the discount offered by the

Postal Service for the worksharing.[1] Thus, shifts from single-piece into workshared First-Class letters may occur for either of two reasons: due to changes in worksharing discounts offered by the Postal Service or due to changes in the cost of worksharing borne by mailers.

i. Shifts Due to Changes in Worksharing Discounts

Shifts between single-piece and workshared First-Class letters due to changes in price are modeled through the inclusion of the worksharing First-Class letters discount in the demand equations for both single-piece and workshared First-Class letters. The discount is used here, rather than the price, to reflect the nature of the decision being made by mailers, which is whether to workshare or not, as opposed to a decision of whether to send the mail or not. The reaction of mailers to changes in worksharing discounts may not fully take effect immediately following rate changes, however. Therefore, to account for possible lagged reactions of mailers to changes in worksharing discounts, the current discount is entered along with the discount lagged one quarter.

The total volume leaving single-piece First-Class letters due to changes in worksharing discounts should be exactly equal to the volume entering workshared First-Class letters. Mathematically, this is a restriction that

$$(\partial V_{sp}/\partial d_{ws}) = -(\partial V_{ws}/\partial d_{ws}) \qquad \text{(II.2)}$$

[1] The basic theory here is equivalent to the theory underlying my share equations, which are discussed in section IV below and are used to divide First-Class and Standard A mail into worksharing categories. The exact implementation of this methodology differs somewhat here, however, in order to integrate the concept of worksharing decisions with the notion that the demand characteristics associated with single-piece and workshared First-Class letters are fundamentally different.

where V_{sp} is the volume of single-piece First-Class letters, V_{ws} is the volume of workshared First-Class letters, and d_{ws} is the worksharing discount. Given the functional form used in this case,

$$(\partial V_{sp}/\partial d_{ws}) = \beta_{sp} \cdot (V_{sp}/d_{ws}) \tag{II.3}$$

$$(\partial V_{ws}/\partial d_{ws}) = \beta_{ws} \cdot (V_{ws}/d_{ws})$$

where β_{sp} is the elasticity with respect to the worksharing discount in the single-piece letters equation and β_{ws} is the elasticity with respect to the worksharing discount in the worksharing letters equation.

Combining these results, and canceling out the d_{ws} from both sides of the equation, we get that

$$\beta_{sp} = -\beta_{ws} \cdot (V_{ws}/V_{sp}) \tag{II.4}$$

The freely-estimated value of β_{WS} from the workshared letters equation is 0.216 with a t-statistic of 3.619, while the freely-estimated value of β_{SP} from the single-piece letters equation is -0.105 (t-statistic of -1.845). This implies a value of 0.486 for (V_{ws}/V_{sp}), which was the approximate value around 1990. Since the purpose of these equations is for forecasting, however, equation (II.4) should approximately hold true in the forecast period. Because the freely-estimated value of β_{WS} (t-statistic of 3.619) is considerably more significant than the freely-estimated value of β_{SP} (t-statistic of -1.845), the freely-estimated value of β_{WS} was used, and the restriction in equation (II.4) was imposed stochastically on the value of β_{SP}. The value of (V_{ws}/V_{sp}) was calculated using 1998 volumes, consistent with the fixed-weight price indices used to run the regressions, and was equal to 0.749.

ii. Shifts Due to Changes in the Cost of Worksharing

The cost to mailers of worksharing has been generally declining over time since the introduction of worksharing discounts. Three effects are principally at work leading to this result. First, there are initial learning costs associated with worksharing, such as understanding Postal requirements and developing proper mailing procedures. These costs will decline over time as mailers become more familiar with worksharing in general. Second, the costs to mailers of worksharing include large fixed costs to buy equipment and adjust mailing practices to facilitate worksharing. Once these fixed costs have been sunk, however, the marginal cost of continuing to workshare is relatively low. Hence, the average cost of worksharing will decline over time as these fixed costs are spread over a greater volume of mail. Finally, the declining cost of new technology works to lower worksharing costs. For example, the cost per-piece of new automation equipment is significantly less expensive than it was five years ago.

The single-piece and workshared First-Class letters equations include logistic time trends as one of their explanatory variables. The logistic time trend (and trend squared) in the single-piece First-Class letters equation explains a decline in single-piece letters volume of 14.3 million pieces from 1988 through 1999, while the logistic time trend in the workshared letters equation explains an increase in workshared letters volume of 15.6 million pieces over the same time period. These trends are due, at least in part, to mail shifting from single-piece to workshared First-Class letters, due to the declining cost of presorting and automating over time. These trends are discussed more fully in section g below.

d. Relationship of First-Class Letters with other Subclasses of Mail

i. Cross-Price Relationship with First-Class Cards

A cross-price with respect to private First-Class cards was included in the First-Class letters equations to acknowledge possible substitution between First-Class cards and First-Class letters. In the present instance, the cross-price elasticity obtained from the demand equation for private First-Class cards appeared more reasonable than the freely estimated cross-price elasticities in the First-Class letters regressions. Therefore, the Slutsky-Schultz equation was applied to the cross-price elasticity from the private First-Class cards regression, and the result was entered as a stochastic constraint in the First-Class letters regressions. See section III.B. below for the derivation of the Slutsky-Schultz relationship and a more detailed discussion of its application to First-Class letters and cards.

ii. Cross-Price Relationship with Standard Regular Mail

A cross-price with respect to Standard Regular mail was included in the workshared First-Class letters equation. No substitution was modeled between single-piece First-Class letters and Standard Regular mail, because, since Standard Regular mail is required to be presorted to the extent possible, it seems probable that any mail that could be sent as Standard Regular mail would be workshared if it were instead sent as First-Class Mail. Some single-piece First-Class letters, however, are direct-mail advertising. It is assumed that the mailers of these pieces have made an explicit decision to send these pieces as single-piece First-Class letters, and that this mail is not likely to instead be sent as Standard Regular mail, regardless of changes in the prices of either First-Class or Standard mail.

The cross-price elasticity between First-Class workshared letters and Standard Regular mail was estimated using data from the 1997 Household Diary Study.

It is assumed that only non-households send advertising mail. Consequently, it is important to know the composition of letter mail by sender and recipient. Table 4-32 of the 1997 Household Diary Study breaks down First-Class letter mail into Household-to-Household, Nonhousehold-to-Household, Household-to-Nonhousehold, and Nonhousehold-to-Nonhousehold. Table 4-35 gives the same breakdown for single piece letters. From this data, the breakdown for workshared letters can be calculated. Using these two tables, it is estimated that, in 1997, 64.2 percent of workshared First-Class letters were sent to households, 34.8 percent of workshared First-Class letters were sent to nonhouseholds, and the destination of 1.0 percent of workshared First-Class letters could not be determined.

It is assumed that only advertising-only mail shifts from First-Class letters to Standard A mail in response to an increase in the price of letters. Advertising-enclosed mail is assumed to remain as First-Class letters since the non-advertising portion of the mailing could not be sent Standard A. Furthermore, the assumption is that changes in the relative prices of First-Class and Standard A mail do not cause changes in workshare decisions. Therefore, only users of workshare advertising-only letters are likely to shift into Standard A mail in response to a change in relative rates.

Table 4-36 of the 1997 Household Diary Study reveals that 9.9 percent of workshared letters were advertising-only mail received by households. It is assumed that nonhouseholds receive advertising mail in proportion to their receipt of total mail from other nonhouseholds.

Consider 100 pieces of workshared mail. The Household Diary Study states that 9.9 percent of this mail is advertising-only mail received by households. If nonhouseholds receive the same proportion of workshared advertising mail as they do of total workshared mail, then 5.4 pieces of workshared mail (9.9*(34.8/64.2) are advertising-only letters sent to nonhouseholds. Combining these two results, it is estimated that 15.3 percent of total workshared First-Class letters are direct-mail advertising (9.9 + 5.4). Given a volume of workshared First-Class letters of 40,634.252 million pieces (GFY 1998 RPW volume), gives the result that there are 6,217 million advertising-only First-Class workshared letters.

If one supposes that the demand for advertising First-Class letters is similar to the demand for advertising Standard A mail, then a reasonable assumption may be that the own-price elasticity of workshared advertising letters is -0.382, equal to the estimated R97-1 own-price elasticity of Standard A Regular mail. Given an own-price elasticity of -0.382, a one percent increase in the price of workshared letters will cause a 0.382 percent decline in the volume of advertising-only workshared letters. Applying this percentage change to the estimated volume of 6,217 million pieces yields a volume decline of 23.749 million pieces.

It is assumed that, at a maximum, each piece of advertising-only letter volume that exits First-Class letters in response to an increase in letter price enters into the corresponding category of Standard A Mail. Therefore, a one percent increase in workshare letter price causes 23.749 million workshare advertising-only letters to shift into Standard A Regular mail.

The cross-price elasticity is equal to the percentage change in Standard A mail category volume that occurs in response to a one percent change in the price of First-

Class letters. In GFY 1998, Standard Regular volume was 35,087.014 million pieces. Hence, the cross-price elasticity is equal to 100*[23.749 / 35,087.014] = 0.068.

Given a cross-price elasticity of Standard Regular mail volume with respect to the price of workshared First-Class letters of 0.068, the cross-price elasticity of workshared First-Class letters with respect to the price of Standard Regular mail can be calculated using the Slutsky-Schultz equation (see section III.B.3.c. below), and is equal to 0.045. These cross-price elasticities are then introduced into the workshared letters and Standard Regular equations as stochastic constraints, with standard errors estimated based on the standard error of the R97-1 Standard Regular own-price elasticity, such that these cross-price elasticity estimates have implicit t-statistics of 3.633 (the t-statistic on the own-price elasticity of Standard Regular mail in R97-1).

iii. Effect of R97-1 on Single-Piece First-Class Letters Volume

As a result of R97-1, the Standard A single-piece subclass was eliminated, requiring this mail to be sent as First-Class Mail if at all. In 1998, the volume of Standard A single-piece mail was 150.276 million pieces. Of this, approximately 95 percent, or 143 million pieces, weighed less than 13 ounces, and would therefore be likely to shift to single-piece First-Class letters (with the remaining 5 percent becoming Priority Mail). This represents 0.26 percent of single-piece First-Class letters volume.

Also in R97-1, the weight breakpoint for mail to be considered Priority Mail was raised from 11 ounces to 13 ounces. Hence, mail weighing between 11 and 13 ounces would have been eligible for single-piece First-Class letters after R97-1. Dr. Musgrave estimated that the loss in Priority Mail volume in the last two quarters of 1999 due to this classification change was approximately 72.4 million pieces of mail (see USPS-LR-I-114), or 0.26 percent of single-piece First-Class letters.

Taken together, the expected impact of these two changes is to increase single-piece First-Class letters volume by approximately 0.5 percent.

A simple dummy variable, equal to zero prior to R97-1 and equal to one thereafter, was included in the single-piece First-Class letters equation to account for these two factors. Freely estimated, this dummy variable implied an increase in single-piece letters volume of slightly more than one percent as a result of R97-1. This was deemed to be somewhat unreasonable. Instead, this dummy variable was constrained to a value of 0.005, which translates to an increase in single-piece letters volume of approximately 0.5 percent, as derived above.

e. Single-Piece First-Class Letters

The demand equation for single-piece First-Class letters models single-piece First-Class letters volume (per adult per business day) as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Transitory Income (lagged three quarters to reflect a lagged reaction of single-piece First-Class mailers to changing economic conditions)
- Logarithmic time trend and logarithmic time trend squared
- Dummy variable reflecting the use of government-distributed volume beginning in 1988Q1
- Dummy variable for classification reform (MC95-1), which took effect in 1996Q4
- Dummy variable for the elimination of the Standard A single-piece subclass and the change of the weight breakpoint between First-Class letters and Priority Mail from 11 to 13 ounces in R97-1, constrained as described above
- Current and one lag of the average worksharing discount for First-Class letters, with the sum of the coefficients stochastically constrained from the worksharing First-Class letters equation as described above
- Current and two lags of the price of private single-piece First-Class cards, with the sum of the coefficients stochastically constrained from the private First-Class cards equation using Slutsky-Schultz equality constraint
- Current and one lag of the price of single-piece First-Class letters

Elasticities are listed in Table II-2.

The own-price elasticity of single-piece First-Class letters is equal to -0.262 (t-statistic of -2.998). In addition to the price of single-piece letters, single-piece First-Class letters volume is also affected by the level of the First-Class letters worksharing discount (elasticity of -0.139, t-statistic of -3.869) due to mailers shifting from single-piece into workshared First-Class letters. The own-price elasticity here is the effect of a change in the price of single-piece First-Class letters holding all other variables in the equation constant. Hence, this represents the impact of a change in the single-piece letters price holding the worksharing discount constant. This is not, however, the impact of a change in the single-piece letters price holding the workshared letters price constant, since changing the single-piece letters price while holding the workshared letters price constant would, of course, change the worksharing discount. The "own-price elasticity" of single-piece First-Class letters, holding the price of workshared letters constant is not -0.262, but is, instead, equal to -0.262 plus the impact of the change in the workshared letters discount on single-piece letters volume.

Single-piece First-Class letters also have a modest positive cross-price elasticity with respect to single-piece First-Class cards. The aggregate elasticity of single-piece First-Class letters with respect to Postal prices (i.e., the impact of an across-the-board Postal rate increase on single-piece First-Class letters volume) is equal to the sum of the own- and cross-price elasticities, including the discount elasticity (since an across-the-board increase in the prices of both single-piece and workshared letters would lead to the same percentage increase in the worksharing discount), and is equal to -0.395, with a t-statistic of -4.662.

Single-piece First-Class letters have a permanent income elasticity of 0.513 (t-statistic of 20.76) versus a transitory income elasticity of 0.156 (t-statistic of 1.993).

Over the past five years, the time trend and trend squared variables have accounted for an 11.2 percent decline in the volume of single-piece First-Class letters, while other factors would have led one to expect single-piece letters volume per adult to grow by 4.9 percent over this same time period. The trends in single-piece and workshared First-Class letters are discussed in section g below.

f. Workshared First-Class Letters

The demand equation for workshared First-Class letters models workshared First-Class letters volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Transitory Income
- Logarithmic time trend
- Dummy variable reflecting the use of government-distributed volume beginning in 1988Q1
- Dummy variable for classification reform (MC95-1), which took effect in 1996Q4
- Current and one lag of the average worksharing discount for First-Class letters
- Current and two lags of the price of workshared First-Class cards, with the sum of the coefficients stochastically constrained from the private First-Class cards equation using Slutsky-Schultz equality constraint
- Current and one lag of the price of Standard Regular mail, with the sum of the coefficients constrained from the Household Diary Study as described above
- Current and three lags of the price of workshared First-Class letters

Elasticities are listed in Table II-3.

The own-price elasticity of workshared First-Class letters is equal to -0.251, with a t-statistic equal to -1.614. The volume of workshared First-Class letters is positively influenced by changes in the First-Class worksharing discount, with a discount elasticity equal to 0.216 (t-statistic of 3.619). Workshared First-Class letters also have modest cross-price elasticities with respect to First-Class cards and Standard Regular mail. In the aggregate, workshared First-Class letters volume is virtually unaffected by Postal rates, with an aggregate Postal price elasticity equal to 0.019 (t-statistic of 0.106).

Workshared First-Class letters have a permanent income elasticity of 0.406 (t-statistic of 19.58), and a transitory income elasticity of 0.452 (t-statistic of 2.399). The permanent income elasticity of workshared First-Class letters is somewhat smaller in magnitude than was the case for single-piece letters. The transitory income elasticity of workshared letters is more than twice as large in magnitude as the transitory income elasticity of single-piece letters. This is due to differences in the originators of single-piece versus worksharing First-Class letters. A large proportion of single-piece First-Class letters are generated by individual consumers, who are driven principally by permanent income in making consumption decisions (see section III.A.2.b. below), whereas much worksharing First-Class letters volume is driven more directly by businesses, who might be expected to be more significantly affected by changes in transitory income in making consumption decisions.

The time trend included in the worksharing First-Class letters equation, which has an estimated coefficient of 0.697 and a t-statistic equal to 31.22, has accounted for an 18.7 percent increase in worksharing letters volume over the past five years. This as well as the single-piece letters trends are discussed below.

The mean-squared error of the workshared First-Class letters equation is equal to 0.000616.

g. First-Class Letters Trends

The most important explanatory variables in the First-Class letters equations are the logistic time trends. The total effect of these variables on First-Class letters volume is summarized in Table II-1 below. Table II-1 shows the cumulative number of pieces explained by the time trends from 1988 through 1999. From 1988 to 1999, the time trends explain a decline in single-piece First-Class letters volume of 14.3 billion pieces and an increase in workshared First-Class letters volume of 15.6 billion pieces.

The time trends in the First-Class letters equations help to explain the impact of several factors which have affected First-Class letters volume in recent years, but which are not readily amenable to econometric estimation. Three of these factors that warrant discussion are the increasing use of First-Class Mail for direct-mail advertising, the declining use of First-Class Mail due to electronic diversion, and shifts of mail from single-piece to workshared First-Class letters over time.

Table II-1
Impact of Time Trends in First-Class Letters Equations
(millions of pieces, 1988 - 1999)

	Single-Piece	Workshared	Total Letters
1989	(782.579)	1,423.532	640.953
1990	(1,767.152)	2,851.286	1,084.134
1991	(2,848.119)	4,211.437	1,363.318
1992	(3,934.940)	5,757.162	1,822.222
1993	(5,360.107)	6,899.274	1,539.167
1994	(6,746.222)	8,423.000	1,676.778
1995	(7,957.103)	10,295.846	2,338.743
1996	(9,519.262)	11,435.102	1,915.840
1997	(11,234.568)	12,537.669	1,303.101
1998	(12,761.341)	13,987.362	1,226.021
1999	(14,322.131)	15,625.368	1,303.237

According to the Household Diary Study, direct-mail advertising First-Class letters volume (advertising-only, invitations, and announcements sent by nonhouseholds) received by households grew at an average annual rate of 6.8 percent from 1988 to 1996, while total First-Class letters volume grew at an average annual rate of 1.8 percent. If direct-mail advertising volume received by households had grown at the same rate as total First-Class letters volume, this would have resulted in 3-4 billion fewer First-Class letters having been sent in 1996. If one assumes that direct-mail advertising received by nonhouseholds has grown at a similar rate, then the increasing use of First-Class letters for direct-mail advertising could have accounted for an increase of as many as 7-8 billion First-Class letters between 1988 and 1999. While some of this growth may be implicitly accounted for in other variables, including permanent income and the cross-price with Standard Regular mail, much of this growth is captured through the inclusion of the time trend variables in the First-Class letters equations.

The computer has been a double-edged sword for the Postal Service. While the availability of database list management has helped to contribute to a surge in direct-mail advertising, electronic alternatives have also emerged for some First-Class Mail. Electronic diversion of First-Class Mail has been going on for at least the past ten years, with such innovations as fax machines, and, more recently, with things such as e-mail, and Electronic Funds Transfer (EFT).

Part of the reason for the negative trend in single-piece First-Class letters volume has been because of this electronic diversion. In addition, while workshared First-Class letters volume has grown considerably, there has nevertheless probably been some diversion of this mail over time as well.

If direct-mail advertising is thought to have generated an additional 7-8 billion First-Class letters over the past eleven years, then the difference between this and the net effect of the First-Class letters time trends, which explain an increase of approximately 1.3 billion pieces, could be attributed to electronic diversion. This translates into a loss of approximately 6-7 billion First-Class letters to electronic diversion between 1988 and 1999.

Even given the fairly significant estimates of the number of First-Class letters affected by direct-mail advertising and electronic diversion above, these factors only explain about 10-12 percent of the total econometric impact of the time trends in the First-Class letters equations. Adjusting for direct-mail advertising and electronic diversion, the econometric time trends therefore suggest that there was a shift of 10 to 15 billion First-Class letters from single-piece into worksharing from 1988 through 1999.

Of course, the sources of trends discussed here are not exhaustive, and these estimates have a great deal of uncertainty surrounding them. Nevertheless, the numbers presented here may be helpful in beginning to understand exactly what is implied by these time trends about First-Class letters volumes.

3. Total Cards

First-Class cards can be divided into two categories: stamped cards and private cards. Stamped cards, also called postal cards or government cards, are cards which are sold by the Postal Service with postage already imprinted. Postal cards represent approximately 8 percent of all First-Class cards in the Test Year (before-rates). Private cards are cards not provided by the Postal Service. Private First-Class cards may be further divided between single-piece and workshared cards, with single-piece First-Class cards representing approximately 43 percent of total First-Class cards and workshared First-Class cards accounting for 49 percent of total First-Class cards. Separate demand equations are estimated for postal and private First-Class cards. Single-piece and workshared private First-Class cards are combined for purposes of estimating a demand equation, but are separated in making volume forecasts.

a. Stamped Cards

The demand equation for stamped cards models stamped cards volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Current price of postal cards

Elasticities are listed in Table II-4.

The price elasticity of postal cards is -0.761 (t-statistic of -1.912). This is comparable to the price elasticity of private First-Class cards, which will be discussed below. In R97-1, stamped cards were priced more expensive than private cards for the first time in Postal history. One might have expected this to have a significant negative effect on stamped cards volume over and above the simple own-price elasticity. This possibility was investigated through the inclusion of a dummy variable equal to zero prior to the implementation of R97-1 rates, and equal to one thereafter. Unfortunately, the regression period included only two and one-half quarters of data since R97-1, and, because of the paucity of the post-R97 data, the estimated coefficient on the R97-1 dummy variable was unexpectedly positive. Hence, this variable was not included in the final equation used for forecasting.

b. Private Cards

As in R97-1, it was not feasible to estimate separate demand equations for single-piece and workshared private cards. This was primarily due to the somewhat erratic volume history of workshared cards.

The demand equation for private First-Class cards used in this case is essentially identical to the demand equation used in Docket No. R97-1. The demand equation for First-Class private cards in this case models private First-Class cards volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Logistic Market Penetration variable (Z-Variable) to reflect the positive impact of enhanced profitability of direct-mail advertising due to computerization of the early 1980s on private First-Class cards volume, as described in section III.B.5. below
- Permanent Income (as described in section III.A.2.b. below)
- Machine Dummy variable to reflect mailer adjustments to Postal Service regulations implemented in 1979Q4 restricting the mailing of First-Class cards with holes punched in them. Variable is equal to zero through 1979Q3, incrementing by 0.25 from 1979Q4 until reaching a value of one in the third quarter of 1980 (to reflect a lag in the enforcement of this particular rule), remaining at one through 1981Q3, and decreasing by 0.25 from 1981Q4 through 1982Q3, remaining at zero thereafter (reflecting mailer adaptation to this rule).
- Crossover Dummy variable reflecting the pricing of 3/5-digit presort First-Class cards less than the price of 3/5-digit presort third-class bulk regular mail over the R87-1 rate regime (13.0¢ versus 13.2¢). Variable is equal to one from 1988Q4 through 1991Q3, zero elsewhere.
- Crossover Dummy variable interacted with a time trend beginning in 1988Q4 to reflect lagged reaction by mailers to R87-1 rate crossover
- Current and two lags of the price of First-Class Letters
- Current and three lags of the price of private First-Class cards

Elasticities are listed in Table II-5.

The own-price elasticity of private First-Class cards was calculated to be equal to -0.860, with a t-statistic of -8.624. Private First-Class cards also have a cross-price elasticity with respect to First-Class letters equal to 0.228 (t-statistic of 1.844). Private First-Class cards have a permanent income elasticity of 0.694 (t-statistic of 17.43), while transitory income is not modeled to have any impact on private cards volume.

The mean-squared error of the private First-Class cards equation is equal to 0.004350.

TABLE II-2
SINGLE-PIECE FIRST-CLASS LETTERS

	Coefficient	T-statistic
First-Class Single-Piece Letters price -- SUM	-0.262	-2.998
current	-0.127	-0.546
lag 1	-0.134	-0.586
First-Class Single-Piece Cards price -- SUM	0.0056	1.789
current	0.0039	0.020
lag 1	0.0012	0.005
lag 2	0.0004	0.004
Worksharing First-Class Letters Discount -- SUM	-0.139	-3.869
current	-0.118	-1.557
lag 1	-0.021	-0.309
Permanent Income	0.513	20.76
Transitory Income (lag 3)	0.156	1.993
Logistic Time Trends:		
Time Trend	2.402	9.514
Time Trend Squared	-0.330	-10.43
Dummy for use of Government-Distributed Volume	0.008	0.841
Dummy for Classification Reform (MC95-1)	0.058	4.600
Dummy for migration of Priority Mail and Standard single-piece after R97-1	0.005	---
Seasonal coefficients:		
September	-0.303	-4.911
October - December 15	0.112	14.35
December 16 - 17	0.945	3.028
December 18 - 23	-0.089	-0.641
December 24 - January 1	-0.946	-2.735
January 2 - February 28	0.191	4.762
March	-0.191	-3.145
April 1 - 15	0.979	2.734
April 16 - May	-0.292	-2.421

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.000206
Degrees of Freedom	45
Adjusted-R^2	0.966

TABLE II-3
WORKSHARED FIRST-CLASS LETTERS

	Coefficient	T-statistic
Worksharing First-Class Letters price -- SUM	-0.251	-1.614
current	-0.009	-0.010
lag 1	-0.057	-0.062
lag 2	-0.085	-0.281
lag 3	-0.100	-0.518
Worksharing First-Class Cards price -- SUM	0.009	1.719
current	0.000	0.000
lag 1	0.004	0.012
lag 2	0.004	0.020
Standard Regular price -- SUM	0.045	3.296
current	0.043	0.091
lag 1	0.002	0.004
Worksharing First-Class Letters Discount -- SUM	0.216	3.619
current	0.078	0.582
lag 1	0.139	1.151
Permanent Income	0.406	19.58
Transitory Income	0.452	2.399
Logistic Time Trend	0.697	31.22
Dummy for use of Government-Distributed Volume	0.032	2.175
Dummy for Classification Reform (MC95-1)	-0.089	-5.805
Seasonal coefficients:		
October	0.190	2.204
November 1 - December 21	0.118	1.724
December 22 - 24	-0.543	-1.456
December 25 - January 1	2.218	2.082
January 2 - February 28	0.000	0.003
March	0.252	2.558
April 1 - 15	-0.518	-1.997
April 16 - June	0.230	2.635

REGRESSION DIAGNOSTICS :

AR-4 coefficient	-0.312
Mean Square Error	0.000616
Degrees of Freedom	38
Adjusted-R^2	0.993

TABLE II-4
FIRST-CLASS STAMPED CARDS

	Coefficient	T-statistic
First-Class postal cards price -- SUM	-0.761	-1.912
current	-0.761	-1.912
Permanent Income	0.708	22.56
Seasonal coefficients:		
September	0.937	1.962
October	-0.256	-0.703
November 1 - December 10	0.654	1.937
December 11 - 12	-1.326	-0.573
December 13 - 19	2.143	1.957
December 20 - 23	-3.458	-2.766
December 24	2.860	0.900
December 25 - June	0.250	1.899

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.852
AR-2 coefficient	0.173
AR-4 coefficient	0.165
Mean Square Error	0.034579
Degrees of Freedom	98
Adjusted-R^2	0.567

TABLE II-5
FIRST-CLASS PRIVATE CARDS

	Coefficient	T-statistic
First-Class private cards price – SUM	-0.860	-8.624
current	-0.206	-0.407
lag 1	-0.342	-0.385
lag 2	-0.005	-0.008
lag 3	-0.306	-1.846
First-Class letters price – SUM	0.228	1.844
current	0.011	0.020
lag 1	0.057	0.059
lag 2	0.159	0.267
Permanent Income	0.694	17.43
Machine dummy variable	-0.092	-5.310
Crossover dummy	0.031	0.815
Crossover trend	0.010	1.875
Parameters used in calculating Z-variable:		
Param1	0.382	7.221
Param2	84.91	0.755
Param3	0.118	3.209
Seasonal coefficients:		
September	0.173	0.545
October	0.978	3.816
November 1 - December 10	-0.555	-3.521
December 11 - 17	-0.168	-0.346
December 18 - January 1	0.977	3.214
January 2 - February 28	0.002	0.025
March	0.242	0.971
April 1 - May	-0.037	-0.450
June	0.238	0.798

REGRESSION DIAGNOSTICS :

AR-2 coefficient	-0.274
AR-4 coefficient	-0.221
Mean Square Error	0.004350
Degrees of Freedom	86
Adjusted-R^2	0.947

C. Periodical Mail

1. General Overview

The demand for Periodical mail is a derived demand, which is derived from the demand of consumers for magazines and newspapers. Those factors which influence the demand for newspapers and magazines would therefore be expected to be the principal drivers of the demand for Periodical mail.

The factors which would be expected to influence the demand for newspapers and magazines are drawn from basic micro-economic theory. These factors include permanent and transitory income (see section III.A.2.b for an overview of the theoretical underpinnings of permanent and transitory income), the price of newspapers and magazines, and the demand for goods which may serve as substitutes for newspapers and magazines.

The price of newspapers and magazines is divided into two components for the purposes of modeling demand equations for Periodical mail. The first component is the price of postage paid by publishers (and paid, implicitly, by consumers through subscription rates). In addition to affecting the price of newspapers and magazines by being incorporated into subscription rates, the price charged by the Postal Service will also affect the demand for Periodical mail directly by affecting publishers' decisions on how to deliver their periodicals. For example, relatively few newspapers are delivered through the mail. This is due, in part, to the existence of inexpensive alternate delivery systems (e.g., paper boys).

The second component of the price of newspapers and magazines considered in this analysis is the price of paper, modeled by the Bureau of Labor Statistics' wholesale price of pulp, paper, and allied products. This index is used in the Periodical mail equations to track the non-Postal price of periodicals. This component of the price of periodicals will only affect the demand for Periodical mail indirectly insofar as it is incorporated into subscription prices.

In R97-1, real cable television expenditures per adult were included as an explanatory variable to model the substitution of television for magazine and newspaper reading over time. While the growth of cable television expenditures has begun to slow somewhat in recent years, declines in magazine and newspaper circulation have continued. In R97-1, this was evident by the need for Dr. Tolley to include negative net trends in his forecasting equations for Periodical mail.

New substitutes, such as the Internet, have emerged. In addition, it appears that substitution away from magazines and newspapers is as much the result of a demographic shift as of substitution with specific media. This is better modeled in the Periodical mail equations by including a simple linear time trend instead of cable television expenditures.

Periodical mail is divided into one regular subclass and three preferred subclasses: within-county, nonprofit, and classroom mail. Separate demand equations were modeled for each of the four subclasses of Periodical mail. Periodical regular mail accounts for approximately 70 percent of total Periodical mail, and is considered first below.

2. Regular Rate

The demand equation for Periodical regular rate mail models Periodical regular rate mail volume as a function of the explanatory variables outlined above. The specific variables used in the Periodical regular mail equation were as follows:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)

- Transitory income (lagged three quarters to reflect a lagged adjustment of economic conditions into changes in subscription bases)
- Time trend
- The wholesale price of pulp and paper
- Current and three lags of the price of Periodical regular mail

Elasticities are listed in Table II-6.

The own-price elasticity of Periodical regular mail is equal to -0.148, with a t-statistic of -2.837. The own-price elasticity of Periodical mail is smaller in magnitude than most other price elasticities presented in my testimony. The reason for this is two-fold. First, the price of postage represents a relatively minor component of the total cost of preparing and delivering a periodical. Hence, the impact of a change in postal prices would be expected to have a relatively modest impact on subscription rates. Even if this were the case, however, the Postal price-elasticity of Periodical regular mail could be quite high if the delivery of periodicals were a highly competitive business. In fact, the delivery of magazines by sources other than the Postal Service is quite minimal, in part because Postal rates are quite favorable to Periodical mail due to Educational, Cultural, Scientific, and Informational (ECSI) considerations. These factors combine to account for the relative price-inelasticity of Periodical regular mail.

The price of paper also has a relatively modest impact on the demand for Periodical regular mail, with an estimated elasticity of -0.122 with a t-statistic of -1.024. This value is also quite small, suggesting that publishers are generally either unable or unwilling to pass increases in input costs along to consumers in the form of higher subscription rates.

The permanent income elasticity of Periodical regular mail is equal to 0.535 (t-statistic of 16.01), while the transitory income elasticity is negligible (coefficient of 0.033, t-statistic of 0.363). The significant difference in impacts of permanent and transitory income is consistent with the permanent income hypothesis and the nature of the demand for Periodical mail as being fundamentally consumer-driven.

Finally, the demand equation for Periodical regular mail has a significant negative trend, with a coefficient of -0.002 (t-statistic -4.651). The trend has accounted for a 3.1 percent decline in Periodical regular volume over the past five years, while the other variables in the econometric equation led to an expectation of 2.7 percent growth in Periodical regular mail volume per adult over this time period.

The regression diagnostics are acceptable for Periodical regular mail, with a mean-squared error equal to 0.000658.

3. Preferred Periodical Subclasses

a. Overview

The Postal Service offers preferred rates for certain types of periodical mailers. Preferred Periodical mail is divided into three subclasses on the basis of either the mailer or the mail content: within-county mail, which is mail sent within a particular county, and is comprised primarily of small local publications (mostly newspapers); nonprofit mail, which is mail sent by not-for-profit organizations; and classroom mail, which is mail for students sent to classrooms and educational institutions.

The basic theory of demand for the preferred categories of Periodical mail is expected to be similar to the theory outlined at the introduction to this section.

The price of paper was investigated in these demand equations, consistent with the theory outlined above. The price of paper was not found to affect the volume of Periodical preferred-rate mail, however. This could have occurred for a variety of reasons, including the possibility that preferred-rate mailers are less sensitive to these prices, or that there are fewer substitutes for printed material within these contexts, so that this type of mail would be less price-sensitive in general.

Linear time trends were included in the preferred Periodical demand equations, just as in the Periodical regular equation. Each of the three preferred Periodical demand equations had a significant negative time trend. In fact, all three preferred Periodical equations had a larger negative time trend than Periodical regular mail.

The specific demand equations for Periodical within county, nonprofit, and classroom mail are described below.

b. Within-County

The demand equation for within-county mail models Periodical within-county mail volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Time trend
- Dummy variable reflecting a change in the reported volume of within-county mail due to a change in the system for reporting within-county volume. Variable is equal to zero through 1984Q4, equal to one thereafter.
- Dummy variable reflecting a change in the requirements for within-county mail, which restricted eligibility to mailings for which at least 50 percent of the mailing was sent within the county of origin. This rule change took effect in 1987Q1.
- Dummy variable reflecting a change in the sampling framework used to report within-county mail volume, starting in 1993Q2. Variable is equal to zero through 1993Q1, equal to one thereafter.
- Current price of within county mail

Elasticities are listed in Table II-7.

The own-price elasticity of within-county mail is equal to -0.142 (t-statistic of -1.569). This is virtually identical to the own-price elasticity of Periodical regular rate mail. The time trend in the within-county equation is considerably greater than that of Periodical regular mail (coefficient of -0.009, t-statistic of -5.348). The time trend has accounted for a decline in Periodical within-county mail of 16.2 percent in the past five years. Overall, Periodical within-county mail volume has declined 11.1 percent over this time period.

The regression diagnostics are less favorable for within-county mail than for regular rate Periodical mail, due to the smaller and inherently more volatile volume series. The mean-squared error associated with within county mail is equal to 0.003499, although the adjusted-R^2 is fairly impressive at 0.965.

c. Nonprofit

The demand equation for Periodical nonprofit mail models Periodical nonprofit mail volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Transitory income (lagged three quarters to reflect a lagged adjustment of economic conditions into changes in subscription bases)
- Time trend
- Current and two lags of the price of Periodical nonprofit mail

Elasticities are listed in Table II-8.

The Periodical nonprofit equation is estimated using a starting period of 1978Q1. In contrast, the other three Periodical equations all use a starting period of 1971Q1. The later starting period for the Periodical nonprofit equation is due to a rate crossover with Standard bulk nonprofit mail that occurred around 1975 or 1976, whereby Periodical nonprofit mail was priced greater than Standard bulk nonprofit mail. The own-price elasticity of Periodical nonprofit mail is more consistently estimated using a sample period which does not span this crossover period.

The own-price elasticity of Periodical nonprofit mail is equal to -0.236, with a t-statistic of -1.554. Periodical nonprofit mail volume is considerably more sensitive to changes in income than regular rate mail, with income elasticities of 0.536 (t-statistic of 20.43) and 0.939 (t-statistic of 2.358) with respect to permanent and transitory income, respectively. The time trend in the Periodical nonprofit equation (coefficient of -0.004, t-statistic of -2.777) explains a 7.8 percent decline in Periodical nonprofit mail volume over the past five years. Overall, Periodical nonprofit volume has declined by 5.6 percent over this time period.

The regression diagnostics from the Periodical nonprofit equation are similar to those from the within-county equation, with a mean-squared error of 0.004105 and an adjusted-R^2 equal to 0.847.

d. Classroom

The demand equation for classroom mail models Periodical classroom mail volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Time trend
- Dummy variable reflecting the addition of a new mailer in 1987 which served to double classroom mail volume. Variable is equal to zero through 1987Q2, equal to one thereafter.
- Current and three lags of the price of classroom mail

Elasticities are listed in Table II-9. Periodical classroom mail has an estimated own-price elasticity of -0.407 (t-statistic of -0.939), with a time trend coefficient of -0.010 (t-statistic of -1.550).

TABLE II-6
PERIODICAL REGULAR RATE

	Coefficient	T-statistic
Periodical regular rate price -- SUM	-0.148	-2.837
current	-0.000	-0.000
lag 1	-0.009	-0.102
lag 2	-0.062	-0.651
lag 3	-0.076	-1.043
Permanent Income	0.535	16.01
Transitory Income (lag 3)	0.033	0.363
Wholesale price of pulp and paper	-0.122	-1.024
Time Trend	-0.002	-4.651
Seasonal coefficients:		
September	-0.296	-4.046
October - December 10	-0.003	-0.169
December 11 - 15	-0.185	-1.113
December 16 - 17	-1.432	-3.740
December 18 - 19	0.396	1.145
December 20 - 24	-0.152	-0.860
December. 25 - January 1	0.126	0.866
January 2 - March	-0.055	-2.162
April 1 - 15	0.357	4.133
April 16 - June	-0.167	-3.611

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.333
AR-2 coefficient	0.330
Mean Square Error	0.000658
Degrees of Freedom	93
Adjusted-R^2	0.867

TABLE II-7
PERIODICAL WITHIN-COUNTY MAIL

	Coefficient	T-statistic
Periodical within-county price -- SUM	-0.142	-1.569
current	-0.142	-1.569
Permanent Income	0.535	16.53
Time Trend	-0.009	-5.348
New reporting dummy	0.350	6.765
Dummy for 1987 rule change restricting within-county eligibility	-0.101	-1.995
Change in paneling method	-0.218	-4.109
Seasonal coefficients:		
September	-0.182	-3.161
October 1 - December 10	0.028	1.530
December 11 - 12	-3.868	-4.795
December 13 - 19	1.417	4.012
December 20 - 24	-1.166	-2.977
December 25 - January 1	0.605	2.313
January 2 - April 15	-0.035	-1.927

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.656
Mean Square Error	0.003499
Degrees of Freedom	100
Adjusted-R^2	0.965

TABLE II-8
PERIODICAL NONPROFIT

	Coefficient	T-statistic
Periodical nonprofit price -- SUM	-0.236	-1.554
current	-0.133	-1.401
lag 1	-0.007	-0.084
lag 2	-0.096	-0.997
Permanent Income	0.536	20.43
Transitory Income (lag 3)	0.939	2.358
Time Trend	-0.004	-2.777
Seasonal coefficients:		
September 1 - December 10	0.360	6.798
December 11 - 12	-0.646	-1.026
December 13 - January 1	0.425	3.620
January 2 - March	0.291	5.758
April 1 - 15	1.267	1.834
April 16 - May	-0.051	-0.228
June	0.629	3.688

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.547
AR-2 coefficient	0.385
AR-4 coefficient	-0.328
Mean Square Error	0.004105
Degrees of Freedom	67
Adjusted-R^2	0.847

TABLE II-9
PERIODICAL CLASSROOM

	Coefficient	T-statistic
Periodical classroom price -- SUM	-0.407	-0.939
current	-0.000	-0.000
lag 1	-0.058	-0.104
lag 2	-0.198	-0.377
lag 3	-0.151	-0.333
Permanent Income	0.536	17.99
Time Trend	-0.010	-1.550
New mailer dummy variable	0.749	3.558
Seasonal coefficients:		
September	-2.039	-2.351
October	1.035	1.585
November 1 - December 19	-2.686	-5.143
December 20 - 21	11.176	3.543
December 22 - 24	-4.305	-1.843
December 25 - January 1	1.426	0.862
January 2 - February	-1.015	-4.415
March	-2.043	-3.454
April 1 - 15	5.646	4.534
April 16 - June	-2.843	-4.672

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.406
AR-2 coefficient	0.337
Mean Square Error	0.055197
Degrees of Freedom	94
Adjusted-R^2	0.627

D. Standard A Mail

The demand for Standard A mail volume is the result of a choice by advertisers regarding how much to spend on direct-mail advertising expenditures. The decision process made by direct-mail advertisers can be decomposed into three separate, but interrelated, decisions:

(1) How much resources to invest in advertising?

(2) Which advertising media to use?

and, (3) Which mail category to use to send mail-based advertising?

These three decisions are integrated into the demand equations associated with Standard A mail volume by including a set of explanatory variables in the demand equations for Standard A mail that addresses each of these three decisions. Each of these three decisions, and the implications for Standard A mail equations, are considered separately below.

1. Advertising Decisions and Their Impact on Mail Volume

a. How Much Resources to Invest in Advertising

The amount of advertising expenditures made by a business is a decision made as part of a profit-maximizing optimization problem. Advertising expenditures are chosen so that the additional sales generated by the last dollar of advertising are equal to the cost of the advertising. Hence, advertising expenditures can be expected to be a function of expected sales. The majority of past work on advertising expenditures has therefore focused on advertising as a function of sales and/or personal consumption expenditures. Professor Richard Schmalensee, for example, hypothesized that total advertising expenditures are a constant percentage of retail sales (*The Economics of Advertising*, 1972).

Following the lead of Schmalensee, retail sales were investigated for inclusion in the demand equations for Standard bulk mail. Retail sales, as measured by the U. S. Census Bureau, do not measure total economic activity within the U. S. economy, however. In particular, retail sales do not include any information on the consumption of services, which are of growing importance in the U. S. economy. In addition, retail sales do not provide any direct information on the sales of primary and intermediate goods. Hence, while retail sales may well be a driving force affecting retail advertising on consumer goods, total advertising expenditures would be expected to be a function of a more encompassing measure of economic activity. To incorporate the effect of consumption of primary and intermediate goods as well as consumption of services, personal consumption expenditures was deemed a more desirable variable than retail sales for modeling the effect of the overall economy on advertising expenditures.

b. Which Advertising Media to Use

The choice of advertising media can be thought of as primarily a pricing decision, so that the demand equation for Standard bulk mail ought to include the prices of direct-mail advertising, as well as the prices of alternate advertising media.

In addition to relative prices, the choice of advertising media may be affected by the overall economy. For example, during a recession, when businesses cut back on advertising, they may not do so proportionally across all advertising media. This possibility is incorporated into the Standard A demand equations by the inclusion of transitory income as an explanatory variable.

i. Price of Direct-Mail Advertising

In R97-1, the cost of direct-mail advertising was separated into four components in the Standard A equations – postage cost, paper cost, printing cost, and technological costs. Unfortunately, the middle two of these components, paper and printing costs, were highly correlated with other variables in the Standard A equations. This multicollinearity problem is exacerbated in this case with the use of the BLS's index of the price of newspaper advertising, which is highly correlated with both of these variables, as well as the inclusion of transitory income as a separate explanatory variable in these equations.

Because of this multicollinearity problem, paper and printing costs were not explicitly included in the Standard A demand equations presented here. Hence, the price of direct-mail advertising includes only delivery and technological costs.

(a) Delivery Costs

Delivery costs represent the cost of sending direct-mail advertising through the mail. Postage costs represent the overwhelming majority of delivery costs. The remaining delivery costs include the category of costs typically referred to as "user costs". These represent worksharing costs borne by mailers to presort and/or automate mail, thereby saving the Postal Service from having to bear these costs. These user costs are incorporated into the price variables used here.

(b) Technological Costs

One of the principal advantages of direct-mail advertising over other forms of advertising is that direct-mail advertising allows an advertiser to address customers on a one-on-one basis. Hence, by identifying specifically who will receive a particular piece of direct-mail advertising, direct-mail advertising is able to provide an inherent level of targeting that is not necessarily available through other advertising media. The ability to target a direct mailing to specific individuals, based on specific advertiser-chosen criteria, has increased dramatically as a result of technological advances, particularly over the past fifteen to twenty years. The ease with which one is able to identify specific consumers or businesses at which to target direct-mail advertising is a key component of the cost of direct-mail advertising. This aspect of direct-mail advertising costs, called "technological costs" here, was modeled by Dr. Tolley in past rate cases through the use of a logistic market penetration variable, or "z-variable".

In R97-1, technological costs were modeled through the price of computer equipment. The actual variable used was the implicit price deflator of consumption expenditures on computers and related equipment, as tracked by the Bureau of Economic Analysis. The price of computer equipment has fallen dramatically over time, reflecting the increasing attractiveness of technology over time.

As this price continues to fall, however, the additional benefit of lower prices is likely to diminish. For example, a decline in the cost of identifying a single individual for targeting from \$10 to \$1 (90 percent) would probably have a significant impact on the use of such technology, and, hence, on the use of direct-mail advertising. An additional decline of 90 percent, from \$1 to 10¢ may have less impact, however, while a further decline of 90 percent, from 10¢ to 1¢ would have still less impact. Finally, a decline in the cost per name from 1¢ to 0.1¢ may, in fact, be trivial.

The diminishing marginal returns of declining computer prices are taken account of in this case by including not only the price of computer equipment, but also the price of computer equipment squared. Taken together, these two variables exert a positive influence on Standard A mail volumes, but at a decreasing rate over time.

ii. Price of Competing Advertising Media

In R97-1, the Standard A demand equations included cost per-thousand (CPM) data for magazines, newspapers, television and radio advertising provided by McCann-Erickson. These data are only available on an annual basis, however. This makes it difficult to track changes in these variables and the impact of these variables on Standard A mail volume.

For this case, alternative measures of the prices of newspaper and magazine advertising were taken from the Bureau of Labor Statistics, which measured the wholesale prices of newspaper and magazine advertising. The wholesale price of magazine advertising was not found to affect Standard A mail volume and was therefore not used here. Unfortunately, no alternatives to McCann-Erickson's radio and television CPM data were found. Hence, substitution between Standard A mail and radio and television advertising is not explicitly modeled here.

iii. Transitory Income

In addition to prices, the choice among advertising media may be a function of the economy. For example, during a recession, when businesses cut back on advertising, they may not do so proportionally across all advertising media. This possibility is incorporated into the Standard A demand equations by the inclusion of transitory income as an explanatory variable. Transitory income may also be an effective proxy for the costs of competing advertising media that are not explicitly included in the Standard A equations. For example, in R97-1, the costs of radio and television advertising were forecasted as functions of transitory income.

The measure of transitory income used in the Standard A equations is the same as that used in the other demand equations, the Federal Reserve's index of capacity utilization for the manufacturing sector.

c. How to Send Mail-Based Advertising

Direct-mail advertising could be sent as either First-Class or Standard A mail. Postal rates have tended to change at the same time and by approximately the same percentage across rate categories and subclasses historically. This makes it problematic to freely estimate cross-price elasticities for competing mail categories.

Since R94-1, substitution between First-Class letters and third-class bulk regular mail was modeled through a cross-price elasticity that was not calculated econometrically but was instead constructed based on Household Diary Study data. This basic technique is again used in this case, although the Household Diary Study estimate is introduced stochastically in this case. This is described in section II.B. above.

In addition to the cross-price between Standard Regular and First-Class letters, substitution between Standard A subclasses is also modeled due to two events. First, in 1993, Congress passed a law which restricted nonprofit eligibility. This law caused some mail to shift from the Standard Nonprofit and Nonprofit ECR subclasses to Standard Regular and ECR. Second, some Standard Regular mail (Automation 5-digit letters) was priced below some Standard ECR mail (basic letters) as a result of R97-1. This caused some Standard ECR mail to be sent as Standard Regular mail instead. Both of these events are modeled by the inclusion of dummy variables which are described below.

2. Final Specifications for Standard A Mail

a. Overview

The demand equations used for modeling Standard A mail volumes are based on the economic theory of advertising laid out above. Based on this theory, the demand equations for Standard A mail volume include three types of explanatory variables (excluding seasonal and other dummy variables) -- variables that affect total advertising expenditures, variables that affect advertisers' decision of which advertising media to use, and variables that affect the choice of mail category for direct-mail advertising.

Total advertising expenditures are modeled as a function of personal consumption expenditures.

The choice of advertising media is modeled through variables measuring the price of direct-mail advertising, the price of newspaper advertising, and transitory income. The price of direct-mail advertising is decomposed in this report into delivery costs (modeled by the price of the relevant category of Standard bulk mail, including user costs) and technological costs (modeled by the price of computer equipment and the price of computer equipment squared).

The only Postal cross-price elasticity which was included in these specifications was a cross-price between Standard Regular mail and First-Class letters. The cross-price elasticity with respect to First-Class letters is constrained in the Standard Regular equation based on information from the Household Diary Study as derived in section II.B. above.

The Standard A specifications also include two dummy variables reflecting shifts between Standard A subclasses. The first of these is a dummy variable entitled RULE94 which reflected a rule change in 1994Q1 limiting nonprofit eligibility, which had the effect of shifting some third-class bulk mail from the nonprofit subclass into third-class bulk regular mail. The coefficient on this dummy variable is freely estimated in the Standard bulk nonprofit equation, and is stochastically constrained within the Standard Regular and ECR equations so that the volume leaving the Standard bulk nonprofit subclasses is approximately equal to the volume entering the Standard bulk regular subclasses. The other of these is a dummy variable entitled D_R97 which reflects a pricing change in R97-1 (January of 1999) which priced Standard Regular automation 5-digit letters below Standard ECR basic letters. The coefficient on this variable is freely estimated in the Standard ECR equation and is stochastically constrained in the Standard Regular equation so that the volume shifting out of Standard ECR is approximately equal to the volume entering the Standard Regular subclass.

Two other dummy variables are also included in the Standard A equations. The first of these, which is equal to one beginning in 1988Q1, reflects the distribution of government mail by subclass. Prior to 1988, government mail was excluded from the volumes reported in the RPW system. The other dummy variable is for classification reform, which took effect in 1996Q4.

b. Standard Regular Mail

The demand equation for Standard Regular mail models Standard Regular mail volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Personal consumption expenditures
- Price of computer equipment
- Price of computer equipment squared
- Transitory income
- Price of newspaper advertising
- Dummy variable reflecting the use of government-distributed volume beginning in 1988Q1, with the coefficient stochastically constrained as described in section III.A.4.b. below

- Dummy variable reflecting the restriction of nonprofit eligibility beginning in 1994Q1, with the coefficient constrained from the Standard bulk nonprofit equation
- Dummy variable for classification reform (MC95-1), which took effect in 1996Q4
- Dummy variable for pricing of automation 5-digit letters less than Standard ECR basic letters when R97-1 rates were implemented, with the coefficient stochastically constrained from the Standard ECR equation
- Current and one lag of the price of First-Class letters, with the sum of the coefficients constrained from the Household Diary Study as described in section B. above
- Current and one lag of the price of Standard Regular mail

Elasticities are listed in Table II-10.

The Postal own-price elasticity of Standard Regular mail is estimated to be equal to -0.570, with a t-statistic of -10.20. Standard Regular mail has a cross-price elasticity with respect to newspaper advertising equal to 0.497 (t-statistic of 2.169).

Standard Regular mail has a consumption elasticity of 0.565, with a t-statistic of 1.237, a transitory income elasticity of 0.308 (t-statistic of 1.718), and elasticities with respect to the price of computer equipment and this price squared of -0.277 and -0.023 (t-statistics of -8.282 and -4.383, respectively).

Taken together, the declining price of computer equipment has accounted for an increase in Standard Regular mail volume of 11.8 percent over the past five years, while other econometric factors have contributed 17.4 percent growth in Standard Regular mail volume per adult over this same time period.

c. Standard Enhanced Carrier Route

The demand equation for Standard Enhanced Carrier Route (ECR) mail models Standard ECR mail volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Personal consumption expenditures
- Transitory income

- Price of newspaper advertising
- Dummy variable reflecting the use of government-distributed volume beginning in 1988Q1, with the coefficient stochastically constrained as described in section III.A.4.b. below.
- Dummy variable reflecting the restriction of nonprofit eligibility beginning in 1994Q1, with the coefficient constrained from the Standard bulk nonprofit equation
- Dummy variable for classification reform (MC95-1), which took effect in 1996Q4.
- Dummy variable for pricing of Standard ECR basic letters greater than Standard Regular automation 5-digit letters when R97-1 rates were implemented.
- Current and three lags of the price of Standard ECR mail

Elasticities are listed in Table II-11.

The Postal own-price elasticity of Standard ECR mail is estimated to be equal to -0.808, with a t-statistic of -7.172. Based on this, Standard ECR mail appears to be approximately 40 percent more sensitive to Postal rates than Standard Regular mail. The difference between the own-price elasticities of Standard Regular and ECR mail is significant at about a 97 percent confidence level (t-statistic on the difference equal to 1.89). Standard ECR mail is also considerably more sensitive to the price of newspaper advertising than Standard Regular mail, with a cross-price elasticity of 0.812 (t-statistic of 3.551).

Standard ECR mail has a consumption elasticity of 0.430, with a t-statistic of 1.487. This is slightly less than the consumption elasticity of Standard Regular mail. On the other hand, Standard ECR mail is much more strongly affected by transitory income than Standard Regular mail, with a transitory income elasticity of 0.886 (t-statistic of 4.458).

Standard ECR mail volume appears to be largely unaffected by technological costs. While the falling price and increasing power of technology have made direct-mail advertising in general a more attractive advertising media over time, the benefits of technology are limited almost exclusively to Standard Regular mail volume, as opposed to Standard ECR mail. In particular, technology has enabled advertisers to target potential customers more accurately, based particularly on past consumption decisions. By enabling advertisers to target individual customers based on individual customer profiles, as opposed to having to target broader groups of customers based on more general demographic profiles, many advertisers may find that much of their mailings do not have sufficient density to be sent as ECR mail, but are instead sent as Standard Regular mail. Hence, while technological improvements have had a positive effect on direct-mail advertising in general, this effect appears to have been offset with regards to Standard ECR mail volume by movement away from carrier-route level targeting toward finer non-carrier-route targeting of customers.

Over the past five years, Standard ECR mail volume has grown by 9.7 percent. Excluding the migration of mail into Standard Regular automation 5-digit letters as a result of R97-1, Standard ECR volume has grown by 17.3 percent over this time period. While this represents solid annual growth of 3.2 percent per year, this is just more than half the growth rate of Standard Regular mail volume (excluding the migration from Standard ECR after R97-1) over the same time period of 31.9 percent (5.7 percent per year). This difference in the growth rates of Standard Regular and Standard ECR mail volume over this time period is virtually identical to the growth in Standard Regular mail volume attributable to falling computer prices. Excluding this factor, Standard Regular mail volume would have grown 17.0 percent over the past five years, virtually identical to the observed growth rate for Standard ECR mail.

The mean-squared error of the Standard ECR equation is equal to 0.000472.

d. Standard Bulk Nonprofit

The demand equation for Standard bulk nonprofit mail models Standard bulk nonprofit mail volume (including both the Nonprofit and Nonprofit ECR subclasses) as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Personal consumption expenditures
- Dummy variable reflecting the restriction of nonprofit eligibility beginning in 1994Q1
- Dummy variable equal to one in the fall of U.S. federal election years
- Dummy variable equal to one in the spring of U.S. federal election years
- Current and three lags of the price of Standard bulk nonprofit mail

Elasticities are listed in Table II-12.

The Postal own-price elasticity of Standard bulk nonprofit mail is estimated to be equal to -0.162, with a t-statistic of -5.362. This is considerably lower than the Postal price elasticities associated with Standard bulk regular mail due to the relatively lower percentage of total costs represented by postage costs for nonprofit mail, due to the favorable nonprofit rates offered by the Postal Service.

Like Standard ECR mail, bulk nonprofit mail volume appears to be unaffected by technological costs.

TABLE II-10
STANDARD REGULAR MAIL

	Coefficient	T-statistic
Standard Regular price -- SUM	-0.570	-10.20
current	-0.298	-0.711
lag 1	-0.272	-0.646
First-Class Letters price -- SUM	0.070	3.497
current	0.059	0.087
lag 1	0.011	0.016
Personal Consumption Expenditures	0.565	1.237
Transitory Income	0.308	1.718
Price of Computer Equipment	-0.277	-8.282
Price of Computer Equipment Squared	-0.023	-4.383
Price of Newspaper Advertising	0.497	2.169
Dummy for use of Government-Distributed Volume	0.009	1.620
Dummy for Rule Restricting Nonprofit Eligibility in 1994	0.016	4.369
Dummy for Classification Reform (MC95-1)	-0.041	-1.889
Dummy for Shift of Mail from ECR into Regular after R97-1	0.088	4.940
Seasonal coefficients:		
September	-0.472	-1.850
October	0.904	5.846
November 1 - December 15	-0.842	-3.357
December 16 - 17	0.021	0.041
December 18 - 24	-1.219	-3.719
December 25 - February	-0.042	-0.546
March	-0.447	-1.678
April 1 - 15	1.061	1.914
April 16 - June	-0.541	-2.079

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean-Squared Error	0.000402
Degrees of Freedom	41
Adjusted-R^2	0.988

TABLE II-11
STANDARD ENHANCED CARRIER ROUTE MAIL

	Coefficient	T-statistic
Standard ECR price -- SUM	-0.808	-7.172
current	-0.217	-1.846
lag 1	-0.146	-1.000
lag 2	-0.144	-0.966
lag 3	-0.301	-2.604
Personal Consumption Expenditures	0.430	1.487
Transitory Income	0.886	4.458
Price of Newspaper Advertising	0.812	3.551
Dummy for use of Government-Distributed Volume	0.022	3.012
Dummy for Rule Restricting Nonprofit Eligibility in 1994	0.005	4.714
Dummy for Classification Reform (MC95-1)	-0.044	-2.300
Dummy for Shift of Mail from ECR into Regular after R97-1	-0.106	-4.168
Seasonal coefficients:		
September	0.387	4.135
October	0.713	7.817
November 1 - December 19	-0.147	-1.750
December 20 - 24	1.182	4.815
December 25 - January 1	-0.371	-1.805
January 2 - June	0.089	3.522

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.352
Mean-Squared Error	0.000472
Degrees of Freedom	44
Adjusted-R^2	0.955

TABLE II-12
STANDARD BULK NONPROFIT MAIL

	Coefficient	T-statistic
Standard Bulk Nonprofit price -- SUM	-0.162	-5.362
current	-0.114	-1.266
lag 1	-0.004	-0.025
lag 2	-0.008	-0.051
lag 3	-0.035	-0.408
Personal Consumption Expenditures	0.772	8.941
Dummy for Rule Restricting Nonprofit Eligibility in 1994	-0.047	-4.538
Dummy for Election Year		
Fall, even-numbered years	0.037	3.119
Spring, even-numbered years	0.031	2.674
Seasonal coefficients:		
October	0.542	4.126
November 1 - December 17	-0.202	-2.257
December 18 - January 1	-0.605	-3.236
January 2 - February	0.073	1.352
March - May	-0.094	-2.788
June	-0.480	-3.680

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean-Squared Error	0.000529
Degrees of Freedom	49
Adjusted-R^2	0.947

E. Standard B Mail

1. General Overview

Standard B mail can be classified broadly as the delivery of goods other than periodicals, advertisements, and correspondence. Examples of this type of mail include mail-order deliveries, such as clothes, and the delivery of books, tapes, or CDs (such as from book or CD clubs), as well as packages sent by households (e.g., Christmas presents).

As with Periodical mail, the demand for Standard B mail is a derived demand, emanating from the demand for the products being delivered. As such, the demand for Standard B mail would be expected to be a function of the usual factors affecting demand, including permanent and transitory income. The demand for Standard B mail will be affected not only by the price of Standard B mail, but also by the availability and price of alternate delivery forms, including non-Postal alternatives.

Separate demand equations are modeled for each of the subclasses making up Standard B mail, which are parcel post, bound printed matter, special rate, and library rate. The specific demand equations associated with each of these types of mail are discussed below.

2. Parcel Post

a. General Overview

Parcel post mail volume consists of packages weighing between one and seventy pounds. Parcel post is the only Standard B subclass for which there are no content restrictions (other than general restrictions on what can be mailed). The content of these packages may include mail-order deliveries (e.g., clothes, food), packages sent by households (e.g., Christmas presents), and other types of goods delivered through the Postal Service.

The demand for parcel post mail volume is a derived demand which is derived from the demand for the goods being delivered. Generally, parcel post demand is specifically generated from the delivery of retail sales. Hence, retail sales is used as the income variable in the parcel post demand equation.

The demand for parcel post mail volume is not merely a function of the factors affecting the underlying demand for the products being delivered via parcel post, but is also affected by factors which influence consumers' decisions of how to send these deliveries. Parcel post competes directly with several outside competitors. Chief among these competitors is United Parcel Service, which currently possesses a majority of the surface parcel market nationally. The relationship between parcel post and UPS is discussed in the next section.

Besides non-postal competitors, parcel post also competes within the Postal Service with Priority Mail. This relationship is modeled by including a cross-price with respect to Priority Mail in the parcel post demand equation.

b. Competition with United Parcel Service

i. A Brief History of Parcel Post versus UPS

In 1971, at the beginning of the sample period used here to analyze the demand for parcel post, parcel post volume was comparable to UPS ground parcel volume. At this time, UPS's potential market was only about 50 percent as great as that of parcel post, however. In addition, UPS faced other restrictions, limiting their potential volume.

Through the 1970s, UPS increased its potential market and saw the lifting of other restrictions. At the same time, UPS aggressively priced its products below parcel post prices. This pricing strategy continued through the 1980s and resulted in UPS consistently gaining market share over this time. From 1971 through 1987, for example, parcel post volume fell from 516 million to 143 million pieces, a decline of 72 percent, or 7.3 percent per year.

Over this time period, UPS prices were lower than those for parcel post for the overwhelming majority of packages. UPS prices were uniformly cheaper than parcel post prices until the mid-1970s, and, using 1998 parcel post billing determinants, an average of only 4.3 percent of packages were cheaper to send as parcel post between 1971 and 1989. Hence, the majority of UPS's gains over these two decades at the expense of parcel post were not due to changes in the relative prices of the two products.

In February of 1990, however, UPS raised its rates in such a way as to fundamentally alter its relationship to parcel post rates. The average rate increase (calculated using 1998 parcel post billing determinants) by UPS at this time was 8.3 percent. More significantly, however, the percentage of packages for which UPS rates were more expensive than parcel post rates leapt from 7.4 percent prior to this rate increase to 82.3 percent after this rate increase. Since 1990, the percentage of packages for which UPS rates are more expensive than parcel post rates has remained extremely high, with 93.3 percent of UPS's residential rates and 76.6 percent of UPS's published commercial rates currently higher than corresponding parcel post rates.

It appears that with UPS's 1990 rate increase, UPS and parcel post began to compete more heavily on price. Competition between UPS and parcel post is therefore modeled differently before and after this 1990 rate change, with pre-1990 competition focusing on non-price shifts of mail from parcel post to UPS and post-1990 competition being primarily price-based.

ii. Competition between Parcel Post and UPS Prior to 1990

(a) Traditional UPS Cross-Price Variable

Competition with UPS is modeled in the demand equation for parcel post through the inclusion of a cross-price with respect to UPS. In Docket No. R90-1, the cross-price with respect to UPS that was included in Dr. Tolley's parcel post equation was calculated as the average revenue per piece for UPS common carrier. Calculating a fixed-weight price index for UPS was not feasible because exact volume weights were not available for UPS. Since R94-1, this problem has been mitigated by using parcel post billing determinants in calculating a fixed-weight price index for UPS. By using parcel post billing determinants, the cross-price with UPS is weighted most heavily toward those areas where parcel post has the largest volume, and hence, is most sensitive in terms of volume gains or losses to UPS rate changes.

(b) Non-Price UPS Variables

As noted above, UPS prices were almost uniformly lower than parcel post rates prior to 1990. Hence, some of the gain in market share achieved by UPS in the 1970s and 1980s must have been due to non-price factors. Some of these factors are quantifiable as explanatory variables. For example, the percentage of the U.S. market served by UPS is included as an explanatory variable, called UPS Potential Market. This variable grew from a value of 0.506 in 1971Q1 to 1.000 by 1981Q2, remaining equal to one thereafter.

Two other dummy variables are included in the parcel post equation which reflect factors which contributed to UPS's increasing market share. The first of these reflects the authorization for UPS to deliver packages for Wards, Sears, and Penneys. This variable takes on a value of zero through 1976Q3, 0.67 from 1976Q4 through 1977Q2, and a value of one from 1977Q3 forward. The second variable reflects the authorization for UPS to deliver packages for all retailers and to deliver more than 100 pounds per day between a given sender and receiver, and is equal to zero through 1980Q2, 0.1 in 1980Q3, 0.5 in 1980Q4, and one thereafter.

Even beyond these variables, however, parcel post volume exhibited a persistent downward trend over this time period. This is modeled in the parcel post demand equation by the inclusion of a simple linear time trend. This time trend ends in 1990Q2, however, to reflect the change in the relationship between parcel post and UPS from one in which UPS consistently gained market share independent of the relative prices of the two products to one in which competition between these two categories is primarily price-based.

iii. Competition between Parcel Post and UPS Since 1990

As noted above, the time trend is truncated in the parcel post equation beginning in 1990, as competition between UPS and parcel post becomes more price-based. In addition, the own-price elasticity of parcel post as well as the cross-price elasticity with respect to UPS are estimated separately for the post-1990 time period to reflect the higher level of price-based competition.

UPS introduced a surcharge of $0.30 for residential parcel deliveries in the second Postal quarter of 1991. The residential surcharge has risen progressively each year, until the residential surcharge is currently equal to $1.00. In 1999, UPS introduced an additional $1.00 surcharge on residential deliveries to selected ZIP Codes. Approximately 18 percent of residential parcel post volume would be subject to this latter surcharge. These two surcharges are combined into a single variable, called residential surcharge. This aggregate residential surcharge variable, which has a current nominal value of \$1.18 (\$1 + \$1•18%), is included in the parcel post equation separate from the UPS cross-price variable, which reflects published commercial rates.

At approximately the same time that UPS was introducing its residential surcharge, the Postal Service introduced DBMC parcel post, which offered significant discounts for parcel post mail dropshipped to the destination BMC. A dummy variable is included in the parcel post equation for the introduction of DBMC parcel post.

c. Demand Equation used for Parcel Post

The demand equation for parcel post mail models parcel post volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Retail sales per adult (1992 dollars)
- Time trend increasing by one per quarter until 1990Q2, remaining constant thereafter, to reflect change in the relationship of UPS and parcel post prices, as described above
- Measure of UPS's potential market, increasing from 0.506 in 1971Q1 to one in 1981Q2, remaining equal to one thereafter
- Man-days lost to strike by UPS (excluding UPS's most recent strike)
- Dummy variable reflecting the authorization for UPS to deliver packages for Wards, Sears, and Penneys is included, taking on a value of zero through 1976Q3, 0.67 from 1976Q4 through 1977Q2, and a value of one from 1977Q3 forward.
- Dummy variable reflecting the authorization for UPS to deliver packages for all retailers and to deliver more than 100 pounds per day between a given sender and receiver, equal to zero through 1980Q2, 0.1 in 1980Q3, 0.5 in 1980Q4, and one thereafter.
- UPS Residential surcharge (which enters the equation unlogged)
- Dummy variable reflecting the use of government-distributed volume beginning in 1988Q1
- Dummy variable for introduction of DBMC discount
- Dummy variable equal to one from 1991Q3 through 1992Q4 to account for data unavailability for the first six quarters after the introduction of the DBMC discount

- Dummy variable equal to one in 1997Q4 for UPS's most recent strike
- *Dummy variable equal to one in 1998Q1 and 1998Q2 to account for the* apparent retention of some volume in the first two quarters after the UPS strike
- Current price of Priority Mail
- Current price of UPS Ground Parcel service
- Current price of UPS Ground Parcel service interacted with a dummy variable equal to zero through 1990Q1, equal to one thereafter
- Current and one lag of the price of parcel post mail
- Current price of parcel post mail interacted with a dummy variable equal to zero through 1990Q1, equal to one thereafter

Elasticities are listed in Table II-13.

Prior to 1990, the own-price elasticity of parcel post was equal to -0.583, with a t-statistic of -4.598, with a cross-price elasticity with respect to UPS of 0.073 (t-statistic *equal to 0.307). The time trend in parcel post, with a coefficient of* -0.023 (t-statistic equal to -10.24), explained an annual decline in parcel post volume of 8.7 percent.

Since 1990, the own-price elasticity of parcel post is equal to -1.230 (t-statistic of -5.348), with a simple cross-price elasticity with respect to UPS equal to 0.849 (t-statistic of 2.688). The coefficient on UPS's residential surcharge in the parcel post demand equation is equal to 0.417 (t-statistic of 2.888). The residential surcharge is entered into the parcel post equation unlogged (because it is equal to zero prior to 1991). This coefficient translates to an elasticity of 0.430 given the current level of the residential surcharge. Combining the cross-price elasticity with the elasticity with respect to the residential surcharge yields an aggregate price elasticity with respect to UPS (i.e., assuming UPS raises all rates, including the residential surcharge, proportionally) of 1.28.

Parcel post mail also has a cross-price elasticity with respect to Priority Mail of 0.148 which is assumed to be constant throughout the sample period. Parcel post mail volume is also strongly affected by retail sales, with an elasticity of 0.749 (t-statistic of 2.953) (also constant throughout the sample).

3. Non-Parcel Post Standard B Mail

a. Subclasses of Standard B Mail

There are three subclasses of Standard B mail in addition to parcel post: bound printed matter, special rate, and library rate. Bound printed matter refers to any mail that is bound and printed, and weighs between one and fifteen pounds. Generally, bound printed matter falls into one of three categories: catalogs, books (including telephone books in some areas), and direct-mail advertising weighing sixteen ounces or more. The special rate subclass is reserved for books, tapes, and CDs. The library rate subclass is a preferred subclass, generally corresponding to the special rate subclass, available to libraries and certain other institutions.

b. History of Bound Printed Matter and Special Rate Mail

Prior to 1976, the bound printed matter subclass was called the Catalog subclass, and was composed entirely of catalogs. Beginning on or around the fourth quarter of 1976, an informal rule change occurred, whereby certain Post Offices began to allow books, which had previously been sent as special rate mail, to be sent as bound printed matter with the inclusion of a single page of advertising. This rule was gradually adopted by most Post Offices over the next several years.

In most cases, bound printed matter rates were, and still are, less expensive than special rate rates. However, bound printed matter rates are zoned, whereas special rate rates are unzoned. Thus, in order for mailers to shift from the special rate to bound printed matter subclass, mailers had to switch from unzoned rates to zoned rates. This structural adaptation, along with an apparent lag in realization by mailers of the existence of this rule change, made it difficult for mailers to immediately shift from special rate to bound printed matter.

Shifts between these two subclasses were particularly erratic in the first two years after this rule change was first implemented gradually. It was decided that it would be best econometrically, therefore, to avoid this early period entirely. Consequently, the demand equations for bound printed matter and special rate mail volume are not modeled using data prior to 1979Q1, allowing two full years for special rate mailers to begin to adapt to the enhanced opportunities available through bound printed matter.

Even after this time period, however, gradual migration from special rate into bound printed matter continued. This effect is modeled by including logistic market penetration variables in the demand equations for bound printed matter and special rate mail volumes. The market penetration variable in the bound printed matter equation is positive to reflect market penetration into bound printed matter, while the market penetration variable in the special rate equation is negative to reflect market penetration out of the special rate subclass.

The Standard library rate equation uses a starting period of 1979Q1 for consistency with the special rate equation.

c. Standard B Regression Equations

i. Bound Printed Matter

The demand equation for bound printed matter models bound printed matter volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Logistic Market Penetration variable (Z-Variable) as described in section III.B.5. below
- Permanent Income (as described in section III.A.2.b. below)

- Dummy variable to reflect a rule change in 1986 allowing bound printed matter and special rate mail to be bundled within a single mailing, equal to zero through 1985Q4, (17.5/66) in 1986Q1 (reflecting the timing of this rule change 17.5 business days into 1986Q1), and one thereafter.
- Dummy variable reflecting the year immediately following the cancellation of the Sears catalog, which had a significant negative initial impact on bound printed matter volume, which was mitigated by other catalog mailers within the next year. Variable is equal to one from 1993Q2 through 1994Q1, zero elsewhere.
- Dummy variable equal to one since 1998Q1 to account for an otherwise unexplained decline in bound printed matter of 10-11 percent since 1998.
- Current and three lags of the price of bound printed matter

Elasticities are listed in Table II-14.

The own-price elasticity of bound printed matter is equal to -0.392 (t-statistic of -2.584). Bound printed matter volume is strongly affected by permanent income, with a permanent income elasticity of 1.327 (t-statistic of 12.06).

Bound printed matter volume has one of the strongest seasonal patterns of any mail category, with volumes particularly high in September (seasonal coefficient of 2.201, t-statistic of 2.623), the week preceding Christmas (coefficient of 1.717, t-statistic of 1.619), March (coefficient of 1.283, t-statistic of 1.694), and late April and May (coefficient of 0.854, t-statistic of 0.967). On the other hand, bound printed matter volume is extremely low in October (coefficient of -1.916, t-statistic of -3.934), the first two weeks of April (-6.960, t-statistic of -3.273), and June (-1.460, -1.726). For the base year, the seasonal variables lead to an expectation regarding bound printed matter that volume was 12.4 percent higher than average in the first Postal quarter, 2.8 percent lower than average in the second Postal quarter, 18.2 percent below average in the third Postal quarter, and 6.3 percent above average in the fourth Postal quarter.

The regression diagnostics associated with the bound printed matter equation are comparable to recent rate cases, with a mean-squared error of 0.009685.

ii. Special Rate

The demand equation for special rate mail models the demand for Standard special rate mail volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Logistic Market Penetration variable (Z-Variable) as described in section III.B.5. below
- Permanent Income (as described in section III.A.2.b. below)
- Transitory Income
- Dummy variable to reflect a rule change in 1986 allowing bound printed matter and special rate mail to be bundled within a single mailing, equal to zero through 1985Q4, (17.5/66) in 1986Q1 (reflecting the timing of this rule change 17.5 business days into 1986Q1), and one thereafter.
- Dummy variable reflecting the use of government-distributed volume beginning in 1988Q1.
- Dummy variable reflecting a rule change in 1994Q1 restricting library rate eligibility
- Dummy variable equal to one in 1997Q4 to account for the impact of UPS's nationwide strike in the summer of 1997
- Current price of special rate mail

Elasticities are listed in Table II-15.

The own-price elasticity of special rate mail is -0.296, with a t-statistic of -2.265. Special rate volume is affected by both permanent and transitory income, with elasticities of 0.232 (t-statistic of 1.302) and 0.808 (t-statistic of 3.739), respectively.

iii. Library Rate

The demand equation for library rate mail models Standard library rate mail volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Dummy variable reflecting a rule change in 1994Q1 restricting library rate eligibility
- Dummy variable equal to one in 1997Q4 to account for the impact of UPS's nationwide strike in the summer of 1997
- Current and three lags of the price of library rate mail

Elasticities for library rate mail are given in Table II-16.

The own-price elasticity of library rate mail is equal to -0.654, with a t-statistic of -8.863. This is considerably greater than the own-price elasticity of special rate mail, reflecting, perhaps, the greater sensitivity of libraries and museums to costs in general due to their not-for-profit stature.

TABLE II-13
STANDARD PARCEL POST

	Coefficient	T-statistic
Parcel post price -- SUM	-1.230	-5.348
current (full sample)	-0.395	-2.117
current (since 1990)	-0.646	-2.566
lag 1 (full sample)	-0.189	-1.095
UPS price -- SUM	0.849	2.688
current (full sample)	0.073	0.307
current (since 1990)	0.776	2.982
UPS Residential Surcharge	0.417	2.888
Priority Mail price	0.148	1.309
Retail Sales	0.749	2.953
UPS Potential Market	-0.305	-3.292
UPS man-days lost to strikes (excludes 1997 strike)	0.768	8.359
Impact of 1997 UPS Strike	0.174	2.908
Retention of Volume from 1997 UPS Strike in 1998Q1 and 2	0.078	1.767
Lifting of UPS retail restriction	-0.020	-0.435
UPS Sears, Wards, Penneys' authorization	-0.068	-1.527
Time Trend ending in 1990Q2	-0.023	-10.24
Dummy for use of Government-Distributed Volume	0.108	3.445
Dummy for Introduction of DBMC Discount	0.276	3.741
Dummy for data unavailability for 1st 6 quarters after introduction of DBMC discount	-0.206	-5.001
Seasonal coefficients:		
September	0.406	1.149
October	0.768	3.003
November 1 - December 10	0.491	3.391
December 11 - 12	-0.595	-0.625
December 13 - January 1	1.470	4.161
January 2 - February	0.237	2.882
March	0.510	1.786
April 1 - 15	-0.409	-0.713
April 16 - June	0.492	1.728

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.003112
Degrees of Freedom	88
Adjusted-R^2	0.990

TABLE II-14
STANDARD BOUND PRINTED MATTER

	Coefficient	T-statistic
Bound printed matter price -- SUM	-0.392	-2.584
current	-0.000	-0.001
lag 1	-0.102	-0.132
lag 2	-0.165	-0.222
lag 3	-0.124	-0.276
Permanent Income	1.327	12.06
Bundling dummy variable	0.041	1.469
Sears catalog dummy	-0.199	-3.982
Dummy variable since 1998Q1	-0.115	-3.271
Parameters used in calculating Z-variable:		
Param1	1.677	10.09
Param2	2.709	3.900
Param3	0.048	4.621
Seasonal coefficients:		
September	2.201	2.623
October	-1.916	-3.934
November 1 - December 17	0.343	0.466
December 18 - 23	1.717	1.619
December 24 - February	-0.539	-2.072
March	1.283	1.694
April 1 - 15	-6.960	-3.273
April 16 - May	0.854	0.967
June	-1.460	-1.726

REGRESSION DIAGNOSTICS :

AR-4 coefficient	-0.142
Mean Square Error	0.009685
Degrees of Freedom	58
Adjusted-R^2	0.971

TABLE II-15
STANDARD SPECIAL RATE

	Coefficient	T-statistic
Standard Special Rate price -- SUM	-0.296	-2.265
current	-0.296	-2.265
Permanent Income	0.232	1.302
Transitory Income	0.808	3.739
Bundling dummy variable	0.095	2.703
1994 Rule Change affecting Library Rate Eligibility	0.166	6.534
Dummy for use of Government-Distributed Volume	0.032	0.812
Dummy for 1997 UPS Strike	0.046	0.587
Parameters used in calculating Z-variable:		
Param1	-0.766	-4.851
Param2	29.94	0.834
Param3	0.172	3.093
Seasonal coefficients:		
September - October	0.786	3.699
November 1 - December 10	0.168	1.627
December 11 - March	0.408	4.003
April 1 - 15	-0.396	-0.939
April 16 - June	0.631	2.588

REGRESSION DIAGNOSTICS :

AR-coefficients	None
Mean Square Error	0.005706
Degrees of Freedom	68
Adjusted-R^2	0.871

TABLE II-16
STANDARD LIBRARY RATE

	Coefficient	T-statistic
Standard Library Rate price -- SUM	-0.654	-8.863
current	-0.306	-0.912
lag 1	-0.133	-0.270
lag 2	-0.002	-0.004
lag 3	-0.214	-0.694
Permanent Income	0.115	0.571
1994 Rule Change affecting Library Rate Eligibility	-0.253	-4.300
Dummy for 1997 UPS Strike	0.048	0.254
Seasonal coefficients:		
September	-0.589	-0.925
October	1.722	1.558
November 1 - December 10	-0.621	-0.623
December 11 - June	0.172	0.954

REGRESSION DIAGNOSTICS :

AR-coefficients	None
Mean Square Error	0.030704
Degrees of Freedom	72
Adjusted-R^2	0.806

F. Other Mail Categories

In addition to the mail volumes described above, demand equations are also modeled for three categories of mail and six special services which are not a part of either the First-Class, Periodical, or Standard mail classes. The three categories of mail are Mailgrams, Postal Penalty mail, and Free-for-the-Blind mail. The six special services considered are registered mail, insured mail, certified mail, COD, return receipts, and money orders.

1. Mailgrams, Postal Penalty, and Free-for-the-Blind Mail

Mailgrams are telegrams delivered by the Postal Service under an agreement with Western Union. Postal Penalty mail refers to mail sent by the Postal Service. Free-for-the-Blind mail is mail that is delivered free of charge by the Postal Service under certain circumstances.

Because there is no direct price charged for Mailgrams, Postal Penalty, and Free-for-the-Blind mail, price was not included in the demand specifications for these categories of mail. Because it was not necessary to estimate a price elasticity for these categories of mail, and due to the small and relatively volatile volumes within these categories of mail, only seasonal variables and time trends were used in these regressions.

Volume data for Mailgrams and Postal Penalty Mail do not extend back to 1971. In these cases, demand equations were run beginning in the first quarter for which volume data are available. Thus, the Mailgrams equation was run beginning in 1975q1, and the Postal Penalty equation was run beginning in 1988q1. The seasonal and trend elasticities from these equations are listed in Tables II-17 through II-19, respectively.

2. Special Services

Special services are not mail volumes, but represent add-ons to mail volumes (i.e., a certified letter would be counted as both a piece of certified mail as well as a First-Class letter), so that the volumes of special services are not included in a calculation of total Postal Service volume. The Postal Service provides these services for a fee. The demand for these services can be specified along the lines of traditional consumer demand theory.

The demand for special service mail is generally a function of permanent and transitory income and the price charged by the Postal Service for utilizing these services. In addition, the special service volumes modeled here have generally exhibited long-run trends. For this reason, a time trend is included in the demand equation associated with each of the special services (except for money orders).

Finally, because special services are merely add-ons to otherwise existing mail volumes, the demand for special services may be affected directly by the demand for complementary categories of mail. For example, insured mail volume is modeled in part as a function of the volume of parcel post mail, since a large portion of insured mail volume is sent as parcel post mail, while the volume of return receipts is a function of the volume of certified mail, since most return receipts accompany certified mail.

a. Registry

The demand equation for registered mail models registered mail volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Transitory Income
- Time trend reflecting a long-run downward trend in registered mail volume
- Dummy variable reflecting the use of government-distributed volume beginning in 1988Q1.
- Current price of registered mail

The registry equation uses a sample period beginning in 1984Q1 to reflect an apparent change in the demand characteristics of registered mail over time, due, in part, to rate and rule changes associated with registered mail in the early 1980s.

Elasticities are listed in Table II-20.

b. Insured

The demand equation for insured mail models insured mail volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Time trend reflecting a long-run downward trend in insured mail volume
- Volume of parcel post mail reflecting complementarity of parcel post and insured mail
- Dummy variable for special service classification reform (MC96-3), which increased the maximum value that can be insured from $600 to $5,000.
- Current and three lags of the price of insured mail

Elasticities are listed in Table II-21.

c. Certified

The demand equation for certified mail models certified mail volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Transitory Income
- Time trend reflecting a long-run trend in certified mail volume
- Dummy variable reflecting the use of government-distributed volume beginning in 1988Q1.
- Current and three lags of the price of certified mail

Elasticities are listed in Table II-22.

d. Collect-on-Delivery (COD)

The demand equation for COD mail models COD mail volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)

- Time trend reflecting a long-run downward trend in COD volume
- Dummy variable for the summer, 1997 UPS strike
- Current and three lags of the price of COD mail

Elasticities are listed in Table II-23.

e. Return Receipts

The demand equation for return receipts models return receipts volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Volume of certified mail reflecting complementarity of certified mail and return receipts
- Dummy variable equal to one starting in 1995Q2, to account for an otherwise unexplained increase in return receipts volume of 15 percent beginning at that time.
- Current price of return receipts

Due to a lack of available data, the return receipts equation is estimated using a sample period only going back to 1993Q1. Return receipts volume excludes delivery confirmation. Elasticities are listed in Table II-24.

f. Money Orders

The demand equation for money orders models money orders volume as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Permanent Income (as described in section III.A.2.b. below)
- Current and three lags of the price of money orders

Elasticities are listed in Table II-25.

TABLE II-17
MAILGRAMS

	Coefficient	T-statistic
Time trend	-0.035	-6.372
Seasonal coefficients:		
September	1.386	2.742
October	0.423	0.747
November 1 - December 10	-0.101	-0.195
December 11 - 12	-4.383	-1.728
December 13 - 19	5.563	4.965
December 20 - 24	-0.553	-0.500
December 25 - February	0.411	3.066
March - June	0.497	3.466

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.688
AR-2 coefficient	0.194
Mean Square Error	0.034507
Degrees of Freedom	86
Adjusted-R^2	0.962

TABLE II-18
POSTAL PENALTY MAIL

	Coefficient	T-statistic
Time trend	-0.016	-5.401
Seasonal coefficients:		
September	0.839	0.791
October	-1.561	-1.437
November 1 - December 15	1.873	2.036
December 16 - 17	-8.080	-2.550
December 18 - January 1	10.84	2.221
January 2 - February	-2.077	-2.029
March	1.588	1.701
April 1 - 15	-4.013	-1.074
April 16 - May	1.044	0.874

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.158
AR-2 coefficient	0.428
Mean Square Error	0.013962
Degrees of Freedom	33
Adjusted-R^2	0.797

TABLE II-19

FREE-FOR-THE-BLIND-AND-HANDICAPPED MAIL

	Coefficient	T-statistic
Time trend	0.007	9.020
Seasonal coefficients:		
September - December 10	0.112	1.147
December 11 - 21	-1.768	-2.033
December 22 - January 1	1.068	1.086

REGRESSION DIAGNOSTICS :

AR-coefficients	None
Mean Square Error	0.085598
Degrees of Freedom	111
Adjusted-R^2	0.421

TABLE II-20
REGISTERED MAIL

	Coefficient	T-statistic
Registered mail price -- SUM	-0.246	-1.629
current	-0.246	-1.629
Permanent Income	0.505	29.03
Transitory Income	0.373	0.922
Time trend	-0.026	-37.11
Dummy for use of Government-Distributed Volume	0.204	6.231
Seasonal coefficients:		
December 11 - 17	0.991	2.468
December 18 - 21	-1.501	-2.227
December 22 - February	0.017	0.408
March	-0.347	-1.586
April 1 - 15	0.871	1.882
April 16 - June	-0.063	-0.627

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.004074
Degrees of Freedom	52
Adjusted-R^2	0.975

TABLE II-21
INSURED MAIL

	Coefficient	T-statistic
Insurance price -- SUM	-0.179	-2.055
current	-0.000	-0.000
lag 1	-0.047	-0.170
lag 2	-0.074	-0.257
lag 3	-0.058	-0.308
Permanent Income	0.505	31.19
Parcel post volume	0.257	6.247
Time trend	-0.016	-27.56
Dummy for Classification Reform (MC96-3)	0.530	8.989
Seasonal coefficients:		
September	-1.464	-4.982
October	-0.742	-3.213
November 1 - December 21	0.475	2.477
December 22 - 24	-2.750	-3.359
December 25 - January 1	-0.939	-1.645
January 2 - February	-0.243	-2.553
March	-0.991	-5.182
April - May	-0.263	-3.234
June	-0.900	-3.798

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.326
Mean Square Error	0.006579
Degrees of Freedom	96
Adjusted-R^2	0.982

TABLE II-22
CERTIFIED MAIL

	Coefficient	T-statistic
Certified mail price -- SUM	-0.289	-4.237
current	-0.087	-0.513
lag 1	-0.078	-0.266
lag 2	-0.000	-0.000
lag 3	-0.124	-0.699
Permanent Income	0.504	29.52
Transitory Income	0.205	0.941
Time trend	0.008	13.18
Dummy for use of Government-Distributed Volume	0.113	2.622
Seasonal coefficients:		
September - October	1.089	2.916
November 1 - December 10	-0.022	-0.188
December 11 - 17	0.740	1.364
December 18 - January 1	1.173	2.076
January 2 - February	0.264	3.065
March	1.227	3.276
April - May	0.305	3.306
June	1.304	3.049

REGRESSION DIAGNOSTICS :

AR-2 coefficient	0.243
Mean Square Error	0.006654
Degrees of Freedom	96
Adjusted-R^2	0.955

TABLE II-23
COLLECT-ON-DELIVERY

	Coefficient	T-statistic
COD price -- SUM	-0.192	-0.864
current	-0.051	-0.251
lag 1	-0.000	-0.001
lag 2	-0.032	-0.124
lag 3	-0.109	-0.528
Permanent Income	0.505	40.88
Time trend	-0.019	-15.30
Dummy for 1997 UPS Strike	0.232	2.772
Seasonal coefficients:		
September - October	0.715	2.097
November 1 - December 10	0.244	2.131
December 11 - 12	-0.515	-0.413
December 13 - 21	1.365	2.687
December 22 - 24	-0.249	-0.267
December 25 - January 1	1.457	2.183
January 2 - February	0.271	3.265
March	0.795	2.307
April 1 - 15	-0.262	-0.242
April 16 - May	0.504	1.235
June	1.040	2.776

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.545
AR-2 coefficient	0.237
Mean Square Error	0.008364
Degrees of Freedom	93
Adjusted-R^2	0.977

TABLE II-24
RETURN RECEIPTS

	Coefficient	T-statistic
Return receipts price -- SUM	-0.451	-0.754
current	-0.451	-0.754
Permanent Income	0.504	34.27
Certified mail volume	0.756	2.693
Dummy variable starting in 1995Q2	0.136	3.048
Seasonal coefficients:		
September	0.210	0.290
October 1 - December 10	0.016	0.220
December 11 - February	0.104	1.048
March - May	0.075	0.754

REGRESSION DIAGNOSTICS :

AR-4 coefficient	-0.550
Mean Square Error	0.007772
Degrees of Freedom	14
Adjusted-R^2	0.561

TABLE II-25
MONEY ORDERS

	Coefficient	T-statistic
Money orders price -- SUM	-0.430	-8.408
current	-0.219	-3.800
lag 1	-0.072	-0.971
lag 2	-0.000	-0.002
lag 3	-0.139	-2.411
Permanent Income	0.505	61.53
Seasonal coefficients:		
September - December 12	0.051	1.613
December 13 - 19	0.474	2.838
December 20 - February	0.009	0.319
March	0.252	3.491
April 1 - 15	-0.520	-2.246
April 16 - June	0.210	2.374

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.435
AR-2 coefficient	0.195
AR-4 coefficient	0.278
Mean Square Error	0.001800
Degrees of Freedom	97
Adjusted-R^2	0.962

III. Econometric Methodology for Modeling Demand Equations

A. General Regression Procedure

1. Theory of Demand

Demand equations relate the demand for some good, in this case, mail volume, to variables that are believed to influence demand. The general form of the demand equations to be estimated express mail volume as a function of income, price, and other variables which are believed to influence mail volume:

$$V_t = f(Y_t, p_t, \text{etc.}) \tag{III.1}$$

Conventionally, when economists discuss the impact of explanatory variables on the demand for a particular good or service, the measure used to describe this impact is the concept of "elasticity." The elasticity of a good, i, with respect to some explanatory variable, x, is equal to the percentage change in the quantity of good i resulting from a one percent change in x. Mathematically, the elasticity of V_t with respect to some variable, x_t, is defined as follows:

$$\eta_t^{Vx} = \frac{\partial V_t}{\partial x_t} \bullet [\frac{x_t}{V_t}] \tag{III.2}$$

where the t subscript denotes the time period for which the elasticity is being calculated.

The goal in modeling demand equations can be thought of as calculating elasticities with respect to all relevant factors affecting demand.

2. Factors Affecting Demand

a. Price

The starting point for traditional micro-economic theory is a demand equation that relates quantity demanded to price. Quantity demanded is inversely related to price, so that if the price of a good were increased, the volume consumed of that good would be expected to decline, all other things being equal.

This fundamental relationship of price to quantity is modeled in the demand equations presented in this testimony by including the price of postage in each of the demand equations discussed above (with the exception of the demand equations associated with Mailgrams, Postal penalty mail, and Free-for-the-Blind mail).

The Postal prices entered into the demand equations are calculated as weighted averages of the various rates within each particular category of mail. For example, the price of single-piece First-Class letters is a weighted average of the single-piece letters rate (33¢), the additional ounce rate (22¢), and the nonstandard surcharge (11¢). The weights used to combine these rates into a single price are the relative proportions of the category which paid each rate in GFY 1998. Because the weights used in constructing these prices do not change over time, these prices are sometimes referred to as "fixed-weight" price indices.

Experience indicates that mailers may not react immediately to changes in Postal rates. For some types of mail it may take up to a year for the full effect of changes in Postal rates to influence mail volumes. To account for the possibility of a lagged reaction to changes in Postal prices on the demand for certain types of mail, the Postal price may be entered into the demand equations lagged.

Initially, the current price as well as the price lagged one, two, and three quarters was included in the demand equations considered here. If, however, the price lagged three quarters was found to have a negligible effect on mail volume, then this price lag was removed from the equation[2]. If, after removing the third lag, the price lagged two quarters was found to have a negligible effect on mail volume, then this price lag was also removed from the equation. Finally, if after removing the second lag, the price lagged one quarter was found to have a negligible effect on mail volume, then it too is removed from the equation. Hence, the price variables included here all include the current price and may also include the price lagged one to three quarters.

The price of postage is not the only price paid by most mailers to send a good or service through the mail. For those cases where the non-Postal price of mail is significant and for which a reliable time series of non-Postal prices is available, these prices are also included explicitly in the demand equations used to explain mail volume. For example, the price of paper is included as an explanatory variable in the demand equation for Periodical regular mail, since paper is an important input in the production of newspapers and magazines.

One unique non-Postal price borne by some mailers is the cost to mailers of presorting or prebarcoding their mail in order to receive discounts from the Postal Service. These costs, called user costs, are added to the Postal prices to take account of the fact that mailers who presort or automate their mail do not receive the full savings of Postal discounts, but only save the difference between Postal discounts and the costs to the mailers necessary to earn these discounts. For those categories for which worksharing share equations are developed in section IV of my testimony below (First-Class and Standard A mail), these user costs can be calculated within the share

---

[2] Technically, negligible price lag coefficients are constrained to zero, but the price lags themselves remain in the equation. This is a minor technical point that has no substantive effect.

equation system using equation (IV.28) below. These user costs are added to the fixed-weight price indices used in modeling the demand for mail.

All prices are expressed in real 1992 dollars. The Personal Consumption Expenditure deflator from the national income accounts is used to deflate the prices.

In general, the price elasticities cited in this testimony and elsewhere refer to long-run price elasticities. The long-run price elasticity of mail category i with respect to the price of mail category i is equal to the sum of the coefficients on the current and lagged price of mail category i. The long-run price elasticity therefore reflects the impact of price on mail volume after allowing time for all of the lag effects to be felt.

b. Income

With the exception of price, the most basic economic factor affecting consumption at a theoretical level is income. As incomes rise, consumers are able to consume more. It follows logically from this that as income rises in the overall economy, overall consumption, including the consumption of Postal services, will generally rise. Thus, mail volumes can be expected to be a function of income.

Leading economists have devoted a tremendous amount of attention to looking at the relationship between income and consumption and the proper means by which to model this relationship, at both a theoretical as well as an empirical level. (For a thorough treatment of the relationship between consumption and income, see, for example, Understanding Consumption, by Angus Deaton, 1992)

i. Distinction Between Current Income and Permanent Income

At a basic theoretical level, consumers have two choices of what to do with income, they can either consume it currently or they can save it, thereby increasing their ability to consume in the future. For a simple two-period model, consumption and income can be related as follows:

> Suppose that there is a single asset, of which the consumer possesses an amount equal to A_1 at the beginning of period 1, and which earns an interest rate r_2 on savings between period 1 and period 2. The consumer also receives income in both time periods equal to y_1 and y_2, respectively. The stock of assets, A_2, will be equal to $(1+r_2)(A_1+y_1-c_1)$, where c_1 is consumption in time period 1, so that $(A_1+y_1-c_1)$ is equal to savings in time period 1. If utility is only a function of consumption, so that savings only provide positive utility insofar as they provide for future consumption, then assets will be equal to zero at the end of period 2, and consumption will be related to income according to the following relationship:

$$c_1 + \frac{c_2}{1+r_2} = A_1 + y_1 + \frac{y_2}{1+r_2} \qquad \text{(III.3)}$$

Extending the above formulation to a T-period model, equation (III.3) becomes the following:

$$\sum_{t=1}^{T} \frac{c_t}{(1+r)^{t-1}} = A_1 + \sum_{t=1}^{T} \frac{y_t}{(1+r)^{t-1}} \qquad \text{(III.4)}$$

Looking at equation (III.4), it is clear that consumption today is affected by the level of not only current income, but also of both past as well as future income. This is because past income generates past savings, which, in turn, generate current income, while current savings generate future income, which, in turn, generate future consumption, so that an increase in current consumption necessarily leads to a decrease in future consumption.

In order for equation (III.4) to hold with certainty over the entire life-cycle of an individual, it would be necessary for the consumer to know with certainty at time t=1 the exact value of T (i.e., at what point in the future the consumer would die) as well as the value of y_t for all time periods, t = 1 to T. In reality, of course, there is uncertainty with respect to both of these things. Changes in expectations regarding future income (or regarding T) may therefore be expected to change consumption decisions even before these expectations are realized.

Milton Friedman, in his seminal work A Theory of the Consumption Function (1957), hypothesized that changes in income which affect expectations about future income would therefore be expected to affect consumption more directly and significantly than would changes in income which did not affect expectations about future income.

Specifically, Friedman distinguished between "permanent" income, which he defined as expected total wealth, and "transitory" income, which he defined as the difference between current income and "permanent" income. Under this set-up, permanent income differs from current income for two reasons: differences between current income and expected future income, and differences between income and wealth.

Friedman's permanent income hypothesis stated that the relationship between consumption and permanent income would be stronger than the relationship between consumption and transitory income. This hypothesis has become a staple of general micro-economic theory, and continues to be applied in a wide range of contexts throughout the economics profession.

The distinction between permanent income and current income in understanding consumption patterns is apparent, for example, in evaluating consumption patterns by age. Young people, anticipating increasing future income, will consume more than would be suggested by current income levels, incurring debt (e.g., student loans, mortgages), which, it is expected, will be paid for by higher future incomes. Using Friedman's terminology, the permanent income of young people exceeds their current income. On the other hand, middle-aged people generally consume less, saving for retirement, when their incomes are expected to decline. Hence, the permanent income of middle-aged people is less than their current income, explaining why middle-aged people consume a smaller proportion of their current income than do young people.

Or, consider a single individual who receives a $1,000 raise at work versus an individual who wins $1,000 in the lottery. In both cases, the current income of the individual is $1,000 greater than it had been. In the first case, however, this $1,000 raise is expected to be permanent, in the sense that this additional $1,000 will also yield an additional $1,000 next year and on into the future. In the latter case, however, the additional $1,000 is not permanent, as expectations regarding future incomes should not be affected by having won the lottery. In this case, the different expectations inherent in the additional $1,000 of current income will likely have dramatically different impacts on current consumption patterns.

ii. Calculation of Permanent Income

Relating equation (III.4) to the permanent income hypothesis, permanent income can be expressed as a function of current and expected future income. Expected future income can be expressed as a function of current and past values of income.

Combining these two relationships, Friedman suggested that permanent income could be expressed as a weighted average of current and past income, where the weights decline exponentially moving farther back from the current period. Thinking about this another way, we can think of permanent income today as being equal to permanent income last time period, adjusted based on new information drawn from the level of current income. This simplifies the calculation of permanent income into a simple function of past permanent income and current income:

$$Y^{p}_{t} = (1-\alpha)Y_{t} + \alpha Y^{p}_{t-1} \qquad \text{(III.5)}$$

where Y refers to current income, and is equal to real personal disposable income per adult in my work, Y^p refers to permanent income, and α is equal to the weight given to last period's permanent income in calculating permanent income. Using annual data, Friedman hypothesized that the value of α was approximately equal to (2/3), or 0.67. This value is converted to a quarterly value by raising this value to the (1/4)th power, yielding a value of α = 0.905, and a value of (1-α) of 0.095.

Based on historical evidence, it is known that income will, in general, rise over time. This expected rise in future income ought to be incorporated, therefore, into the calculation of permanent income. This is done in my work by adjusting the calculated value of permanent income in equation (III.5) above by a growth rate, G, which is equal to the historical quarterly compound growth rate of income. This presumes that expectations of future income growth are based on observed historical growth rates. The historical value of G used here is equal to 1.00314, or 0.314% quarterly compound growth over this time period, which is equal to the average quarterly growth in personal disposable income from 1970 to the present time. Hence, the permanent income variable is calculated based on the following equation:

$$Y^{p}_{t} = 0.905 \bullet (1.00314 \bullet Y^{p}_{t-1}) + 0.095 \bullet Y_{t} \qquad \text{(III.6)}$$

iii. Income Variables used in Postal Demand Equations

(a) Use of Permanent and Transitory Income

For those types of mail which are either basic consumption goods or services (i.e., provide utility to consumers directly, such as greeting cards or personal correspondence) or which are derived demands which derive directly from basic consumption goods or services (e.g., bills and bill-payments, which derive from consumption purchases), personal consumption theory is appropriate in understanding the relationship between income and the demand for these types of goods and services. Hence, it is appropriate to distinguish the effects of permanent and transitory income on the demand for these types of mail.

For demand equations for this type of mail -- which includes First-Class, Periodical, and most Standard B mail, as well as special services -- separate measures of permanent and transitory income are included in the demand equations estimated for this case.

Permanent income in the time series regressions is calculated using equation (III.6) above. Permanent income is expressed in constant 1992 dollars, and is deflated by adult population for consistency with the mail volume variables used as the dependent variables in the equations.

The measure of transitory income used is the Federal Reserve Board index of capacity utilization for the manufacturing sector of the economy, which has been found to track the general business cycle quite closely. For several categories of mail, transitory income is entered into the demand equations lagged, to reflect a lagged relationship between overall consumption and the derived consumption of mail volumes. In some cases, transitory income was found to have no impact on the demand for mail volumes. This is consistent with the permanent income hypothesis outlined above.

(b) Use of Personal Consumption Expenditures

Income does not play the same role in the demand for direct-mail advertising as it does in the demand for other mail categories. The demand for direct-mail advertising, from the perspective of the advertiser, is a function of expected consumption. The permanent income hypothesis can be used to express expected consumption as a function of expected permanent income. Hence, the demand for advertising mail volume could logically be expressed as a function of permanent (and transitory) income. In this case, however, the relationship is more directly between advertising mail volume and consumption expenditures, rather than between advertising mail volume and the factors which would be expected to drive consumption expenditures. Hence, for this case, the more direct relationship between direct-mail advertising volume and consumption expenditures was modeled by including personal consumption expenditures in the demand equations for direct-mail advertising (i.e., Standard A mail volume).

(c) Use of Retail Sales

Parcel post mail is almost exclusively the delivery of products bought by the sender or recipient of parcel post. Hence, parcel post volume derives almost directly from retail sales. While retail sales are, of course, a function of permanent and transitory income, retail sales are included directly in the parcel post demand equation above to reflect the more direct relationship between retail sales and parcel post volume.

c. Treatment of Seasonality

The volume data used in modeling the demand for mail are quarterly in nature. In observing quarterly mail volumes historically, one of the dominant characteristics of the mail is the strong quarterly seasonal pattern. For example, Christmas is a strong season for most mail categories, with volumes being significantly greater than at other times of the year. Individual mail categories also have other individual seasonal patterns in specific time periods (e.g., single-piece First-Class letters volume is strong on April 15th due to individual tax returns, bound printed matter volume is strong in September due in part to the delivery of seasonal catalogs).

For quarterly time series data, the traditional econometric technique for modeling seasonality is to include dummy variables associated with the four quarters of the year (i.e., a variable equal to one in the first quarter of every year, and equal to zero otherwise; a variable equal to one in the second quarter of every year, and equal to zero otherwise; etc.). Three of these dummy variables are then traditionally included as explanatory variables in a regression (with the impact of the fourth season captured within the regression's constant term). Alternatively, more sophisticated techniques of modeling seasonality include introducing fourth-order autoregressive processes or more advanced mathematical techniques such as spectral analysis which model mail volume in a particular period as being determined in part by mail volume in the same period the year before.

i. The Postal Calendar

The Postal Service reports data using a 52-week Postal calendar, composed of 13 28-day accounting periods. Because the 52-week Postal year is only 364 days long, the beginning of the Postal year, as well as the beginning of each Postal quarter, shifts over time relative to the traditional Gregorian calendar. Specifically, the Postal calendar loses five days every four years relative to the Gregorian calendar.

Postal 1971 began on October 17, 1970. Postal 1999 ended on September 10, 1999. Hence, these twenty-nine Postal years are, in fact, 36 days short of 29 full years. From the first day of Postal 1971 through the end of Postal 1999 (the longest sample period used for any of the demand equations modeled in my testimony), a total of 141 days shifted between Postal quarters (e.g., were in Quarter 1 for part of the time period and in Quarter 2 for the remainder of the time period) -- September 11th through October 16th, December 4th through January 8th, February 27th through April 2nd, and May 23rd through June 25th.

Prior to 1983, Christmas Day fell in the first Postal quarter of the year (the Postal year begins in the previous Fall -- e.g., Postal 2000 began on September 11, 1999). Since 1983, however, Christmas Day has fallen within the second Postal quarter. Between 1983 and 1999, the second Postal quarter gained 22 days in December preceding Christmas (December 4th through December 25th) which are among the Postal Service's heaviest days in terms of mail volume. Not surprisingly, therefore, the relative volumes of mail in Postal Quarter 1 and Postal Quarter 2 have changed over this time period for most mail categories, as Christmas-related mailings have shifted from the first Postal quarter to the second Postal quarter, due solely to the effect of the Postal Service's moving calendar.

This creates a potential source of difficulty in attempting to model the seasonal pattern of mail volume using traditional econometric techniques, such as simple quarterly dummy variables. If the seasonal pattern of mail volume is due to seasonal variations within the Gregorian calendar (e.g., Christmas), then the perceived seasonal pattern across Postal quarters may not be constant over time, even if the true seasonal pattern across periods of the Gregorian calendar is constant over time.

ii. Definition of Seasons for Econometric Purposes

In Docket No. R94-1, seasonality was modeled by simple quarterly dummies which corresponded to the Postal calendar. Movements in seasonality over time were accounted for by the use of an X-11 seasonal adjustment procedure.

In R97-1, the seasonal variables used in the regressions were redefined to correspond to constant time periods in the Gregorian calendar. Defining seasons in this way turns the moving Postal calendar into an advantage, because it allows us to isolate more than just four seasons, even with simple quarterly data.

A total of seventeen seasonal variables were used in R97-1. These seasons correspond to the following periods of the Gregorian calendar:

September
October
November 1 - December 10
December 11 - December 12
December 13 - December 15
December 16 - December 17
December 18 - December 19
December 20 - December 21
December 22 - December 23
December 24
December 25 - January 1
January 2 - February 28 (29th in leap years)
March 1 - March 31
April 1 - April 15[3]
April 16 - May 31

[3] This season runs through the day that Federal income tax returns are due. This is April 15th unless April 15th falls on a weekend, in which case it is the Monday immediately following April 15th.

June 1 - June 30
July 1 - August 31

For any given quarter, the value of each seasonal variable was set equal to the proportion of business days within the quarter that fell within the season of interest. For purposes of calculating business days, Sundays were not counted, while Saturdays were counted as one-half business days. In addition, seven common business holidays were not counted as business days to reflect the lack of business activity (and hence, mail volume) on these days. The seven holidays excluded from the count of business days here are: January 1st, Memorial Day, July 4th, Labor Day, Thanksgiving, the day after Thanksgiving, and Christmas. These same variables are again used in this case.

An example of the construction of two of these variables may be instructive. Consider, for example, the values of the seasons, September and October, for Postal 1996.

Postal 1996Q1 spans the time period from September 16, 1995 through December 8, 1995, and includes a total of 64 business days (12 weeks @ 5.5 business days per week minus Thanksgiving and the day after Thanksgiving). The period from September 16, 1995 through September 30, 1995 falls within the season of September as well as 1996Q1. This time period encompasses a total of 11.5 business days (15 total days less 2 Sundays and one-half of 3 Saturdays). Hence, the seasonal variable September has a value equal to (11.5/64) in 1996Q1. The period from October 1, 1995 through October 31, 1995 falls within the season of October as well as 1996Q1. This time period encompasses a total of 24 business days (31 total days less 5 Sundays and one-half of 4 Saturdays). Hence, the seasonal variable October has a value equal to (24/64) in 1996Q1.

Postal 1996Q2 spans the time period from December 9, 1995 through March 1, 1996. Postal 1996Q3 spans the time period from March 2, 1996 through May 24, 1996. Neither of these quarters overlap with any of September or October. Hence, the value of both September and October are set equal to zero for both 1996Q2 and 1996Q3.

Postal 1996Q4 spans the time period from May 25, 1996 through September 13, 1996, and includes a total of 85 business days (16 weeks @ 5.5 business days per week minus Memorial Day, July 4th, and Labor Day). The period from September 1, 1996 through September 13, 1996 falls within the season of September as well as 1996Q4. This time period encompasses a total of 9.5 business days (13 total days less Labor Day, 2 Sundays, and one-half of 1 Saturday). Hence, the seasonal variable September has a value equal to (9.5/85) in 1996Q4. The month of October does not intersect with 1996Q4 at all. Hence, the value of October is set equal to zero for 1996Q4.

iii. Use of Seasonal Variables Econometrically

The 17 seasonal variables defined as outlined above are used to model the seasonal pattern of mail volumes econometrically. Sixteen of the 17 seasonal variables are included in each econometric equation. The excluded seasonal variable is the variable covering the period from July 1st through August 31st, the effect of which is captured implicitly within the constant term. The coefficients on the sixteen included seasonal variables are estimated along with the other econometric parameters as described below.

In an effort to maximize the explanatory power of the seasonal variables, taking into account the cost of including these variables, in terms of degrees of freedom, the coefficients on adjoining seasons that were similar in sign and magnitude were constrained to be equal. For example, the coefficients on the seasonal variables spanning the time period from December 18th through January 1st were constrained to be equal in the private First-Class cards equation. These constraints across seasons were done on an equation-by-equation basis. The criterion used for this constraining process was generally to minimize the mean-squared error of the equation, which is equal to the sum of squared residuals divided by degrees of freedom.

The estimated effects of the 16 seasonal variables can be combined into a seasonal index, which can be arrayed by Postal quarter to observe the quarterly seasonal pattern and to understand how this seasonal pattern changes over time as a result of the moving Postal calendar. Such an index is presented as part of the full econometric output from my demand equations filed in Workpaper 1 accompanying my testimony.

3. Functional Form of the Equation

a. General Specification of Demand Equations

The demand equations modeled in my testimony take on the following form:

$$V_t = \alpha \bullet X_{1t}^{\beta_1} \bullet X_{2t}^{\beta_2} \bullet X_{3t}^{\beta_3} \bullet \ldots e^{\epsilon_t} \qquad \text{(III.7)}$$

where V_t is the volume of mail at time t; X_1, X_2, X_3, ... are explanatory variables which influence mail volume, and ϵ_t is a residual term reflecting other influences on mail volume, which is assumed to be identically and independently normally distributed with an expected value of zero (so that e^{ϵ_t} is lognormally distributed with an expected value of one).

This demand function is a common functional form in empirical econometric work. It was chosen in this case because it has been found to model mail volume quite well historically. In addition, the demand equation in equation (III.7) possesses two desirable properties. First, by taking logarithmic transformations of both sides of equation (III.7), the natural logarithm of V_t can be expressed as a linear function of the natural logarithms of the X_i variables as follows:

$$\ln(V_t) = \ln(\alpha) + \beta_1 \bullet \ln(X_{1t}) + \beta_2 \bullet \ln(X_{2t}) + \beta_3 \bullet \ln(X_{3t}) + \ldots + \epsilon_t \qquad \text{(III.8)}$$

Equation (III.8) satisfies the traditional least squares assumptions, and is amenable to solving by Ordinary Least Squares. To acknowledge this property, this demand function is sometimes referred to as a log-log demand function, to reflect the fact that the natural logarithm of volume is a linear function of the natural logarithm of the explanatory variables.

The second desirable property of equation (III.7) is that the β_i parameters are exactly equal to the elasticities with respect to the various explanatory variables. Hence, the estimated elasticities do not vary over time, nor do they vary with changes in either the volume or any of the explanatory variables. For this reason, this demand function is sometimes referred to as a constant-elasticity demand specification.

b. Data Used in Modeling Demand Equations

Quarterly mail volumes for the various mail categories are used in each regression as the dependent variable in the demand equations presented in my testimony. These quarterly volume figures were taken from the Postal Service's RPW system.

Quarterly volumes are divided by the number of business days in the quarter to obtain volume per business day. Mondays through Fridays are counted as one business day. Saturdays are counted as ½ business day. Sundays are not considered business days. In addition, seven holidays -- New Year's Day, Memorial Day, July 4th, Labor Day, Thanksgiving, the day after Thanksgiving, and Christmas -- are not considered business days.

One factor affecting changes in mail volume historically is population. As the population of the United States grows, mail volume can be expected to grow approximately in proportion. It is extremely difficult to estimate the impact of population growth on mail volume growth econometrically, however, due to the relatively smooth series of population historically. An assumption that a one percent change in the adult population of the United States would lead to a comparable one percent change in mail volume for all categories of mail provides a reasonable way around this unfortunate shortcoming. For this reason, mail volumes were further divided by the population of persons 22 years of age and older prior to being used in the demand equations.

The resulting series of quarterly volume per business day per adult is then used as the dependent variable in the demand equations described in section II above.

The volumes used in the demand equations discussed above exclude government mail prior to 1988. Since 1988, however, the volumes include government mail, distributed by mail category. This break in the data is modeled by the inclusion of a dummy variable (named GDIST) which is equal to zero through 1987Q4 and equal to one thereafter, to reflect that data after that time is Government-Distributed, in the equations for those mail categories for which there is a non-trivial amount of government mail.

If the volume of government mail was proportional to the volume of non-government mail for a particular category of mail, then the volume of mail in that category including government mail could be related to the volume excluding government mail according to the following formula:

$$\mathrm{Vol}_{\mathrm{incl.\ govt.\ mail}} = e^{k} \cdot \mathrm{Vol}_{\mathrm{excl.\ govt.\ mail}} \qquad \text{(III.9)}$$

for some constant k. Taking the natural logarithm of both sides of equation (III.9) yields the following equation:

$$Ln(Vol_{incl.\ govt.\ mail}) = k + Ln(Vol_{excl.\ govt.\ mail}) \quad (III.10)$$

If the value of k were truly constant across all time periods, and the demand equation for mail volume were perfectly specified otherwise, then the coefficient on GDIST would be exactly equal to k for each mail category (where k could vary across mail categories). A fitted value of k can be calculated for any quarter for which mail volumes were reported both with and without government mail volume distributed, and would be equal to

$$k_t = Ln(Vol_{incl.\ govt.\ mail}) - Ln(Vol_{excl.\ govt.\ mail}) \quad (III.11)$$

Ideally, the coefficient on GDIST ought to be freely estimated in order to maximize its explanatory power. In the cases of Standard Regular and Standard ECR mail, however, the freely estimated coefficients on GDIST were somewhat unstable. Hence, these coefficients were constrained based on the observed level of government mail volume between 1988 and 1992 using equation (III.11). These constraints were introduced stochastically based on the observed variance in the value of k_t between 1988 and 1992.

The natural logarithm of mail volume per adult per business day is modeled as a function of a set of explanatory variables of the form of equation (III.8) above. In general, the explanatory variables are entered into the demand equation in logarithmic form. An exception, however, is those variables which take on a value equal to zero over some portion of their relevant history. The natural logarithm of zero does not exist. Consequently, variables which take on a value of zero at some point in the regression period must be entered into the demand equations in their natural state, unlogged. For variables which are entered into the equation unlogged, the modeled relationship between mail volume and these variables is the following:

$$V_t = A \cdot e^{X_t \beta} \qquad \text{(III.12)}$$

and the elasticity of V_t with respect to X_t is equal to $\beta \cdot X_t$.

B. Methodology for Solving Equation (III.8)

1. Basic Ordinary Least Squares Model

Equation (III.8) can be re-written in matrix form as follows:

$$y = X\beta + \epsilon \qquad \text{(III.13)}$$

where y is equal to $\ln(V_t)$, expressed as a vector, X is a matrix with columns equal to explanatory variables, $\ln(X_1)$, $\ln(X_2)$, $\ln(X_3)$, etc., expressed as vectors, β is a vector of β_1, β_2, β_3, etc., and ϵ is equal to ϵ_t, expressed as a vector.

If $E(\epsilon_t) = 0$, and $var(\epsilon_t)$ is equal to σ^2 for all t, so that $var(\epsilon) = \sigma^2 I_T$, then the best linear unbiased estimate of the coefficient vector, β, is equal to

$$b = (X'X)^{-1}X'y \qquad \text{(III.14)}$$

This is the Ordinary Least Squares (OLS) estimate and is among the oldest and most traditional results in all of econometrics. If the error term is not identically distributed (i.e., $var(\epsilon_t)$ is not equal to σ^2 for all t), or if the error term is not uncorrelated through time (i.e., $cov(\epsilon_t, \epsilon_{t-j}) \neq 0$ for some $j \neq 0$), then the variance-covariance matrix of ϵ can be expressed as, $var(\epsilon) = \sigma^2\Sigma$, and the restriction on the variance of ϵ_t can be eased by introducing Σ into equation (III.14) as follows:

$$b = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}y \qquad \text{(III.15)}$$

Equation (III.15) is called the Generalized Least Squares (GLS) estimate of β.

2. Introduction of Outside Restrictions into OLS Estimation

To introduce restrictions into the OLS estimator, define a vector of restrictions, d, and a restriction matrix, C, such that $C \bullet \beta = d$. If the restrictions are known with certainty, as for example, the restrictions imposed upon the seasonal variables that concurrent seasons with comparable coefficients are constrained to have equal coefficients, then the OLS estimator is modified as follows to yield a Restricted Least Squares (RLS) estimate of the regression coefficients:

(OLS Estimator) $\quad b = (X'X)^{-1}X'y$

(RLS Estimator) $\quad b^{\wedge} = b + (X'X)^{-1}C'[C\,(X'X)^{-1}C']^{-1} \bullet (d - Cb) \qquad$ (III.16)

To introduce restrictions which are not known with certainty (i.e., stochastic restrictions), define a restriction matrix, R and a vector of restrictions, r, such that

$$r = R\beta + v$$

where v is a random variable, such that $E(v) = 0$ and $var(v) = \sigma^2\Omega$.

In all cases where stochastic restrictions are introduced in this case, the matrix Ω is a diagonal matrix with the variances associated with r along the diagonal.

The OLS estimator is modified as follows to yield a Least Squares estimate with stochastic restrictions:

(Stochastic Restrictions Estimator) $\quad b^{*} = (X'X + R'\Omega^{-1}R)^{-1}(X'y + R'\Omega^{-1}r) \qquad$ (III.17)

Finally, exact and stochastic restrictions can be combined within a single estimator, which satisfies the following formula:

(OLS Estimator incorporating outside information)

$$b^{*} = (X'X + R'\Omega^{-1}R)^{-1}(X'y + R'\Omega^{-1}r)$$

$$b^{**} = b^{*} + (X'X + R'\Omega^{-1}R)^{-1}C'[C\,(X'X + R'\Omega^{-1}R)^{-1}C']^{-1}\bullet(d-Cb^{*}) \qquad \text{(III.18)}$$

If $E(R\beta) = r$, then the most efficient, unbiased GLS estimator incorporating outside information is similarly modified from equation (III.15) as follows:

$$b^{*} = (X'\Sigma^{-1}X + R'\Omega^{-1}R)^{-1}(X'\Sigma^{-1}y + R'\Omega^{-1}r)$$
$$b^{**} = b^{*} + (X'\Sigma^{-1}X + R'\Omega^{-1}R)^{-1}C'[C\,(X'\Sigma^{-1}X + R'\Omega^{-1}R)^{-1}C']^{-1}\bullet(d-Cb^{*}) \qquad \text{(III.19)}$$

For a full treatment of the introduction of outside restrictions into the OLS model, see, for example, The Theory and Practice of Econometrics, by Judge, et al., pp. 51 - 62.

Equation (III.19) forms the basis for estimating the demand coefficients presented and discussed here in my testimony.

3. Multicollinearity

In order for the OLS estimator, b, to be defined, the value of $(X'X)^{-1}$ must be defined. This requires that the matrix (X'X) must be of rank k if (X'X) is a k-by-k matrix. This will be strictly true as long as there is no independent variable in X which can be expressed as a linear combination of the other variables that make up X. So long as this is the case, perfect multicollinearity will not exist, and equation (III.14) above will be uniquely solvable.

As a practical matter, if there are variables within X which are near-perfect linear combinations of one another, however, there will exist some degree of multicollinearity. In such a case, the OLS estimators will be unbiased, but may have extremely large variances about the estimates.

Suppose, for example, that the X-matrix of explanatory variables in equation (III.14) were to be divided into two separate matrices, X_1 and X_2, so that

$$y = X_1\beta_1 + X_2\beta_2 + \epsilon \quad \text{(III.20)}$$

Suppose further that the explanatory variables that make up X_1 (e.g., x_1, x_2, x_3) are highly correlated, so that, for example, $x_1 \approx a_1 \bullet x_2 + a_2 \bullet x_3$, for some constants a_1, a_2. The aggregate impact of these variables on the dependent variable ($X_1\beta_1$ in equation (III.20)) will be accurately estimated. The estimated standard errors associated with the coefficients on x_1, x_2, and x_3 will be quite large, however, so that the values of b_1, b_2, and b_3, associated with x_1, x_2, and x_3, respectively, will be poorly estimated.

If one's goal is simply to fit y as well as possible (i.e., to minimize ϵ), then Ordinary Least Squares should be sufficient. If, however, one's goal is to obtain the best possible estimate for each individual coefficient, β_i , it may be necessary to develop independent estimates of some of the elasticities, in cases where high multicollinearity is known to exist,.

The need for additional information is expounded on quite clearly in The Theory and Practice of Econometrics, 2nd edition, by George G. Judge, et al. (1985):

> "Once detected, the best and obvious solution to [this] problem is to ... incorporate more information. This additional information may be reflected in the form of new data, a priori restrictions based on theoretical relations, prior statistical information in the form of previous statistical estimates of some of the coefficients and/or subjective information." (p. 897)

Multicollinearity will be a problem to at least some degree in any empirical econometric work. In the present work, multicollinearity is particularly acute with regard to a high degree of correlation between permanent income and other economic and trend variables, a high degree of correlation between current and lagged prices of Postal products, and a high degree of correlation between the prices of competing Postal products. The techniques by which the demand equation estimation procedure is refined to account for each of these cases of multicollinearity are described below.

a. Income Coefficients

Permanent income is highly correlated with many other economic and trend variables, making estimation of permanent income elasticities difficult using quarterly time series data. For example, the simple correlation between permanent income and a simple time trend between 1971Q1 and 1999Q4 is equal to 0.9945, indicating near-perfect multicollinearity between these variables.

Because of the high degree of correlation between permanent income and other explanatory variables, permanent income elasticities estimated exclusively from the quarterly time series data are somewhat unstable, and often take on implausible values. Table III-1 below presents freely-estimated permanent income elasticities for those categories of mail for which permanent income is included in the demand equations discussed in section II above.

As Table III-1 indicates, the estimated permanent income elasticity is unexpectedly negative in many cases, and appears to be larger than might be expected from economic theory in several other cases. Even for those estimated permanent income elasticities that are of a reasonable magnitude, the t-statistics associated with these estimates are fairly low in most cases.

Table III-1
Permanent Income Elasticities Estimated from Time Series Data

Mail Category	Permanent Income Elasticity Estimated from Time Series Data (T-Statistics in Parentheses)	
First-Class Mail		
First-Class Letters		
Single-Piece	0.596	(1.565)
Workshared	0.650	(0.907)
First-Class Cards		
Stamped Cards	-1.031	(-1.335)
Private Cards	-0.055	(-0.530)
Periodical Mail		
Regular Rate	0.216	(0.281)
Within County	-2.285	(-1.649)
Nonprofit	2.041	(0.761)
Classroom	-0.487	(-0.067)
Standard B Mail		
Bound Printed Matter	0.930	(2.440)
Special Rate	-0.394	(-0.809)
Library Rate	-2.514	(-3.650)
Special Services		
Registered Mail	4.380	(2.875)
Insured Mail	0.824	(0.646)
Certified Mail	-3.495	(-4.364)
COD	0.430	(0.135)
Return Receipts	-0.837	(-1.363)
Money Orders	0.441	(0.879)

In addition to the quarterly time series data, however, it is also possible to estimate the relationship between income and mail volume from the Household Diary Study. The Household Diary Study contains cross-sectional data on mail volume received by households as well as on demographic characteristics including household income. The Household Diary Study can thus be used to measure the difference in mail volume received across households based on differences in the income of these households. This provides an estimate of the impact of mail volume received by households on changes in household income. At an aggregate level, this is equivalent to the impact on mail volume of changes in the level of income in the economy as a whole.

The permanent income elasticities are introduced into the quarterly time series regressions as stochastic restrictions using equation (III.19) above. The details of the cross-sectional estimation of the permanent income elasticities and their standard errors are given in Workpaper 2 accompanying my testimony.

The Household Diary Study does not provide explicit information on consumption expenditures or retail sales by household. Hence, it was not possible to estimate the relationship between Standard A mail volumes and personal consumption expenditures or the relationship between parcel post and retail sales from the Household Diary Study. These effects are hence estimated exclusively from the time series data on Standard A and parcel post mail.

b. Shiller Smoothness Priors

Experience suggests that there may be a lagged reaction by mailers to changes in Postal prices, so that mail volumes are affected not only by the current Postal price but also by lagged prices. Because Postal prices change relatively infrequently, however, the current Postal price is highly correlated with lagged Postal prices. For example, the simple correlation coefficient on the price of Periodical regular mail and the price of Periodical regular mail lagged one quarter is equal to 0.987 over the Periodical regular sample period used in this case. This represents a classic case of the multicollinearity problem outlined in equation (III.20) above. The aggregate effect of price on mail volume can be very accurately modeled, while the coefficients on the individual lags of price may be highly erratic and unstable.

Because the lags of price play an important role in forecasting the impact of the proposed rate changes in this case, however, it is important not only that the long-run (i.e., aggregate) impact of price on mail volume be accurately modeled, but also that the impacts of the individual lags be accurately modeled.

Dr. Robert Shiller proposed a solution to this problem in a 1973 article in Econometrica (Robert J. Shiller, "A Distributed Lag Estimator Derived from Smoothness Priors," Econometrica, July 1973, pp. 775-788). Dr. Shiller's technique allows a polynomial equation to be used to adjust a set of coefficients so that the coefficients will follow a reasonable pattern. For this testimony, the current and four lags of Postal prices are included initially in the demand equations for mail volumes. A quadratic pattern is stochastically imposed on the price coefficients. Dr. Shiller refers to the quadratic constraint used in this case as a constraint with a degree of smoothness equal to one.

Dr. Shiller's proposed technique represents a special case of a stochastic restriction, as outlined above in equation (III.19). In particular, the GLS estimator is modified as follows to generate Shiller distributed lags:

$$b^S = (X'\Sigma^{-1}X + \sum_{i=1}^{P} k_i^2 \cdot S_i' S_i)^{-1} X' \Sigma^{-1} y \qquad \text{(III.21)}$$

A unique matrix, S_i, is developed for each price distribution for which Shiller restrictions are applied. P in equation (III.21) refers to the number of such distributions. If there are k explanatory variables in the equation and variables j through j+4 are the current and first through fourth lag of price i, the S_i matrix will assume the following form:

$$S_i = \begin{array}{c} \begin{array}{ccccccccccccc} x_1 & x_2 & \cdots & x_{j-1} & x_j & x_{j+1} & x_{j+2} & x_{j+3} & x_{j+4} & x_{j+5} & \cdots & x_k \end{array} \\ \left| \begin{array}{ccccccccccccc} 0 & 0 & \cdots & 0 & 1 & -2 & 1 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 1 & -2 & 1 & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 1 & -2 & 1 & 0 & \cdots & 0 \end{array} \right| \end{array}$$

The variable k_i^2 is equal to the variance of the full model (σ^2) divided by the variance of the smoothness restriction (ρ_i^2). As ρ_i^2 approaches zero, k_i^2 will approach infinity, and b^S will approach a strict quadratic (Almon) Distributed lag. As ρ_i^2 approaches infinity, k_i^2 will approach zero, and b^S in equation (III.21) will approach the GLS estimator, b in equation (III.15). A unique value of k_i^2 is estimated for each price to which the Shiller restriction is being applied.

The values of k^2_i are chosen prior to estimation. The goal of the estimation procedure used in this case was to minimize the value of k^2_i, subject to a prior expectation about the general shape of the price distribution. The values of k^2_i are minimized through a search technique which evaluates the price distribution for each value of k^2_i. An acceptable pattern for price coefficients is defined as one for which all price coefficients have the same sign.

The smallest values of k^2_i for each price distribution which yield price coefficients which are all the same sign are chosen and used in making the final coefficient estimates presented in my testimony.

In all cases, the coefficient on the fourth lag of price is constrained to be exactly equal to zero. This is based on an expectation that all mailers should be able to fully adjust to any rate changes within three quarters. If, given the optimal value of k^2_i, the coefficient on the third price lag is negligible, then the coefficient on the third lag of price is constrained to be equal to zero, and the value of k^2_i is re-optimized. If, given this new optimal value of k^2_i, the coefficient on the second price lag is negligible, then the coefficient on the second lag of price is constrained to be equal to zero, and the value of k^2_i is re-optimized. Finally, if, given this new optimal value of k^2_i, the coefficient on the first price lag is negligible, then the coefficient on the first lag of price is constrained to be equal to zero. In this last case, only the current price appears in the demand equation, so that no Shiller restriction is necessary.

c. Slutsky-Schultz Symmetry Condition

i. Derivation of the Slutsky-Schultz Condition

In addition to Postal prices being highly correlated with their own lags, Postal prices are also highly correlated with one another. All Postal prices tend to rise at the same time every three years or so in response to omnibus rate cases. Between rate cases, all real Postal prices fall together at the rate of inflation. For example, the simple correlation coefficient between the prices of single-piece First-Class letters and private single-piece First-Class cards was equal to 0.733 between 1983Q1 and 1999Q4. This correlation between Postal prices makes it difficult to estimate cross-price relationships between Postal categories.

Cross-price relationships are modeled between First-Class letters and cards, between First-Class letters and Standard Regular mail, and between parcel post and Priority Mail in my testimony. Because of the difficulty in isolating the effects of these prices separately due to multicollinearity, the cross-price elasticity between First-Class letters and Standard Regular mail is not estimated from the quarterly time series data, but is instead derived from the Household Diary Study. The econometric estimation of cross-price relationships between First-Class letters and cards are helped by a relationship known as the Slutsky-Schultz relationship.

The Slutsky-Schultz cross-price relationship is premised on the fact that, for two goods i and j, the change in the volume of good i attributable to a change in the price of good j is equal to the change in the volume of good j attributable to a change in the price of good i, or, mathematically,

$$\frac{\partial V_i}{\partial p_j} = \frac{\partial V_j}{\partial p_i} \qquad \text{(III.22)}$$

The elasticity of V_i with respect to p_j is equal to

$$e_{ij} = \frac{\partial V_i}{\partial p_j} \bullet \frac{p_j}{V_i}, \text{ so that, rearranging terms: } \frac{\partial V_i}{\partial p_j} = e_{ij} \bullet \frac{V_i}{p_j} \qquad \text{(III.23)}$$

Combining equation (III.22) with equation (III.23) yields the following relationship:

$$e_{ij} \bullet \frac{V_i}{p_j} = e_{ji} \bullet \frac{V_j}{p_i}, \text{ so that, rearranging terms, } \frac{e_{ij}}{e_{ji}} = \frac{V_j \bullet p_j}{V_i \bullet p_i} \qquad \text{(III.24)}$$

In words, equation (III.24) states that the ratio of cross-price elasticities is equivalent to the ratio of expenditures on goods i and j. This is called the Slutsky-Schultz symmetry condition.

The Slutsky-Schultz symmetry condition can be used to gauge the reasonableness of the cross-price elasticities between Postal categories estimated from the quarterly time series data, and, if necessary, to adjust the cross-price elasticities to more reasonable values.

If the ratio of expenditures between goods i and j varies over time, equation (III.24) indicates that the ratio of the cross-price elasticities will vary in the same way. This suggests that one or both of the cross-price elasticities must be non-constant over time. The functional form used to model demand in my testimony treats both cross-price elasticities as if they were constant over time, however. Hence, at best, a strict application of equation (III.24) can only be imposed for a single point in time.

While it may be mathematically possible to devise an equation system whereby equation (III.24) holds at all points in time, such a procedure would introduce a significant level of complication into the present model, with relatively little gain in terms of understanding the factors which drive mail volume. It would, however, be ill-advised to forgo the underlying theory of equation (III.24) in modeling cross-price relationships between Postal categories simply because equation (III.24) cannot be made to hold with exact equality throughout the sample period.

For our purposes, equation (III.24) is imposed when necessary using a fixed set of expenditures, so that equation (III.24) is absolutely true at only one particular point in time. Since the primary purpose of the demand equations developed here is for forecasting, equation (III.24) is imposed using expenditure ratios in a recent year, 1998. The use of 1998 is consistent with the use of 1998 billing determinants in constructing the fixed-weight price indices used in estimating the demand equations. By using the expenditure ratio from a recent year in this way, the Slutsky-Schultz relationship is maintained as strictly as possible in the forecast period, while maintaining the overall simplicity of the demand equation estimation procedure.

ii. Cross-Price Relationship between First-Class Letters and Cards

The cross-price elasticity between First-Class letters and First-Class cards can be estimated from each of three equations: the single-piece First-Class letters equation, the workshared First-Class letters equation, and the private First-Class cards equation. These three estimates are as follows (t-statistics in parentheses):

Equation	Cross Price with respect to	Free
Single-Piece Letters	Single-Piece Cards	-0.010 (-0.079)
Workshared Letters	Workshared Cards	0.068 (0.662)
First-Class Cards	First-Class Letters	0.228 (1.844)

The cross-price elasticities with respect to cards from the First-Class letters equations are not essentially different from zero, while the elasticity from the cards equation is significant at the 90 percent level. Hence, the cross-price relationship between First-Class letters and cards was estimated from the private First-Class cards equation, and the cross-price elasticities with respect to single-piece and workshared First-Class letters were calculated from the private cards equation using the Slutsky-Schultz relationship. The Slutsky-Schultz relationship was stochastically imposed on the sum of the current and lagged cross-price variables in the First-Class letters equations. The relationship was imposed stochastically to reflect the fact that the cross-price elasticity in the private cards equation was estimated with some degree of uncertainty. In addition, the stochastic constraint allows the estimated cross-price elasticities to differ somewhat with respect to single-piece and workshared First-Class letters.

4. Autocorrelation

The restriction on the OLS estimator in equation (III.14) that $var(\epsilon_t) = \sigma^2$ requires an assumption that the error term is independently distributed, so that $cov(\epsilon_t, \epsilon_{t-k}) = 0$ for all t, $k \neq 0$. If this is not the case, the residuals are said to be autocorrelated. In this case, the Least Squares estimator will be unbiased. It will not, however, be efficient. That is, the estimated variance of b will be very high, and the traditional least squares test statistics may not be valid.

Autocorrelation is tested for and corrected in the residuals using a traditional econometric method called the Cochrane-Orcutt procedure (D. Cochrane and G. H. Orcutt, "Application of Least Squares Regressions to Relationships Containing Autocorrelated Error Terms," Journal of the American Statistical Association, vol. 44, 1949, pp. 32-61).

An OLS regression (with outside restrictions as outlined above) is initially run. The residuals from this regression are then inspected to assess the presence of autocorrelation.

Three degrees of autocorrelation are tested for – first-order autocorrelation, whereby residuals are affected by residuals one quarter earlier, second-order autocorrelation, whereby residuals are affected by residuals two quarters earlier, and fourth-order autocorrelation, whereby residuals are affected by residuals four quarters, i.e., one year, earlier.

The exact nature of the autoregressive process is identified by testing the significance of the partial autocorrelation of the residuals at one, two, and four lags. A

95 percent confidence level is used to test for the presence of autocorrelation. The following relationship is then fit to the residuals:

$$e_t = \rho_1 \bullet e_{t-1} + \rho_2 \bullet e_{t-2} + \rho_4 \bullet e_{t-4} + u_t \qquad \text{(III.25)}$$

where u_t is assumed to satisfy the OLS assumptions. The values of ρ_1, ρ_2, and ρ_4 are estimated using traditional OLS. If significant fourth-order autocorrelation is not identified, then ρ_4 is set equal to zero. If second-order autocorrelation is not identified as significant, then $\rho_2 = 0$. Finally, if first-order autocorrelation is not identified, then $\rho_1 = 0$.

The values of ρ_1, ρ_2, and ρ_4 are used to adjust the variance-covariance matrix of the residuals, Σ, and the β-vector is re-estimated using the Generalized Least Squares equation:

$$\beta^{\wedge} = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}y \qquad \text{(III.15)}$$

The variance-covariance matrix of the residuals, Σ, is set equal to $(P'P)^{-1}$, where P is a (T-i)-by-T matrix (where T is the total number of observations in the sample period and i is the largest lag for which significant autocorrelation was detected) that takes on the following form:

$$P_0 = \left| \begin{array}{cccccccccc} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \ldots & 0 \\ -\rho_1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & \ldots & 0 \\ -\rho_2 & -\rho_1 & 1 & 0 & 0 & 0 & 0 & 0 & \ldots & 0 \\ 0 & -\rho_2 & -\rho_1 & 1 & 0 & 0 & 0 & 0 & \ldots & 0 \\ -\rho_4 & 0 & -\rho_2 & -\rho_1 & 1 & 0 & 0 & 0 & \ldots & 0 \\ 0 & -\rho_4 & 0 & -\rho_2 & -\rho_1 & 1 & 0 & 0 & \ldots & 0 \\ 0 & 0 & -\rho_4 & 0 & -\rho_2 & -\rho_1 & 1 & 0 & \ldots & 0 \\ & & & & \ldots & & & & & \\ 0 & 0 & 0 & \ldots & 0 & -\rho_4 & 0 & -\rho_2 & -\rho_1 & 1 \end{array} \right|$$

where P_0 is a T-by-T matrix, and P is equal to the last T-i rows of P_0. In other words, if i=0, then $\rho_1=\rho_2=\rho_4=0$, P is simply equivalent to P_0, and the GLS equation above is exactly equivalent to Ordinary Least Squares. If i=1, then $\rho_2=\rho_4=0$, and the first row of P is equal to $[-\rho_1\ 1\ 0\ 0\ \ldots\ 0]$. If i=2, then $\rho_4=0$, and the first row of P is equal to $[-\rho_2\ -\rho_1\ 1\ 0\ 0\ \ldots\ 0]$. Finally, if i=4, the first row of P is equal to $[-\rho_4\ 0\ -\rho_2\ -\rho_1\ 1\ 0\ 0\ \ldots\ 0]$.

Modifying Σ in this way, and estimating β using Generalized Least Squares is equivalent to using the rho-coefficients (ρ_1, ρ_2, and ρ_4) to transform the dependent variable as well as all of the independent variables as follows:

$$x'_t = x_t - \rho_1 \bullet x_{t-1} - \rho_2 \bullet x_{t-2} - \rho_4 \bullet x_{t-4} \qquad \text{(III.26)}$$

removing the first i observations of the regression period, re-defining y and X using the transformed data, and re-estimating β using the OLS estimator on the transformed variables.

The values of ρ_1, ρ_2, and ρ_4 are optimized through a simple iteration process. First, the β vector is solved for as described above, assuming that ρ_1, ρ_2, and ρ_4 are equal to zero. Given the value of β, ρ_1, ρ_2, and ρ_4 are then estimated using equation (III.25).

Given these values for ρ_1, ρ_2, and ρ_4, β is re-estimated. Given β, ρ_1, ρ_2, and ρ_4 are then re-estimated. This iteration process continues until the estimated values of ρ_1, ρ_2, and ρ_4 do not vary between iterations. This is mathematically equivalent to estimating the β vector simultaneously with ρ_1, ρ_2, and ρ_4.

5. Logistic Market Penetration Variable

a. Theory

It is always desirable to be able to explain the behavior of a variable which is being estimated econometrically as a function of other observable variables. Occasionally, however, the behavior of a variable is either unexpected or is due to factors which do not easily lend themselves to capture within a time series variable suitable for inclusion in an econometric experiment. For example, it is not uncommon for inexplicable and/or persistent trends in data series to be modeled in part through the use of a trend variable.

While it would certainly be better if one could include an explanatory variable that is more pleasing theoretically than simply "time" or a "trend", the failure to include any variable to account for observed behavior may bias one's other coefficient estimates. In cases of this type, it may therefore be necessary to introduce some type of trend variable into certain demand equations.

Several mail volume equations include some type of trend. For example, the First-Class letters equations include logistic trend variables which are discussed above. The Periodical equations as well as several special service equations include linear time trends to account for long-run trends in the volumes of these types of mail, for which either economic sources have not been found or which are most readily modeled by a simple trend variable.

Once one makes a decision that a trend variable is needed within a particular demand equation, an equally important question becomes what form the trend variable ought to take.

A trend is a trend is a trend
But the question is, will it end?
Will it alter its course
Through some unforeseen force,
And come to a premature end?
Sir Alec Cairncross

One common source of trends in data that are difficult to model econometrically by relating behavior to other economic variables is the problem of market penetration. Research into the rate at which new products or new technology are adopted has shown that a typical adoption cycle for a new product is initially gradual, followed by increasingly-rapid adoption until some point in time at which the adoption curve reaches an inflection point and the rate of adoption slows until the adoption curve eventually plateaus and the product or technology exhibits a more traditional stable growth pattern attributable to common economic factors.

An adoption curve of this sort can be modeled through a type of logistic curve, referred to in earlier rate cases as a "z-variable". The z-variable formulation fits the following equation:

$$z_t = (d_1 \cdot p_1) / (1 + p_2 \cdot e^{(-p_3 \cdot t)}) \qquad (III.27)$$

where d_1 is a dummy variable which is equal to zero before the initiation of the market penetration, and equal to one thereafter, t is a time trend beginning the quarter after the beginning of the market penetration, and p_1, p_2, and p_3 are defined below, and are calculated econometrically.

In Docket No. R94-1, those subclasses of mail which included a significant direct-mail advertising component, which included First-Class letters and cards, as well as third-class bulk regular and nonprofit mail, were all modeled incorporating a z-variable of the form of equation (III.27). This z-variable was incorporated to account for a dramatic rise in the volumes of these mail categories in the early 1980s, which is believed to have come about due to a tremendous surge in the use of direct-mail advertising at that time, attributable primarily to tremendous gains in direct-mail advertising technology. Due to the re-specification of First-Class letters and Standard A mail in R97-1, which limited their sample periods to beginning in the mid-1980s, these demand equations no longer require the z-variable construction. The demand equation for private First-Class cards, however, is estimated over a sample period which begins in 1971Q1. As such, the advertising phenomenon described above must be accounted for within the private First-Class cards equation somehow. This is done through the inclusion of a "z-variable" in the private First-Class cards demand equation. The dummy variable, d_1, in equation (III.27) is equal to one beginning in 1979Q2, as in earlier rate cases.

Besides private First-Class cards, the demand equations for Standard bound printed matter and special rate mail also include z-variables. These variables model more pure market penetration from special rate mail into bound printed matter as a result of gradual rule changes and easing of Postal restrictions beginning in the late 1970s that allowed mailers to shift mail from special rate into bound printed matter, thereby saving on the cost of postage. Coincidentally, these z-variables begin in 1979Q2, at the same time as the private First-Class cards z-variable.

b. Implementation

The z-variable methodology is implemented in two stages. The first stage involves nonlinear estimation. The general demand equation is modified as follows:

$$\mathrm{Ln}(V_t) = X_t\beta + z_t + \epsilon_t \qquad \text{(III.28)}$$

where X_t is the full matrix of explanatory variables, and

$$z_t = (d_1 \cdot p_1) / (1+p_2 \cdot e^{(-p_3 \cdot t)}) \qquad \text{(III.27)}$$

as described above. The z-parameters, p_1, p_2, and p_3 are estimated together with the b_i's in equation (III.28)

The parameter p_1 represents the maximum level of adoption. Market penetration into a particular mail volume is reflected by a positive value of p_1, as is the case with private First-Class cards and bound printed matter, while market penetration out of a particular mail volume is reflected by a negative value of p_1, as is the case with Standard special rate mail.

The parameter, p_2 is equal to $(p_1 / z_0) - 1$, where z_0 is the value of the market penetration variable in the first period for which z_t is not equal to zero. The parameter p_3 is referred to as the rate of adoption, and controls how rapidly z_t approaches p_1.

Both p_2 and p_3 must be positive. To enforce convergence to a minimum in a part of the parameter space where these conditions hold, two penalty function terms are added as follows:

$$\mathrm{Ln}(V_t) = X_t\beta + z_t + 100000 \cdot (p_2 - \mathrm{abs}(p_2)) + 100000 \cdot (p_3 - \mathrm{abs}(p_3)) + \epsilon_t \qquad \text{(III.29)}$$

with abs indicating absolute value. The two new terms are equal to zero when p_2 and p_3 are positive, but would drive the sum of squared residuals excessively high if p_2 or p_3 were to be negative.

Equation (III.29) is fit via nonlinear least squares using a modified Gauss-Newton iteration procedure. The direction of change is that in which one would be carried by a linear approximation to the residuals, but which ensures that the criterion decreases at each stage.

The estimated values of p_1, p_2, and p_3 are then used to compute z_t using equation (III.27) above.

Finally, the dependent variable, y_t, is adjusted by subtracting z_t from it, and the coefficient vector, β, is estimated, taking account of autocorrelation, as well as Shiller and all other restrictions, as described above, using a transformed dependent variable,

$$\hat{y}_t = y_t - z_t.$$

C. Regression Model Used

1. Demand Equation Specification

Demand equations are estimated using a Generalized Least Squares technique, as outlined above. The basic demand equation specification used in this case is a demand equation of the form:

$$\begin{aligned} V_t \;=\; & \alpha \bullet Y_t^{\beta_1} \bullet \ldots \bullet [p_t^{\beta_2} \bullet p_{t-1}^{\beta_3} \bullet p_{t-2}^{\beta_4} \bullet p_{t-3}^{\beta_5} \bullet p_{t-4}^{\beta_6}] \bullet \\ & [e^{S_1\beta_{s1}} \bullet e^{S_2\beta_{s2}} \bullet e^{S_3\beta_{s3}} \bullet e^{S_4\beta_{s4}} \bullet e^{S_5\beta_{s5}} \bullet \ldots \bullet e^{S_{16}\beta_{s16}}] \bullet e^{\epsilon_t} \end{aligned} \qquad \text{(III.30)}$$

where V_t is equal to mail volume per adult per business day in Postal quarter t, Y_t refers to permanent income, consumption, or retail sales at time period t, depending on the mail category, p_t - p_{t-4} are the Postal price of the mail category in the current period, and lagged one through four quarters, S_1 - S_{16} correspond to the sixteen seasonal variables described in section A.3. above, and the ... reflects the presence of other explanatory variables in each of the demand equations as described in section II above.

The variable, ϵ_t captures non-modeled changes in V_t. The expected value of ϵ_t is assumed to be equal to zero.

2. Solution of β Coefficients

The natural logarithm of both sides of equation (III.30) is taken, and the resulting equation is solved using Generalized Least Squares. The vector of elasticities,

$$b^{\wedge} = [\beta_1\ \beta_2\ \beta_3\ \ldots]$$

is calculated by the following formula:

$$\begin{aligned} b^{*} &= (X'\Sigma^{-1}X + R'\Omega^{-1}R + \sum_{i=1}^{P} k_i^2 S_i' S_i)^{-1}(X'\Sigma^{-1}y + R'\Omega^{-1}r) \\ b^{\wedge} &= b^{*} + (X'\Sigma^{-1}X + R'\Omega^{-1}R + \sum_{i=1}^{P} k_i^2 S_i' S_i)^{-1} C' [C((X'\Sigma^{-1}X + R'\Omega^{-1}R + \sum_{i=1}^{P} k_i^2 S_i' S_i))^{-1} C']^{-1} \bullet (d - C \bullet b^{*}) \end{aligned} \tag{III.31}$$

where C and d are a matrix and vector of fixed restrictions, such that $d = C \bullet \beta$, R and r are a matrix and vector of stochastic restrictions, such that $r = R\beta + v$, where $E(v) = 0$, and $var(v) = \sigma^2\Omega$, S_i is a matrix of Shiller smoothness priors for price distribution i as described in section B.3.b. above, k_i^2 is the ratio of the model variance to the variance of the smoothness restriction associated with S_i, and P is the number of price distributions for which Shiller distributed lag restrictions are imposed.

The matrix, Σ, is set equal to $(P'P)^{-1}$, where P is defined as a function of autocorrelation coefficients, ρ_1, ρ_2, and ρ_4. The calculation of ρ_1, ρ_2, and ρ_4, as well as the construction of the matrix P are described in section B.4. above.

The vector y is a vector of length T, where T is the number of quarterly observations in the sample period, which contains the natural logarithm of mail volume per adult per business day. The matrix X is a T-by-k matrix, where k is the number of explanatory variables used to explain V_t. Each column of the matrix X corresponds to the natural logarithm of an explanatory variable from the demand equation (III.30) above.

The vector of coefficients, $b^{\wedge}$ calculated in equation (III.31) has the following statistical properties:

$$
\begin{aligned}
E(b^{\wedge}) &= \beta + [(X'\Sigma^{-1}X + R'\Omega^{-1}R + \sum_{i=1}^{P} k_i^2 S'S)^{-1} R'\Omega^{-1}] \cdot [E(r - R\beta) + \sum_{i=1}^{P} E(S_i\beta)] \\
var(b^{\wedge}) &= \sigma^2 (X'\Sigma^{-1}X + R'\Omega^{-1}R + \sum_{i=1}^{P} k_i^2 S'S)^{-1}
\end{aligned}
\qquad \text{(III.32)}
$$

If the stochastic restrictions and Shiller restrictions are unbiased, so that:

$$E(r - R\beta) = 0 \ \ and \ \ E(S_i\beta) = 0 \ \ for \ i=1 \ to \ P$$

then $b^{\wedge}$ will be an unbiased estimator of β and will be the best linear unbiased estimate which incorporates stochastic prior information, r, and Shiller information, S.

The variance-covariance matrix associated with $b^{\wedge}$ in equation (III.32) can be best understood if one respecifies equation (III.31) slightly. Define a matrix, $X^{\wedge}$, which is equal to X from equation (III.31) with rows added to the bottom of the matrix which are equal to R•W, where W'W equals Ω^{-1}, and k_iS_i, for i = 1 to P. That is,

$$
X^{\wedge} = \left| \begin{matrix} X \\ R \bullet W \\ k_1 \bullet S_1 \\ \cdots \\ k_P \bullet S_P \end{matrix} \right|
$$

Now, define a vector ŷ equal to y from equation (III.31) with rows added to the bottom corresponding to r, as well as rows of 0 corresponding to S_i, for i = 1 to P, so that

$$\hat{y} = \begin{vmatrix} y \\ r \\ 3 \cdot P \text{ rows of } 0 \end{vmatrix}$$

Equation (III.31) can be re-written in terms of $X^{\wedge}$ and $\hat{y}$, instead of X and y, as follows:

$$\begin{aligned} b^{*} &= (X^{\wedge\prime}\Sigma^{-1}X^{\wedge})^{-1}(X^{\wedge}\Sigma^{-1}\hat{y}) \\ b^{\wedge} &= b^{*} + (X^{\wedge\prime}\Sigma^{-1}X^{\wedge})^{-1}C^{\prime}[C(X^{\wedge\prime}\Sigma^{-1}X^{\wedge})^{-1}C^{\prime}]^{-1}\cdot(d - C\cdot b^{*}) \end{aligned} \tag{III.33}$$

From equation (III.33), it is seen that $b^{\wedge}$ is simply equal to the traditional GLS estimate of β, with outside restrictions imposed. Hence, the variance-covariance matrix of $b^{\wedge}$ is simply equal to $\sigma^2(X^{\wedge\prime}\Sigma^{-1}X^{\wedge})^{-1}$ and $b^{\wedge}$ is the best linear unbiased estimate of β that incorporates the outside information within C, R, and S_i, i = 1 to P.

3. Example: Periodical Regular Mail

An example of the use of equation (III.31) to model the demand for mail volume may be instructive. Consider, for example, the demand for Periodical regular mail, which is modeled as follows:

$$(\text{Vol2r / Population / Business Days})_t =$$

$$\begin{aligned} &\alpha \cdot (Y^P)_t^{\beta_1} \cdot (Y^T \text{ lag } 3)_t^{\beta_2} \cdot (e^{Trend})_t^{\beta_3} \cdot (P^{paper})_t^{\beta_4} \cdot \\ &[px2r_t^{\beta_{p0}} \cdot px2r_{t-1}^{\beta_{p1}} \cdot px2r_{t-2}^{\beta_{p2}} \cdot px2r_{t-3}^{\beta_{p3}} \cdot p_{t-4}^{\beta_{p4}}] \cdot \\ &[e^{S_1\beta_{s1}} \cdot e^{S_2\beta_{s2}} \cdot e^{S_3\beta_{s3}} \cdot e^{S_4\beta_{s4}} \cdot e^{S_5\beta_{s5}} \cdot \ldots \cdot e^{S_{16}\beta_{s16}}] \cdot e^{\varepsilon_t} \end{aligned} \tag{III.34}$$

where Vol2r is the volume of Periodical regular mail, Y^P is permanent income in 1992 dollars, Y^T is transitory income, proxied by the Federal Reserve's index of capacity utilization for the manufacturing sector, Trend is a linear time trend[4], P^{Paper} is the wholesale price of pulp, paper, and allied products in 1992 dollars, px2r is the fixed-weight average price of Periodical regular mail, and S_1 through S_{16} are the first sixteen seasonal variables defined in section A.3. above.

The vector y associated with equation (III.34) contains the natural logarithm of (Vol2r / Population / Business Days)$_t$ for t = 1971Q1 through 1999Q4. The matrix X contains the natural logarithm of the explanatory variables in equation (III.34), Y^P, Y^T, etc.[5] Matrix X has dimensions T-by-k, where k equals 26 and T equals 116.

The β-vector to be solved by equation (III.31) contains the following elements:

$$\beta_{2r} = [\alpha\ \beta_1\ \beta_2\ \beta_3\ \beta_4\ \beta_{p0}\ \beta_{p1}\ \beta_{p2}\ \beta_{p3}\ \beta_{p4}\ \beta_{s1}\ \beta_{s2}\ \beta_{s3}\ \beta_{s4}\ \beta_{s5}\ \beta_{s6}\ \beta_{s7}\ \beta_{s8}\ \beta_{s9}\ \beta_{s10}\ \beta_{s11}\ \beta_{s12}\ \beta_{s13}\ \beta_{s14}\ \beta_{s15}\ \beta_{s16}]$$

The matrix of restrictions which are imposed with certainty, C, is as follows:

$$C = \begin{vmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -1
\end{vmatrix}$$

[4] The time trend enters the regression linearly such that, $\ln(V_t) = A + \beta_3 \cdot \text{Trend}$. Taking the anti-log of both sides of the equation yields the relationship in equation (III.34) above, namely that $V_t = A^* \cdot (e^{\text{Trend}})^{\beta_3}$.

[5] Note that the seasonal variables are e^{S_1}, e^{S_2}, etc. The natural logarithms of these variables are then equal to S_1, S_2, etc., which are entered into the X matrix in this form.

The vector, d, associated with these restrictions is equal to [0 0 0 0 0 0 0]. This matrix restricts $\beta_{p4} = 0$, $\beta_{s2} = \beta_{s3}$, $\beta_{s4} = \beta_{s5}$, $\beta_{s8} = \beta_{s9} = \beta_{s10}$, $\beta_{s12} = \beta_{s13}$, and $\beta_{s15} = \beta_{s16}$, respectively. The first of these restrictions is a general restriction applied to all Postal prices based on historical observation. The latter six restrictions were imposed on the basis of an earlier estimate of β without these restrictions imposed, which found these values to be approximately equivalent.

The permanent income elasticity, β_1, is constrained stochastically from the Household Diary Study, to a value of 0.5361. The Household Diary Study estimate has a variance associated with it equal to 0.00145. Hence, R, r, and Ω in equation (III.31) are equal to the following:

$$R = [0\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0]$$
$$r = [0.5361]$$
$$\Omega = [0.00145]$$

The demand equation for Periodical regular mail contains a single Postal price to which a Shiller restriction is imposed. The S-matrix is equal to the following:

$$S = \begin{vmatrix} 0 & 0 & 0 & 0 & 0 & 1 & -2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & -2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & -2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{vmatrix}$$

The minimum value of k^2 which yielded a reasonable price distribution was chosen based on a search of alternate values for k^2. The chosen value of k^2 was 0.160938.

Based on estimating equation (III.31), the autocorrelation coefficients, ρ_1, ρ_2, and ρ_4 were estimated to be equal to 0.332551, 0.329801, and zero respectively. The variance-covariance matrix of the residuals, Σ, was adjusted using these values as described in section B.4. above.

Based on these results, the β-coefficient associated with Periodical regular mail was estimated using equation (III.31) above. The resulting β-vector was calculated to be equal to:

$$\hat{b}_{2r} = [-3.703\ 0.535\ 0.033\ -0.122\ -0.002\ -0.000\ -0.009\ -0.062\ -0.076\ 0.000\ -0.296\ -0.003\ -0.003\ -0.185\ -0.185\ -1.432\ 0.396\ -0.152\ -0.152\ -0.152\ 0.126\ -0.055\ -0.055\ 0.357\ -0.167\ -0.167]$$

IV. Shares of Mail within Worksharing Categories

A. Theory of Consumer Worksharing

1. Cost-Minimization Problem

Traditionally, economists have modeled consumer demand as an effort by consumers to maximize utility given income. On the other side of consumer demand, however, is a basic cost-minimization problem of minimizing costs for any given level of utility.

Mathematically, consumers' cost-minimization problem can be expressed as:

$$\min C(x) \text{ s.t. } U(x) \geq u_R \qquad \text{(IV.1)}$$

where x is the quantity of the good of interest, U is the consumer's utility function, C is the consumer's cost function, and u_R is the consumer's reservation utility.

In general, C(x) is equivalent to the price of good x, including any transactions costs, so that

$$C(x) = p \bullet x + \text{transactions costs} \qquad \text{(IV.2)}$$

where p is the price of good x.

Assuming that transactions costs are exogenous to the consumer and the consumer takes price as given in equation (IV.2), the minimand of equation (IV.1) will simply be x.

For some categories of mail, however, the Postal Service offers discounts to mailers who presort or barcode their mail, thereby making the Postal Service's job easier. In such a case, equation (IV.2) could be re-written as follows:

$$C(x) = (p-d+u(x))\cdot x + \text{transactions costs} \qquad \text{(IV.3)}$$

where d is the discount obtained by the consumer for doing additional work, and u is the unit cost to the consumer of doing the additional work, which may vary with x. In this case, in addition to choosing x in equation (IV.1), the consumer will also choose the level of worksharing.

For any given value of x, minimizing C(x) is equivalent to minimizing the price paid for good x, or minimizing [p - d + u(x)]. Taking p as fixed for the consumer, this can be further simplified to a simple choice of minimizing [-d + u(x)], or, rearranging terms, maximizing [d - u(x)].

This leads to the First Law of Consumer Worksharing:

A consumer will choose the worksharing option that maximizes his or her benefit of worksharing, where the consumer's benefit to worksharing is equal to d - u.

In general, the level of worksharing will not be a continuous function, but will instead involve a choice from among discrete levels of worksharing. Thus, the First Law of Consumer Worksharing can be expressed mathematically as follows:

$$\max_i \, (d_i - u_i(x)) \qquad \text{(IV.4)}$$

for i equals the set of all possible worksharing options, where d_i is the discount associated with worksharing option i, u_i is the cost to the consumer of qualifying for worksharing option i, and x is the quantity of the good consumed.

2. Making Equation (IV.4) a Tractable Problem

Solving equation (IV.4) requires information about the user costs associated with all possible worksharing categories. If there are N worksharing options, this becomes an N-dimensional problem. If N is very large at all, this can quickly become an intractable problem.

One possible way of making equation (IV.4) a more tractable problem is to introduce the concept of opportunity costs into u(x). Economists generally think of the opportunity cost associated with a product as the forgone benefit of not doing anything different with the product. In the context of equation (IV.4), then, the opportunity cost of using worksharing option i is the maximum benefit, where benefit is defined as d - u, that could be achieved by using a different worksharing category. Explicitly incorporating *opportunity costs into equation* (IV.4) *yields the following consumer maximization* problem:

$$\max_i \left[d_i - (w_i(x) + \max_{j\neq i}(d_j - u_j))\right] \qquad \text{(IV.5)}$$

where w_i equals the cost of qualifying for worksharing option i, excluding opportunity costs, and $u_i = (w_i(x) + \max_{j\neq i}(d_j - u_j))$.

If $\max_{j\neq i}(d_j - u_j) > d_i - w_i$, for some worksharing option j, then $d_i - (w_i(x) + \max_{j\neq i}(d_j - u_j))$ will be strictly less than zero. If worksharing discounts are defined as discounts from a base price for which consumers are eligible at no additional cost (i.e., d=0 and w=0 for the base worksharing option), then $\max_i (d_i - u_i) \geq 0$, since, if any given worksharing option were more costly to the consumer than the discount earned as a result of qualifying for the option, the consumer could still choose to do no worksharing at no cost.

Combining the two facts outlined in the above paragraph yields the following result:

$$d_i - u_i \geq 0 \text{ if, and only if, } d_i - w_i \geq d_j - w_j \text{ for all worksharing options } j.$$

Stated in words, this becomes the Fundamental Theorem of Consumer Worksharing:

A consumer will utilize a worksharing option if, and only if, the costs to the consumer of doing so are less than the discount offered by the seller for doing so.

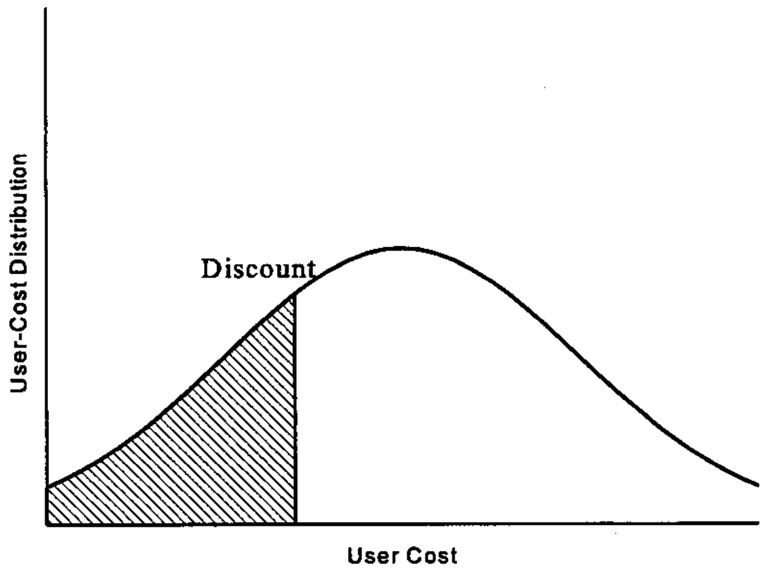
3. Modeling Consumers' Use of Worksharing Options

a. General Form of the Problem

The Fundamental Theorem of Consumer Worksharing reduces equation (IV.5) from an N-dimensional problem to a system of N 1-dimensional problems.[6] A consumer will use worksharing option i if, and only if, $d_i - u_i \geq 0$. Given a distribution of user costs associated with worksharing option i, the percentage of consumers who will use worksharing option i can be represented graphically as shown below in Figure IV-1.

[6] N-1 problems if one considers one of the N worksharing options to be no worksharing.

Figure IV-1
Generalized User-Cost Distribution



Consumers with user costs less than the discount, represented by the striped region to the left of the discount, will use worksharing option i, while consumers with user costs greater than the discount will not use worksharing option i.

Mathematically, the above picture could be represented by equation (IV.6) below:

$$(\text{Percentage of mail within a category}) = \int_0^d \text{p.d.f.}(u)\, du \qquad (\text{IV.6})$$ [7]

[7] The integral in equation (IV.6) reflects the fact that the minimum bound on user costs must be equal to 0. This is based on the definition of user costs implicit in equation (IV.3) and the fact that there is a minimum worksharing option associated with d = 0 and u = 0. In this case, the user costs are the costs above the costs associated with the minimum category, which are accounted for in the transactions costs in equation (IV.3).

Thus, the share of a good that will be sent as part of a particular worksharing option can be solved for by estimating equation (IV.6).

b. Modeling User-Cost Distributions

i. Shape of User-Cost Distribution

The first step in solving equation (IV.6) is to define what type of distribution best describes the user-cost distribution. The most likely candidate would seem to be the normal distribution.

(a) Theoretical Appeal of the Normal Distribution

Probably the most common empirical distribution is the normal distribution. A number of social and economic variables have been shown to be generally normally distributed, including income. In addition, user costs that decline at a constant rate would lead to logistic growth in the use of worksharing options.[8] This is generally consistent with historical growth patterns in the use of presortation and automation discounts offered by the Postal Service.

Finally, the Central Limit Theorem states that:

> If an arbitrary population distribution has a mean μ and finite variance σ^2, then the distribution of the sample mean approaches the normal distribution with mean μ and variance σ^2/n as the sample size n increases. (Anderson and Bancroft, Statistical Theory in Research, McGraw-Hill, 1952, p. 71)

This means that any sample distribution with finite mean and variance is approximately normal. A consumer user-cost distribution would certainly be expected

[8] A normal user-cost distribution would lead to logistic growth in worksharing shares because, as user costs declined over time, the share of a product taking advantage of the worksharing option would take on the shape of the cumulative distribution function (c.d.f.) of user costs. The c.d.f. of the normal distribution is logistic in shape.

to have both a finite mean and variance. Thus, it is reasonable to assume that user costs are normally distributed for consumer worksharing options.

(b) Empirical Drawbacks to Normal Distribution

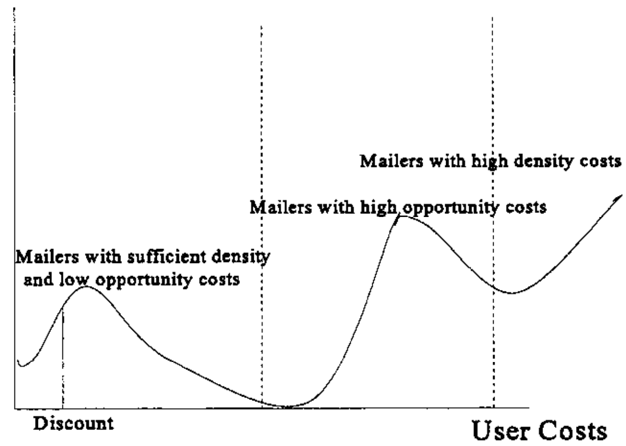
Despite the appeal of the normal distribution, it is not without its limitations. In particular, the normal distribution has three drawbacks which make it less than ideal for modeling consumer user costs: the likelihood of user-cost clusters about several different levels of user costs, the fact that user costs are non-negative by definition, and the non-integrability of the normal p.d.f., leaving equation (IV.6) unsolvable.

The first issue to be resolved in modeling the share of consumers that will use a particular worksharing option is to properly identify the consumer population of potential work sharers. For example, not everybody who mails a letter has a realistic option of presorting or automating their mail, due to limitations imposed by the Postal Service that presorted mailings must include at least 500 pieces or practical limitations against purchasing barcoding equipment that can cost more than $100,000. On the other hand, consider a mailer who sends a letter to every address in a particular city (e.g., utility bills and saturation advertising). This mailer will likely either presort as fine as possible (carrier-route presorting or saturation presorting) or not presort at all, but would have little reason to consider intermediate presort options (e.g., 3- or 5-digit presorting).

In reality, therefore, user-cost distributions may have several clusters of consumers. For example, the user-cost distribution associated with 3-digit Automated mail may look like Figure IV-2 below.

Figure IV-2

Multi-Peaked User-Cost Distribution



The right-most hump represents mailers who mail letters one or two at a time. The "costs" to these mailers of qualifying for the Postal Service's 3-digit presort requirement would basically involve preparing an additional 400-500 letters to meet the minimum mailing requirement for the 3-digit presort requirement. In addition, such mailers may have to purchase barcoding equipment, which would be prohibitively expensive. The middle hump, identified as "Mailers with high opportunity costs", represent mailers who would never consider only 3-digit presorting their mail as long as more attractive discounts existed for 5-digit or carrier-route presorting.

The user-cost distribution is normally distributed over the small subset of mailers who have sufficient density and low opportunity costs[9] associated with 3-digit Automation. As long as the discount for the worksharing category falls within this area of the user-cost distribution, however, then a normal distribution over that subset of consumers will be a valid approximation to the true user-cost distribution.

[9] These opportunity costs may still, however, be prohibitive for some of these mailers.

Technically, a normal user-cost distribution would assume that user costs can take on any value from $-\infty$ to $+\infty$. If user costs are defined as the costs associated with qualifying for a worksharing category, above and beyond the cost of qualifying for the corresponding non-workshared category, then this means that the true distribution of user costs associated with any worksharing option must be non-negative. Thus, the true user-cost distribution associated with any worksharing category for which a non-worksharing option exists will have a lower bound of zero user costs.

Finally, an empirical problem with a normal user-cost distribution is that the normal probability density function (p.d.f.) is not integrable, so that equation (IV.6) would be non-solvable. Solving equation (IV.6) for a normal user-cost distribution would require either a discrete approximation to the normal c.d.f., or an approximation to the normal p.d.f. which is integrable. The latter of these two options is chosen here.

(c) Solution: Censored Logistic Distribution over a Subset of Consumers

A distribution which is often used to approximate the normal distribution, due to its similarity to the normal distribution and numerical simplicity, is the logistic distribution. (See, for example, Judge, et al. The Theory and Practice of Econometrics, 2nd edition, John Wiley and Sons, 1985, p. 762).

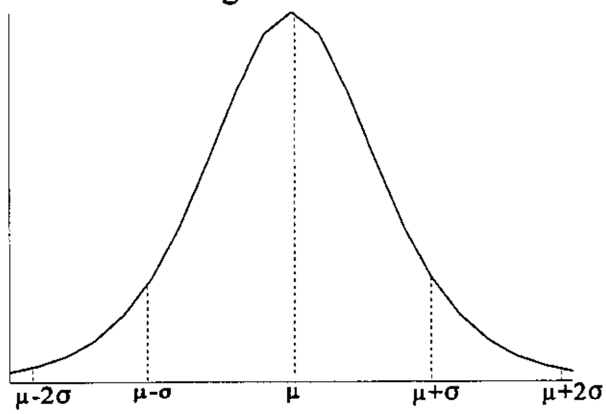
The logistic p.d.f. takes the following form:

$$Logistic\ p.d.f. = \frac{e^{-((x-\mu)/\sigma)}}{\sigma[1+e^{-((x-\mu)/\sigma)}]^2} \qquad \text{(IV.7)}$$

Graphically, the logistic p.d.f. is shown in Figure IV-3 below.

Figure IV-3

Logistic P.D.F.



The main advantage of the logistic distribution over the normal distribution is that the logistic p.d.f. is integrable. Inserting the logistic p.d.f. into equation (IV.6) allows the equation to be solved as follows:

$$(\textit{Pct. of good x within worksharing category i}) = \int_{-\infty}^{(d_i)} \frac{e^{-((u_i-\mu_i)/\sigma_i)}}{\sigma_i[1+e^{-((u_i-\mu_i)/\sigma_i)}]^2}\, du_i \qquad \text{(IV.8)}$$

or, integrating the logistic p.d.f.,

$$(\textit{Pct. of good x within worksharing category i}) = \frac{1}{1+e^{-(d_i-\mu_i)/\sigma_i}} \qquad \text{(IV.9)}$$

As discussed above, user costs may be normally (or logistically) distributed only over a subset of the total consumers of good x. Equation (IV.9) actually measures the percentage of good x for which the user-cost distribution is normally distributed which will be sent within category i. The percentage of all of good x within worksharing category i is the product of equation (IV.9) and the percentage of good x over which the user-cost distribution associated with worksharing category i is logistically distributed, or

$$\textit{(Pct. of good x within worksharing category i)} = (\alpha_i)\cdot\left(\frac{1}{1 + e^{-(d_i - \mu_i)/\sigma_i}}\right) \qquad \text{(IV.10)}$$

where α_i is the percentage of good x for which user costs associated with worksharing category i are logistically distributed. The parameter α_i represents the maximum percentage of good x which would ever take advantage of worksharing category i, for any likely discount associated with category i.[10] Thus, α_i may be called the "ceiling" share associated with worksharing category i.

The general equation for the percentage of a good that will utilize a particular worksharing option is summarized by equation (IV.11) below.

$$\textit{(Pct. of good x within worksharing category i)} = \frac{\alpha_i}{1 + e^{-(d_i - \mu_i)/\sigma_i}} \qquad \text{(IV.11)}$$

The logistic distribution has the same drawback as the normal distribution that the logistic distribution assumes that user costs can take on any value from $-\infty$ to $+\infty$. In reality, however, user costs have a lower bound of zero, by definition, for reasons discussed above.

The simplest way of constraining user costs to be greater than or equal to zero is to assume that user costs falling below zero in equation (IV.8), are actually exactly equal to zero. This leads to a censored logistic distribution associated with user costs. A logistic distribution censored at zero has the following p.d.f. and c.d.f. associated with it.

[10] The term "likely discount" is intentionally left somewhat vague. At a minimum, a "likely discount" can be thought of as a discount that is strictly less than the base price of good x.

$$p.d.f. = \begin{cases} \dfrac{e^{-((\tilde{u}_i-\mu_i)/\sigma_i)}}{\sigma_i[1+e^{-((\tilde{u}_i-\mu_i)/\sigma_i)}]^2}, & \tilde{u}_i>0 \\ \dfrac{1}{1+e^{\mu/\sigma}}, & \tilde{u}_i=0 \\ 0, & \tilde{u}_i<0 \end{cases} \qquad \text{(IV.12)}$$

$$c.d.f. = \begin{cases} \dfrac{1}{1+e^{-((\tilde{u}_i-\mu_i)/\sigma)}}, & \tilde{u}_i \geq 0 \\ 0, & \tilde{u}_i<0 \end{cases}$$

where $\tilde{u}_i$ is the user cost associated with worksharing category i. The variable $\tilde{u}$ is used here rather than u to distinguish the censored logistic user-cost distribution from the logistic user-cost distribution in equation (IV.8) above.

As long as $d_i \geq 0$, equation (IV.11) above will be unchanged due to this type of censoring.

ii. Changes in the User-Cost Distribution over Time

If equation (IV.11) is to be used in evaluating the use of worksharing options over time or in forecasting the future use of worksharing options, then the user-cost distribution outlined in equation (IV.11) must be allowed to vary over time. There is no reason to believe that user costs are constant for any or all consumers over time. In fact, if the shares of worksharing categories change independent of changes in discounts, as has happened with Postal worksharing categories, then the user-cost distributions associated with these categories must be changing over time.

The crucial need, then, in modeling the use of worksharing categories is to adequately model the changes in user-cost distributions over time. There are four types of changes in user-cost distributions which may occur over time: changes in the type of distribution, changes in the standard deviation of the distribution (σ), changes in the percentage of the good over which user costs are normally Distributed (α), and changes in the mean of the user-cost distribution (μ). These four issues are considered separately below.

(a) Changes in the Type of Distribution

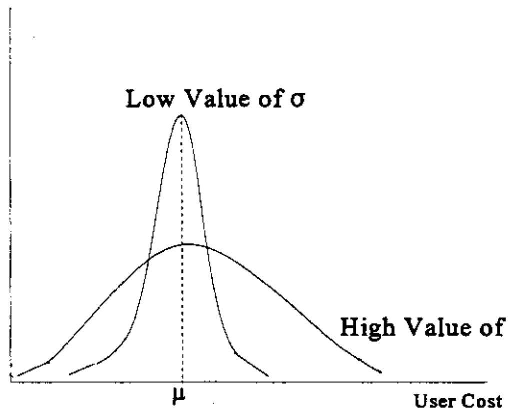
Arbitrary changes in the general shape of user-cost distributions over time would be extremely problematic empirically. At the extreme, if the type of user-cost distribution changed over time, then it would not be valid to base forecasts of future use of worksharing categories on historical patterns, as there would be no guarantee that the distribution might not change shape in the future.

Fortunately, there is no reason to believe that user-cost distributions would change type over time. The Central Limit Theorem suggests that, if anything, user-cost distributions ought to appear more normal over time. Thus, as an empirical matter, it is likely to be a valid assumption that all user-cost distributions are logistically distributed over their entire histories.

(b) Changes in the Standard Deviation of the Distribution

There is no *a priori* reason to assume that the standard deviation of the user-cost distribution, σ, would remain constant over time. A potential difficulty in modeling changes in σ, however, arises in interpreting changes in σ over time. Figure IV-4 below shows the difference in the user-cost distribution between a high value of σ and a low value of σ.

Figure IV-4
User-Cost Distributions with Alternate Values of σ



The effects of changes in σ are dependent on where the discount lies along the user-cost distribution. A decline in the standard deviation of the distribution will lead to an increase in the use of the worksharing option if the discount is greater than the mean of the user-cost distribution, but will lead to a decrease in the use of the worksharing option if the discount is less than the mean.

Another empirical difficulty in permitting σ to change over time is a computational difficulty in modeling unique shifts in d, μ, and σ over time in equation (IV.11). A convergent solution to (IV.11) is facilitated if one takes either the numerator (i.e., -(d-μ)) or the denominator (i.e., σ) of the exponential expression as constant over time. Since d is taken as given, and can be expected to change over time, it is convenient to hold σ constant.

(c) Changes in the Ceiling of the Distribution

If new categories are introduced, the opportunity costs associated with older lower-discount categories may rise dramatically for many consumers as they shift into the newer more-discounted worksharing category. This may cause some consumers to shift from the left-most region of Figure IV-2 above into the middle section of Figure IV-2. Alternately, long-run shifts in the concentration of mail (to use the example diagramed in Figure IV-2) may lead some mail to shift from the right-most region of Figure IV-2 into the left-most region of Figure IV-2.

Shifts of this nature over time would be modeled in equation (IV.11) through a change in the value of α over time. Empirically, it should be noted, however, that it may be difficult to isolate gradual changes in α (modeled, for example, through a simple time trend) from changes in μ which will be discussed below. Thus, it may be desirable as a practical matter to be cautious in modeling changes in α over time.

(d) Changes in the Mean of the User-Cost Distribution

In estimating the share of a good which would take advantage of a particular worksharing option over time, the variable which would generally be expected to change the most over time (except, perhaps, for the discount) would be the mean of the user-cost distribution. Changing the mean of the user-cost distribution suggests that user costs shift proportionally across all consumers. This would generally be true of such things as fixed capital costs associated with worksharing (e.g., barcoding machines to prebarcode mail), shocks to costs from changes in worksharing requirements, and falling user costs in the initial periods following the introduction of worksharing options as consumers optimize their costs of worksharing.

Estimating the share of a good, x, that takes advantage of a particular worksharing option, i, historically then becomes a matter of incorporating historical changes in the discount associated with worksharing option i, the mean user-cost associated with worksharing i, and the percentage of good x for which user costs associated with worksharing category i are logistically distributed into equation (IV.11). Forecasting the share of good x that would be expected to use worksharing option i would require forecasts of d_i, μ_i, and α_i.

For consumer goods with multiple worksharing options (e.g., separate discounts for various levels of presortation offered by the Postal Service), a critical component of the user costs of worksharing will be opportunity costs as outlined in section A.2 above. The next section considers the empirical treatment of opportunity costs in estimating equation (IV.11).

iii. Opportunity Costs

Opportunity costs as derived in equation (IV.5) can be decomposed into the opportunity costs associated with not using all other categories. That is,

$$oc_i = \Sigma oc_{\text{not using } j} \text{ for all } j \neq i \qquad \text{(IV.13)}$$

For any individual mailer, the opportunity costs associated with not using category j will be equal to zero for all categories except for the one category that the mailer actually chooses. For the distribution of all mailers, however, equation (IV.13) makes the calculation of opportunity costs rather straightforward.

A logistical user-cost distribution is uniquely defined by three parameters -- α, μ, and σ. In general, opportunity costs do not directly affect α. For computational simplicity, it is best to treat σ as remaining constant over time. Thus, opportunity costs would only affect σ implicitly.

The mean of the user-cost distribution, μ, can be decomposed into the following equation, based on the theoretical implications of equation (IV.5) above.

$$\mu_i = \mu_{non\text{-}oc} + \Sigma_{j\neq i}\, E(oc_{ij}) \qquad \text{(IV.14)}$$

where $\mu_{non\text{-}oc}$ is equal to the mean user cost, excluding opportunity costs, and oc_{ij} is the forgone benefit of using category i instead of category j.

For those consumers for whom category j is the most attractive worksharing option (and would, thus, use worksharing category j), oc_{ij} will equal $d_j - u_j$, the benefit of using category j. For those consumers for whom category j is not the most attractive worksharing option, oc_{ij} is equal to zero. This leads to the following formula for the expected value of oc_{ij}:

$$E(oc_{ij}) = (d_j - \bar{u}_j)\bullet(\hat{s}_{ij}) \qquad \text{(IV.15)}$$

where $\bar{u}_j$ is equal to the average cost of using worksharing category j by consumers who actually use category j, and $\hat{s}_{ij}$ is equal to the percentage of good x for which user costs associated with worksharing category i are logistically distributed that take advantage of worksharing category j.

The derivation of $\bar{u}_j$ and $\hat{s}_{ij}$ are discussed next.

(a) Average User Costs: $\bar{u}_j$

The average user cost associated with worksharing category j borne by consumers who actually use category j can be expressed mathematically as the average user cost over the portion of the user-cost distribution associated with category j for which user costs are less than or equal to the discount, i.e.,

$$\bar{u}_j = E(\tilde{u}_j \mid \tilde{u}_j \leq d_j) \qquad \text{(IV.16)}$$

where $\tilde{u}_j$ is distributed using a censored logistic distribution, as described in equation (IV.12) above.

The following equality is true for any distribution of x

$$E(x|x\le y) = E(x|x\le 0)\bullet prob(x\le 0|x\le y) + E(x|0<x\le y)\bullet prob(x>0|x\le y), \text{ for any value of } y\ge 0 \qquad \text{(IV.17)}$$

Thus, the average user cost associated with worksharing category j (if $d_j \ge 0$) must satisfy the following equation:

$$E(\tilde{u}_j|\tilde{u}_j\le d_j) = E(\tilde{u}_j|\tilde{u}_j\le 0)\bullet prob(\tilde{u}_j\le 0|\tilde{u}_j\le d_j) + E(\tilde{u}_j|0<\tilde{u}_j\le d_j)\bullet prob(\tilde{u}_j>0|\tilde{u}_j\le d_j) \qquad \text{(IV.18)}$$

The probabilities associated with $\tilde{u}_j \le 0$ and $0<\tilde{u}_j\le d_j$ can be calculated directly from the c.d.f. in equation (IV.12) and are equal to

$$\frac{1}{1+e^{\mu_j/\sigma_j}} \quad \text{and} \quad \frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}} - \frac{1}{1+e^{\mu_j/\sigma_j}}$$

respectively.

The mean value of a truncated logistic distribution satisfies the following equation:

$$E(x|x\le y) = y + \frac{\ln[1-F(y)]}{F(y)} \qquad \text{(IV.19)}$$

where $F(y) = \dfrac{1}{1+e^{-y}}$ is the c.d.f. of the logistic distribution evaluated at y. (Maddala, G.S. Limited-Dependent and Qualitative Variables in Econometrics, Cambridge, 1983, p. 369)

Since equation (IV.11) relies on a non-standard logistic distribution (i.e., μ_j is allowed to differ from 0, and σ_j can be different from 1), the value x in equation (IV.19) needs to be replaced by the value $x = (u-\mu_t)/\sigma$.

If user costs followed an uncensored logistic distribution, the average user cost associated with mail in a given category could be calculated by solving equation (IV.19) above at the value $y = (d_t - \mu_t)/\sigma$. Substituting for x and y in equation (IV.19), we get:

$$E[((u_j-\mu_j)/\sigma_j) \mid ((u_j-\mu_j)/\sigma_j) \le ((d_j-\mu_j)/\sigma_j)] = ((d_j-\mu_j)/\sigma_j) + \ln[1 - \frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}}] \Big/ \frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}} \qquad \text{(IV.20)}$$

which could be simplified to:

$$\begin{aligned} (E(u_j) - \mu_j)/\sigma_j &= (d_j - \mu_j)/\sigma_j + \ln[1 - \frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}}]/[\frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}}], \\ E(u_j|u_j \le d_j) &= d_j + \sigma_j \ln[1 - \frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}}]/[\frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}}] \end{aligned} \qquad \text{(IV.21)}$$

where $E(u_j|u_j \le d_j)$ would be the average user cost associated with consumers actually utilizing worksharing category j, assuming user costs are logistically distributed.

The average user cost associated with users of worksharing category j for which user costs are less than or equal to zero can be calculated in the same way as follows:

$$E(u_j|u_j \le 0) = 0 + \sigma_j \ln[1 - \frac{1}{1+e^{-(0-\mu_j)/\sigma_j}}]/[\frac{1}{1+e^{-(0-\mu_j)/\sigma_j}}] = \sigma_j \ln[1 - \frac{1}{1+e^{\mu/\sigma_j}}]/[\frac{1}{1+e^{\mu/\sigma_j}}] \qquad \text{(IV.22)}$$

The value $E(u_j|u_j \le d_j)$ can also be calculated from equation (IV.17) above, yielding:

$$E(u_j|u_j \le d_j) = E(u_j|u_j \le 0) \cdot prob(u_j \le 0|u_j \le d_j) + E(u_j|0<u_j \le d_j) \cdot prob(u_j > 0|u_j \le d_j) \qquad \text{(IV.23)}$$

The probabilities in equation (IV.23) can be solved by evaluating the logistic c.d.f. at the values 0 and d_t. Finally, substituting equations (IV.21) and (IV.22) into equation (IV.23), we can solve for $E(u_j|0<u_j \le d_j)$.

$$E(u_j|0<u_j\le d_j) = (\frac{1}{prob(u_j>0\,|\,u_j\le d_j)})[(d_j + \sigma_j \ln[1 - \frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}}]/[\frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}}]) - (\sigma_j \ln[1 - \frac{1}{1+e^{\mu/\sigma_j}}]/[\frac{1}{1+e^{\mu/\sigma_j}}])prob(u_j\le 0\,|\,u_j\le d_j)] \tag{IV.24}$$

The distributions associated with u and ũ are equivalent for ũ>0. It therefore follows that

$$E(\tilde{u}_j|0<\tilde{u}_j\le d_j) = E(u_j|0<u_j\le d_j) \tag{IV.25}$$

Equation (IV.18) can thus be rewritten:

$$E(\tilde{u}_j|\,\tilde{u}_j\le d_j) = E(\tilde{u}_j|\,\tilde{u}_j\le 0)\cdot prob(\tilde{u}_j\le 0\,|\,\tilde{u}_j\le d_j) + E(u_j|0<u_j\le d_j)\cdot prob(\tilde{u}_j>0\,|\,\tilde{u}_j\le d_j) \tag{IV.26}$$

By definition, E(ũ|ũ≤0) = 0. Thus, the first term on the right-hand side in equation (IV.26) is equal to zero, and equation (IV.24) can be substituted for the second term, yielding:

$$E(\tilde{u}_j|\,\tilde{u}_j\le d_j) = \{(\frac{1}{prob(u_j>0\,|\,u_j\le d_j)})[(d_j + \sigma_j \ln[1 - \frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}}]/[\frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}}]) - (\sigma_j \ln[1 - \frac{1}{1+e^{\mu/\sigma_j}}]/[\frac{1}{1+e^{\mu/\sigma_j}}])prob(u_j\le 0\,|\,u_j\le d_j))]\}\cdot prob(\tilde{u}_j>0\,|\,\tilde{u}_j\le d_j) \tag{IV.27}$$

For values greater than zero, the c.d.f. associated with u and ũ are equivalent, so that the prob($\tilde{u}_j$>0|$\tilde{u}_j \le d_j$) term cancels with the $\frac{1}{prob(u_j>0\,|\,u_j\le d_j)}$ term, yielding the following equation for the average user cost associated with users of worksharing category j:

$$\bar{u}_j = (d_j + \sigma_j \ln[1 - \frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}}]/[\frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}}]) - (\sigma_j \ln[1 - \frac{1}{1+e^{\mu/\sigma_j}}]/[\frac{1}{1+e^{\mu/\sigma_j}}]) \cdot [(\frac{1}{1+e^{\mu/\sigma_j}})/(\frac{1}{1+e^{-(d_j-\mu_j)/\sigma_j}})] \qquad \text{(IV.28)}$$

(b) Share of Potential Users of Category i using Category j: $\hat{s}_{ij}$

As a first approximation, the share of category j in equation (IV.15), $\hat{s}_{ij}$, may be approximately equal to the total share of good x in worksharing category j. However, this share, $\hat{s}_{ij}$, need not be exactly equal to the total share of good x in worksharing category j, due to the presence of the ceiling parameter, α_i, in equation (IV.11) for worksharing category i.

If some portion of good x that is sent as part of worksharing category j could never reasonably be sent as part of worksharing category i then that portion of worksharing category j would not factor into the opportunity cost associated with potential users of category i.

Mathematically, this can be most easily accomplished by modifying equation (IV.15) above to include a "coefficient" on the opportunity cost of not using category j as follows:

$$E(oc_{ij}) = (d_j - \bar{u}_j) \cdot (\beta_{ij} \cdot s_j) \qquad \text{(IV.29)}$$

where $\bar{u}_j$ can be calculated from equation (IV.28) above, s_j can be calculated from equation (IV.11), and $\beta_{ij} \cdot s_j = \hat{s}_{ij}$, the share of potential users of category i using category j. The variable, $\hat{s}_{ij}$, can be re-stated as the share of α_i that uses worksharing category j. This yields the following interpretation for β_{ij}:

$$\beta_{ij} = [\text{the share of } \alpha_i \text{ that uses category j}] / s_j \qquad \text{(IV.30)}$$

Based on the understanding of β_{ij} inherent in equation (IV.30), three key restrictions can be developed associated with the value of β_{ij} for any worksharing categories i and j.

(1) $\beta_{ij} \geq 0$

Shares must, by definition, be between zero and one. Therefore, β_{ij}, as defined in equation (IV.30) is the quotient of two non-negative numbers. A non-negative number divided by a non-negative number must, of course, be equal to a non-negative number. Hence, $\beta_{ij} \geq 0$.

In layman's terms, this is equivalent to stating that distinct worksharing categories of a single good cannot be complementary goods. This elucidates a requirement implicit in this methodology that worksharing options must be fully specified and must be mutually exclusive. Suppose, for example, the Postal Service offered three levels of presort discounts -- basic, 3-digit, and 5-digit -- and two levels of barcoding discounts -- nonbarcoded and barcoded. The methodology outlined here would require a set of six equations of the form of equation (IV.11) to fully account for all possible worksharing categories -- basic nonbarcoded, basic barcoded, 3-digit nonbarcoded, 3-digit barcoded, 5-digit nonbarcoded, and 5-digit barcoded. The methodology of this paper would not, however, work for a set of five non-mutually exclusive equations for basic, 3-digit, and 5-digit presort, nonbarcoded, and barcoded. The user costs associated with the five non-mutually exclusive equations would not satisfy the Fundamental Theorem of Consumer Worksharing because a mailer may find more than one category (e.g., 5-digit presorting and barcoding) for which $d - u > 0$.

(2) $\beta_{ij} \leq 1 / \alpha_i$

At most, all mail that uses worksharing category j could have potentially been sent using worksharing category i. In this case, the share of α_i that uses worksharing category j is equal to s_j / α_i. Substituting this into equation (IV.30) yields

$$\beta_{ij} \leq (s_j / \alpha_i) / s_j = 1 / \alpha_i \tag{IV.31}$$

This condition can be helpful in approximating β-coefficients for categories that are generally more similar than other categories.

(3) $\beta_{ij} \geq \dfrac{1}{\alpha_i} - \dfrac{1-\alpha_i}{\alpha_i \cdot s_j}$

Among consumers who could not potentially use category i (i.e., $1 - \alpha_i$), suppose all of them actually used category j. Then, the share of mailers who could potentially use category i that are actually using category j would be equal to $s_j - (1-\alpha_i)$ (i.e., everybody using category j minus those using category j that could not potentially use category i). Substituting this into equation (IV.30) yields the following:

$$\beta_{ij} \geq \frac{\dfrac{s_j-(1-\alpha_i)}{\alpha_i}}{s_j} = \frac{1}{\alpha_i} - \frac{1-\alpha_i}{\alpha_i \cdot s_j} \tag{IV.32}$$

Equation (IV.32) can be helpful in providing insight into approximate values of β_{ij} for cases where the requirements associated with worksharing categories i and j are quite different.

An extremely useful result of equations (IV.31) and (IV.32) is that, if $\alpha_i = 1$, then $\beta_{ij} = 1$ for all worksharing categories $j \neq i$.

4. Empirical Problem to Be Solved to Model Use of Worksharing

For a good x, whose seller offers consumers discounts from the basic price of good x associated with N distinct mutually exclusive worksharing options to consumers, identified as option 1, option 2, ..., option N, where option 1 reflects no worksharing and is offered for the base-line price of good x, the share of good x that will take advantage of each of the N various worksharing categories can be determined by a system of N equations, (N-1) of which are variations of equation (IV.11) as follows:

$$s_{it} = \frac{\alpha_{it}}{1 + e^{-(d_{it} - [\mu_{it} + \sum_{j \neq i} oc_{ijt}])/\sigma_i}}, \ for \ i,j = 2, \ldots, N \qquad \text{(IV.33)}$$

where

$$oc_{ijt} = (d_{jt} - \bar{u}_{jt}) \cdot (\beta_{ijt} \cdot s_{jt}), \text{ where } \beta_{ijt} \text{ equals the share of } \alpha_i \text{ that utilizes worksharing category } j + s_{jt} \qquad \text{(IV.34)}$$

where μ_{it} in equation (IV.33) excludes opportunity costs, with $\bar{u}_{jt}$ calculated as in equation (IV.28), and $\beta_{ijt} \geq 0$ and satisfying equations (IV.31) and (IV.32).

The share of good x that will take advantage of the base worksharing category, category 1, is then simply equal to

$$s_1 = 1 - \Sigma_{i=2,\ldots,N}\, s_i \qquad \text{(IV.35)}$$

The dependent variables of this equation system are s_{it}, i = 1 to N. Values of d_{it} must be taken as given. The values for α_{it}, μ_{it}, σ_i, and β_{ijt} for i,j = 2 to N, $i \neq j$ are then the parameters to be estimated in this system of equations.

B. Econometric Share Equations

Equation (IV.33) is fit historically for each worksharing category of First-Class letters, First-Class cards, Standard Regular, and Standard Nonprofit mail. The resulting econometric values of α_t, μ_t, and σ are then used to forecast the shares of the various worksharing categories.

First-Class letters are divided into two categories for forecasting purposes: single-piece and workshared First-Class letters. Share equations are used to separate workshared First-Class letters into eight categories: presort nonautomated letter, flats, and IPPs, automation basic letters, automation 3-digit letters, automation 5-digit letters, automation basic flats, automation 3/5-digit flats, carrier-route presort letters and ZIP+4 letters.

Private First-Class cards are also forecasted separately for single-piece and workshared cards. Share equations are used to separate workshared cards into six categories: presort nonautomation, automation basic, automation 3-digit, automation 5-digit, carrier-route presort, and ZIP+4.

Standard Regular and Standard Nonprofit mail are divided into four categories apiece for forecasting purposes: basic letters, basic nonletters, presort letters, and presort nonletters. Three of these four categories (basic letters, basic nonletters, and presort nonletters) are divided into nonautomation and automation through share equations. Share equations are used to divide presort letters into three categories: nonautomation, automation 3-digit, and automation 5-digit. Mail that migrated into Standard Regular automation 5-digit letters from Standard ECR basic letters as a result of R97-1 is subtracted from Standard Regular automation 5-digit letters volume prior to the estimation of the share equations.

Share equations are estimated over a sample period of 1993Q1 through 1999Q4. Starting with the 1993 data, the Postal Service relies almost exclusively on mailing statement data to calculate the volumes of workshared First-Class Mail as well as Standard A mail. Hence, volume data since 1993 is more accurately measured than prior to 1993. This sample period spans four distinct rate regimes.

Econometric values are estimated for α_t, μ_t, and σ for each of the 24 share equations estimated for this case (Standard Regular and Nonprofit nonautomation share equations were not estimated; the share of these categories is instead equal to one minus the share of automation mail within the relevant mail category).

In general, the only factor which was modeled as having any effect on the value of α_t over time was classification reform, so that, in general, α_t was fitted to the following specification:

$$\alpha = \alpha_0 + \alpha_1 \cdot d_{MC95} \qquad \text{(IV.36)}$$

where d_{MC95} is a dummy variable equal to zero prior to classification reform and one since the implementation of MC95-1. In the case of Standard Nonprofit mail, d_{MC95} is replaced with d_{MC96}, which is equal to zero prior to the implementation of nonprofit classification reform, MC96-2, one thereafter. In many cases, the value of α_1 was found to be insignificantly different from zero. In these cases, α_1 was set equal to zero.

The specification for α_t was somewhat more complicated in the cases of First-Class carrier-route presort letters and cards. In these cases, classification reform restricted the eligibility for these discounts to a limited number of Post Offices. Further, the number of Post Offices at which these discounts are available has changed over time since classification reform first took effect more than three years ago. To take account of these factors, α_t is fit to the following specification for carrier-route presort First-Class letters and cards:

$$\alpha = \alpha_0 \cdot (1-d_{MC95}) + (c_0 - c_1 \cdot t_{MC95}) \cdot \alpha_0 \cdot d_{MC95} \qquad \text{(IV.37)}$$

where t_{MC95} is a time trend, starting with classification reform, so that it is equal to zero through 1996Q4, equal to one in 1997Q1, increasing by one thereafter, so that $(c_0 - c_1 \cdot t_{MC95})$ represents the percentage of workshared First-Class letters which are sent to Post Offices which enable them to qualify for the automation carrier-route letters and cards discounts. For forecasting purposes, the value of α_t beginning in 2000Q1 was set equal to the value of α_t in 1999Q4, so that the percentage of workshared letters sent to qualifying Post Offices was assumed to remain constant throughout the forecast period.

The general specification used to model the mean of the user-cost distribution, μ_t, for the 24 share equations presented below was the following:

$$\mu = \mu_0 - \mu_T \cdot t - \mu_{TM} \cdot t_{MC95} + \mu_1 \cdot Q_1 + \mu_2 \cdot Q_2 + \mu_3 \cdot Q_3 + \mu_M \cdot d_{MC95} + \Sigma_i oc_{ij} \qquad \text{(IV.38)}$$

where t is a time trend, equal to zero in 1993Q1, increasing by one each quarter thereafter, Q_1, Q_2, and Q_3 are dummy variables equal to one in Postal quarter 1, 2, and 3, respectively, zero otherwise, and $\Sigma_i oc_{ij}$ reflects the inclusion of opportunity costs in the share equations, as described above. For simplicity, the value of β_{ij} as defined in equation (IV.34) above is set equal to either zero or one in all cases here, so that, if an opportunity cost relationship is assumed to exist between two categories of mail, the share of potential users of category i using category j is assumed to be exactly equal to the aggregate share of category j. The specific opportunity costs included in each of the equations are discussed below. In some cases, one or more of these coefficients was found to not be significantly different from zero. In these cases, the relevant coefficients were constrained to be equal to zero.

Because of the interrelationships between α_t, d_t, μ_t, and σ, it is very difficult to freely estimate all of these parameters simultaneously. Because of this, the share equations were actually estimated using a two-step iterative procedure. First, μ_t was held constant, and α_t and σ were estimated econometrically. Then, holding α_t and σ constant, μ_t was estimated econometrically. This procedure was then repeated to ensure convergence. This procedure will lead to unbiased and efficient coefficient estimates, just as if all of the parameters were estimated simultaneously. Because of the nature of the estimation, however, the coefficient estimates do not have true standard error estimates. Hence, there are no true t-statistics associated with the parameter estimates, nor are there traditional goodness-of-fit measures such as R^2. The goodness-of-fit measure used to evaluate these equations is mean absolute percentage error. Given a set of fitted shares, f_t, and actual shares, s_t, the mean absolute percentage error is calculated as follows:

$$\text{(mean abs. pct. error)} = \Sigma^N{}_{i=1}(\text{abs}[(f_t / s_t) - 1]\bullet s_t) / \Sigma^N{}_{i=1} s_t \qquad \text{(IV.39)}$$

where N is the number of observations in the equation.

The forecasting equation is derived in section C. below. The specific econometric share equations are described next.

1. First-Class Letters

a. Opportunity Cost Relationships

The following opportunity cost relationships were modeled explicitly in the First-Class letters share equations. Nonautomation presort First-Class letters, flats, and IPPs have opportunity cost relationships with respect to all other categories of First-

Class letters. Automation basic and 3/5-digit flats and carrier-route letters have opportunity costs with respect to nonautomation presort letters and flats only.

Automation basic letters have opportunity cost relationships with respect to nonautomation presort letters and automation 3-digit letters. Automation 3-digit letters have opportunity costs with respect to nonautomation presort letters, ZIP+4 letters, automation basic letters and automation 5-digit letters. Automation 5-digit letters have opportunity costs with respect to nonautomation presort letters, ZIP+4 letters, and automation 3-digit letters. Finally, ZIP+4 letters have opportunity costs with nonautomation presort, automation 3-digit, and automation 5-digit letters.

b. Nonautomation Presort

Nonautomation presort First-Class letters, flats, and IPPs are those pieces of mail which are presorted but would not qualify for either a ZIP+4 discount (prior to MC95-1) or a prebarcode discount. Prior to MC95-1, the volume of this category included mail classified as "Presort, Residual" mail. This was mail that was sent as part of a bulk mailing for which some mail qualified for a presort or automation discount but which had insufficient density to earn a 3/5-digit presort discount. Since MC95-1, the presort discount does not require a minimum density. Hence, the category "Presort, Residual" no longer exists.

The value of α, the ceiling parameter, is constrained to be less than or equal to one. In this case, this has the effect of constraining the value of α to be exactly equal to one (i.e., any worksharing mail could have been sent as nonautomation presort mail at any point in time). Classification reform was not found to have any effect on the value of α, so α_1 was set equal to zero. In addition, the value of μ_M was constrained to zero.

The coefficients for the nonautomation presort share equation are:

$\alpha_0 = 1.000000$
$\mu_0 = 0.027419$
$\mu_T = -0.000847$
$\mu_{TM} = -0.000246$
$\mu_1 = 0.000376$
$\mu_2 = 0.000739$
$\mu_3 = 0.000410$
$\sigma = 0.031273$

Mean Absolute Percentage Error 1.465%

c. Automation Basic Letters

Automation basic letters are letters that are automated, but are not presorted to the 3-digit level or finer. This category was first introduced in MC95-1. Because an automation basic letters discount was not introduced until MC95-1, the values of α_0, μ_M, and μ_T are constrained to be equal to zero.

The coefficients for the automation basic letters share equation are:

$\alpha_1 = 0.121251$
$\mu_0 = -0.015183$
$\mu_{TM} = 0.004564$
$\mu_1 = 0.008426$
$\mu_2 = 0.016284$
$\mu_3 = 0.004264$
$\sigma = 0.025562$

Mean Absolute Percentage Error 0.718%

d. Automation Basic Flats

Automation basic flats are flats that are automated, but are not presorted to the 3-digit level or finer. Classification reform had relatively little impact on automation basic flats. The impact it did have can be summarized in a single variable, μ_M, so α_1 and μ_{TM} are constrained to be equal to zero. In addition, the values of μ_1 and μ_2 were also found to be essentially equal to zero, and were therefore constrained as such. The coefficients for the automation basic flats share equation are:

α_0 = 0.001292
μ_0 = 0.013235
μ_T = -0.000226
μ_3 = -0.002625
μ_M = 0.003632
σ = 0.001665

Mean Absolute Percentage Error 19.82%

e. Automation 3-Digit Letters

Automation 3-digit letters are letters that are automated and presorted to the 3-digit level. There is no apparent seasonal pattern to the share of automation 3-digit letters, with μ_1, μ_2, and μ_3 set equal to zero. The coefficients for the automation 3-digit letters share equation are:

α_0 = 0.409131
α_1 = 0.098297
μ_0 = 0.026457
μ_T = 0.001421
μ_{TM} = -0.000480
μ_M = -0.002654
σ = 0.015827

Mean Absolute Percentage Error 0.879%

f. Automation 5-Digit Letters

Automation 5-digit letters are letters that are automated and presorted to the 5-digit level. As with automation 3-digit letters, there is no apparent seasonal pattern to the share of automation 3-digit letters, so that μ_1, μ_2, and μ_3 are set equal to zero. In addition, classification reform did not appear to have any effect on the ceiling share of automation 5-digit letters, so α_1 was also set equal to zero.

The coefficients for the automation 5-digit letters share equation are:

α_0 = 0.274427
μ_0 = 0.034943
μ_T = 0.001717

$\mu_{TM} = 0.000855$
$\mu_M = 0.028794$
$\sigma = 0.012096$

Mean Absolute Percentage Error 1.550%

g. Automation 3/5-Digit Flats

Automation 3/5-digit flats are flats that are automated and presorted to at least the 3-digit level. As with automation basic flats, classification reform had relatively little impact on automation 3/5-digit flats, with the impact it did have summarized in a single variable, μ_M, so α_1 and μ_{TM} are constrained to be equal to zero. The coefficients for the automation 3/5-digit flats share equation are:

$\alpha_0 = 0.006658$
$\mu_0 = 0.060688$
$\mu_T = 0.000283$
$\mu_1 = -0.003013$
$\mu_2 = -0.003201$
$\mu_3 = -0.001712$
$\mu_M = -0.019321$
$\sigma = 0.005753$

Mean Absolute Percentage Error 9.101%

h. Carrier-Route Presort

Carrier-route presort First-Class letters, flats, and IPPs includes all mail which received a carrier-route presort discount. As part of classification reform in MC95-1, carrier-route discounts were restricted to letter-sized mail which was barcoded and was sent to a carrier route which met certain operational restrictions. This is dealt with through the econometric estimation of α_t, as described above.

The coefficients for the carrier-route presort share equation are:

$\alpha_0 = 1.000000$
$c_0 = 0.763055$
$c_1 = 0.024306$

$\mu_0 = 1.132100$
$\mu_T = 0.002511$
$\mu_{TM} = 0.007398$
$\mu_1 = -0.021400$
$\mu_2 = -0.030022$
$\mu_3 = -0.016793$
$\mu_M = 0.307036$
$\sigma = 0.430912$

Mean Absolute Percentage Error 4.096%

i. ZIP+4 Letters

ZIP+4 letters discounts were first introduced in 1984Q1 and were eliminated with the implementation of MC95-1 in 1996Q4. Consequently, this share is not used for forecasting. It is included here, however, due to an historical opportunity cost relationship between ZIP+4 letters and other types of First-Class letters. Because ZIP+4 letters discounts were eliminated in MC95-1, the value of α_1 is equal to the negative of α_0 (i.e., the ceiling is equal to zero post-MC95-1), and the values of μ_M and μ_{TM} are constrained to be equal to zero.

The coefficients for the ZIP+4 letters share equation are:

$\alpha_0 = 1.000000$
$\mu_0 = 0.139859$
$\mu_T = -0.003955$
$\mu_1 = 0.003040$
$\mu_2 = 0.004723$
$\mu_3 = -0.001946$
$\sigma = 0.052917$

Mean Absolute Percentage Error 5.466%

2. First-Class Cards

a. *Opportunity Cost Relationships*

The following opportunity cost relationships were modeled explicitly in the First-Class cards share equations. Nonautomation presort and ZIP+4 First-Class cards have opportunity cost relationships with respect to all other categories of First-Class cards. Automation basic cards have opportunity cost relationships with respect to nonautomation presort cards, ZIP+4 cards, and automation 3-digit cards. Automation 3-digit cards have opportunity costs with respect to nonautomation presort cards, ZIP+4 cards, automation basic cards and automation 5-digit cards. Automation 5-digit cards have opportunity costs with respect to nonautomation presort cards, ZIP+4 cards, automation 3-digit cards, and carrier-route presort cards. Finally, carrier-route presort cards have opportunity costs with nonautomation presort, ZIP+4, and automation 5-digit cards.

b. Nonautomation Presort

Nonautomation presort First-Class cards are cards which are presorted but would not qualify for either a ZIP+4 discount (prior to MC95-1) or a prebarcode discount. Prior to MC95-1, the volume of this category included mail classified as "Presort, Residual" mail. This was mail that was sent as part of a bulk mailing for which some mail qualified for a presort or automation discount but which had insufficient density to earn a 3/5-digit presort discount. Since MC95-1, the presort discount does not require a minimum density. Hence, the category "Presort, Residual" no longer exists.

The value of α, the ceiling parameter, is constrained to be less than or equal to one. In this case, this has the effect of constraining the value of α to be exactly equal to one (i.e., any worksharing cards could have been sent as nonautomation presort cards at any point in time). The ceiling parameter for nonautomated cards was unaffected by classification reform.

The coefficients for the nonautomation presort share equation are:

$$\alpha_0 = 1.000000$$
$$\mu_0 = 0.006424$$

μ_T = -0.002039
μ_{TM} = -0.001237
μ_1 = -0.002188
μ_2 = 0.006723
μ_3 = -0.002573
μ_M = 0.014756
σ = 0.071003

Mean Absolute Percentage Error 3.112%

c. Automation Basic

Automation basic cards are cards that are automated, but are not presorted to the 3-digit level or finer. The values of μ_{TM} and μ_3 were constrained to be equal to zero. The coefficients for the automation basic share equation are:

α_0 = 0.389050
α_1 = 0.187461
μ_0 = 0.184489
μ_T = 0.002069
μ_1 = 0.006579
μ_2 = 0.012608
μ_M = -0.059630
σ = 0.071328

Mean Absolute Percentage Error 6.158%

d. Automation 3-Digit

Automation 3-digit cards are cards that are automated and presorted to the 3-digit level. The value of μ_3 is constrained to zero. The coefficients for the automation 3-digit share equation are:

α_0 = 0.394770
α_1 = 0.103819
μ_0 = 0.093583
μ_T = 0.003251
μ_{TM} = -0.001271
μ_1 = 0.003950
μ_2 = 0.004796
μ_M = -0.045749

σ = 0.053564

Mean Absolute Percentage Error 4.221%

e. Automation 5-Digit

Automation 5-digit cards are cards that are automated and presorted to the 5-digit level. Classification reform did not appear to affect the ceiling share of automation 5-digit cards, so α_1 was set equal to zero. The coefficients for the automation 5-digit share equation are:

α_0 = 0.273844
μ_0 = 0.020339
μ_T = 0.012268
μ_{TM} = -0.007663
μ_1 = 0.009792
μ_2 = 0.009099
μ_3 = 0.017713
μ_M = 0.128499
σ = 0.051922

Mean Absolute Percentage Error 4.819%

f. Carrier-Route Presort

Carrier-route presort First-Class cards includes all cards which received a carrier-route presort discount. As part of classification reform in MC95-1, carrier-route cards discounts were restricted to cards which were barcoded and were sent to a carrier route which met certain operational restrictions. This is dealt with through the econometric estimation of α_t, as described above.

The value of μ_3 is set equal to zero. The coefficients for the carrier-route presort share equation are:

α_0 = 1.000000
c_0 = 0.625826
c_1 = 0.042824
μ_0 = 0.668404

μ_T = -0.004577
μ_{TM} = 0.051326
μ_1 = -0.031619
μ_2 = -0.159310
μ_M = 0.348868
σ = 0.432699

Mean Absolute Percentage Error 7.596%

g. ZIP+4 Cards

ZIP+4 cards discounts were first introduced in 1984Q1 and were eliminated with the implementation of MC95-1 in 1996Q4. Consequently, this share is not used for forecasting. It is included here, however, due to an historical opportunity cost relationship between ZIP+4 cards and other types of First-Class cards. Because ZIP+4 cards discounts were eliminated in MC95-1, the value of α_1 is equal to the negative of α_0 (i.e., the ceiling is equal to zero post-MC95-1), and the values of μ_M and μ_{TM} are constrained to be equal to zero.

The coefficients for the ZIP+4 cards share equation are:

α_0 = 1.000000
μ_0 = 0.134274
μ_T = -0.006949
μ_1 = -0.010096
μ_2 = -0.019211
μ_3 = -0.009702
σ = 0.052658

Mean Absolute Percentage Error 17.19%

3. Standard Regular Mail

a. Opportunity Cost Relationships

The following opportunity cost relationships were modeled explicitly in the Standard Regular share equations. Automation basic letters and basic ZIP+4 letters have opportunity cost relationships with respect to each other, as do automation 3-digit letters, automation 5-digit letters, and presort ZIP+4 letters.

b. Automation Basic Letters

Automation basic letters are letters that are automated, but are not presorted to the 3-digit level or finer. The share of automation basic letters is taken as a share of total basic letters.

The coefficients for the automation basic letters share equation are:

α_0 = 0.639274
α_1 = 0.283576

μ_0 = 0.050438
μ_T = 0.002270
μ_{TM} = 0.003953
μ_1 = 0.004122
μ_2 = -0.003608
μ_3 = 0.004734
μ_M = 0.008948

σ = 0.064435

Mean Absolute Percentage Error 4.112%

c. Automation Basic Flats

Automation basic flats are flats that are automated, but are not presorted to the 3-digit level or finer. The share of automation basic flats is taken as a share of total basic nonletters. The values of α_1, μ_1, μ_2, and μ_3 were constrained to be equal to zero. The coefficients for the automation basic flats share equation are:

$\alpha_0 = 0.837332$

$\mu_0 = 0.210955$
$\mu_T = 0.003639$
$\mu_{TM} = -0.002596$
$\mu_M = -0.045659$

$\sigma = 0.062965$

Mean Absolute Percentage Error 9.715%

d. Automation 3-Digit Letters

Automation 3-digit letters are letters that are automated and presorted to the 3-digit level. The share of automation 3-digit letters is taken as a share of total presorted letters. The values of μ_1 and μ_{TM} were constrained to be equal to zero. The coefficients for the automation 3-digit letters share equation are:

$\alpha_0 = 0.607493$
$\alpha_1 = 0.353171$

$\mu_0 = 0.105102$
$\mu_T = 0.001807$
$\mu_2 = -0.009178$
$\mu_3 = -0.003561$
$\mu_M = -0.087596$

$\sigma = 0.074806$

Mean Absolute Percentage Error 2.154%

e. Automation 5-Digit Letters

Automation 5-digit letters are letters that are automated and presorted to the 5-digit level. The share of automation 5-digit letters is taken as a share of total presorted letters. The values of α_1 and μ_{TM} were constrained to be equal to zero. The coefficients for the automation 5-digit letters share equation are:

$\alpha_0 = 0.628866$

μ_0 = -0.018069
μ_T = 0.000987
μ_1 = 0.016682
μ_2 = 0.007887
μ_3 = 0.009315
μ_M = 0.100810

σ = 0.070905

Mean Absolute Percentage Error 7.157%

f. Automation 3/5-Digit Flats

Automation 3/5-digit flats are flats that are automated and presorted to at least the 3-digit level. The share of automation 3/5-digit flats is taken as a share of total presorted nonletters. The values of α_1, μ_{TM}, μ_1, μ_2, and μ_3 were constrained to be equal to zero. The coefficients for the automation 3/5-digit flats share equation are:

α_0 = 0.848936

μ_0 = 0.017253
μ_T = 0.005886
μ_M = 0.019727

σ = 0.037610

Mean Absolute Percentage Error 4.102%

g. Basic ZIP+4 Letters

The share of basic ZIP+4 letters is taken as a share of total basic letters. ZIP+4 letters discounts were eliminated as part of MC95-1. Consequently, the value of α_1 was set equal to $-\alpha_0$, and the values of μ_M and μ_{TM} were set equal to zero. In addition, μ_3 was constrained to be equal to zero. The coefficients for the basic ZIP+4 letters share equation are:

α_0 = 1.000000

$\mu_0 = 0.120047$
$\mu_T = 0.004027$
$\mu_1 = 0.002320$
$\mu_2 = -0.002050$

$\sigma = 0.037038$

Mean Absolute Percentage Error 9.223%

h. Presort ZIP+4 Letters

The share of presort ZIP+4 letters is taken as a share of total presort letters. ZIP+4 letters discounts were eliminated as part of MC95-1. Consequently, the value of α_1 was set equal to $-\alpha_0$, and the values of μ_M and μ_{TM} were set equal to zero. In addition, μ_1 and μ_3 were constrained to be equal to zero. The coefficients for the presort ZIP+4 letters share equation are:

$\alpha_0 = 1.000000$

$\mu_0 = 0.126776$
$\mu_T = 0.002431$
$\mu_2 = 0.005039$

$\sigma = 0.037039$

Mean Absolute Percentage Error 10.35%

4. Standard Nonprofit Mail

a. Opportunity Cost Relationships

The only opportunity cost relationships explicitly modeled in the Standard Nonprofit share equations are between basic ZIP+4 letters and automation basic letters and between presort ZIP+4 letters and automation 3-digit and 5-digit letters.

b. Automation Basic Letters

Automation basic letters are letters that are automated, but are not presorted to the 3-digit level or finer. The values of μ_{TM}, μ_1, μ_2, and μ_3 were constrained to be equal to zero. The share of automation basic letters is taken as a share of total basic letters.

The coefficients for the automation basic letters share equation are:

$\alpha_0 =$ 0.602223
$\alpha_1 =$ 0.344095

$\mu_0 =$ 0.102527
$\mu_T =$ 0.003531
$\mu_M =$ -0.013098

$\sigma =$ 0.075624

Mean Absolute Percentage Error 6.044%

c. Automation Basic Flats

Automation basic flats are flats that are automated, but are not presorted to the 3-digit level or finer. The share of automation basic flats is taken as a share of total basic nonletters. The value of α_1 was constrained to be equal to zero. The coefficients for the automation basic flats share equation are:

$\alpha_0 =$ 0.818703

$\mu_0 =$ 0.276057
$\mu_T =$ 0.007272
$\mu_{TM} =$ -0.004429
$\mu_1 =$ 0.000571
$\mu_2 =$ 0.007238
$\mu_3 =$ 0.004322
$\mu_M =$ -0.034252

$\sigma =$ 0.063923

Mean Absolute Percentage Error 11.54%

d. Automation 3-Digit Letters

Automation 3-digit letters are letters that are automated and presorted to the 3-digit level. The share of automation 3-digit letters is taken as a share of total presorted letters. The coefficients for the automation 3-digit letters share equation are:

$\alpha_0 =$ 0.603290
$\alpha_1 =$ 0.353671

$\mu_0 =$ 0.132096
$\mu_T =$ 0.003935
$\mu_{TM} =$ -0.003655
$\mu_1 =$ 0.003466
$\mu_2 =$ 0.005224
$\mu_3 =$ 0.005461
$\mu_M =$ -0.048965

$\sigma =$ 0.075682

Mean Absolute Percentage Error 3.822%

e. Automation 5-Digit Letters

Automation 5-digit letters are letters that are automated and presorted to the 5-digit level. The share of automation 5-digit letters is taken as a share of total presorted letters. The values of α_1 and μ_{TM} were constrained to be equal to zero. The coefficients for the automation 5-digit letters share equation are:

$\alpha_0 =$ 0.619937

$\mu_0 =$ 0.054764
$\mu_T =$ 0.002295
$\mu_1 =$ -0.014406
$\mu_2 =$ -0.007946
$\mu_3 =$ -0.011483
$\mu_M =$ 0.079014

$\sigma =$ 0.077322

Mean Absolute Percentage Error 7.130%

f. Automation 3/5-Digit Flats

Automation 3/5-digit flats are flats that are automated and presorted to at least the 3-digit level. The share of automation 3/5-digit flats is taken as a share of total presorted nonletters. The values of α_1 and μ_{TM} were constrained to be equal to zero. The coefficients for the automation 3/5-digit flats share equation are:

α_0 = 0.867364

μ_0 = 0.054637
μ_T = 0.003780
μ_1 = 0.008345
μ_2 = 0.006997
μ_3 = 0.003475
μ_M = -0.012674

σ = 0.042321

Mean Absolute Percentage Error 4.049%

g. Basic ZIP+4 Letters

The share of basic ZIP+4 letters is taken as a share of total basic letters. ZIP+4 letters discounts were eliminated as part of MC96-2. Consequently, the value of α_1 was set equal to $-\alpha_0$, and the values of μ_M and μ_{TM} were set equal to zero. In addition, μ_1, μ_2, and μ_3 were constrained to be equal to zero. The coefficients for the basic ZIP+4 letters share equation are:

α_0 = 1.000000
μ_0 = 0.120996
μ_T = -0.002176
σ = 0.037054

Mean Absolute Percentage Error 12.04%

h. Presort ZIP+4 Letters

The share of presort ZIP+4 letters is taken as a share of total presort letters. ZIP+4 letters discounts were eliminated as part of MC95-1. Consequently, the value of α_1 was set equal to $-\alpha_0$, and the values of μ_M and μ_{TM} were set equal to zero. In addition, μ_1, μ_2, and μ_3 were constrained to be equal to zero. The coefficients for the presort ZIP+4 letters share equation are:

α_0 = 1.000000
μ_0 = 0.109878
μ_T = -0.001995
σ = 0.037053

Mean Absolute Percentage Error 7.756%

C. Technique for Forecasting Shares

1. Derivation of Share Forecasting Formula

The basis for forecasting the worksharing proportions is equation (IV.33) described in Section A which says for any category of worksharing mail:

$$s_t = \frac{\alpha_t}{1 + e^{-(d_t - \mu_t)/\sigma}} \qquad \text{(IV.33)}$$

where

s_t is the share of worksharing mail during time t,

α_t is the proportion of worksharing mail for which this worksharing activity is a reasonable alternative at time t.

d_t is the discount offered by the Postal Service at time t,

μ_t is the mean of the user-cost distribution at time t, and

σ is the standard deviation of the user-cost distribution

In applying (IV.33) to forecasting share equations, a base share approach is used. The base share approach utilizes the ratio of equation (IV.33) evaluated at time t and equation (IV.33) evaluated during a base time period to determine the forecast share during time t. The base period for calculating shares in this case is Postal Fiscal Year 1999.

Using equation (IV.33) from above, the forecasting formula is derived as follows:

$$s_t = \frac{\alpha_t}{1 + e^{-(d_t - \mu_t)/\sigma}} \quad ; \quad s_{base} = \frac{\alpha_{base}}{1 + e^{-(d_{base} - \mu_{base})/\sigma}}$$
$$s_t = s_{base} \cdot \left(\frac{\alpha_t}{\alpha_{base}}\right) \cdot \left[\frac{(1 + e^{-(d_{base} - \mu_{base})/\sigma})}{(1 + e^{-(d_t - \mu_t)/\sigma})}\right] \qquad \text{(IV.40)}$$

2. Values used in the Forecasting Formula

The data used to make share forecasts in this case are summarized in Tables IV-1 through IV-4 below. The base period used here is 1999Q1 through 1999Q4, while the Test Year is Government Fiscal Year, 2001 (October 1, 2000 through September 30, 2001).

Table IV-1 presents base shares used in forecasting, base- and test-year values of α, the ceiling parameter, and σ, the standard deviation of the user-cost distribution. Base shares of Standard Regular letters are calculated excluding mail which migrated from Standard ECR as a result of R97-1. An explicit adjustment is made for this shift in Dr. Tolley's testimony. The values of α and σ come from the econometric equations discussed above.

Table IV-2 presents the base-year and test-year discounts. R97-1 took effect approximately 30 percent of the way into the base year. In column 1 of Table IV-2, the nominal discounts associated with the worksharing categories of First-Class and

Standard A mail are presented. As with most economic work, the discounts are deflated for forecasting purposes. The real base-year discounts are shown in column 2 of Table IV-2. The real test-year before-rates discounts are presented in column 3. Finally, column 4 of Table IV-2 presents the real after-rates discounts.

Table IV-3 presents the values of μ, the mean of the user-cost distribution, used in forecasting. In the first column of Table IV-3 are base values of μ, excluding opportunity costs. The second column of Table IV-3 presents base values of μ with opportunity costs included. The third column of Table IV-3 presents test year before-rates values of μ with opportunity costs included. Finally, in the fourth column of Table IV-3 are test year after-rates values of μ including opportunity costs. The difference between columns 3 and 4 of Table IV-3 represents the effect of proposed changes to other discounts on the shares of workshared First-Class and Standard A mail.

Table IV-4 summarizes the share forecasts. Base shares are presented in column 1 of Table IV-4. This column is identical to the first column of Table IV-1. Test-year before-rates forecasts are presented in column 2 of Table IV-4. The share forecasts are actually made on a quarterly basis. Test-year after-rates share forecasts are presented in column 3 of Table IV-4.

Table IV-1
Summary of Parameters used in Forecasting Shares

	Base Share	α_{Base}	$\alpha_{Test\ Year}$	σ
First-Class Letters				
Workshared				
Presort Nonautomation	9.85%	100.00%	100.00%	3.13¢
Automation Basic Letters	11.69%	12.13%	12.13%	2.56¢
Automation Basic Flats	0.10%	0.13%	0.13%	0.17¢
Automation 3-Digit Letters	48.36%	50.74%	50.74%	1.58¢
Automation 5-Digit Letters	26.43%	27.44%	27.44%	1.21¢
Automation 3/5-Digit Flats	0.61%	0.67%	0.67%	0.58¢
Automation Carrier-Route	2.95%	50.50%	47.14%	43.09¢
First-Class Cards				
Private Workshared				
Presort Nonautomation	21.18%	100.00%	100.00%	7.10¢
Automation Basic	17.18%	57.65%	57.65%	7.13¢
Automation 3-Digit	33.36%	49.86%	49.86%	5.36¢
Automation 5-Digit	23.83%	27.38%	27.38%	5.19¢
Automation Carrier Route	4.45%	17.12%	11.19%	43.27¢
Standard Regular				
Letters				
Basic				
Nonautomation	25.63%	NA	NA	NA
Automation	74.37%	92.28%	92.28%	6.44¢
Presort				
Nonautomation	12.61%	NA	NA	NA
Automation 3-Digit	63.35%	96.07%	96.07%	7.48¢
Automation 5-Digit	24.03%	62.89%	62.89%	7.09¢
Nonletters				
Basic				
Nonautomation	76.32%	NA	NA	NA
Automation	23.68%	83.73%	83.73%	6.30¢
Presort				
Nonautomation	14.75%	NA	NA	NA
Automation	85.25%	84.89%	84.89%	3.76¢
Standard Nonprofit				
Letters				
Basic				
Nonautomation	42.02%	NA	NA	NA
Automation	57.98%	94.63%	94.63%	7.56¢
Presort				
Nonautomation	27.47%	NA	NA	NA
Automation 3-Digit	47.61%	95.70%	95.70%	7.57¢
Automation 5-Digit	24.92%	61.99%	61.99%	7.73¢
Nonletters				
Basic				
Nonautomation	78.48%	NA	NA	NA
Automation	21.52%	81.87%	81.87%	6.39¢
Presort				
Nonautomation	26.67%	NA	NA	NA
Automation	73.33%	86.74%	86.74%	4.23¢

Table IV-2
Summary of Parameters used in Forecasting Shares

	d_{Base} (nominal)	d_{Base} (real)	d_{TYBR} (real)	d_{TYAR} (real)
First-Class Letters				
Workshared				
Presort Nonautomation	2.50¢	2.20¢	2.12¢	1.71¢
Automation Basic Letters	5.97¢	5.25¢	5.09¢	5.09¢
Automation Basic Flats	3.00¢	2.64¢	2.54¢	2.54¢
Automation 3-Digit Letters	6.80¢	5.98¢	5.85¢	5.85¢
Automation 5-Digit Letters	8.54¢	7.51¢	7.37¢	7.37¢
Automation 3/5-Digit Flats	5.67¢	4.99¢	5.09¢	5.31¢
Automation Carrier-Route	9.13¢	8.03¢	7.80¢	7.80¢
First-Class Cards				
Private Workshared				
Presort Nonautomation	2.00¢	1.76¢	1.70¢	1.70¢
Automation Basic	3.40¢	2.99¢	2.88¢	3.04¢
Automation 3-Digit	4.10¢	3.61¢	3.48¢	3.64¢
Automation 5-Digit	5.50¢	4.84¢	4.58¢	4.74¢
Automation Carrier Route	5.93¢	5.22¢	5.00¢	5.16¢
Standard Regular				
Letters				
Basic				
Nonautomation	NA	NA	NA	NA
Automation	5.89¢	5.18¢	4.41¢	3.60¢
Presort				
Nonautomation	NA	NA	NA	NA
Automation 3-Digit	3.20¢	2.81¢	2.63¢	2.71¢
Automation 5-Digit	4.93¢	4.34¢	3.98¢	4.47¢
Nonletters				
Basic				
Nonautomation	NA	NA	NA	NA
Automation	4.92¢	4.32¢	5.00¢	3.79¢
Presort				
Nonautomation	NA	NA	NA	NA
Automation	3.67¢	3.23¢	3.14¢	2.33¢
Standard Nonprofit				
Letters				
Basic				
Nonautomation	NA	NA	NA	NA
Automation	4.44¢	3.91¢	4.24¢	2.62¢
Presort				
Nonautomation	NA	NA	NA	NA
Automation 3-Digit	2.51¢	2.20¢	2.37¢	2.37¢
Automation 5-Digit	4.34¢	3.82¢	4.15¢	4.15¢
Nonletters				
Basic				
Nonautomation	NA	NA	NA	NA
Automation	4.22¢	3.71¢	4.32¢	3.51¢
Presort				
Nonautomation	NA	NA	NA	NA
Automation	2.20¢	1.93¢	1.78¢	1.46¢

Table IV-3
Summary of Parameters used in Forecasting Shares

	μ_{Base} (excl. o.c.)	μ_{Base} (incl. o.c.)	μ_{TYBR} (incl. o.c.)	μ_{TYAR} (incl. o.c.)
First-Class Letters				
Workshared				
Presort Nonautomation	5.21¢	9.31¢	10.81¢	10.83¢
Automation Basic Letters	-5.70¢	-3.31¢	-7.11¢	-7.13¢
Automation Basic Flats	2.20¢	2.36¢	2.49¢	2.46¢
Automation 3-Digit Letters	-0.75¢	1.05¢	0.78¢	0.76¢
Automation 5-Digit Letters	1.07¢	3.45¢	1.30¢	1.28¢
Automation 3/5-Digit Flats	3.23¢	3.39¢	3.09¢	3.07¢
Automation Carrier-Route	128.05¢	128.21¢	119.98¢	119.96¢
First-Class Cards				
Private Workshared				
Presort Nonautomation	8.70¢	11.49¢	14.41¢	14.55¢
Automation Basic	13.59¢	14.99¢	13.25¢	13.30¢
Automation 3-Digit	-1.99¢	-0.15¢	-1.77¢	-1.71¢
Automation 5-Digit	-7.56¢	-5.94¢	-9.73¢	-9.67¢
Automation Carrier Route	54.58¢	55.99¢	17.39¢	17.42¢
Standard Regular				
Letters				
Basic				
Nonautomation	NA	NA	NA	NA
Automation	-3.95¢	-3.95¢	-9.08¢	-9.08¢
Presort				
Nonautomation	NA	NA	NA	NA
Automation 3-Digit	-3.17¢	-2.32¢	-3.83¢	-3.71¢
Automation 5-Digit	6.53¢	8.20¢	7.38¢	7.43¢
Nonletters				
Basic				
Nonautomation	NA	NA	NA	NA
Automation	9.96¢	9.96¢	9.10¢	9.10¢
Presort				
Nonautomation	NA	NA	NA	NA
Automation	-11.38¢	-11.38¢	-16.23¢	-16.23¢
Standard Nonprofit				
Letters				
Basic				
Nonautomation	NA	NA	NA	NA
Automation	-0.10¢	-0.10¢	-3.01¢	-3.01¢
Presort				
Nonautomation	NA	NA	NA	NA
Automation 3-Digit	2.09¢	2.09¢	1.86¢	1.86¢
Automation 5-Digit	6.72¢	6.72¢	4.82¢	4.82¢
Nonletters				
Basic				
Nonautomation	NA	NA	NA	NA
Automation	10.09¢	10.09¢	7.75¢	7.75¢
Presort				
Nonautomation	NA	NA	NA	NA
Automation	-5.05¢	-5.05¢	-8.17¢	-8.17¢

Table IV-4
Summary of Parameters used in Forecasting Shares

	Base Share	Test-Year Before-Rates Share	Test Year After-Rates Share
First-Class Letters			
Workshared			
Presort Nonautomation	9.85%	6.23%	5.51%
Automation Basic Letters	11.69%	11.88%	11.96%
Automation Basic Flats	0.10%	0.11%	0.11%
Automation 3-Digit Letters	48.36%	51.77%	52.17%
Automation 5-Digit Letters	26.43%	26.11%	26.32%
Automation 3/5-Digit Flats	0.61%	0.64%	0.65%
Automation Carrier-Route	2.95%	3.26%	3.29%
First-Class Cards			
Private Workshared			
Presort Nonautomation	21.18%	14.65%	14.37%
Automation Basic	17.18%	20.28%	20.53%
Automation 3-Digit	33.36%	35.08%	35.19%
Automation 5-Digit	23.83%	24.83%	24.76%
Automation Carrier Route	4.45%	5.17%	5.15%
Standard Regular			
Letters			
Basic			
Nonautomation	25.63%	18.01%	19.72%
Automation	74.37%	81.99%	80.28%
Presort			
Nonautomation	12.61%	7.68%	6.84%
Automation 3-Digit	63.35%	63.57%	63.19%
Automation 5-Digit	24.03%	28.75%	29.97%
Nonletters			
Basic			
Nonautomation	76.32%	71.37%	75.05%
Automation	23.68%	28.63%	24.95%
Presort			
Nonautomation	14.75%	13.30%	13.58%
Automation	85.25%	86.70%	86.42%
Standard Nonprofit			
Letters			
Basic			
Nonautomation	42.02%	33.37%	38.06%
Automation	57.98%	66.63%	61.94%
Presort			
Nonautomation	27.47%	21.77%	21.81%
Automation 3-Digit	47.61%	48.78%	48.79%
Automation 5-Digit	24.92%	29.44%	29.40%
Nonletters			
Basic			
Nonautomation	78.48%	70.33%	72.77%
Automation	21.52%	29.67%	27.23%
Presort			
Nonautomation	26.67%	20.38%	21.00%
Automation	73.33%	79.62%	79.00%

3. The Residual Share

Nonautomated Standard Regular and Nonprofit mail categories are not forecasted using equation (IV.60) above. Instead, these represent "residual" categories. These are the categories from which the Standard discounts used in forecasting are based. Consequently, these categories have no discounts by definition. The forecasted shares of these categories are estimated using equation (IV.35) above, and are equal to one minus the forecasted shares of all of the worksharing categories within the particular category of interest.

Because the shares of workshared First-Class letters and cards are taken as shares of total workshared First-Class letters and cards, respectively, there is no residual category associated with these two groups of mail. Instead of calculating a residual share, therefore, using equation (IV.35), the forecasted shares of workshared First-Class letters and workshared First-Class cards are normalized to sum to 100 percent.

4. Enhanced Carrier Route Shares

Standard ECR shares are not forecasted using equation (IV.40) above. The before-rates shares of Standard ECR and Nonprofit ECR mail are simply projected to be equal to the base shares in the forecast period. The one exception to this is Standard ECR letters. In this case, the base share forecast for Standard ECR letters was calculated after adding back in the volume which shifted to Standard Regular automation 5-digit letters after R97-1. The effect of this shift on the forecasted volumes was then included as a vol-adjust, which is described in Dr. Tolley's volume forecasting testimony.

The after-rates shares of ECR mail are equivalent to the before-rates shares of these categories. The share forecasts for Standard ECR and Nonprofit ECR mail are the following:

Table IV-5
Forecasted Shares of Standard ECR and Nonprofit ECR Mail

Standard ECR	
Letters	
Basic	58.436%
Automation	15.921%
High Density	3.263%
Saturation	22.379%
Nonletters	
Basic	53.145%
High Density	6.392%
Saturation	40.463%
Standard ECR Nonprofit	
Letters	
Basic	42.844%
Automation	20.471%
High Density	3.132%
Saturation	33.553%
Nonletters	
Basic	74.428%
High Density	0.755%
Saturation	24.818%

D. Final Forecasted Shares of Worksharing Categories of First-Class and Standard A Mail

Tables IV-6 and IV-7 below present final forecasted shares of First-Class and Standard A mail before- and after-rates from 2000Q1 through 2002Q1.

Table IV-6
Before-Rates Share Forecasts

	2000Q1	2000Q2	2000Q3	2000Q4	2001Q1	2001Q2	2001Q3	2001Q4	2002Q1
Workshared First-Class Letters									
Presort Nonautomation	8.476%	7.936%	7.479%	7.287%	6.835%	6.444%	6.118%	6.032%	5.698%
Automation Basic Letters	11.736%	11.696%	11.857%	11.886%	11.868%	11.857%	11.966%	11.991%	11.981%
Automation Basic Flats	0.106%	0.107%	0.108%	0.108%	0.109%	0.110%	0.110%	0.111%	0.111%
Automation 3-Digit Letters	49.729%	50.161%	50.437%	50.686%	50.915%	51.142%	51.327%	51.447%	51.544%
Automation 5-Digit Letters	26.390%	26.413%	26.455%	26.426%	26.446%	26.485%	26.539%	26.537%	26.547%
Automation 3/5-Digit Flats	0.632%	0.634%	0.631%	0.623%	0.635%	0.637%	0.634%	0.627%	0.638%
Automation Carrier-Route Letters	2.930%	3.052%	3.033%	2.983%	3.193%	3.326%	3.306%	3.254%	3.480%
Workshared First-Class Cards									
Presort Nonautomation	20.149%	17.715%	18.043%	16.596%	16.631%	14.498%	14.814%	13.607%	13.619%
Automation Basic	17.835%	17.406%	19.610%	19.993%	19.217%	18.680%	21.013%	21.389%	20.563%
Automation 3-Digit	34.112%	35.100%	34.734%	34.840%	34.925%	35.765%	35.311%	35.390%	35.479%
Automation 5-Digit	24.432%	25.127%	23.865%	24.560%	24.667%	25.210%	24.021%	24.489%	24.625%
Automation Carrier Route	3.472%	4.652%	3.748%	4.011%	4.561%	5.847%	4.841%	5.124%	5.714%
Standard Regular									
Letters									
Basic									
Nonautomation	24.444%	21.688%	22.120%	20.193%	19.880%	17.782%	18.117%	16.665%	16.433%
Automation	75.556%	78.312%	77.880%	79.807%	80.120%	82.218%	81.883%	83.335%	83.567%
Presort									
Nonautomation	14.037%	9.341%	10.443%	8.912%	11.565%	6.952%	8.030%	6.464%	9.181%
Automation 3-Digit	63.702%	66.518%	65.469%	64.728%	65.549%	68.260%	67.244%	66.524%	67.314%
Automation 5-Digit	22.261%	24.141%	24.088%	26.360%	22.886%	24.787%	24.727%	27.012%	23.505%
Nonletters									
Basic									
Nonautomation	73.391%	73.137%	72.898%	72.666%	72.438%	72.207%	71.979%	71.759%	71.536%
Automation	26.609%	26.863%	27.102%	27.334%	27.562%	27.793%	28.021%	28.241%	28.464%
Presort									
Nonautomation	14.212%	14.041%	13.894%	13.768%	13.660%	13.566%	13.486%	13.417%	13.358%
Automation	85.788%	85.959%	86.106%	86.232%	86.340%	86.434%	86.514%	86.583%	86.642%
Standard Nonprofit									
Letters									
Basic									
Nonautomation	38.456%	37.545%	36.660%	35.797%	34.952%	34.121%	33.308%	32.517%	31.740%
Automation	61.544%	62.455%	63.340%	64.203%	65.048%	65.879%	66.692%	67.483%	68.260%
Presort									
Nonautomation	23.395%	24.723%	23.634%	23.719%	21.515%	22.879%	21.799%	21.916%	19.702%
Automation 3-Digit	48.485%	47.999%	47.978%	49.729%	48.696%	48.195%	48.167%	49.909%	48.872%
Automation 5-Digit	28.120%	27.279%	28.388%	26.552%	29.789%	28.926%	30.035%	28.175%	31.426%
Nonletters									
Basic									
Nonautomation	74.228%	75.298%	73.783%	71.830%	71.243%	72.396%	70.811%	68.779%	68.173%
Automation	25.772%	24.702%	26.217%	28.170%	28.757%	27.604%	29.189%	31.221%	31.827%
Presort									
Nonautomation	25.610%	24.338%	22.709%	21.291%	22.190%	21.220%	19.985%	18.920%	19.597%
Automation	74.390%	75.662%	77.291%	78.709%	77.810%	78.780%	80.015%	81.080%	80.403%

Table IV-7
After-Rates Share Forecasts

	2001Q1	2001Q2	2001Q3	2001Q4	2002Q1
Workshared First-Class Letters					
Presort Nonautomation	6.240%	5.698%	5.410%	5.338%	5.044%
Automation Basic Letters	11.942%	11.951%	12.055%	12.078%	12.064%
Automation Basic Flats	0.110%	0.111%	0.111%	0.112%	0.112%
Automation 3-Digit Letters	51.240%	51.549%	51.712%	51.823%	51.899%
Automation 5-Digit Letters	26.610%	26.691%	26.733%	26.728%	26.728%
Automation 3/5-Digit Flats	0.644%	0.648%	0.646%	0.641%	0.648%
Automation Carrier-Route Letters	3.214%	3.354%	3.332%	3.279%	3.506%
Workshared First-Class Cards					
Presort Nonautomation	16.405%	14.223%	14.531%	13.342%	13.356%
Automation Basic	19.380%	18.890%	21.237%	21.614%	20.780%
Automation 3-Digit	35.007%	35.868%	35.397%	35.470%	35.563%
Automation 5-Digit	24.650%	25.178%	23.997%	24.454%	24.591%
Automation Carrier Route	4.559%	5.841%	4.838%	5.121%	5.710%
Standard Regular					
Letters					
Basic					
Nonautomation	20.969%	19.043%	19.406%	17.792%	17.527%
Automation	79.031%	80.957%	80.594%	82.208%	82.473%
Presort					
Nonautomation	10.894%	6.044%	7.127%	5.567%	8.294%
Automation 3-Digit	65.488%	68.157%	67.139%	66.388%	67.227%
Automation 5-Digit	23.619%	25.799%	25.734%	28.046%	24.480%
Nonletters					
Basic					
Nonautomation	75.131%	75.799%	75.569%	75.343%	75.116%
Automation	24.869%	24.201%	24.431%	24.657%	24.884%
Presort					
Nonautomation	13.781%	13.710%	13.609%	13.523%	13.448%
Automation	86.219%	86.290%	86.391%	86.477%	86.552%
Standard Nonprofit					
Letters					
Basic					
Nonautomation	38.270%	38.541%	37.629%	36.735%	35.856%
Automation	61.730%	61.459%	62.371%	63.265%	64.144%
Presort					
Nonautomation	21.515%	22.879%	21.799%	21.916%	19.702%
Automation 3-Digit	48.696%	48.195%	48.167%	49.909%	48.872%
Automation 5-Digit	29.789%	28.926%	30.035%	28.175%	31.426%
Nonletters					
Basic					
Nonautomation	73.047%	74.752%	73.221%	71.247%	70.647%
Automation	26.953%	25.248%	26.779%	28.753%	29.353%
Presort					
Nonautomation	22.715%	21.866%	20.544%	19.403%	20.124%
Automation	77.285%	78.134%	79.456%	80.597%	79.876%