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POSTAL RATE COMMISSION
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POSTAL RATE AND FEE CHANGES, 2001

Docket No. R2001-1

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

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Library References:

USPS-LR-J-127 Data, Programs, and Results for Witness Thress's Econometric Work (Thress)

USPS-LR-J-128 Estimation of Permanent Income Elasticities (Thress)

USPS-LR-J-129 Witness Thress's Econometric Choice Trail (Thress)

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 Nos. R97-1 and R2000-1. 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. Musgrave, USPS-T-8), and to provide forecasts of the worksharing categories of First-Class, Standard, and parcel post 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-7).

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. Tolley in making volume forecasts, as described in USPS-T-7. This work builds upon the testimony of Dr. Tolley and me in R2000-1 and R97-1, as well as Dr. Tolley's work in earlier rate cases, going back to R80-1. As in earlier cases, 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 mail and destination entry categories of parcel post are forecasted in section IV of my testimony below.

My direct testimony is supported by three category 2 library references. The first of these, USPS-LR-J-127, presents the data used in my econometric work, the programs used to do my econometric work, as well as the econometric results presented here. My second library reference, USPS-LR-J-128, presents the estimation of certain long-run income elasticities from Household Diary Study data. Finally, USPS-LR-J-129 presents some intermediate econometric results which were used in the development of my testimony. In addition, Library Reference LR-J-122, 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 Library Reference LR-J-127, 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, Periodical nonprofit and classroom mail, for which a single equation is estimated, Standard bulk nonprofit mail, where a single equation is modeled for Nonprofit and Nonprofit Enhanced Carrier Route mail, and Media and Library rate mail, for which a single equation is estimated. The coefficients estimated from these equations are used as inputs in the Postal Service's forecasting model to forecast future mail volumes for each subclass of mail. Volume forecasts are presented by Dr. George Tolley in USPS-T-7.

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 mail is discussed in section II.D.; Package Services 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, Standard Regular and Nonprofit, and parcel post mail that have taken advantage of various Postal Service worksharing discounts are projected in section IV below. The general methodology for modeling worksharing shares was originally presented in Dr. Tolley's testimony in MC95-1 (USPS-T-16), and 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. Parcel post shares by drop-ship category are forecasted using a similar methodology, although relative discounts are not included as explanatory variables in this analysis.

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,

$$Q_t = f(Y_t, P_t, \ldots) \qquad \text{(II.1)}$$

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 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 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 the Postal Service's Package Services class. 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 R2000-1

There have been some improvements to the econometric demand equations since R2000-1. These include the following:

- Separation of September seasonal variable into two variables, September 1 - 15 and September 16 - 30,
- More stringent test statistic for introducing autocorrelation correction coefficients,
- Combining Periodical nonprofit and classroom mail and Media and Library Rate mail within single demand equations,

- Later starting periods for some econometric demand equations, including parcel post, Media Mail, and money orders,
- Freely estimating the long-run income elasticity in the workshared First-Class letters, insurance, and money orders equations,
- Introduction of variables to measure the effect of the Internet on mail volume – consumption expenditures on Internet Service Providers, which is included in the single-piece First-Class letters, private First-Class cards, and Periodical regular rate equations, and Internet advertising expenditures, which is included in the Standard Regular and Standard ECR equations
- Use of the wholesale price of direct-mail advertising in the Standard mail equations,
- Use of consumption expenditures and retail sales, with freely esimated elasticities, instead of long-run income in Package Services equations,
- Introduction of cross-volume variable with respect to First-Class letters in registered and certified mail equations,
- Removal of long-run income from registered mail, certified mail, COD, and return receipts demand equations,
- Z-Variable in Insurance equation starting with the significant increase in the maximum level of insurance available as a result of MC96-3, and
- Estimation of a separate demand equation for delivery confirmation

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 variables 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 to 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 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 nearly 50 percent of all mail and generating approximately 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.

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. Thus, separate demand equations are estimated for single-piece and workshared First-Class letters.

b. 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 46.5 percent in 2000.

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 migration 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

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[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 workshared First-Class and Standard 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.

discounts offered by the Postal Service or due to changes in the costs of worksharing faced 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 average 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 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

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

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 log-log functional form used throughout my testimony,

$$(\partial V_{sp}/\partial d_{ws}) = \beta_{sp} \bullet (V_{sp}/d_{ws}) \qquad \text{(II.3)}$$

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

where β_{sp} is the coefficient on the worksharing discount in the single-piece letters equation, which is equivalent to the elasticity with respect to the worksharing discount in the single-piece letters equation, and β_{ws} is the coefficient on the worksharing discount in the worksharing letters equation, which is equivalent to 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

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

The ratio (V_{ws}/V_{sp}) varies over time. This implies that β_{sp} and/or β_{ws} also varies over time. Since, as noted above, (V_{ws}/V_{sp}) has grown over time, the value of β_{sp} must also have grown over time relative to β_{ws}. This could be accomplished either through an increase in the value of β_{sp} over time or by a decline in the value of β_{ws} over time (or both).

The latter of these options, a decline in the value of β_{ws} over time, seems more plausible. As more and more mail shifts from single-piece into workshared, the volume of mail left in single-piece letters that could possibly shift as a result of subsequent increases in the worksharing discount becomes less and less. Hence, one might reasonably expect the percentage increase in worksharing letters volume due to changes in the worksharing discount to decline as the ratio of workshared to single-piece letters increases.

The demand equations used here are log-log equations of the following form:

$$Ln(V_{sp}) = a + \beta_{sp} \bullet Ln(d_{ws}) + \ldots \qquad \text{(II.5)}$$

$$Ln(V_{ws}) = a + \beta_{ws} \bullet Ln(d_{ws}) + \ldots$$

Using equation (II.4), the latter of these equations can be restated as follows:

$$Ln(V_{ws}) = a - \beta_{sp} \bullet [Ln(d_{ws}) / (V_{ws}/V_{sp})] + \ldots \qquad \text{(II.6)}$$

The worksharing discount is divided by the ratio of workshared to single-piece letters in the workshared letters equation. Using this specification, the coefficient on this variable from the workshared letters equation, $[Ln(d_{ws}) / (V_{ws}/V_{sp})]$, is equal to the negative of the discount elasticity in the single-piece letters equation. Hence, the coefficient from the workshared letters equation can be used as a (stochastic) constraint in the single-piece letters equation.

There is, however, one problem with equation (II.6) above: the volume of workshared letters (V_{ws}) is expressed, in part, as a function of the volume of workshared letters. To solve this problem, the discount was not divided by the true ratio of workshared to single-piece letters in the demand equation actually used here. Instead, the discount was divided by a fitted ratio of workshared to single-piece letters. This fitted value was constructed by fitting the following equation:

$$Ln(V'_{ws} / V'_{sp}) = a + b_0 \bullet d_{84Q1} + b_1 \bullet d_{93Q1} + b_3 \bullet d_{MC95} + b_4 \bullet t \qquad (II.7)$$

where V'_{ws} and V'_{sp} are seasonally adjusted volumes of workshared and single-piece letters, respectively, d_{84Q1} and d_{93Q1} are dummy variables equal to one starting in 1984Q1 and 1993Q1, respectively, d_{MC95} is a dummy variable equal to zero prior to MC95-1 and equal to one after MC95-1, and t is a time trend. Equation (II.7) was estimated using a sample period from 1982Q1 through 2001Q3.

Another feature of equation (II.6) is that the term $[Ln(d_{ws}) / (V_{ws}/V_{sp})]$ has the effect of introducing another time trend into the workshared letters equation through the (V_{ws}/V_{sp}) term. This aspect of this variable reflects, in large part, shifts in mail between single-piece and workshared letters due to changes in the cost of worksharing. This issue is discussed below.

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 decline over time as mailers become more familiar with worksharing in general. Second, the costs to mailers of worksharing include fairly 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 among of their explanatory variables. In addition, as noted above, the adjustment factor which is applied to the worksharing discount in the workshared letters equation works as a time trend in the workshared letters equation as well.

These trends are discussed more fully in section h below.

c. 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.3.c. 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 freely estimated in the workshared letters equation here, and was constrained using the Slutsky-Schultz equation in the Standard Regular equation.

d. Impact of the Internet on First-Class Mail Volume

One factor affecting First-Class Mail volume which has received a great deal of attention recently is the diversion of First-Class Mail by the Internet and other electronic sources. In past rate cases, this diversion of mail has not been modeled explicitly in the First-Class Mail equations, but has, instead, been accounted for implicitly through trend variables. In R2000-1, for example, it was estimated that the time trends in the First-Class letters equation implied that electronic diversion had reduced First-Class letters volume by 6 - 7 billion pieces from 1988 through 1999.

As the Internet has grown, a number of variables which measure Internet usage have become available which were not previously available. One of these variables in consumption expenditures on Internet Service Providers (ISPs), which has grown from approximately $25 million in 1988 to $14.6 billion in 2000. This variable was included in the demand specifications for single-piece First-Class letters, private First-Class cards, and Periodical regular rate mail to help explain losses in these mail volumes due to electronic diversion. Attempts to also include this variable in the workshared First-Class letters equation were unsuccessful.

Like all income and consumption variables used here, consumption expenditures on Internet Service Providers was divided by adult population prior to inclusion in the demand equations. Unlike other income and consumption variables, however, it was not possible to take the natural logarithm of ISP consumption because this variable has a value equal to zero prior to 1988.

Instead, a Box-Cox transformation was performed on the ISP consumption variable. That is, ISP consumption expenditures entered the demand equations in the following way:

$$\mathrm{Ln(Volume)} = a + \ldots + b_I \bullet [\mathrm{ISP\ Consumption}]^{\gamma} + \ldots \qquad \text{(II.8)}$$

A value of γ equal to one would be equivalent to entering ISP consumption expenditures directly in the demand equation, and would mean that a given dollar increase in the level of ISP consumption would lead to the same percentage decrease in mail volume. For example, an increase in ISP consumption expenditures from $25 million to $50 million would have the same effect as an increase from $14.600 billion to $14.625 billion.

A value of γ approximately equal to zero would be equivalent to entering the natural logarithm of ISP consumption in the demand equation, and would mean that a given percentage increase in the level of ISP consumption would lead to the same percentage decrease in mail volume. For example, an increase in ISP consumption expenditures from $25 million to $50 million would have the same effect as an increase from $14.6 billion to $29.2 billion.

The value of γ was estimated from the single-piece First-Class letters equation using *nonlinear least squares. The estimated value of* γ *used here is equal to 0.560, which* had a t-statistic associated with it of 1.859. This value of γ was used for all of the demand equations in which ISP consumption appears as a variable. A value of γ equal to 0.560 would mean that an increase in ISP consumption expenditures from $25 million to $50 million would have the same effect as an increase from $14.6 billion to $14.95 billion.

A detailed discussion of the relationship between the Internet and mail volume is contained in the Direct Testimony of Peter Bernstein in this case (USPS-T-8).

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)
- Long-Run Income (as described in section III.A.2.b. below)
- Short-Run Income (lagged four quarters to reflect a lagged reaction of single-piece First-Class mailers to changing economic conditions)
- Consumption expenditures on Internet Service Providers (as described in section d above)
- 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
- The average worksharing discount for First-Class letters, stochastically constrained from the worksharing First-Class letters equation as described above
- The price of private single-piece First-Class cards, stochastically constrained from the private First-Class cards equation using the 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 -0.311 (t-statistic of -4.619). 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 -0.027, t-statistic of -2.351) 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 -0.311, but is, instead, equal to -0.311 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 -0.335, with a t-statistic of -5.001.

Single-piece First-Class letters have a long-run income elasticity of 0.512 (stochastically constrained from the Household Diary Study, t-statistic of 21.16) and a short-run income elasticity of 0.099 (t-statistic of 1.484).

Over the past five years, the time trend and trend squared variables have accounted for an 8.9 percent decline in the volume of single-piece First-Class letters. In addition, the proliferation of the Internet has accounted for an additional 8.6 percent decline in single-piece letters volume. In contrast, taken together, other factors would have led one to expect single-piece letters volume per adult to grow by 10.5 percent over this same time period. The trends in single-piece and workshared First-Class letters are discussed in section h 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)
- Long-Run Income (as described in section III.A.2.b. below)
- Short-Run 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
- The average worksharing discount for First-Class letters (divided by fitted ratio of workshared to single-piece letters as described in section b.i. above)
- The price of workshared First-Class cards, stochastically constrained from the private First-Class cards equation using Slutsky-Schultz equality constraint

- The price of Standard Regular mail
- 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 -0.071, with a t-statistic equal to -0.149. The volume of workshared First-Class letters is positively influenced by changes in the First-Class worksharing discount. The coefficient on the worksharing discount variable is 0.027 (t-statistic of 2.271). Given a value for (V'_{ws}/V'_{sp}) of 0.95 in 2001Q3, this translates into a current discount elasticity equal to 0.028. 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 -0.028 (t-statistic of -0.121) in 2001Q3.

Workshared First-Class letters have a long-run income elasticity, which is no longer constrained from the Household Diary Study, of 0.844 (t-statistic of 2.194), and a short-run income elasticity of 0.373 (t-statistic of 2.073).

The time trend included in the worksharing First-Class letters equation, which has an estimated coefficient of 0.430 and a t-statistic equal to 3.656, has accounted for a 10.3 percent increase in worksharing letters volume over the past five years. The trend imbedded in the discount variable has added an additional 2.5 percent to workshared letters volume over this same time period. The First-Class trends are discussed below.

g. First-Class Letters Trends

In my R2000-1 testimony, I devoted several pages to a discussion of the factors which were implicitly included within the time trend variables in the First-Class letters equations. The current demand specifications contain two additional trend variables, which allow for a somewhat better look at the trend factors affecting First-Class letters volume.

In the single-piece First-Class letters equation, ISP consumption has been added to the demand specification in addition to the logistic time trends which have been in the single-piece letters equation since R97-1. In the workshared letters equation, the discount is divided by a fitted ratio of workshared to single-piece letters. This variable has a very pronounced trend component. In addition, the workshared letters equation also still includes the logistic time trend used in past rate cases.

The individual and combined impacts of these various trend variables on First-Class letters volume are summarized in Table II-1 below.

Overall, the trend variables explain a decline in single-piece letters volume of 20 billion pieces from 1987 through 2001, with 37 percent of this attributable to the ISP consumption variable. Overall, ISP consumption expenditures account for a decline in single-piece First-Class letters volume of nearly 7.5 billion pieces from 1987 through 2001, with more than 56 percent of this decline occurring over the past three years.

The trend variables explain an increase in workshared letters volume of 15.3 billion pieces from 1987 through 2001. This growth has been fairly steady throughout this time period.

The cumulative effect of the trend variables was modestly positive through about 1994, after which time increasing electronic diversion has helped to turn the net effect of the trend variables negative. Since 1996, the net effect of the trend variables has been a loss of 4.9 billion First-Class letters, or about one billion letters per year.

A more detailed analysis of these trends, particularly as they relate to electronic diversion and the Internet, is provided in the Direct Testimony of Peter Bernstein (USPS-T-8).

Table II-1
Impact of Time Trends in First-Class Letters Equations
(millions of pieces, cumulative since 1987)

	Single-Piece			Workshared			
	Logistic Trend	Internet	Total	Logistic Trend	Discount Ratio	Total	Total Letters
1988	(541.155)	(101.801)	(642.956)	880.449	317.813	1,198.261	555.305
1989	(1,213.630)	(283.145)	(1,496.775)	1,770.062	646.508	2,416.570	919.795
1990	(1,988.646)	(398.350)	(2,386.996)	2,629.041	948.618	3,577.659	1,190.664
1991	(2,848.052)	(602.992)	(3,451.044)	3,477.897	1,288.771	4,766.668	1,315.625
1992	(3,727.396)	(769.491)	(4,496.886)	4,325.526	1,619.045	5,944.570	1,447.684
1993	(4,650.356)	(891.858)	(5,542.214)	5,159.388	1,606.382	6,765.770	1,223.557
1994	(5,618.229)	(1,210.991)	(6,829.220)	5,971.865	1,925.003	7,896.869	1,067.649
1995	(6,597.245)	(1,763.106)	(8,360.351)	6,804.419	2,273.462	9,077.881	717.531
1996	(7,569.847)	(2,404.782)	(9,974.630)	7,650.155	2,505.051	10,155.206	180.577
1997	(8,561.754)	(2,895.681)	(11,457.435)	8,459.731	2,430.423	10,890.153	(567.281)
1998	(9,567.222)	(3,252.560)	(12,819.782)	9,255.657	2,730.599	11,986.256	(833.526)
1999	(10,568.597)	(3,938.613)	(14,507.210)	10,054.725	3,031.737	13,086.462	(1,420.748)
2000	(11,563.617)	(5,240.705)	(16,804.322)	10,861.872	3,320.445	14,182.317	(2,622.005)
2001[2]	(12,531.732)	(7,480.088)	(20,011.819)	11,674.613	3,601.853	15,276.466	(4,735.353)

[2] 2001Q4 is forecasted

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 3 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 45 percent of total First-Class cards and workshared First-Class cards accounting for 52 percent of total First-Class cards. Separate demand equations are estimated for postal and private First-Class cards.

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)
- Long-Run Income (as described in section III.A.2.b. below)
- A linear time trend
- A dummy variable equal to one starting with the implementation of R97-1 rates in 1999Q2, at which time stamped cards were priced greater than private cards for the first time
- A dummy variable equal to one starting in 2001Q1, reflecting a change in the source of stamped cards volume by the Postal Service
- Current price of postal cards

Elasticities are listed in Table II-4.

The price elasticity of postal cards is -0.808 (t-statistic of -1.734). In R97-1, stamped cards were priced more expensive than private cards for the first time in Postal history. The impact of this change in the relative prices of these two types of mail is modeled through a simple dummy variable, equal to zero prior to R97-1, and equal to one thereafter. The coefficient on this dummy variable suggests that the additional fee charged for stamped cards starting at that time caused a reduction in stamped cards volume of 5.6 percent.

The volume of postal cards has been somewhat unstable over time. Hence, the demand equation for postal cards is not fit nearly as reliably as the demand equations for other categories of First-Class Mail. The mean-squared error of the postal cards equation is 0.034419, with an adjusted-R^2 of 0.755.

b. Private Cards

A single equation was estimated for total private First-Class cards. As in past rate cases, separate equations for single-piece and workshared private cards were not feasible, primarily due to the somewhat erratic volume history of workshared cards.

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
- Long-Run Income (as described in section III.A.2.b. below)
- Consumption expenditures on Internet Service Providers (as described in section d above)
- 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, which is equal to the percentage of cards for which First-Class cards rates are less than corresponding Standard Regular rates. This variable has a value of zero until R87-1 (1988Q3), at which time it reached a value of 100 percent. The value of this variable fell to a value of

20.0 percent with the implementation of R90-1 rates (1991Q2). It has a current value of 88.4 percent.

- Crossover Dummy variable interacted with a time trend beginning in 1988Q4 and plateauing in 1990Q4 to reflect lagged reaction by mailers to the R87-1 rate crossover
- Dummy variables equal to one in 1988Q4 and 1991Q3, respectively, and zero elsewhere, to adjust for apparent outliers in these quarters. These outliers may be due, in large part, to the R87-1 rate crossover which priced First-Class cards less than Standard Regular mail and the R90-1 rates which reversed this relationship for most mail as noted above.
- Current and three lags of the price of First-Class Letters
- Current and four 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 -1.157, with a t-statistic of -8.818. Private First-Class cards also have a cross-price elasticity with respect to First-Class letters equal to 0.163 (t-statistic of 1.435).

The crossover dummy variable has an estimated coefficient of 0.030 with a t-statistic of 1.112. This implies, for example, that the initial implementation of R2000-1 rates in January of 2001 caused an increase in private First-Class cards volume of approximately 0.42 percent due to changes in the relative rates associated with First-Class cards and Standard Regular mail.

Private First-Class cards have a long-run income elasticity, which is stochastically constrained from the Household Diary Study, equal to 0.700 (t-statistic of 16.07). Short-Run income is not modeled to have any impact on private cards volume.

TABLE II-2
SINGLE-PIECE FIRST-CLASS LETTERS

	Coefficient	T-statistic
First-Class Single-Piece Letters price -- SUM	-0.311	-4.619
current	-0.168	-1.659
lag 1	-0.143	-1.449
First-Class Single-Piece Cards price -- current only	0.0038	0.995
Worksharing First-Class Letters Discount -- current only	-0.027	-2.351
Long-Run Income	0.512	21.16
Short-Run Income (lag 4)	0.099	1.484
Logistic Time Trends:		
Time Trend	1.599	6.496
Time Trend Squared	-0.224	-7.005
Consumption Expenditures, Internet Service Providers	-0.498	-5.839
Dummy for use of Government-Distributed Volume	0.017	2.129
Dummy for Classification Reform (MC95-1)	0.035	3.976
Seasonal coefficients:		
September - October	-0.106	-2.418
November - December 21	0.409	11.01
December 22 - January 1	-0.435	-2.303
January 2 - February 28	0.208	5.330
March	-0.016	-0.257
April 1 - 15	0.614	2.738
April 16 - May	-0.105	-1.569
June	0.178	1.572

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.000188
Degrees of Freedom	55
Adjusted-R^2	0.974

TABLE II-3
WORKSHARED FIRST-CLASS LETTERS

	Coefficient	T-statistic
Worksharing First-Class Letters price -- SUM	-0.071	-0.149
current	-0.000	-0.000
lag 1	-0.018	-0.062
lag 2	-0.028	-0.099
lag 3	-0.025	-0.125
Worksharing First-Class Cards price -- current only	0.006	0.897
Standard Regular price -- current only	0.008	0.029
Worksharing First-Class Letters Discount -- current only	0.027	2.271
Long-Run Income	0.844	2.194
Short-Run Income	0.373	2.073
Logistic Time Trend	0.430	3.656
Dummy for use of Government-Distributed Volume	0.034	1.621
Dummy for Classification Reform (MC95-1)	-0.046	-2.940
Seasonal coefficients:		
September - October	0.196	1.423
November 1 - December 10	0.246	3.270
December 11 - 17	0.413	1.677
December 18 - 24	-0.268	-1.114
December 25 - January 1	2.916	2.580
January 2 - February 28	0.038	0.321
March	0.354	2.272
April - May	0.113	1.814
June	0.479	1.903

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.000650
Degrees of Freedom	53
Adjusted-R^2	0.993

TABLE II-4
FIRST-CLASS STAMPED CARDS

	Coefficient	T-statistic
First-Class postal cards price -- current only	-0.808	-1.734
Long-Run Income	0.711	23.93
Time Trend	-0.005	-1.917
Dummy for R97-1	-0.057	-0.265
Dummy since 2000Q4 (change in RPW methodology)	-0.822	-4.323
Seasonal coefficients:		
September 1 - 15	-1.752	-1.270
September 16 - 30	0.375	0.946
October	-0.827	-2.153
November 1 - December 17	0.242	0.671
December 18 - 19	1.288	0.728
December 20 - 23	-3.136	-3.344
December 24 - June	-0.235	-1.001

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.778
Mean Square Error	0.034419
Degrees of Freedom	108
Adjusted-R^2	0.755

TABLE II-5
FIRST-CLASS PRIVATE CARDS

	Coefficient	T-statistic
First-Class private cards price -- SUM	-1.157	-8.818
current	-0.533	-1.200
lag 1	-0.319	-0.405
lag 2	-0.001	-0.001
lag 3	-0.106	-0.196
lag 4	-0.198	-1.240
First-Class letters price -- SUM	0.163	1.435
current	0.002	0.004
lag 1	0.041	0.046
lag 2	0.073	0.078
lag 3	0.047	0.097
Long-Run Income	0.700	16.07
Consumption Expenditures, Internet Service Providers	-0.170	-1.478
Machine dummy variable	-0.143	-6.239
Crossover dummy	0.030	1.112
Crossover trend	0.013	5.901
Dummy for 1988Q4	0.245	3.257
Dummy for 1991Q3	0.253	3.631
Parameters used in calculating Z-variable:		
Param1	0.230	2.114
Param2	214.1	0.301
Param3	0.141	1.881
Seasonal coefficients:		
September	0.128	1.491
October	0.906	5.079
November 1 - December 12	-0.641	-4.659
December 13 - January 1	0.555	5.224
REGRESSION DIAGNOSTICS :		
AR-2 coefficient	-0.242	
Mean Square Error	0.003890	
Degrees of Freedom	96	
Adjusted-R^2	0.956	

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 long-run and short-run income (see section III.A.2.b for an overview of the theoretical underpinnings of long-run and short-run 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 over 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 R94-1, 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 in the need for Dr. Tolley to include negative net trends in his forecasting equations for Periodical mail.

Two explanations exist for the persistence of this trend. First, new substitutes, such as the Internet, have emerged just as cable television expenditures growth began to slow. Second, 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 latter phenomenon is better modeled in the Periodical mail equations by including a simple linear time trend instead of cable television expenditures.

In addition to this time trend, consumption expenditures on Internet Service Providers (see section B.2.d. above for a description of this variable) were also included in the Periodical regular equation. On the other hand, this Internet variable was not found to work in the Periodical within-county and nonprofit equations.

Periodical mail is divided into one regular subclass and three preferred subclasses: within-county, nonprofit, and classroom mail. For estimation purposes, Periodical nonprofit and classroom mail were combined and estimated in a single demand equation. Hence, three demand equations were modeled, one each for Periodical regular rate, within-county, and nonprofit and classroom mail. Periodical regular mail accounts for more than 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)
- Long-Run Income (as described in section III.A.2.b. below)
- Short-Run income (lagged four quarters to reflect a lagged adjustment of economic conditions into changes in subscription bases)
- Time trend
- The wholesale price of pulp and paper (lagged two quarters to reflect a lagged impact of input prices on subscription bases)
- Consumption expenditures on Internet Service Providers
- 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 -0.166, with a t-statistic of -3.133. 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 -0.141 with a t-statistic of -1.185. 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 long-run income elasticity of Periodical regular mail is stochastically constrained from the Household Diary Study and has a value of 0.534 (t-statistic of 14.97), while the short-run income elasticity is 0.077 (t-statistic of 0.832).

The demand equation for Periodical regular mail has a significant negative trend, with a coefficient of -0.002 (t-statistic -3.285). The trend has accounted for a 3.2 percent decline in Periodical regular volume over the past five years. The Internet has accounted for an additional 2.4 percent decline in Periodical regular volume over this time period, while the other variables in the econometric equation led to an expectation of 4.7 percent growth in Periodical regular mail volume per adult over this time period.

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. These latter two subclasses are combined in my analysis.

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 within-county mail, however. This could have occurred for a variety of reasons, including the possibility that within-county 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. In addition, as noted above, the Internet Service Providers consumption variable in the Periodical regular equation did not work in either of the preferred-rate demand equations.

Linear time trends were included in the preferred Periodical demand equations, just as in the Periodical regular equation. Both of the preferred Periodical demand equations had a larger negative time trend than Periodical regular mail.

The specific demand equations for Periodical within county and nonprofit (including 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)
- Long-Run 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 -0.157 (t-statistic of -1.917). 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, however (coefficient of -0.009, t-statistic of -6.165). The time trend has accounted for a decline in Periodical within-county mail of 16.7 percent in the past five years. Overall, Periodical within-county mail volume has declined 2.5 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 0.003435, although the adjusted-R^2 is fairly impressive at 0.970.

c. Nonprofit and Classroom Mail

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

- Seasonal Variables (as described in section III.A.2.c. below)
- Long-Run Income (as described in section III.A.2.b. below)
- Short-Run income (lagged four quarters to reflect a lagged adjustment of economic conditions into changes in subscription bases)
- The wholesale price of pulp and paper (lagged one quarter)
- Time trend
- Current 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 two Periodical equations 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 -0.092, with a t-statistic of -1.414. Periodical nonprofit mail volume is considerably more sensitive to changes in income and the price of paper than regular rate mail, with income elasticities of 0.537 (t-statistic of 19.37) and 1.306 (t-statistic of 4.030) with respect to long-run and short-run income, respectively, and a paper price elasticity of -0.382 (t-statistic of -0.740).

The time trend in the Periodical nonprofit equation (coefficient of -0.006, t-statistic of -6.139) explains a 10.5 percent decline in Periodical nonprofit mail volume over the past five years. Overall, Periodical nonprofit volume has declined by 5.3 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 0.003710 and an adjusted-R^2 equal to 0.864.

TABLE II-6
PERIODICAL REGULAR RATE

	Coefficient	T-statistic
Periodical regular rate price -- SUM	-0.166	-3.133
current	-0.000	-0.000
lag 1	-0.022	-0.243
lag 2	-0.072	-0.794
lag 3	-0.071	-0.974
Long-Run Income	0.534	14.97
Short-Run Income (lag 4)	0.077	0.832
Wholesale price of pulp and paper (lag 2)	-0.141	-1.185
Consumption Expenditures, Internet Service Providers	-0.136	-0.936
Time Trend	-0.0016	-3.285
Seasonal coefficients:		
September	-0.418	-4.025
October	-0.150	-1.942
November - December 10	0.037	0.677
December 11 - 24	-0.438	-3.492
December 25 - February	-0.070	-2.544
March	-0.207	-2.530
April 1 - 15	0.187	0.685
April 16 - May	-0.139	-1.301
June	-0.329	-3.584
REGRESSION DIAGNOSTICS :		
AR-1 coefficient	0.324	
AR-2 coefficient	0.291	
Mean Square Error	0.000711	
Degrees of Freedom	100	
Adjusted-R^2	0.855	

TABLE II-7
PERIODICAL WITHIN-COUNTY MAIL

	Coefficient	T-statistic
Periodical within-county price -- current only	-0.157	-1.917
Long-Run Income	0.535	16.32
Time Trend	-0.009	-6.165
New reporting dummy	0.357	7.073
Dummy for 1987 rule change restricting within-county eligibility	-0.103	-2.084
Change in paneling method	-0.226	-4.418
Seasonal coefficients:		
September 16 - December 10	0.054	2.988
December 11 - 12	-3.488	-4.519
December 13 - 19	1.549	4.491
December 20 - 24	-1.049	-2.710
December 25 - January 1	0.618	2.379
January 2 - April 15	0.016	0.933
April 16 - June	0.063	3.228
REGRESSION DIAGNOSTICS :		
AR-1 coefficient	0.645	
Mean Square Error	0.003435	
Degrees of Freedom	107	
Adjusted-R^2	0.970	

TABLE II-8
PERIODICAL NONPROFIT AND CLASSROOM MAIL

	Coefficient	T-statistic
Periodical nonprofit price -- current only	-0.092	-1.414
Long-Run Income	0.537	19.37
Short-Run Income (lag 4)	1.306	4.030
Wholesale price of pulp and paper (lag 1)	-0.382	-0.740
Time Trend	-0.006	-6.139
Seasonal coefficients:		
September 16 - December 12	0.166	9.022
December 13 - 17	0.664	2.296
December 18 - 21	-0.712	-1.978
December 22 - 24	0.497	1.228
December 25 - June	0.139	9.202
REGRESSION DIAGNOSTICS :		
AR-1 coefficient	0.393	
AR-2 coefficient	0.486	
AR-4 coefficient	-0.330	
Mean Square Error	0.003710	
Degrees of Freedom	77	
Adjusted-R^2	0.864	

D. Standard Mail

The demand for Standard 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 mail volume by including a set of explanatory variables in the demand equations for Standard mail that addresses each of these three decisions. Each of these three decisions, and the implications for Standard 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 expected 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).

Several alternate measures of economic activity were investigated in the Standard mail equations, including personal consumption expenditures, personal disposable income, and retail sales. Various lags of these variables were also investigated. The resulting variables which were included in the Standard mail equations were retail sales lagged two quarters in the Standard Regular equation, retail sales (with no lag) in the Standard Enhanced Carrier Route (ECR) equation, and personal consumption expenditures lagged one quarter in the Standard bulk nonprofit equation.

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 mail ought to include the prices of direct-mail advertising, as well as the prices of alternate advertising media.

i. Price of Direct-Mail Advertising

In R97-1, the cost of direct-mail advertising was separated into four components in the Standard equations – postage cost, paper cost, printing cost, and technological costs. In R2000-1, the middle two of these components, paper and printing costs, were removed from the Standard mail equations due to multicollinearity problems. These costs have been re-introduced in this case, through a single variable, the Bureau of Labor Statistics' wholesale price of direct-mail advertising printing.

(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) Paper and Printing Costs

As mentioned above, non-postage costs associated with direct-mail advertising are modeled through the inclusion of the Bureau of Labor Statistics' wholesale price index for direct-mail advertising printing.

(c) 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 whom 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. In R2000-1, the price of computer equipment was also included in the Standard Regular equation squared. This created some problems, however.

In this case, the price of computer equipment has been replaced by a simple linear time trend. Time trends are included in all three Standard mail demand equations. The time trend in the Standard Regular equation has a positive coefficient, reflecting the positive influence of targeting described above. The time trends in the Standard ECR and bulk nonprofit equations, on the other hand, have negative coefficients, suggesting, in part, that these types of mail have been adversely affected by technological developments. For example, by targeting individuals rather than neighborhoods, advertisers are less likely to have enough density within carrier routes to qualify for Standard ECR rates.

ii. Competing Advertising Media

In R97-1, the Standard demand equations included cost per-thousand (CPM) data for magazines, newspapers, television and radio advertising provided by McCann-Erickson. In R2000-1, an alternative measure of the price of newspaper advertising was taken from the Bureau of Labor Statistics, which measured the wholesale price of newspaper advertising, while substitution between Standard mail and radio and television advertising was not explicitly modeled. The use of the BLS's price of newspaper advertising index continues in this case.

Another advertising medium which has become a significant substitute for direct-mail advertising in recent years is the Internet. While I am unaware of any good source on the price of Internet advertising, the Internet Advertising Bureau reports total Internet advertising expenditures on a quarterly basis[3], and has done so for some time.

This measure of Internet advertising expenditures is included in the Standard Regular and ECR demand equations. Combined, the results suggest that every dollar spent on Internet advertising results in 35-40 cents less in direct-mail advertising.

As with consumption expenditures on Internet Service Providers (see section II.B.2.d. above), Internet advertising expenditures were equal to zero for much of the sample period considered here. Hence, it is not possible to use the natural logarithm of Internet advertising expenditures as an explanatory variable in the Standard mail equations, since the natural logarithm of zero is undefined.

Instead, as was done with consumption expenditures on Internet Service Providers, Internet advertising expenditures were transformed using a Box-Cox type of transformation, so that Internet advertising expenditures entered the Standard mail demand equations in the following way:

$$\text{Ln(Volume)} = a + \ldots + b_I \bullet [\text{Internet Adv. Exp.}]^{\gamma} + \ldots \qquad \text{(II.9)}$$

The value of γ was estimated from basic Standard Regular and ECR equations which were simultaneously estimated. The estimated value of γ used here is equal to 0.893, which had a t-statistic associated with it of 3.570.

c. How to Send Mail-Based Advertising

Direct-mail advertising can be sent as either First-Class or Standard mail. To reflect possible substitution between First-Class and Standard mail, a cross-price with respect to workshared First-Class letters is included in the Standard Regular equation. The

[3] Internet advertising expenditures are compiled by PriceWaterhouseCoopers for the Internet Advertising Bureau.

cross-price elasticity with respect to First-Class letters is constrained in the Standard Regular equation using the Slutsky-Schultz equality constraint from the workshared letters equation. Cross prices are not included in the Standard ECR and bulk nonprofit equations, however, because these subclasses are priced significantly below First-Class Mail, so that price-based substitution between these mail categories seems unlikely.

In addition to the cross-price between Standard Regular and First-Class letters, substitution between Standard Regular and ECR mail is also modeled due to a rate crossover in which 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.

This event is modeled by the inclusion of a dummy variable equal to one starting with the implementation of R97-1 rates in January of 1999. 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.

2. Final Specifications for Standard Mail

a. 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)
- Retail sales (lagged two quarters)
- Price of newspaper advertising
- Price of direct-mail advertising (lagged four quarters)
- Linear time trend

- Internet advertising expenditures
- 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
- The price of workshared First-Class letters, with the coefficient constrained from the workshared First-Class letters equation
- Current and one lag of the price of Standard Regular mail

Elasticities are listed in Table II-9.

The Postal own-price elasticity of Standard Regular mail is estimated to be equal to -0.388, with a t-statistic of -9.418. The non-postage direct-mail price elasticity is equal to -1.006 (t-statistic of -7.335). Taken together, the own-price elasticity of Standard Regular direct-mail advertising is -1.394, with postage accounting for approximately 30 percent of this elasticity.

Standard Regular mail has a cross-price elasticity with respect to newspaper advertising equal to 0.135 (t-statistic of 1.471). This has led to a 2.2 percent increase in Standard Regular mail volume over the past five years. This has been more than offset, however, by a 7.5 percent decline attributable to Internet advertising expenditures.

Standard Regular mail has a retail sales elasticity of 0.700, with a t-statistic of 10.80. Over the past five years, retail sales has contributed more to Standard Regular growth than any other variable, accounting for 13.2 percent growth in Standard Regular mail volume over that time period. The next most important variable is the time trend in the Standard Regular equation, which has a coefficient of 0.006 (t-statistic of 8.314), and has accounted for an increase in Standard Regular mail volume of 12.0 percent over the past five years.

b. 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)
- Retail sales
- Price of newspaper advertising
- Price of direct-mail advertising (lagged one quarter)
- Linear time trend
- Internet advertising expenditures
- Dummy variable equal to one in the Fall of even-numbered years, to account for the seasonal pattern of election mailings
- Dummy variable for pricing of Automation 5-digit letters less than Standard ECR Basic letters when R97-1 rates were implemented
- Current and four lags of the price of Standard ECR mail

Elasticities are listed in Table II-10.

The Postal own-price elasticity of Standard ECR mail is estimated to be equal to -0.770, with a t-statistic of -6.628, while the non-Postal price elasticity of Standard ECR direct-mail advertising is -1.612 (t-statistic of -4.831). Overall, Standard ECR mail is about 70 percent more price-sensitive than Standard Regular mail, and approximately one-third of the overall price elasticity of ECR direct-mail advertising is Postal. Standard ECR mail is also considerably more sensitive to the price of newspaper advertising than Standard Regular mail, with a cross-price elasticity of 0.839 (t-statistic of 5.094), as well as Internet advertising expenditures (coefficient of -0.754, t-statistic of -4.514 versus -0.441 and -4.733 for Standard Regular mail). Standard ECR mail has a retail sales elasticity of 1.223, with a t-statistic of 8.284.

The Standard ECR demand equation has a time trend coefficient of -0.007 (t-statistic of -4.602). As noted above, this is consistent with the general observation that, 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.

c. 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 (lagged one quarter)
- Price of direct-mail advertising (lagged two quarters)
- Linear time trend
- 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 four lags of the price of Standard bulk nonprofit mail

Elasticities are listed in Table II-11.

The Postal own-price elasticity of Standard bulk nonprofit mail is estimated to be equal to -0.230, with a t-statistic of -2.838. The non-Postal direct-mail price elasticity is estimated to be -0.236 (t-statistic of -0.904). Both of these elasticities are considerably lower than the price elasticities associated with Standard bulk regular mail.

Standard bulk nonprofit mail has a consumption elasticity of 1.019 with a t-statistic of 10.28, and a modest negative time trend (coefficient of -0.003, t-statistic of -3.058).

TABLE II-9
STANDARD REGULAR MAIL

	Coefficient	T-statistic
Standard Regular price -- SUM	-0.388	-9.418
current	-0.157	-1.942
lag 1	-0.231	-2.975
First-Class Letters price (current only)	0.012	--
Retail Sales (lag 2)	0.700	10.80
Price of Newspaper Advertising	0.135	1.471
Price of Direct-Mail Advertising (lag 4)	-1.006	-7.335
Time Trend	0.006	8.314
Internet Advertising Expenditures	-0.441	-4.733
Dummy for Shift of Mail from ECR into Regular after R97-1	0.101	9.547
Seasonal coefficients:		
October	0.987	8.766
November 1 - December 15	-0.295	-7.076
December 16 - March	0.181	3.622
April 1 - 15	0.783	4.123
April 16 - May	-0.121	-1.961
June	0.479	2.815
REGRESSION DIAGNOSTICS :		
AR-2 coefficient	-0.458	
AR-4 coefficient	-0.535	
Mean-Squared Error	0.000244	
Degrees of Freedom	34	
Adjusted-R^2	0.994	

TABLE II-10
STANDARD ENHANCED CARRIER ROUTE MAIL

	Coefficient	T-statistic
Standard ECR price -- SUM	-0.770	-6.628
current	-0.233	-1.789
lag 1	-0.110	-0.578
lag 2	-0.012	-0.064
lag 3	-0.124	-0.702
lag 4	-0.291	-2.340
Retail Sales	1.223	8.284
Price of Newspaper Advertising	0.839	5.094
Price of Direct-Mail Advertising (lag 1)	-1.612	-4.831
Internet Advertising Expenditures	-0.754	-4.514
Time Trend	-0.007	-4.602
Dummy for Federal General Elections	0.010	1.000
Dummy for Shift of Mail from ECR into Regular after R97-1	-0.137	-6.810
Seasonal coefficients:		
September 16 - October	0.685	3.710
November 1 - December 10	-0.154	-1.252
December 11 - 19	0.050	0.245
December 20 - 24	1.057	2.130
December 25 - January 1	-0.471	-1.108
January 2 - May	0.132	1.077
June	0.377	0.889

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean-Squared Error	0.000336
Degrees of Freedom	35
Adjusted-R^2	0.962

TABLE II-11
STANDARD BULK NONPROFIT MAIL

	Coefficient	T-statistic
Standard bulk Nonprofit price -- SUM	-0.230	-2.838
current	-0.058	-0.404
lag 1	-0.011	-0.046
lag 2	-0.000	-0.002
lag 3	-0.044	-0.193
lag 4	-0.117	-0.845
Personal Consumption Expenditures (lag 1)	1.019	10.28
Price of Direct-Mail Advertising (lag 2)	-0.236	-0.904
Time Trend	-0.003	-3.058
Dummy for Rule Restricting Nonprofit Eligibility in 1994	-0.021	-2.106
Dummy for Election Year		
Fall, even-numbered years	0.058	3.521
Spring, even-numbered years	0.038	2.314
Seasonal coefficients:		
September	-0.096	-0.561
October	0.502	3.405
November 1 - January 1	-0.383	-2.466
January 2 - February	-0.094	-0.684
March - May	-0.204	-1.490
June	-0.810	-1.956

REGRESSION DIAGNOSTICS :

AR-4 coefficient	-0.392
Mean-Squared Error	0.000345
Degrees of Freedom	32
Adjusted-R^2	0.973

E. Package Services Mail

1. General Overview

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

Three demand equations are modeled for various Packages Services. Separate equations are estimated for parcel post and bound printed matter, while a single equation is estimated for Media and Library rate mail. 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 Package Services 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 (UPS), 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

At the time of Postal Reorganization, parcel post was the dominant parcel carrier in the United States, with roughly 60 percent of the ground parcel market. At this time, UPS's potential market was only about 50 percent as great as that of parcel post. 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. Using 2000 parcel post billing determinants, an average of only 9.5 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 2000 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 7.3 percent prior to this rate increase to 81.9 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 92.1 percent of UPS's published residential rates and 75.4 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. In R2000-1, competition between UPS and parcel post was therefore modeled differently before and after the 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. For the present case, however, the sample period has simply been shortened, beginning in 1990Q1, to focus attention on the post-1990 relationship between UPS and 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)
- Dummy variable for introduction of DBMC discount (which actually starts six quarters after the introduction of the DBMC discount, in 1993Q1, due to data issues prior to this)
- 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
- Dummy variable for the introduction of delivery confirmation
- Current price of Priority Mail
- Current price and four lags of residential UPS Ground Parcel service
- Current and one lag of the price of parcel post mail

Elasticities are listed in Table II-12.

The own-price elasticity of parcel post mail is equal to -1.194 (t-statistic of -3.271), with a cross-price elasticity with respect to UPS equal to 1.385 (t-statistic of 6.729). Parcel post mail also has a cross-price elasticity with respect to Priority Mail of 0.467 with a t-statistic of 1.013. Parcel post mail volume is also affected by retail sales, with an elasticity of 0.428 (t-statistic of 0.955).

3. Non-Parcel Post Package Services Mail

a. Subclasses of Package Services Mail

There are three subclasses of Package Services mail in addition to parcel post: bound printed matter, Media mail, 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 Media mail subclass is reserved for books, tapes, and CDs. The library rate subclass is a preferred subclass, generally corresponding to the Media mail subclass, available to libraries and certain other institutions. In this testimony, a single demand equation is estimated for the combined volume of Media mail and library rate mail.

b. Bound Printed Matter and Media Mail Demand Equations

i. General Overview

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 Media mail (then called 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 Media mail rates. However, bound printed matter rates are zoned, whereas Media mail rates are unzoned. Thus, in order for mailers to shift from the Media mail to the 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 Media mail 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, since

R97-1, the demand equations for bound printed matter and Media mail volume have been modeled using data starting in 1979Q1, allowing two full years for Media mailers to begin to adapt to the enhanced opportunities available through bound printed matter.

Even after this time period, however, gradual migration from Media mail into bound printed matter continued. In R97-1 and R2000-1, this effect was modeled by including logistic market penetration variables in the demand equations for bound printed matter and Media mail volumes. The market penetration variable in the bound printed matter equation was positive to reflect market penetration into bound printed matter, while the market penetration variable in the Media mail equation was negative to reflect market penetration out of the Media mail subclass.

In the present case, the Media mail sample period was further truncated to begin in 1988Q1. This provided an opportunity to remove the z-variable from the Media mail equation. Efforts to shorten the bound printed matter sample period in a parallel way were unsuccessful, however. Consequently, the bound printed matter equation continues to be estimated using data starting in 1979Q1 and continues to include a market penetration z-variable.

In past rate cases, the bound printed matter and Media mail demand equations, like virtually all of the Postal Service's demand equations, included long-run and short-run income, with long-run income elasticities constrained from the Household Diary Study. In the present case, long-run and short-run income have been replaced by personal consumption expenditures in the bound printed matter equation and by retail sales (lagged one quarter) in the Media mail equation. The elasticities associated with these variables are also freely estimated in the demand equations presented here.

ii. 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
- Personal consumption expenditures
- 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 10-15 percent since 1998
- Current and two lags of the price of bound printed matter

Elasticities are listed in Table II-13.

The own-price elasticity of bound printed matter is equal to -0.231 (t-statistic of -1.931). Bound printed matter volume is strongly affected by consumption expenditures, with a consumption elasticity of 0.743 (t-statistic of 6.275).

Bound printed matter volume has one of the strongest seasonal patterns of any mail category, with volumes particularly high in the second half of September (seasonal coefficient of 2.001, t-statistic of 2.696), and December 16th through the 19th (coefficient of 1.927, t-statistic of 1.551). On the other hand, bound printed matter volume is extremely low in the first half of September (coefficient of -1.820, t-statistic of -1.640), October (coefficient of -2.304, t-statistic of -5.139), the first two weeks of April (-5.522, t-statistic of -3.506), and June (-1.794, -2.425). For the base year, the seasonal variables led to an expectation regarding bound printed matter that volume was 2.8 percent lower than average in the first Postal quarter, 2.0 percent lower than average in the second Postal quarter, 16.7 percent below average in the third Postal quarter, and 14.8 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 0.008524.

iii. Media and Library Mail

The demand equation for Media and Library mail models the demand for Media and Library Rate mail volumes as a function of the following explanatory variables:

- Seasonal Variables (as described in section III.A.2.c. below)
- Retail Sales lagged one quarter
- Dummy variable equal to one since 1998Q1 to account for an otherwise unexplained decline in Media mail volume of 10-15 percent since 1998
- Dummy variable equal to one since 2001Q1 to account for an additional unexplained decline in Media mail volume of 25-30 percent in 2001
- Current and three lags of the price of Media mail

Elasticities are listed in Table II-14.

The own-price elasticity of Media mail is -0.144, with a t-statistic of -0.889, while the retail sales elasticity is equal to 0.902 (t-statistic of 3.520).

TABLE II-12
PARCEL POST

	Coefficient	T-statistic
Parcel post price -- SUM	-1.194	-3.271
current	-0.865	-1.502
lag 1	-0.329	-0.660
Residential UPS price -- SUM	1.385	6.729
current	0.523	0.912
lag 1	0.162	0.220
lag 2	0.004	0.006
lag 3	0.147	0.226
lag 4	0.549	1.149
Priority Mail price -- current only	0.467	1.013
Retail Sales	0.428	0.955
Impact of 1997 UPS Strike	0.158	2.606
Retention of Volume from 1997 UPS Strike in 1998Q1-2	0.061	1.380
Dummy for Introduction of DBMC Discount	0.115	2.128
Dummy for Introduction of Delivery Confirmation	-0.087	-1.986
Seasonal coefficients:		
September 1 - 15	0.138	0.218
September 16 - December 10	0.520	4.137
December 11 - 17	0.188	0.383
December 18 - 24	4.967	1.234
December 25 - January 1	-1.593	-0.369
January 2 - March	0.097	0.577
April - June	0.360	1.577
REGRESSION DIAGNOSTICS :		
AR coefficients	None	
Mean Square Error	0.003014	
Degrees of Freedom	26	
Adjusted-R^2	0.972	

TABLE II-13
BOUND PRINTED MATTER

	Coefficient	T-statistic
Bound printed matter price -- SUM	-0.231	-1.931
current	-0.001	-0.001
lag 1	-0.105	-0.165
lag 2	-0.126	-0.332
Personal Consumption Expenditures	0.743	6.275
Sears catalog dummy	-0.190	-3.950
Dummy variable since 1998Q1	-0.129	-3.252
Parameters used in calculating Z-variable:		
Param1	1.678	8.850
Param2	3.309	3.683
Param3	0.053	7.796
Seasonal coefficients:		
September 1 - 15	-1.820	-1.640
September 16 - 30	2.001	2.696
October	-2.304	-5.139
November 1 - December 15	-0.536	-0.923
December 16 - 19	1.927	1.551
December 20 - 24	0.461	0.503
December 25 - February	-1.168	-4.889
March	0.669	1.053
April 1 - 15	-5.522	-3.506
April 16 - May	-0.483	-0.744
June	-1.794	-2.425

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.008524
Degrees of Freedom	70
Adjusted-R^2	0.974

TABLE II-14
MEDIA & LIBRARY RATE MAIL

	Coefficient	T-statistic
Standard Media & Library Rate price -- SUM	-0.144	-0.889
current	-0.000	-0.000
lag 1	-0.040	-0.086
lag 2	-0.061	-0.125
lag 3	-0.043	-0.137
Retail Sales (lag 1)	0.902	3.520
Dummy variable since 1998Q1	-0.120	-2.736
Dummy variable since 2001Q1	-0.331	-5.798
Seasonal coefficients:		
September 1 - 15	0.611	0.830
September 16 - 30	-0.748	-1.348
October - December 12	0.502	3.275
December 13 - 19	-0.844	-1.103
December 20 - January 1	7.621	2.878
January 2 - February	-1.108	-2.403
March	0.535	2.120

REGRESSION DIAGNOSTICS :

AR-coefficients	None
Mean Square Error	0.005519
Degrees of Freedom	40
Adjusted-R^2	0.668

F. Other Mail Categories

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

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-15 through II-17, 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.

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, the volumes of both registered and certified mail are modeled in part as functions of the volume of First-Class letters, since most registered and certified mail is, in fact, First-Class Mail. In addition, 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, the volume of return receipts is a function of the volume of certified mail, since most return receipts accompany certified mail, and the volume of delivery confirmation is modeled in part as a function of Priority Mail volume, since the vast majority of delivery confirmation volume is Priority Mail.

The demand for special service mail is also a function of 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). In addition, most of the special service equations also include some equation-specific variables, which are described below.

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)
- First-Class letters volume
- Time trend reflecting a long-run downward trend in registered mail volume
- Dummy variable reflecting the use of government-distributed volume beginning in 1988Q1
- Dummy variable for the implementation of special service classification reform (MC96-3) in 1997Q4
- Time trend since MC96-3
- 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.

Registered mail has an estimated own-price elasticity of -0.133 (t-statistic of -0.686) and a cross-volume elasticity with respect to First-Class letters of 0.820 (t-statistic of 1.862). In addition, registered mail has a negative long-run trend of 9.9 percent per year, although this time trend has mitigated somewhat since MC96-3 to an annual rate of only 7.4 percent.

Elasticities are listed in Table II-18.

b. Insured

As part of special service classification reform (MC96-3), the maximum value that can be insured was increased from $500 to $6,000. This helped contribute to average annual growth from 1997 through 2000 of 19.6 percent. This dramatic growth is modeled through a market penetration z-variable starting with the implementation of MC96-3 in 1999Q4. In addition, insured mail is modeled, in part, as a function of long-run income, reflecting an increasing demand for insurance as incomes increase.

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)
- Long-Run Income
- 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 equal to one starting in 1993Q1 to reflect a change in the RPW methodology associated with parcel post mail volume
- Dummy variable equal to one in 1997Q4 for UPS's most recent strike
- Market penetration z-variable starting in 1997Q4, to reflect the impact of special service classification reform (MC96-3), which increased the maximum value that can be insured from $500 to $6,000
- Current and three lags of the price of insured mail

The market penetration variable has explained a 108 percent increase in insured mail volume from 1997Q3 (just prior to MC96-3) through 2001Q3, a period during which insured mail volume grew by a total of 105 percent.

The own-price elasticity of insured mail is -0.110 with a t-statistic of -1.887. Insured mail also has a cross-volume elasticity with respect to parcel post mail volume of 0.371 (t-statistic of 9.403) and a long-run income elasticity of 0.355 (t-statistic of 0.480).

Elasticities are listed in Table II-19.

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)
- First-Class letters volume
- Time trend reflecting a long-run trend in certified mail volume
- Dummy variable reflecting the use of government-distributed volume beginning in 1988Q1
- Dummy variable for the introduction of delivery confirmation
- Current and four lags of the price of certified mail

Certified mail volume has an own-price elasticity of -0.176 (t-statistic of -3.225), a cross-volume elasticity with respect to First-Class letters of 0.856 (t-statistic of 3.805), and a time trend which explains annual growth of 3.0 percent.

Elasticities are listed in Table II-20.

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

COD mail has an own-price elasticity of -0.533 with a t-statistic of -2.847 and a time trend which explains -6.6 percent annual growth.

Elasticities are listed in Table II-21.

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)
- Time trend
- Volume of certified mail
- Dummy variable equal to one starting in 1995Q2, to account for an otherwise unexplained increase in return receipts volume of 15-20 percent beginning at that time
- Current and one lag of the price of return receipts

Return receipts have an own-price elasticity of -0.290 (t-statistic of -0.763), a cross-volume elasticity with respect to certified mail of 0.660 (t-statistic of 3.683), and a time trend variable which explains -0.6 percent annual volume growth.

Elasticities are listed in Table II-22.

f. Money Orders

Money orders are the one special service modeled here which is not an add-on to another mail category, but which is, instead, a stand-alone product. Hence, money orders volume is modeled according to traditional demand theory, as a function of long-run and short-run income. The money orders demand equation is estimated using a sample period going back only to 1988Q1.

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)
- Long-Run income
- Short-Run income
- Current and four lags of the price of money orders

Money orders have an own-price elasticity of -0.515 with a t-statistic of -6.415, a long-run income elasticity of 0.972 (t-statistic of 5.896), and a short-run income elasticity of 0.763 (t-statistic of 1.981).

Elasticities are listed in Table II-23.

g. Delivery and Signature Confirmation

Delivery confirmation was first introduced by the Postal Service in 1999. Signature confirmation was first introduced in 2000. These two special services are considered together here. This is the first rate case in which an attempt has been made to estimate a demand equation for delivery and signature confirmation volume. The delivery confirmation demand equation is estimated using data only since 2000Q1. This results in a mere seven observations. Delivery confirmation volume is explained here as a function of six explanatory variables. This leaves a mere one degree of freedom. Generally speaking, econometric equations with only one degree of freedom are not a good idea. Nevertheless, the resulting elasticity estimates for this equation are generally reasonable. Hence, it was decided that the coefficient estimates presented here, while admittedly unreliable due to a severe lack of degrees of freedom, are undoubtedly better than nothing and do provide some information on the factors which affect delivery confirmation volume.

The most prominent feature of delivery confirmation volume since its introduction is fairly consistent positive growth. This growth is modeled through a market penetration z-variable throughout the sample period modeled here. In addition, delivery confirmation volume is modeled as a function of Priority Mail volume (as more than 80 percent of delivery confirmation volume is Priority Mail), and the average price of delivery confirmation.

The market penetration variable has explained a 139 percent increase in delivery confirmation volume from 2000Q1 through 2001Q3, a period during which delivery confirmation volume grew by a total of 110 percent.

In addition to market penetration, delivery confirmation has an estimated own-price elasticity of -0.717 with a t-statistic of -1.008, and a cross-volume elasticity with respect to Priority Mail of 1.172 (t-statistic of 21.57). It should be noted that, due to data limitations, no seasonal variables were estimated within the delivery confirmation demand equation.

Elasticities are listed in Table II-24.

TABLE II-15
MAILGRAMS

	Coefficient	T-statistic
Time trend	-0.035	-7.857
Seasonal coefficients:		
September 16 - 30	0.617	1.192
October	-1.090	-2.826
November 1 - December 23	0.574	2.079
December 24 - March	0.006	0.045
April 1 - 15	-1.260	-0.700
April 16 - May	0.589	0.929
June	-0.434	-0.974
REGRESSION DIAGNOSTICS :		
AR-1 coefficient	0.594	
AR-2 coefficient	0.256	
Mean Square Error	0.043340	
Degrees of Freedom	94	
Adjusted-R^2	0.957	

TABLE II-16
POSTAL PENALTY MAIL

	Coefficient	T-statistic
Full-Sample Time trend	-0.015	-5.608
Time Trend since 1997	0.004	0.568
Seasonal coefficients:		
September	-1.167	-2.452
October - December 15	0.303	2.605
December 16 - January 1	-0.800	-2.620
January 2 - June	-0.041	-0.287
REGRESSION DIAGNOSTICS :		
AR-2 coefficient	0.501	
Mean Square Error	0.014288	
Degrees of Freedom	45	
Adjusted-R^2	0.799	

TABLE II-17
FREE-FOR-THE-BLIND-AND-HANDICAPPED MAIL

	Coefficient	T-statistic
Time trend	0.007	8.706
Seasonal coefficients:		
September 1 - 15	-1.542	-0.488
September 16 - October	0.022	0.040
November - December 10	-0.316	-0.409
December 11 - 21	-2.094	-1.777
December 22 - 24	1.644	0.542
December 25 - January 1	0.632	0.387
January 2 - June	-0.271	-0.494

REGRESSION DIAGNOSTICS :

AR-coefficients	None
Mean Square Error	0.086906
Degrees of Freedom	114
Adjusted-R^2	0.387

TABLE II-18
REGISTERED MAIL

	Coefficient	T-statistic
Registered mail price -- current only	-0.133	-0.686
First-Class Letters Volume	0.820	1.862
Full-Sample Time trend	-0.026	-19.37
Time Trend since MC96-3	0.007	1.137
Dummy for use of Government-Distributed Volume	0.153	3.343
Dummy for Special Service Reclassification (MC96-3)	-0.052	-1.146
Seasonal coefficients:		
September 1 - 15	1.170	1.249
September 16 - 30	0.667	0.910
October	-0.066	-0.141
November - December 10	0.312	0.468
December 11 - 17	1.335	1.498
December 18 - 21	-1.087	-1.090
December 22 - January 1	1.383	1.295
January 2 - February	0.001	0.005
March	0.231	0.301
April 1 - 15	0.068	0.042
April 16 - June	0.419	0.603

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.003946
Degrees of Freedom	53
Adjusted-R^2	0.980

TABLE II-19
INSURED MAIL

	Coefficient	T-statistic
Insurance price -- SUM	-0.110	-1.887
current	-0.000	-0.000
lag 1	-0.029	-0.094
lag 2	-0.046	-0.148
lag 3	-0.036	-0.203
Long-Run Income	0.355	0.480
Parcel post volume	0.371	9.403
Dummy for Restatement of Parcel Post Data (1993)	-0.159	-3.106
Time trend	-0.013	-4.524
Dummy for 1997 UPS Strike	0.107	1.253
Parameters used in calculating Z-variable:		
Param1	0.921	9.563
Param2	5.026	3.201
Param3	0.319	4.233
Seasonal coefficients:		
September	-0.946	-2.731
October	-0.455	-1.970
November 1 - December 15	0.428	2.274
December 16 - 19	1.694	2.104
December 20 - 24	-1.711	-2.464
December 25 - February	-0.146	-1.540
March	-0.670	-2.631
April 1 - 15	0.270	0.286
April 16 - May	-0.286	-0.779
June	-0.528	-1.843

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.006441
Degrees of Freedom	100
Adjusted-R^2	0.981

TABLE II-20
CERTIFIED MAIL

	Coefficient	T-statistic
Certified mail price -- SUM	-0.176	-3.225
current	-0.000	-0.000
lag 1	-0.034	-0.122
lag 2	-0.048	-0.155
lag 3	-0.049	-0.169
lag 4	-0.045	-0.275
First-Class Letters Volume	0.856	3.805
Time trend	0.007	10.99
Dummy for use of Government-Distributed Volume	0.066	1.826
Dummy for Introduction of Delivery Confirmation	-0.117	-3.590
Seasonal coefficients:		
September 1 - 15	-0.620	-0.721
September 16 - 30	1.354	3.433
October	0.850	2.583
November 1 - December 10	-0.524	-1.860
December 11 - January 1	0.744	1.851
January 2 - February	-0.057	-0.375
March	1.112	3.703
April - May	0.004	0.029
June	1.265	3.503

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.005799
Degrees of Freedom	104
Adjusted-R^2	0.962

TABLE II-21
COLLECT-ON-DELIVERY

	Coefficient	T-statistic
COD price -- SUM	-0.533	-2.847
current	-0.168	-0.782
lag 1	-0.015	-0.059
lag 2	-0.001	-0.005
lag 3	-0.210	-0.814
lag 4	-0.138	-0.644
Time trend	-0.017	-21.12
Dummy for 1997 UPS Strike	0.165	1.888
Seasonal coefficients:		
September 1 - 15	-1.071	-1.376
September 16 - October	0.373	1.489
November 1 - December 12	-0.129	-0.542
December 13 - January 1	0.729	1.977
January 2 - February	-0.091	-0.628
March	0.488	1.794
April 1 - 15	-1.963	-2.861
April 16 - June	0.639	2.341

REGRESSION DIAGNOSTICS :

AR-1 coefficient	0.622
Mean Square Error	0.009740
Degrees of Freedom	105
Adjusted-R^2	0.977

TABLE II-22
RETURN RECEIPTS

	Coefficient	T-statistic
Return receipts price -- SUM	-0.290	-0.763
current	-0.015	-0.026
lag 1	-0.276	-0.429
Time Trend	-0.0016	-0.677
Certified Mail Volume	0.660	3.683
Dummy variable starting in 1995Q2	0.181	3.816
Seasonal coefficients:		
September - December 12	0.083	1.243
December 13 - January 1	0.000	0.000
January 2 - June	0.103	1.458

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.005473
Degrees of Freedom	26
Adjusted-R^2	0.658

TABLE II-23
MONEY ORDERS

	Coefficient	T-statistic
Money orders price -- SUM	-0.515	-6.415
current	-0.147	-0.435
lag 1	-0.099	-0.217
lag 2	-0.008	-0.018
lag 3	-0.076	-0.168
lag 4	-0.185	-0.718
Long-Run Income	0.972	5.896
Short-Run Income	0.763	1.981
Seasonal coefficients:		
September	-1.279	-3.045
October	-0.034	-0.103
November - December 17	-1.302	-3.126
December 18 - 24	2.044	1.509
December 25 - March	-1.054	-2.845
April 1 - 15	0.168	0.222
April 16 - May	-0.951	-2.580
June	-2.181	-2.430

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.001209
Degrees of Freedom	39
Adjusted-R^2	0.916

TABLE II-24
DELIVERY CONFIRMATION

	Coefficient	T-statistic
Delivery confirmation price (current only)	-0.717	-1.008
Priority Mail volume	1.172	21.57
Parameters used in calculating Z-variable:		
Param1	1.631	2.807
Param2	1.592	1.890
Param3	0.484	2.597

REGRESSION DIAGNOSTICS :

AR coefficients	None
Mean Square Error	0.000102
Degrees of Freedom	1
Adjusted-R^2	0.999

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:

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

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 these 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 (34¢), the additional ounce rate (23¢), 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 2000. 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, three, and four quarters are included in the demand equations considered here. If, however, the price lagged four quarters is found to have a negligible effect on mail volume, then this price lag is removed from the equation[4]. If, after removing the fourth lag, the price lagged three quarters is found to have a negligible effect on mail volume, then this price lag is also removed from the equation. If, after removing the third lag, the price lagged two quarters is found to have a negligible effect on mail volume, then this price lag is also removed from the equation. Finally, if after removing the second lag, the price lagged one quarter is 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 four 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 equations for Periodical regular and nonprofit 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 automating 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-

[4] 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.

Class and Standard mail), these user costs can be calculated within the share 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 1996 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 Long-Run 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 what he called "permanent" income, which he defined as expected total wealth, and what he called "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 Long-Run 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. Hence, one way to view "permanent" income is as "long-run" income, while "transitory" income can be viewed as "short-run" income.

Combining these two relationships, Friedman suggested that long-run, or 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 long-run income today as being equal to long-run income last time period, adjusted based on new information drawn from the level of current income. This simplifies the calculation of long-run income into a simple function of past long-run 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 long-run income, and α is equal to the weight given to last period's long-run income in calculating long-run 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 $\alpha = 0.905$, and a value of $(1-\alpha)$ 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 long-run income. This is done in my work by adjusting the calculated value of long-run 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 1.00381, or 0.381% 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 long-run income variable is calculated based on the following equation:

$$Y^{P}_{t} = 0.905 \cdot (1.00381 \cdot Y^{P}_{t-1}) + 0.095 \cdot Y_{t} \qquad \text{(III.6)}$$

iii. Income Variables used in Postal Demand Equations

(a) Use of Long-Run and Short-Run Income

For those types of mail which 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 long-run and short-run income on the demand for these types of mail.

For demand equations for this type of mail -- which includes First-Class, Periodical, and some special services (insurance and money orders) -- separate measures of long-run and short-run income are included in the demand equations estimated for this case.

Long-Run income in the time series regressions is calculated using equation (III.6) above. Long-Run income is expressed in constant 1996 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 short-run 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, short-run 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, short-run income was found to have no impact on the demand for mail volumes. This is consistent with the long-run income hypothesis outlined above.

(b) Use of Personal Consumption Expenditures and Retail Sales

i) Direct-Mail Advertising

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 sales. The long-run income hypothesis can be used to express expected sales as a function of expected long-run income. Hence, the demand for advertising mail volume could logically be expressed as a function of long-run (and short-run) income. In this case, however, the relationship is more directly between advertising mail volume and consumption expenditures or retail sales, rather than between advertising mail volume and the factors which would be expected to drive these expenditures. Hence, for this case, the more direct relationship between direct-mail advertising volume and either consumption expenditures or retail sales was modeled by including personal consumption expenditures in the demand equations for Standard bulk nonprofit mail and bound printed matter and by including retail sales in the demand equations for Standard Regular and Enhanced Carrier Route mail.

ii) Package Services

With the exception of catalogs and heavy pieces of direct-mail advertising sent as bound printed matter, Package Services mail is almost exclusively the delivery of products bought by the sender or recipient of the mail. Hence, this type of mail volume derives almost directly from retail sales. While retail sales are, of course, a function of long-run and short-run income, retail sales are included directly in the parcel post and

Media mail demand equations above to reflect the more direct relationship between retail sales and these mail volumes.

c. Treatment of Seasonality

The volume data used in modeling the demand for mail is 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 late 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 for modeling seasonality include advanced mathematical techniques such as spectral analysis, or introducing fourth-order autoregressive processes 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 2001 ended on September 7, 2001. Hence, these thirty-one Postal years are, in fact, 39 days short of 31 full years. From the first day of Postal 1971 through the end of the third quarter of Postal 2001 (the longest sample period used for any of the demand equations modeled in my testimony), a total of 152 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 9th through October 16th, December 2nd through January 8th, February 24th through April 2nd, and May 19th 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 2000, the second Postal quarter gained 23 days in December preceding Christmas (December 2nd through December 24th) 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

Since R97-1, the seasonal variables used in the regressions have been defined 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 eighteen seasonal variables are used in the demand equations in this case. These seasons correspond to the following periods of the Gregorian calendar:

September 1 - 15
September 16 - 30
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[5]

[5] 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

April 16 - May 31
June 1 - June 30
July 1 - August 31

For any given quarter, the value of each seasonal variable is 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 are not counted, while Saturdays are counted as one-half business days. In addition, seven common business holidays are 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.

An example of the construction of one of these variables may be instructive. Consider, for example, the values of the season, November 1 - December 10, for the four quarters of 2001.

Postal 2001Q1 spans the time period from September 9, 2000 through December 1, 2000, 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 November 1, 2000 through December 1, 2000 falls within the season of November 1 - December 10 as well as 2001Q1. This time period encompasses a total of 23 business days (31 total days less 2 Holidays, 4 Sundays and one-half of 4 Saturdays). Hence, the seasonal variable November 1 - December 10 has a value equal to (23/64) in 2001Q1.

Postal 2001Q2 spans the time period from December 2, 2000 through February 23, 2001, and contains 64 business days (12 weeks @ 5.5 business days per week minus

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immediately following April 15th.

Christmas and New Year's Day). The period from December 2, 2000 through December 10, 2000 falls within the season of November 1 - December 10 as well as 2001Q2. This time period encompasses a total of 6 business days (9 days less 2 Sundays and one-half of 2 Saturdays). Hence, the seasonal variable November 1 - December 10 has a value equal to (6/64) in 2001Q1.

None of the seasonal variable November 1 - December 10 falls within either the third or fourth Postal quarters. Hence, this variable has a value of zero in both 2001Q3 and 2001Q4.

iii. Use of Seasonal Variables Econometrically

The 18 seasonal variables defined as outlined above are used to model the seasonal pattern of mail volumes econometrically. Seventeen of the 18 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 seventeen 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 13th 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 17 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:

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

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:

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

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 mail volume historically is population. As the population of the United States grows, mail volume would be expected to grow 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 seemed to provide 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.

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 some other form. In the case of dummy variables and seasonal variables, these variables are simply entered in their natural state.

In the cases of consumption expenditures on Internet Service Providers and Internet advertising expenditures, however, these variables are adjusted by something called a Box-Cox transformation, so that

$$\mathrm{Ln(Volume)} = a + b \bullet (\mathrm{Variable})^{\gamma} + \ldots^{6} \qquad \text{(III.9)}$$

The calculated values of γ are discussed in section II above in the sections on First-Class letters and Standard mail, respectively. In these cases, the values of b are technically not elasticities.

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:

$$y = X\beta + \varepsilon \qquad \text{(III.10)}$$

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

$$b = (X'X)^{-1}X'y \qquad \text{(III.11)}$$

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., $\mathrm{var}(\varepsilon_t)$ is not equal to σ^2 for all t), or if the error term is not uncorrelated

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[6] Technically, the Box-Cox transformation fits the following formula:

$$\mathrm{Volume} / \gamma_1 = a + b^* \bullet (X^{\gamma_2})/\gamma_2$$

Here, γ_1 is set equal to zero, so the left-hand side becomes simply Ln(Volume), and b in equation (III.9) above is equal to (b^* / γ_2).

through time (i.e., $\text{cov}(\varepsilon_t, \varepsilon_{t-j}) \neq 0$ for some $j \neq 0$), then the variance-covariance matrix of ε can be expressed as, $\text{var}(\varepsilon) = \sigma^2\Sigma$, and the restriction on the variance of ε_t can be eased by introducing Σ into equation (III.11) as follows:

$$b = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}y \qquad \text{(III.12)}$$

Equation (III.12) 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:

$$\text{(OLS Estimator)} \qquad b = (X'X)^{-1}X'y$$
$$\text{(RLS Estimator)} \qquad b^{\wedge} = b + (X'X)^{-1}C'[C\,(X'X)^{-1}C']^{-1} \bullet (d - Cb) \qquad \text{(III.13)}$$

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 $\text{var}(v) = \sigma^2\Omega$.

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:

$$\text{(Stochastic Restrictions Estimator)} \qquad b^{*} = (X'X + R'\Omega^{-1}R)^{-1}(X'y + R'\Omega^{-1}r) \qquad \text{(III.14)}$$

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

(OLS Estimator incorporating outside information)

$$b^{*} = (X'X + R'\Omega^{-1}R)^{-1}(X'y + R'\Omega^{-1}r)$$
$$b^{**} = b^{*} + (X'X + R'\Omega^{-1}R)^{-1}C'[C\,(X'X + R'\Omega^{-1}R)^{-1}C']^{-1}\bullet(d-Cb^{*}) \qquad \text{(III.15)}$$

If $E(R\beta) = r$, then the most efficient, unbiased GLS estimator incorporating outside information is similarly modified from equation (III.12) as follows:

$$b^{*} = (X'\Sigma^{-1}X + R'\Omega^{-1}R)^{-1}(X'\Sigma^{-1}y + R'\Omega^{-1}r)$$
$$b^{**} = b^{*} + (X'\Sigma^{-1}X + R'\Omega^{-1}R)^{-1}C'[C\,(X'\Sigma^{-1}X + R'\Omega^{-1}R)^{-1}C']^{-1}\bullet(d-Cb^{*}) \qquad \text{(III.16)}$$

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.16) 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.11) 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.11) were to be divided into two separate matrices, X_1 and X_2, so that

$$y = X_1\beta_1 + X_2\beta_2 + \varepsilon \qquad \text{(III.17)}$$

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.17)) 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 long-run 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

Long-Run income is highly correlated with many other economic and trend variables, making estimation of long-run income elasticities difficult using quarterly time series data. For example, the simple correlation between long-run income and a simple time trend between 1971Q1 and 2001Q3 is equal to 0.996, indicating near-perfect multicollinearity between these variables.

Because of the high degree of correlation between long-run income and other explanatory variables, some long-run income elasticities estimated exclusively from the quarterly time series data may be somewhat unstable, and occasionally take on implausible values.

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.

For this reason, the long-run income elasticities associated with single-piece First-Class letters, First-Class cards, and Periodical mail are estimated from the Household Diary Study and introduced as stochastic restrictions in these demand equations using equation (III.16) above. The details of the cross-sectional estimation of the long-run income elasticities and their standard errors are given in Workpaper 2 accompanying my testimony.

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 0.988 over the Periodical regular sample period used in this case. This represents a classic case of the multicollinearity problem outlined in equation (III.17) 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.16). In particular, the GLS estimator is modified as follows to generate Shiller distributed lags:

$$b^S = (X'\Sigma^{-1}X + \sum_{i=1}^{P} k_i^2 \bullet S_i' S_i)^{-1} X'\Sigma^{-1} y \tag{III.18}$$

A unique matrix, S_i, is developed for each price distribution for which Shiller restrictions are applied. P in equation (III.18) 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:

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

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.18) will approach the GLS estimator, b in equation (III.12). 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.

If, given the optimal value of k^2_i, the coefficient on the fourth price lag is negligible, then the coefficient on the fourth 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 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 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 0.846 between 1983Q1 and 2001Q3. 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 workshared First-Class letters and Standard regular mail, and between parcel post and Priority Mail in my testimony. In the first two of these cases, the econometric estimation of the cross-price relationships is helped by a relationship known as the Slutsky-Schultz relationship.

The Slutsky-Schultz cross-price relationship is premised on an assumption 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,

$$\frac{\partial V_i}{\partial p_j} = \frac{\partial V_j}{\partial p_i} \qquad \text{(III.19)}$$

The elasticity of V_i with respect to p_j is equal to

$$e_{ij} = \frac{\partial V_i}{\partial p_j} \bullet \frac{p_j}{V_i}, \textit{ so that, rearranging terms: } \frac{\partial V_i}{\partial p_j} = e_{ij} \bullet \frac{V_i}{p_j} \qquad \text{(III.20)}$$

Combining equation (III.19) with equation (III.20) yields the following relationship:

$$e_{ij} \bullet \frac{V_i}{p_j} = e_{ji} \bullet \frac{V_j}{p_i}, \text{ so that, rearranging terms, } \frac{e_{ij}}{e_{ji}} = \frac{V_j \bullet p_j}{V_i \bullet p_i} \qquad \text{(III.21)}$$

In words, equation (III.21) 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.21) suggests 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.21) can only be imposed for a single point in time.

For our purposes, equation (III.21) is imposed when necessary using a fixed set of expenditures, so that equation (III.21) 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.21) is imposed using expenditure ratios over the last full year of the regression period, 2000. The use of 2000 is also consistent with the use of 2000 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 our 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	-0.078
		(-0.689)
Workshared Letters	Workshared Cards	0.128
		(0.770)
First-Class Cards	First-Class Letters	0.163
		(1.435)

The cross-price elasticities with respect to cards from the First-Class letters equations are not significantly different from zero, while the elasticity from the cards equation is significant at about an 85 percent significance 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 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.

iii. Cross-Price Relationship between Workshared First-Class Letters and Standard Regular Mail

The cross-price elasticity between workshared First-Class letters and Standard Regular mail can be estimated from either of two equations: the workshared First-Class letters equation or the Standard Regular equation. These two estimates are as follows (t-statistics in parentheses):

Equation	Cross Price with respect to	Free
Workshared Letters	Standard Regular Mail	0.008
		(0.029)
Standard Regular	Workshared Letters	-0.191
		(-0.538)

The choices here are between a result which has an unexpected sign (the Standard Regular equation) or a result which is highly insignificant (the workshared letters equation). Because of the theoretical appeal of this cross-price relationship, it was decided to include this cross-price in the workshared letters and Standard Regular equation, despite the tenuous nature of the estimated elasticity.

Because of the high standard error associated with the Standard Regular cross-price elasticity in the workshared letters equation, it was not possible to obtain a reasonable elasticity in the Standard Regular equation using a stochastic restriction. Hence, the cross-price elasticity in the workshared letters equation was treated as if it was known with certainty in imposing the Slutsky-Schultz restriction in the Standard Regular equation.

4. Autocorrelation

The restriction on the OLS estimator in equation (III.10) that $\mathrm{var}(\varepsilon_t) = \sigma^2$ requires an assumption that the error term is independently distributed, so that $\mathrm{cov}(\varepsilon_t, \varepsilon_{t-k}) = 0$ 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 99 percent confidence level is used to test for the presence of autocorrelation. The following relationship is then fit to the residuals:

$$e_t = \rho_1 \bullet e_{t-1} + \rho_2 \bullet e_{t-2} + \rho_4 \bullet e_{t-4} + u_t \qquad \text{(III.22)}$$

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, 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:

$$\beta^{\wedge} = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}y$$

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:

$$P_0 = \begin{vmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ -\rho_1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ -\rho_2 & -\rho_1 & 1 & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & -\rho_2 & -\rho_1 & 1 & 0 & 0 & 0 & 0 & \dots & 0 \\ -\rho_4 & 0 & -\rho_2 & -\rho_1 & 1 & 0 & 0 & 0 & \dots & 0 \\ 0 & -\rho_4 & 0 & -\rho_2 & -\rho_1 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & -\rho_4 & 0 & -\rho_2 & -\rho_1 & 1 & 0 & \dots & 0 \\ & & & & \dots & & & & & \\ 0 & 0 & 0 & \dots & 0 & -\rho_4 & 0 & -\rho_2 & -\rho_1 & 1 \end{vmatrix}$$

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 $[-\rho_1\ 1\ 0\ 0\ \dots\ 0]$. If i=2, then $\rho_4=0$, and the first row of P is equal to $[-\rho_2\ -\rho_1\ 1\ 0\ 0\ \dots\ 0]$. Finally, if i=4, the first row of P is equal to $[-\rho_4\ 0\ -\rho_2\ -\rho_1\ 1\ 0\ 0\ \dots\ 0]$.

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:

$$x_t = x_t - \rho_1 \bullet x_{t-1} - \rho_2 \bullet x_{t-2} - \rho_4 \bullet x_{t-4} \quad \text{(III.23)}$$

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.22). 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 due to factors which are either unknown or 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 most of the 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:

$$z_t = (d_1 \bullet p_1) / (1+p_2 \bullet e^{(-p_3 \bullet t)}) \qquad \text{(III.24)}$$

where d_1 is a dummy variable which is zero before the initiation of the market penetration, and 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.24). 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 mail in R97-1, which limit the sample period to beginning in the mid-to-late 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.24) is equal to one beginning in 1979Q2, as in earlier rate cases.

Besides private First-Class cards, the demand equations for bound printed matter, insurance, and delivery confirmation also include z-variables. The first of these variables models market penetration from Media 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 Media mail (then called special rate) into bound printed matter, thereby saving on the cost of postage. Coincidentally, this z-variable begins in 1979Q2, at the same time as the private First-Class cards z-variable.

The second z-variable mentioned above, in the insurance equation, models market penetration into insurance as a result of the expansion of the maximum level of insurance available from \$500 to \$6,000 as part of special service classification reform (MC96-3). This z-variable begins in 1997Q4, the quarter in which MC96-3 was implemented.

The final z-variable models the introduction of delivery confirmation as a special service and begins in 2000Q2.

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:

$$\mathrm{Ln}(V_t) = X_t\beta + z_t + \varepsilon_t \qquad \text{(III.25)}$$

where X_t is the full matrix of explanatory variables, and

$$z_t = (d_1 \bullet p_1) / (1+p_2 \bullet e^{(-p_3 \bullet t)})$$

as described above. The z-parameters, p_1, p_2, and p_3 are estimated together with the b_i's in equation (III.25).

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 all of the z-variables estimated here, while market penetration out of a particular mail volume would be reflected by a negative value of p_1 (as was the case with Media mail in past rate cases).

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:

$$\mathrm{Ln}(V_t) = X_t\beta + z_t + 100000\bullet(p_2 - \mathrm{abs}(p_2)) + 100000\bullet(p_3 - \mathrm{abs}(p_3)) + \varepsilon_t \qquad \text{(III.26)}$$

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.26) 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.24) 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,

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

Due to a lack of available degrees of freedom, this last step is not undertaken with respect to delivery confirmation. Instead, the demand coefficients for delivery confirmation come directly from equation (III.26) above.

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:

$$\begin{aligned} V_t \;=\; & \alpha \bullet Y_t^{\beta_1} \bullet \ldots \bullet [p_t^{\beta_2} \bullet p_{t-1}^{\beta_3} \bullet p_{t-2}^{\beta_4} \bullet p_{t-3}^{\beta_5} \bullet p_{t-4}^{\beta_6}] \bullet \\ & [e^{S_1\beta_{s1}} \bullet e^{S_2\beta_{s2}} \bullet e^{S_3\beta_{s3}} \bullet e^{S_4\beta_{s4}} \bullet e^{S_5\beta_{s5}} \bullet \ldots \bullet e^{S_{17}\beta_{s17}}] \bullet e^{\varepsilon_t} \end{aligned} \qquad \text{(III.27)}$$

where V_t is equal to mail volume per adult per business day in Postal quarter t, Y_t refers to long-run 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_{17} correspond to the seventeen 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.27) 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:

$$\begin{aligned} b^{*} &= \left(X'\Sigma^{-1}X + R'\Omega^{-1}R + \sum_{i=1}^{P} k_i^2 S_i' S_i\right)^{-1}\left(X'\Sigma^{-1}y + R'\Omega^{-1}r\right) \\ b^{\wedge} &= b^{*} + \left(X'\Sigma^{-1}X + R'\Omega^{-1}R + \sum_{i=1}^{P} k_i^2 S_i' S_i\right)^{-1} C' \left[C\left(\left(X'\Sigma^{-1}X + R'\Omega^{-1}R + \sum_{i=1}^{P} k_i^2 S_i' S_i\right)\right)^{-1} C'\right]^{-1} \bullet \left(d - C \bullet b^{*}\right) \end{aligned} \quad \text{(III.28)}$$

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.27) above.

The vector of coefficients, $b^{\wedge}$ calculated in equation (III.28) has the following statistical properties:

$$E(b^{\wedge}) = \beta + [(X'\Sigma^{-1}X + R'\Omega^{-1}R + \sum_{i=1}^{P} k_i^2 S'S)^{-1} R'\Omega^{-1}] \bullet [E(r - R\beta) + \sum_{i=1}^{P} E(S_i\beta)]$$
$$var(b^{\wedge}) = \sigma^2 (X'\Sigma^{-1}X + R'\Omega^{-1}R + \sum_{i=1}^{P} k_i^2 S'S)^{-1} \qquad \text{(III.29)}$$

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

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

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.29) can be best understood if one respecifies equation (III.28) slightly. Define a matrix, $X^{\wedge}$, which is equal to X from equation (III.28) 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,

$$X^{\wedge} = \begin{vmatrix} X \\ R \bullet W \\ k_1 \bullet S_1 \\ \ldots \\ k_P \bullet S_P \end{vmatrix}$$

Now, define a vector ŷ equal to y from equation (III.28) 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

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

Equation (III.28) can be re-written in terms of $X^{\wedge}$ and $\hat{y}$, instead of X and y, as follows:

$$\begin{aligned} b^{*} &= (X^{\wedge\prime}\Sigma^{-1}X^{\wedge})^{-1}(X^{\wedge}\Sigma^{-1}\hat{y}) \\ b^{\wedge} &= b^{*} + (X^{\wedge\prime}\Sigma^{-1}X^{\wedge})^{-1}C^{\prime}[C(X^{\wedge\prime}\Sigma^{-1}X^{\wedge})^{-1}C^{\prime}]^{-1}\bullet(d - C\bullet b^{*}) \end{aligned} \qquad \text{(III.30)}$$

From equation (III.30), 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.28) to model the demand for mail volume may be instructive. Consider, for example, the demand for Periodical Regular rate mail, which is modeled as follows:

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

$$\begin{aligned} &\alpha \bullet (Y^P)_t^{\beta_1} \bullet (Y^T \text{ lag } 4)_t^{\beta_2} \bullet (e^{\text{Trend}})_t^{\beta_3} \bullet (P^{\text{paper}} \text{ lag } 2)_t^{\beta_4} \bullet (e^{\text{ISP Cons}})_t^{\beta_5} \\ &[px2r_t^{\beta_{p0}} \bullet px2r_{t-1}^{\beta_{p1}} \bullet px2r_{t-2}^{\beta_{p2}} \bullet px2r_{t-3}^{\beta_{p3}} \bullet px2r_{t-4}^{\beta_{p4}}] \bullet \\ &[e^{S_1 \beta_{s1}} \bullet e^{S_2 \beta_{s2}} \bullet e^{S_3 \beta_{s3}} \bullet e^{S_4 \beta_{s4}} \bullet e^{S_5 \beta_{s5}} \bullet \ldots \bullet e^{S_{17} \beta_{s17}}] \bullet e^{\varepsilon}_t \end{aligned} \qquad \text{(III.31)}$$

where Vol2r is the volume of Periodical regular mail, Y^P is long-run income in 1996 dollars, Y^T is short-run income, proxied by the Federal Reserve's index of capacity utilization for the manufacturing sector, Trend is a linear time trend[7], P^{Paper} is the wholesale price of pulp, paper, and allied products in 1996 dollars, ISP Cons is consumption expenditures on Internet Service Providers (raised to the power γ=0.560 as discussed in section II.B.2.d. above), px2r is the fixed-weight average price of Periodical regular mail, and S_1 through S_{17} are the first seventeen seasonal variables defined in section A.3. above.

The vector y associated with equation (III.31) contains the natural logarithm of $(\text{Vol2r / Population / Business Days})_t$ for t = 1971Q1 through 2001Q3. The matrix X contains the natural logarithm of the explanatory variables in equation (III.31), Y^P, Y^T, etc.[8] Matrix X has dimensions T-by-k, where k equals 28 and T equals 123.

The β-vector to be solved by equation (III.28) contains the following elements:

$$\beta_{2r} = [\alpha\ \beta_1\ \beta_2\ \beta_3\ \beta_4\ \beta_5\ \beta_{p0}\ \beta_{p1}\ \beta_{p2}\ \beta_{p3}\ \beta_{p4}\ \beta_{s1}\ \beta_{s2}\ \beta_{s3}\ \beta_{s4}\ \beta_{s5}\ \beta_{s6}\ \beta_{s7}\ \beta_{s8}\ \beta_{s9}\ \beta_{s10}\ \beta_{s11}\ \beta_{s12}\ \beta_{s13}\ \beta_{s14}\ \beta_{s15}\ \beta_{s16}\ \beta_{s17}]$$

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

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[7] The time trend enters the regression linearly such that, $\ln(V_t) = A + \beta_3 \bullet \text{Trend}$. Taking the anti-log of both sides of the equation yields the relationship in equation (III.31) above, namely that $V_t = A^* \bullet (e^{\text{Trend}})^{\beta_3}$.

[8] 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.

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

The vector, d, associated with these restrictions is equal to [0 0 0 0 0 0 0 0 0]. This matrix restricts $\beta_{p4} = 0$, $\beta_{s1} = \beta_{s2}$, $\beta_{s5} = \beta_{s6} = \beta_{s7} = \beta_{s8} = \beta_{s9} = \beta_{s10} = \beta_{s11}$ and $\beta_{s12} = \beta_{s13}$, respectively.

The long-run 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.32) are equal to the following:

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

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:

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

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 0.218750.

Based on estimating equation (III.28), the autocorrelation coefficients, ρ_1, ρ_2, and ρ_4 were estimated to be equal to 0.323634, 0.290874, 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.28) above. The resulting β-vector was calculated to be equal to:

$\hat{b}_{2r}$ = [-3.679 0.534 0.077 -0.141 -0.0016 -0.136 -0.000 -0.022 -0.072 -0.071 0.000 -0.418 -0.418 -0.150 0.037 -0.438 -0.438 -0.438 -0.438 -0.438 -0.438 -0.438 -0.070 -0.070 -0.207 0.187 -0.139 -0.329]

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:

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

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

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

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:

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

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.[9] 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.

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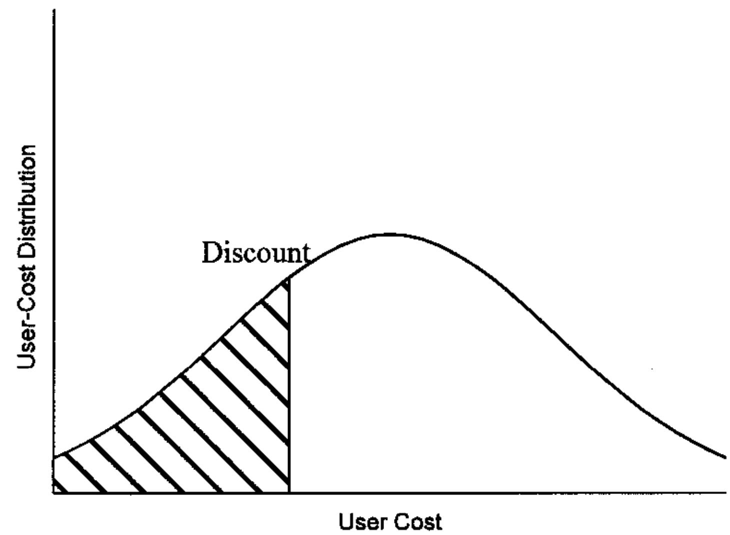
[9] (N minus 1) problems if one considers one of the N worksharing options to be no worksharing.

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:

$$\text{(Percentage of mail within a category)} = \int_0^d \text{p.d.f. } (u)\, du \qquad \text{(IV.6)}$$[10]

---

[10] 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.[11] 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

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[11] 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

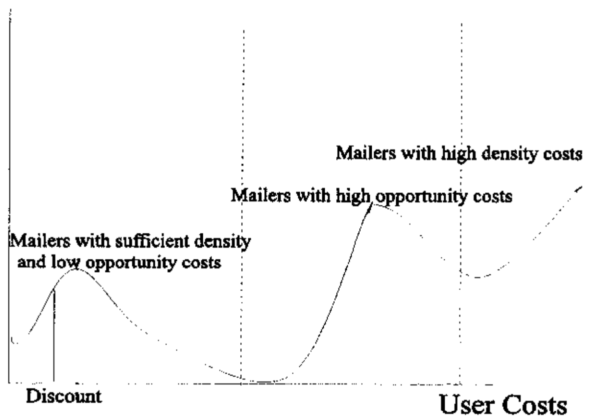
Despite the appeal of the normal distribution, it is not without its limitations. In particular, the normal distribution has three drawbacks which make it less than ideal for modeling consumer user costs: the likelihood of user-cost clusters about several different levels of user costs, the fact that 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[12] 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.

[12] 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).

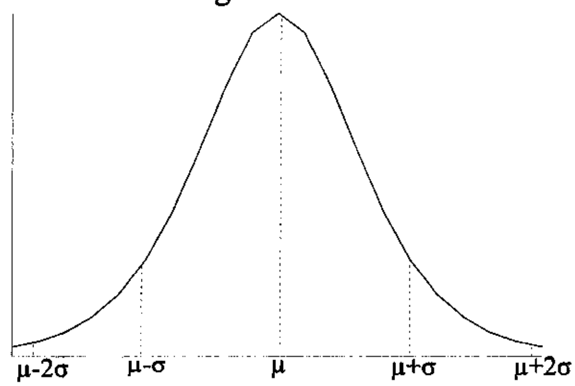
The logistic p.d.f. takes the following form:

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

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:

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

or, integrating the logistic p.d.f.

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

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.[13] 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.

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[13] 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

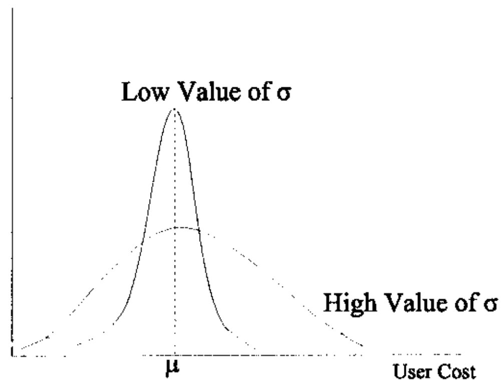
Arbitrary changes in the general shape of user-cost distributions over time would be extremely problematic empirically. At the extreme, if the type of user-cost distribution changed over time, then it would not be valid to base forecasts of future use of worksharing categories on historical patterns, 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

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

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

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

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

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

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:

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

which could be simplified to:

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

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:

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

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

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

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 $E(u_j|0 < u_j \le d_j)$.

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

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

$$E(\tilde{u}_j|0<\tilde{u}_j\leq d_j) = E(u_j|0<u_j\leq d_j) \quad \text{(IV.25)}$$

Equation (IV.18) can thus be rewritten:

$$E(\tilde{u}_j|\tilde{u}_j\leq d_j) = E(\tilde{u}_j|\tilde{u}_j\leq 0)\cdot prob(\tilde{u}_j\leq 0|\tilde{u}_j\leq d_j) + E(u_j|0<u_j\leq d_j)\cdot prob(\tilde{u}_j>0|\tilde{u}_j\leq d_j) \quad \text{(IV.26)}$$

By definition, $E(\tilde{u}|\tilde{u}\leq 0) = 0$. 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:

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

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

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

(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:

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

where $\bar{u}_j$ can be calculated from equation (IV.28) above, s_j can be calculated from equation (IV.11), and $\beta_{ij} \bullet s_j = \hat{s}_{ij}$, 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}:

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

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

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

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

$$\textbf{(3)} \quad \beta ij \geq \frac{1}{\alpha_i} - \frac{1-\alpha_i}{\alpha_i \cdot s_j}$$

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:

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

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:

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

where

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

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 treated as a single group of mail. Share equations are estimated for six categories of workshared cards: 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 letter, 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.

For First-Class and Standard Regular mail, share equations are estimated over a sample period of 1993Q1 through 2001Q3. 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 mail. Hence, volume data since 1993 is more accurately measured than prior to 1993. For Standard Nonprofit mail, the share equations are estimated starting in 1994Q1, due to some concerns with the 1993 nonprofit data based upon the mailing statement data. Counting classification reform (MC95-1 and MC96-2), this sample period spans five distinct rate regimes.

Econometric values are estimated for α_t, μ_t, and σ for each of the share equations estimated for this case. First-Class nonautomation presort, single-piece First-Class cards, and Standard Regular and Nonprofit nonautomation share equations were not estimated; the share of these categories is instead equal to one minus the share of more highly workshared 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:

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

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 five 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:

$$\alpha_t = \alpha_0 \bullet (1-d_{MC95}) + (c_0 - c_1 \bullet d_{2000}) \bullet \alpha_0 \bullet d_{MC95} \qquad \text{(IV.37)}$$

where d_{2000} is a dummy variable, equal to one starting in 2000Q2 in the case of First-Class cards and equal to one starting in 2000Q3 in the case of First-Class letters. This was based on observation which suggested that the share of mail eligible for automation carrier-route may have declined around this time.

The general specification used to model the mean of the user-cost distribution, μ_t, for the 27 First-Class and Standard share equations presented below was the following:

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

where trd is a time trend, equal to zero in 1993Q1, increasing by one each quarter thereafter, t_{MC95} is a time trend interacted with d_{MC95}, equal to zero through 1996Q4, 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. 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, in some cases, the share equations were actually estimated using a two-step iterative procedure, whereby α_t and/or σ were estimated holding μ_t constant prior to estimating the other parameters. 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. Nevertheless, t-statistics are presented here, although these numbers should be viewed with caution.

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:

$$\text{(mean abs. pct. error)} = \Sigma^N{}_{i=1}[(f_t / s_t) - 1]^2 \qquad \text{(IV.39)}$$

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. Workshared First-Class Letters

In R2000-1, eight share equations were estimated for workshared First-Class letters. In this case, only seven share equations are estimated. The eighth category of mail, presort nonautomation, is now treated as the baseline category of workshared First-Class letters. Hence, the discounts used to estimate the remaining seven equations are discounts relative to nonautomation presort rates.

a. Opportunity Cost Relationships

The following opportunity cost relationships were modeled explicitly in the First-Class letters share equations. Automation basic letters have an opportunity cost relationships with respect to automation 3-digit letters. Automation 3-digit letters have opportunity costs with respect to ZIP+4 letters, automation basic letters and automation 5-digit letters. Automation 5-digit letters have opportunity costs with respect to ZIP+4 letters and automation 3-digit letters. Automation carrier-route letters have opportunity costs with respect to automation 5-digit letters. Automation basic and 3/5-digit flats have opportunity costs with each other. Finally, ZIP+4 letters have opportunity costs with respect to automation 3-digit, and automation 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. 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.

In this case, a new forecast is being introduced for mail sorted to the Area Distribution Center (ADC). For the after-rates forecast, both ADC and mixed-ADC letters are treated as "basic" letters here.

The coefficients for the automation basic letters share equation (t-statistics are in parentheses) are:

$$\begin{aligned}
\alpha_1 &= 0.116009 && (154.07)\\
\mu_0 &= -0.116101 && (-1.256)\\
\mu_{TM} &= 0.017855 && (1.017)\\
\mu_1 &= 0.036709 && (2.639)\\
\mu_2 &= 0.063599 && (1.854)\\
\mu_3 &= 0.019355 && (0.898)\\
\sigma &= 0.061689 && (1.106)
\end{aligned}$$

Mean Absolute Percentage Error 1.410%

c. Automation Basic Flats

Automation basic flats are flats that are automated, but are not presorted to the 3-digit level or finer. For the after-rates forecast, both ADC and mixed ADC flats are treated as "basic" flats here. The values of μ_1, μ_2, μ_M, and μ_{TM} were found to be essentially equal to zero, and were therefore constrained as such. The coefficients for the automation basic flats share equation (t-statistics in parentheses) are:

α_0 = 0.000894 (3.541)
α_1 = 0.001923 (2.864)
μ_0 = 0.011041 (2.835)
μ_T = 0.000196 (2.366)
μ_3 = -0.002052 (-2.052)
σ = 0.004050 (1.839)

Mean Absolute Percentage Error 18.76%

d. Automation 3-Digit Letters

Automation 3-digit letters are letters that are automated and presorted to the 3-digit level. The values of μ_M, μ_2 and μ_3 were found to be basically equal to zero, and were therefore set equal to zero. The coefficients for the automation 3-digit letters share equation (t-statistics in parentheses) are:

α_0 = 0.410471 (18.16)
α_1 = 0.078137 (3.978)
μ_0 = 0.002965 (2.040)
μ_1 = -0.000164 (-0.465)
μ_T = 0.000901 (3.212)
μ_{TM} = -0.000903 (-2.596)
σ = 0.008272 (2.877)

Mean Absolute Percentage Error 0.816%

e. Automation 5-Digit Letters

Automation 5-digit letters are letters that are automated and presorted to the 5-digit level. Classification reform did not appear to have any effect on the ceiling share of automation 5-digit letters, so α_1 was set equal to zero. In addition, the values of μ_1 and μ_2 were found to be basically equal to zero, and were therefore set equal to zero.

The coefficients for the automation 5-digit letters share equation (t-statistics in parentheses) are:

α_0 = 0.310996 (32.82)
μ_0 = 0.014835 (5.833)
μ_3 = 0.002659 (1.832)

$$\mu_T = 0.004610 \quad (3.526)$$
$$\mu_{TM} = -0.000689 \quad (-1.483)$$
$$\mu_M = 0.062753 \quad (5.636)$$
$$\sigma = 0.041081 \quad (3.326)$$

Mean Absolute Percentage Error 1.386%

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. In R2000-1, separate rates were set for 3-digit and 5-digit automation flats. Because separate volumes for 3-digit and 5-digit automation flats were only available for two quarters, however, a single share equation was estimated for the combined share of these two categories. The values of μ_3 and μ_M were found to be essentially equal to zero, and were therefore constrained as such.

The coefficients for the automation 3/5-digit flats share equation (t-statistics in parentheses) are:

$$\alpha_0 = 0.555316 \quad (0.001)$$
$$\alpha_1 = 0.444650 \quad (0.001)$$
$$\mu_0 = 0.410288 \quad (0.007)$$
$$\mu_T = -0.005432 \quad (-0.266)$$
$$\mu_{TM} = 0.005432 \quad (0.266)$$
$$\mu_1 = -0.000428 \quad (-0.076)$$
$$\mu_2 = -0.000428 \quad (-0.076)$$
$$\sigma = 0.059992 \quad (0.147)$$

Mean Absolute Percentage Error 19.52%

g. 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 values of μ_M, and μ_{TM} were found to be essentially equal to zero, and were therefore constrained as such. On the other hand, an additional term was added to equation (IV.38), equal to $\mu_{94} \bullet d_{94}$, where d_{94} is a dummy variable equal to zero through 1994Q1, equal to one thereafter.

Finally, the opportunity cost with respect to automation 5-digit letters is set equal to zero prior to MC95-1, and is set equal to $(d_{A5} - \bar{u}_{A5}) \bullet (\beta_{A5C} \bullet s_{A5})$, where A5 refers to automation 5-digit letters and β_{A5C} is solved for within the econometric automation carrier-route letters equation, since that time.

The coefficients for the carrier-route presort share equation (t-statistics in parentheses) are:

α_0 =	0.116476	(2.021)
c_0 =	0.419592	(9.883)
c_1 =	0.059077	(2.113)
μ_0 =	-0.014792	(-0.178)
μ_T =	-0.001990	(-0.838)
μ_{94} =	-0.035233	(-0.877)
μ_1 =	-0.011030	(-0.927)
μ_2 =	-0.009777	(-0.871)
μ_3 =	-0.007532	(-0.859)
β_{A5C} =	3.539303	(2.263)
σ =	0.060840	(2.307)

Mean Absolute Percentage Error 3.020%

h. 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. In addition, the values of μ_1 and μ_3 are also constrained to be equal to zero.

The coefficients for the ZIP+4 letters share equation (t-statistics in parentheses) are:

α_0 =	0.226786	(2.018)
μ_0 =	0.002740	(1.284)
μ_T =	-0.000102	(-1.317)
μ_2 =	0.000185	(1.722)
σ =	0.002267	(2.375)

Mean Absolute Percentage Error 5.037%

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 cards have opportunity cost relationships with respect to basic, 3-digit, and 5-digit automation cards. ZIP+4 cards have opportunity cost relationships with respect to 3-digit and 5-digit automation cards. Automation basic cards have opportunity cost relationships with respect to nonautomation presort 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, and automation 3-digit cards. Carrier-route presort cards have no opportunity costs explicitly modeled.

b. Nonautomation Presort

Nonautomation presort First-Class cards 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 ceiling parameter for nonautomated cards was unaffected by classification reform, so that α_1 is set equal to zero. In addition, the value of μ_1 was not found to be notably different from zero and was, therefore, constrained to be equal to zero.

The coefficients for the nonautomation presort share equation (t-statistics in parentheses) are:

α_0 =	0.180243	(34.65)
μ_0 =	-0.010987	(-0.582)
μ_T =	-0.000668	(-0.524)
μ_{TM} =	0.000722	(0.570)
μ_2 =	-0.002345	(-4.505)
μ_3 =	0.000125	(0.284)
μ_M =	0.009719	(2.739)
σ =	0.003891	(3.065)

Mean Absolute Percentage Error 4.382%

c. Automation Basic

Automation basic cards are cards that are automated, but are not presorted to the 3-digit level or finer. For the after-rates forecast, both ADC and mixed ADC cards are treated as "basic" cards here. The opportunity cost with respect to automation 3-digit cards is set equal to zero prior to classification reform. After classification reform, the value of β is assumed to be equal to one.

The coefficients for the automation basic share equation (t-statistics in parentheses) are:

α_0	=	0.016489	(9.573)
α_1	=	0.080276	(19.16)
μ_0	=	0.020707	(8.268)
μ_T	=	0.000837	(2.313)
μ_{TM}	=	-0.000267	(-1.078)
μ_1	=	0.001623	(1.240)
μ_2	=	-0.000715	(-1.065)
μ_3	=	-0.000396	(-0.492)
μ_M	=	0.019213	(4.332)
σ	=	0.003621	(1.198)

Mean Absolute Percentage Error 4.034%

d. Automation 3-Digit

Automation 3-digit cards are cards that are automated and presorted to the 3-digit level. An additional term was added to equation (IV.36) in the case of automation 3-digit cards, $\alpha' \bullet d_{93Q4}$, where d_{93Q4} is a dummy variable equal to zero through 1993Q3, equal to one thereafter.

The value of μ_{TM} is constrained to zero. As in the automation basic equation, the opportunity cost with respect to automation basic cards is equal to zero prior to classification reform and is estimated using a value of $\beta = 1$ thereafter.

The coefficients for the automation 3-digit share equation (t-statistics in parentheses) are:

α_0	=	0.101484	(5.539)
α'	=	0.070963	(4.160)
α_1	=	0.110849	(6.179)
μ_0	=	0.052170	(57.49)
μ_T	=	0.000820	(15.92)

$$\mu_1 = 0.002120 \quad (2.823)$$
$$\mu_2 = -0.002701 \quad (-3.569)$$
$$\mu_3 = 0.001168 \quad (1.536)$$
$$\mu_M = -0.004574 \quad (-4.047)$$
$$\sigma = 0.015576 \quad (9.280)$$

Mean Absolute Percentage Error 3.644%

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 (t-statistics in parentheses) are:

$$\alpha_0 = 0.179423 \quad (3.167)$$
$$\mu_0 = 0.085396 \quad (0.845)$$
$$\mu_T = 0.007603 \quad (0.475)$$
$$\mu_{TM} = -0.004544 \quad (-0.426)$$
$$\mu_1 = 0.008736 \quad (0.484)$$
$$\mu_2 = -0.012542 \quad (-0.428)$$
$$\mu_3 = 0.011866 \quad (0.463)$$
$$\mu_M = 0.063648 \quad (0.599)$$
$$\sigma = 0.059672 \quad (0.469)$$

Mean Absolute Percentage Error 7.388%

f. Carrier-Route Presort

Carrier-route presort First-Class cards includes all mail 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 values of μ_1 and μ_M are set equal to zero. The coefficients for the carrier-route presort share equation (t-statistics in parentheses) are:

α_0 = 0.160830 (40.49)
c_0 = 0.284289 (12.18)
c_1 = 0.065988 (1.368)
μ_0 = 0.045498 (14.26)
μ_T = 0.000283 (0.824)
μ_{TM} = -0.001942 (-2.523)
μ_2 = -0.024996 (-6.547)
μ_3 = 0.003207 (0.907)
σ = 0.030267 (6.973)

Mean Absolute Percentage Error 9.286%

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 (t-statistics in parentheses) are:

α_0 = 0.227949 (30.33)
μ_0 = 0.032410 (177.05)
μ_T = 0.000043 (2.790)
μ_1 = 0.000050 (0.252)
μ_2 = -0.000696 (-3.562)
μ_3 = -0.000149 (-0.716)
σ = 0.004955 (57.37)

Mean Absolute Percentage Error 5.151%

3. Standard Regular Mail

a. Opportunity Cost Relationships

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

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 values of α_1, μ_2, and μ_M were found to be approximately equal to zero, and were hence constrained to be exactly equal to zero.

The coefficients for the automation basic letters share equation (t-statistics in parentheses) are:

$$\alpha_0 = 0.772507 \quad (23.76)$$
$$\mu_0 = 0.042985 \quad (12.56)$$
$$\mu_T = 0.001050 \quad (3.733)$$
$$\mu_{TM} = 0.004816 \quad (1.971)$$
$$\mu_1 = 0.004999 \quad (1.642)$$
$$\mu_3 = 0.005791 \quad (1.872)$$
$$\sigma = 0.031146 \quad (20.25)$$

Mean Absolute Percentage Error 3.895%

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 (t-statistics in parentheses) are:

$$\alpha_0 = 0.351086 \quad (7.751)$$
$$\mu_0 = 0.160061 \quad (8.758)$$
$$\mu_T = 0.004503 \quad (2.684)$$
$$\mu_{TM} = 0.002451 \quad (0.801)$$
$$\mu_M = -0.039011 \quad (-2.405)$$
$$\sigma = 0.064527 \quad (18.32)$$

Mean Absolute Percentage Error 7.680%

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.

With the implementation of R97-1 rates, basic ECR letters were priced less than automation Regular 5-digit letters. This led to a significant increase in the share of presorted letters that were automation 5-digit and a significant decrease in the share that were automation 3-digit. This is modeled here as affecting the ceiling shares of automation 3-digit and 5-digit letters. In effect, this new volume is excluded from the share of automation 3-digit letters, as this mail could, instead, opt for the less-expensive ECR basic letters category. On the other hand, this new volume increases the ceiling share for automation 5-digit letters. Equation (IV.36) is replaced with equation (IV.40) below, where d_{R97} is a dummy equal to one with the implementation of R97-1 rates, and α_{97} has a positive value for automation 5-digit letters and a negative value for automation 3-digit letters.

$$\alpha = \alpha_0 + \alpha_1 \bullet d_{MC95} + \alpha_{97} \bullet d_{R97} \qquad \text{(IV.40)}$$

The value of β used in calculating the opportunity cost with respect to automation 5-digit letters was fit to the following equation:

$$\beta_5 = 1 / [\alpha_0 + \alpha_1 \bullet d_{MC95}] \qquad \text{(IV.41)}$$

The values of μ_2, μ_M, and μ_{TM} were constrained to be equal to zero. The coefficients for the automation 3-digit letters share equation (t-statistics in parentheses) are:

α_0 =	0.393994	(11.63)
α_1 =	0.288872	(5.426)
α_{97} =	-0.081383	(-5.316)
μ_0 =	0.008583	(2.791)
μ_T =	0.000502	(3.457)
μ_1 =	0.002015	(2.159)
μ_3 =	0.001434	(1.545)
σ =	0.012689	(3.495)

Mean Absolute Percentage Error 2.382%

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 μ_T and μ_2 were constrained to be equal to zero. In addition, a dummy variable equal to one in 1996Q4 is added to equation (IV.38) here.

The value of β used in calculating the opportunity cost with respect to automation 3-digit letters was fit to the following equation:

$$\beta_3 = 1 / \alpha_0 \qquad \text{(IV.42)}$$

The coefficients for the automation 5-digit letters share equation (t-statistics in parentheses) are:

α_0 =	0.708051	(3.676)
α_1 =	-0.365080	(-1.903)
α_{97} =	0.118874	(5.875)
μ_0 =	0.015925	(2.635)
μ_{96} =	-0.013951	(-3.534)
μ_{TM} =	0.001447	(2.884)
μ_1 =	0.001992	(2.912)
μ_3 =	0.000894	(1.694)
μ_M =	0.014709	(6.492)
σ =	0.009919	(2.510)

Mean Absolute Percentage Error 2.642%

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}, and μ_M were constrained to be equal to zero. The coefficients for the automation 3/5-digit flats share equation (t-statistics in parentheses) are:

α_0	=	0.902538	(41.49)
μ_0	=	0.014287	(3.134)
μ_T	=	0.003706	(6.720)
μ_1	=	0.008360	(1.644)
μ_2	=	0.004959	(0.955)
μ_3	=	0.005280	(1.005)
σ	=	0.039335	(7.230)

Mean Absolute Percentage Error 3.099%

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_1, μ_2, and μ_3 were also constrained to be equal to zero. In addition, a second time trend, which plateaus starting in 1994Q4 was added to equation (IV.38). The coefficient on this time trend is identified as μ_{T94} below.

The coefficients for the basic ZIP+4 letters share equation (t-statistics in parentheses) are:

α_0	=	0.060723	(2.686)
μ_0	=	0.005779	(1.034)
μ_T	=	-0.000634	(-6.744)

$$\mu_{T94} = 0.000561 \quad (1.138)$$
$$\sigma = 0.005052 \quad (22.58)$$

Mean Absolute Percentage Error 8.994%

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_2 was constrained to be equal to zero, and, as with basic ZIP+4 letters, a time trend through 1994 was also included in the specification of μ.

The coefficients for the presort ZIP+4 letters share equation (t-statistics in parentheses) are:

$$\alpha_0 = 0.034106 \quad (5.118)$$
$$\mu_0 = -0.031612 \quad (-1.165)$$
$$\mu_T = -0.008759 \quad (-4.500)$$
$$\mu_{T94} = -0.006807 \quad (-3.761)$$
$$\mu_1 = -0.020511 \quad (-2.635)$$
$$\mu_3 = -0.016323 \quad (-2.406)$$
$$\sigma = 0.038271 \quad (17.74)$$

Mean Absolute Percentage Error 7.686%

4. Standard Nonprofit Mail

a. Opportunity Cost Relationships

The only opportunity cost relationships explicitly modeled in the Standard Nonprofit share equations are between presort ZIP+4, automation 3-digit, and automation 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 α_1, μ_1, μ_3, and μ_T 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 (t-statistics in parentheses) are:

$$\begin{array}{lrl}
\alpha_0 = & 0.668064 & (23.11) \\
\mu_0 = & 0.040838 & (15.28) \\
\mu_2 = & 0.003976 & (1.186) \\
\mu_{TM} = & 0.003925 & (2.707) \\
\mu_M = & -0.027976 & (-6.579) \\
\sigma = & 0.027958 & (0.640)
\end{array}$$

Mean Absolute Percentage Error 4.674%

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 and μ_1 were constrained to be equal to zero. The coefficients for the automation basic flats share equation (t-statistics in parentheses) are:

$$\begin{array}{lrl}
\alpha_0 = & 0.886462 & (1.171) \\
\mu_0 = & 4.673637 & (0.331) \\
\mu_T = & 0.158913 & (0.317) \\
\mu_{TM} = & -0.078798 & (-0.333) \\
\mu_2 = & 0.140730 & (0.302) \\
\mu_3 = & -0.006978 & (-0.132) \\
\mu_M = & -0.224740 & (-0.326) \\
\sigma = & 1.013348 & (0.321)
\end{array}$$

Mean Absolute Percentage Error 6.372%

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 α_1, μ_{TM}, μ_1, μ_2, and μ_3 were constrained to be equal to zero. In addition, a dummy variable equal to one starting in 1996Q1 is added to equation (IV.38) here. The coefficients for the automation 3-digit letters share equation (t-statistics in parentheses) are:

$$\begin{array}{lll}
\alpha_0 = & 0.551911 & (11.27) \\
\mu_0 = & 0.031492 & (1.549) \\
\mu_{96} = & -0.003555 & (-0.875) \\
\mu_T = & 0.000707 & (1.734) \\
\mu_M = & -0.028604 & (-1.089) \\
\sigma = & 0.017245 & (1.248)
\end{array}$$

Mean Absolute Percentage Error 3.207%

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, μ_3, and μ_{TM} were constrained to be equal to zero. The coefficients for the automation 5-digit letters share equation (t-statistics in parentheses) are:

$$\begin{array}{lll}
\alpha_0 = & 0.517071 & (1.369) \\
\mu_0 = & 0.048452 & (0.363) \\
\mu_T = & 0.005275 & (1.200) \\
\mu_1 = & -0.026495 & (-1.146) \\
\mu_2 = & -0.007590 & (-0.691) \\
\mu_M = & 0.129299 & (1.363) \\
\sigma = & 0.107649 & (0.382)
\end{array}$$

Mean Absolute Percentage Error 6.038%

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_M were constrained to be equal to zero. The coefficients for the automation 3/5-digit flats share equation (t-statistics in parentheses) are:

α_0 =	1.000000	(5.537)
μ_0 =	0.038871	(3.840)
μ_T =	0.001459	(2.941)
μ_{TM} =	0.000420	(0.766)
μ_1 =	0.001646	(1.320)
μ_2 =	0.003092	(2.129)
μ_3 =	0.001773	(1.331)
σ =	0.021654	(3.684)

Mean Absolute Percentage Error 2.856%

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 (t-statistics in parentheses) are:

α_0 =	0.029600	(8.720)
μ_0 =	-0.014185	(-0.797)
μ_T =	-0.001082	(-1.153)
σ =	0.007533	(1.507)

Mean Absolute Percentage Error 4.100%

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 (t-statistics in parentheses) are:

α_0	=	0.219879	(0.095)
μ_0	=	0.032445	(0.103)
μ_T	=	-0.000503	(-1.400)
σ	=	0.020948	(0.641)

Mean Absolute Percentage Error 4.665%

5. Parcel Post Shares

a. General Overview

Parcel post is divided into five categories by means of share equations: inter-BMC, intra-BMC, destination BMC (DBMC), destination SCF (DSCF), and destination delivery unit (DDU).

A variant of equation (IV.33) is used to estimate these share equations. The equation used differs from equation (IV.33) in that the discount is set equal to zero in all cases. This is done for simplicity's sake, and has the effect that before- and after-rates share forecasts are, therefore, identical for the categories of parcel post mail. For added simplicity, the value of σ is also excluded from the explicit specification. The resulting equation that is solved to estimate the parcel post share equations is the following:

$$(\textit{Parcel Post share}) = \left(\frac{\alpha_i}{1 + e^{\mu_i}}\right) \qquad \text{(IV.43)}$$

Three share equations are estimated for parcel post mail: a DDU equation, a DSCF equation, and a total destination entry equation. The share of parcel post sent as DBMC is equal to the total destination entry share minus DSCF and DDU. These equations are outlined below.

DSCF and DDU discounts were first introduced for parcel post in January of 1999. Hence, the parcel post share equations are estimated beginning in 1999Q3, the first full quarter for which DSCF and DDU discounts were offered.

For all three equations, the ceiling parameter, α, is assumed to be constant throughout the sample period for DSCF parcel post. The value of μ is fit to the following specification:

$$\mu = \mu_0 + \mu_T \bullet t + \mu_1 \bullet Q_1 + \mu_2 \bullet Q_2 + \mu_3 \bullet Q_3 + \mu_{2000} \bullet d_{R2000} \qquad \text{(IV.44)}$$

where d_{R2000} is a dummy variable equal to one starting with the implementation of R2000-1 rates in January of 2001.

The share of non-destination entry (inter-BMC plus intra-BMC) is then equal to one minus the share of destination entry. Total non-destination entry is divided between inter-BMC and intra-BMC parcel post in the same proportions as in the base year.

b. DSCF Parcel Post

The coefficients for the DSCF parcel post share equation (t-statistics in parentheses) are:

α =	0.032044	(2.591)
μ_0 =	1.280837	(2.895)
μ_T =	-0.241033	(-2.033)
μ_1 =	-0.745904	(-1.550)
μ_2 =	-0.031990	(-0.110)
μ_3 =	0.387109	(1.258)
μ_{2000} =	1.474531	(1.915)

Mean Absolute Percentage Error 6.471%

c. DDU Parcel Post

The coefficients for the DDU parcel post share equation (t-statistics in parentheses) are:

α	=	0.243842	(8.928)
μ_0	=	1.148121	(3.775)
μ_T	=	-0.247011	(-4.013)
μ_1	=	-0.591413	(-2.151)
μ_2	=	0.519782	(1.590)
μ_3	=	0.221623	(0.862)
μ_{2000}	=	-2.221009	(-1.660)

Mean Absolute Percentage Error 3.557%

d. DBMC Parcel Post

The share of parcel post that is DBMC is equal to the share for total destination entry parcel post less the shares associated with DSCF and DDU parcel post. The coefficients for the destination entry parcel post share equation (t-statistics in parentheses) are:

α	=	1.000000	(1.019)
μ_0	=	-0.751140	(-0.255)
μ_T	=	-0.067286	(-0.343)
μ_1	=	-0.118547	(-0.325)
μ_2	=	0.006988	(0.071)
μ_3	=	-0.079392	(-0.325)
μ_{2000}	=	0.686136	(0.363)

Mean Absolute Percentage Error
(for DBMC Parcel Post) 1.428%

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 the four quarters ending in 2001Q3.

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

$$s_t = \frac{\alpha_t}{1 + e^{-(d_t - \mu_t)/\sigma}} \; ; \quad s_{base} = \frac{\alpha_{base}}{1 + e^{-(d_{base} - \mu_{base})/\sigma}}$$

$$s_t = s_{base} \bullet \left(\frac{\alpha_t}{\alpha_{base}}\right) \bullet \left[\frac{(1 + e^{-(d_{base} - \mu_{base})/\sigma})}{(1 + e^{-(d_t - \mu_t)/\sigma})}\right] \qquad \text{(IV.45)}$$

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 2000Q4 through 2001Q3, while the

Test Year is Government Fiscal Year, 2003 (October 1, 2002 through September 30, 2003).

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. The values of α and σ come from the econometric equations discussed above.

Table IV-2 presents the base-year and test-year discounts. R2000-1 took effect approximately two-thirds 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 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 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. The numbers presented here are actually calculated based on the Test Year volume forecasts. 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
Workshared First-Class Letters				
Automation Basic Letters	11.56%	11.60%	11.60%	6.17¢
Automation Basic Flats	0.18%	0.28%	0.28%	0.40¢
Automation 3-Digit Letters	47.87%	48.86%	48.86%	0.83¢
Automation 5-Digit Letters	28.88%	31.10%	31.10%	4.11¢
Automation 3/5-Digit Flats	1.00%	100.00%	100.00%	6.00¢
Automation Carrier-Route	2.15%	4.20%	4.20%	6.08¢
Private First-Class Cards				
Presort Nonautomation	9.86%	18.02%	18.02%	0.39¢
Automation Basic	8.86%	9.68%	9.68%	0.36¢
Automation 3-Digit	18.88%	28.33%	28.33%	1.56¢
Automation 5-Digit	13.27%	17.94%	17.94%	5.97¢
Automation Carrier Route	1.51%	3.51%	3.51%	3.03¢
Standard Regular				
Letters				
Basic				
Automation	76.60%	77.25%	77.25%	3.11¢
Presort				
Automation 3-Digit	50.32%	60.15%	60.15%	1.27¢
Automation 5-Digit	42.55%	46.18%	46.18%	0.99¢
Nonletters				
Basic				
Automation	31.97%	35.11%	35.11%	6.45¢
Presort				
Automation	88.23%	90.25%	90.25%	3.93¢
Standard Nonprofit				
Letters				
Basic				
Automation	66.09%	66.81%	66.81%	2.80¢
Presort				
Automation 3-Digit	48.65%	55.19%	55.19%	1.72¢
Automation 5-Digit	30.33%	51.71%	51.71%	10.76¢
Nonletters				
Basic				
Automation	31.41%	88.65%	88.65%	101.33¢
Presort				
Automation	81.96%	100.00%	100.00%	2.17¢

Table IV-2
Summary of Parameters used in Forecasting Shares

	d_{Base} (nominal)	d_{Base} (real)	d_{TYBR} (real)	d_{TYAR} (real)
Workshared First-Class Letters				
Automation Basic Letters	3.76¢	3.47¢	3.68¢	4.13¢
Automation Basic Flats	0.68¢	0.63¢	0.88¢	1.21¢
Automation 3-Digit Letters	4.73¢	4.37¢	4.64¢	5.08¢
Automation 5-Digit Letters	6.38¢	5.90¢	5.87¢	6.31¢
Automation 3/5-Digit Flats	3.79¢	3.50¢	3.75¢	4.19¢
Automation Carrier-Route	7.07¢	6.53¢	6.75¢	6.75¢
Private First-Class Cards				
Presort Nonautomation	2.00¢	1.85¢	1.75¢	1.58¢
Automation Basic	3.47¢	3.21¢	3.15¢	3.45¢
Automation 3-Digit	4.14¢	3.82¢	3.68¢	4.12¢
Automation 5-Digit	5.22¢	4.82¢	4.29¢	4.73¢
Automation Carrier Route	5.94¢	5.48¢	5.26¢	5.26¢
Standard Regular				
Letters				
Basic				
Automation	5.24¢	4.84¢	4.64¢	4.64¢
Presort				
Automation 3-Digit	3.54¢	3.27¢	3.77¢	3.94¢
Automation 5-Digit	5.03¢	4.65¢	4.91¢	5.08¢
Nonletters				
Basic				
Automation	5.35¢	4.94¢	3.85¢	3.85¢
Presort				
Automation	3.33¢	3.08¢	2.37¢	2.37¢
Standard Nonprofit				
Letters				
Basic				
Automation	4.08¢	3.77¢	2.19¢	2.21¢
Presort				
Automation 3-Digit	2.62¢	2.42¢	2.02¢	2.10¢
Automation 5-Digit	4.49¢	4.15¢	3.33¢	3.42¢
Nonletters				
Basic				
Automation	4.73¢	4.37¢	3.59¢	3.59¢
Presort				
Automation	1.95¢	1.80¢	1.49¢	1.49¢

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.)
Workshared First-Class Letters				
Automation Basic Letters	-39.92¢	-38.34¢	-55.20¢	-55.06¢
Automation Basic Flats	0.42¢	0.45¢	0.26¢	0.27¢
Automation 3-Digit Letters	-1.06¢	0.90¢	1.07¢	1.25¢
Automation 5-Digit Letters	-5.92¢	-4.34¢	-7.99¢	-7.85¢
Automation 3/5-Digit Flats	32.86¢	32.86¢	32.86¢	32.86¢
Automation Carrier-Route	0.79¢	6.32¢	8.71¢	9.17¢
Private First-Class Cards				
Presort Nonautomation	0.73¢	1.80¢	1.88¢	2.05¢
Automation Basic	1.76¢	2.22¢	1.75¢	1.81¢
Automation 3-Digit	2.12¢	2.83¢	2.08¢	2.15¢
Automation 5-Digit	-1.63¢	-1.17¢	-4.00¢	-3.93¢
Automation Carrier Route	6.51¢	6.51¢	8.09¢	8.09¢
Standard Regular				
Letters				
Basic				
Automation	-7.23¢	-7.23¢	-12.79¢	-12.79¢
Presort				
Automation 3-Digit	-0.69¢	0.92¢	1.24¢	1.31¢
Automation 5-Digit	0.61¢	2.29¢	1.12¢	1.21¢
Nonletters				
Basic				
Automation	-6.75¢	-6.75¢	-13.34¢	-13.34¢
Presort				
Automation	-10.15¢	-10.15¢	-13.66¢	-13.66¢
Standard Nonprofit				
Letters				
Basic				
Automation	-5.06¢	-5.06¢	-8.78¢	-8.78¢
Presort				
Automation 3-Digit	-2.36¢	-1.22¢	-1.91¢	-1.88¢
Automation 5-Digit	-0.10¢	0.96¢	-4.18¢	-4.14¢
Nonletters				
Basic				
Automation	62.32¢	62.32¢	-13.67¢	-13.67¢
Presort				
Automation	-1.38¢	-1.38¢	-3.16¢	-3.16¢

Table IV-4
Summary of Parameters used in Forecasting Shares

	Base Share	Test-Year Before-Rates Share	Test Year After-Rates Share
Workshared First-Class Letters			
Presort Nonautomation	8.36%	7.17%	6.97%
Automation Basic Letters	11.56%	11.58%	11.58%
Automation Basic Flats	0.18%	0.25%	0.28%
Automation 3-Digit Letters	47.87%	47.98%	48.12%
Automation 5-Digit Letters	28.88%	30.20%	30.24%
Automation 3/5-Digit Flats	1.00%	1.04%	1.13%
Automation Carrier-Route	2.95%	1.78%	1.70%
Private First-Class Cards			
Single-Piece	47.61%	46.24%	48.15%
Presort Nonautomation	9.86%	7.79%	4.24%
Automation Basic	8.86%	9.46%	9.59%
Automation 3-Digit	18.88%	21.42%	22.76%
Automation 5-Digit	13.27%	14.07%	14.25%
Automation Carrier Route	1.51%	1.02%	1.01%
Standard Regular			
Letters			
Basic			
Nonautomation	23.40%	22.15%	22.01%
Automation	76.60%	77.85%	77.99%
Presort			
Nonautomation	7.13%	3.27%	2.67%
Automation 3-Digit	50.32%	50.82%	51.35%
Automation 5-Digit	42.55%	45.92%	45.98%
Nonletters			
Basic			
Nonautomation	68.03%	65.36%	65.29%
Automation	31.97%	34.64%	34.71%
Presort			
Nonautomation	11.77%	10.36%	10.31%
Automation	88.23%	89.64%	89.69%
Standard Nonprofit			
Letters			
Basic			
Nonautomation	33.91%	33.19%	33.11%
Automation	66.09%	66.81%	66.89%
Presort			
Nonautomation	21.02%	15.30%	15.04%
Automation 3-Digit	48.65%	49.62%	49.81%
Automation 5-Digit	30.33%	35.08%	35.15%
Nonletters			
Basic			
Nonautomation	68.59%	52.96%	52.97%
Automation	31.41%	47.04%	47.03%
Presort			
Nonautomation	18.04%	9.89%	9.89%
Automation	81.96%	90.11%	90.11%

3. The Residual Share

First-Class nonautomation presort letters, single-piece First-Class cards, Standard Regular basic letters and nonletters, Standard Regular presort letters and nonletters, Standard Nonprofit basic letters and nonletters, and Standard Nonprofit presort letters and nonletters are not forecasted using equation (IV.45) above. Instead, these represent "residual" categories. These are the categories from which the 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.

4. Enhanced Carrier Route Shares

Standard ECR shares are not forecasted using equation (IV.45) 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 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	36.462%
Automation	20.272%
High Density	3.706%
Saturation	39.560%
Nonletters	
Basic	53.079%
High Density	7.366%
Saturation	39.556%
Standard ECR Nonprofit	
Letters	
Basic	33.577%
Automation	18.310%
High Density	4.556%
Saturation	43.557%
Nonletters	
Basic	74.311%
High Density	0.904%
Saturation	24.785%

D. Final Forecasted Shares

Tables IV-6 and IV-7 below present final forecasted shares of First-Class, Standard and parcel post mail before- and after-rates from 2001Q4 through 2005Q1.

Table IV-6
Before-Rates Share Forecasts

	2001Q4	2002Q1	2002Q2	2002Q3	2002Q4	2003Q1	2003Q2	2003Q3	2003Q4	2004Q1	2004Q2	2004Q3	2004Q4	2005Q1
Workshared First-Class Letters														
Presort Nonautomation	7.682%	7.391%	7.337%	7.372%	7.400%	7.151%	7.135%	7.184%	7.264%	7.044%	7.053%	7.111%	7.225%	7.030%
Automation Basic Letters	11.565%	11.563%	11.562%	11.566%	11.567%	11.567%	11.567%	11.568%	11.568%	11.568%	11.568%	11.568%	11.568%	11.568%
Automation Basic Flats	0.228%	0.230%	0.232%	0.257%	0.236%	0.238%	0.240%	0.262%	0.243%	0.245%	0.246%	0.267%	0.249%	0.250%
Automation 3-Digit Letters	48.085%	48.076%	48.057%	48.045%	48.006%	47.998%	47.978%	47.965%	47.927%	47.921%	47.904%	47.892%	47.856%	47.853%
Automation 5-Digit Letters	29.410%	29.561%	29.704%	29.741%	29.954%	30.062%	30.162%	30.189%	30.340%	30.417%	30.485%	30.497%	30.597%	30.641%
Automation 3/5-Digit Flats	1.066%	1.070%	1.067%	1.056%	1.053%	1.056%	1.053%	1.042%	1.038%	1.042%	1.038%	1.028%	1.024%	1.028%
Automation Carrier-Route Letters	1.964%	2.109%	2.041%	1.963%	1.784%	1.929%	1.865%	1.790%	1.619%	1.764%	1.706%	1.637%	1.481%	1.629%
Private First-Class Cards														
Single-Piece	47.540%	48.003%	43.153%	47.884%	47.088%	47.492%	42.891%	47.464%	46.707%	47.054%	42.698%	47.072%	46.370%	46.711%
Presort Nonautomation	8.665%	9.200%	10.159%	8.319%	7.739%	8.251%	9.274%	7.398%	6.883%	7.364%	8.456%	6.591%	6.170%	6.652%
Automation Basic	9.097%	8.986%	9.173%	9.215%	9.204%	9.125%	9.255%	9.284%	9.276%	9.221%	9.312%	9.331%	9.323%	9.279%
Automation 3-Digit	19.836%	19.336%	21.111%	20.147%	20.705%	20.220%	21.906%	20.979%	21.513%	21.055%	22.644%	21.742%	22.218%	21.739%
Automation 5-Digit	13.621%	13.286%	14.548%	13.424%	14.223%	13.918%	15.052%	14.042%	14.761%	14.488%	15.493%	14.580%	15.206%	14.936%
Automation Carrier Route	1.241%	1.189%	1.856%	1.011%	1.041%	0.994%	1.622%	0.833%	0.860%	0.818%	1.397%	0.685%	0.713%	0.683%
Standard Regular														
Letters														
Basic														
Nonautomation	22.727%	22.709%	22.452%	22.455%	22.259%	22.251%	22.125%	22.127%	22.031%	22.027%	21.967%	21.970%	21.925%	21.927%
Automation	77.273%	77.291%	77.548%	77.545%	77.741%	77.749%	77.875%	77.873%	77.969%	77.973%	78.033%	78.030%	78.075%	78.073%
Presort														
Nonautomation	3.172%	3.852%	2.946%	3.509%	2.885%	3.676%	2.918%	3.612%	2.983%	3.837%	3.034%	3.752%	3.053%	3.934%
Automation 3-Digit	52.907%	52.196%	52.483%	51.702%	52.064%	51.260%	51.677%	50.863%	51.350%	50.490%	51.108%	50.333%	50.961%	50.093%
Automation 5-Digit	43.922%	43.952%	44.572%	44.789%	45.051%	45.064%	45.405%	45.524%	45.667%	45.673%	45.857%	45.915%	45.986%	45.973%
Nonletters														
Basic														
Nonautomation	67.458%	67.048%	66.669%	66.322%	66.003%	65.712%	65.444%	65.199%	64.976%	64.772%	64.595%	64.442%	64.309%	64.194%
Automation	32.542%	32.952%	33.331%	33.678%	33.997%	34.288%	34.556%	34.801%	35.024%	35.228%	35.405%	35.558%	35.691%	35.806%
Presort														
Nonautomation	11.247%	11.563%	11.112%	10.926%	10.489%	10.714%	10.395%	10.264%	9.957%	10.115%	9.896%	9.813%	9.606%	9.739%
Automation	88.753%	88.437%	88.888%	89.074%	89.511%	89.286%	89.605%	89.736%	90.043%	89.885%	90.104%	90.187%	90.394%	90.261%

	2001Q4	2002Q1	2002Q2	2002Q3	2002Q4	2003Q1	2003Q2	2003Q3	2003Q4	2004Q1	2004Q2	2004Q3	2004Q4	2005Q1
Standard Nonprofit														
Letters														
Basic														
Nonautomation	34.309%	33.917%	33.932%	33.266%	32.998%	32.757%	32.764%	32.368%	32.210%	32.071%	32.083%	31.858%	31.776%	31.708%
Automation	65.691%	66.083%	66.068%	66.734%	67.002%	67.243%	67.236%	67.632%	67.790%	67.929%	67.917%	68.142%	68.224%	68.292%
Presort														
Nonautomation	20.944%	17.446%	18.664%	18.740%	18.022%	14.515%	15.632%	15.717%	15.042%	11.888%	13.024%	13.171%	12.634%	9.801%
Automation 3-Digit	48.706%	48.504%	48.875%	49.093%	49.218%	49.171%	49.539%	49.734%	49.847%	49.714%	49.996%	50.163%	50.253%	50.130%
Automation 5-Digit	30.350%	34.050%	32.461%	32.167%	32.760%	36.314%	34.828%	34.549%	35.111%	38.398%	36.980%	36.666%	37.113%	40.069%
Nonletters														
Basic														
Nonautomation	63.849%	62.171%	63.449%	58.619%	57.054%	55.338%	56.644%	51.774%	50.232%	48.561%	49.915%	45.396%	44.182%	42.930%
Automation	36.151%	37.829%	36.551%	41.381%	42.946%	44.662%	43.356%	48.226%	49.768%	51.439%	50.085%	54.604%	55.818%	57.070%
Presort														
Nonautomation	15.499%	15.401%	15.174%	13.330%	11.442%	11.370%	11.197%	9.756%	8.296%	8.241%	8.140%	7.093%	6.055%	6.122%
Automation	84.501%	84.599%	84.826%	86.670%	88.558%	88.630%	88.803%	90.244%	91.704%	91.759%	91.860%	92.907%	93.945%	93.878%
Parcel Post														
Non-Destination Entry														
Inter-BMC	14.375%	12.794%	13.212%	12.667%	12.146%	10.828%	11.174%	10.722%	10.293%	9.214%	9.496%	9.128%	8.779%	7.908%
Intra-BMC	9.252%	8.235%	8.503%	8.153%	7.817%	6.969%	7.192%	6.901%	6.625%	5.930%	6.112%	5.875%	5.650%	5.090%
Destination Entry														
DBMC	53.088%	52.444%	52.894%	52.976%	53.160%	53.831%	53.761%	54.144%	54.563%	55.729%	55.463%	55.925%	56.386%	57.582%
DSCF	1.838%	2.171%	2.027%	2.102%	2.165%	2.325%	2.260%	2.295%	2.323%	2.390%	2.363%	2.378%	2.389%	2.416%
DDU	21.447%	24.357%	23.364%	24.102%	24.712%	26.047%	25.613%	25.937%	26.196%	26.737%	26.566%	26.694%	26.796%	27.004%

Table IV-7
After-Rates Share Forecasts

	2001Q4	2002Q1	2002Q2	2002Q3	2002Q4	2003Q1	2003Q2	2003Q3	2003Q4	2004Q1	2004Q2	2004Q3	2004Q4	2005Q1
Workshared First-Class Letters														
Presort Nonautomation	7.682%	7.391%	7.337%	7.372%	7.400%	6.944%	6.864%	6.923%	6.994%	6.782%	6.793%	6.859%	6.961%	6.774%
Automation Basic Letters	11.565%	11.563%	11.562%	11.566%	11.567%	11.567%	11.567%	11.568%	11.568%	11.568%	11.568%	11.568%	11.568%	11.568%
Automation Basic Flats	0.228%	0.230%	0.232%	0.257%	0.236%	0.262%	0.270%	0.282%	0.272%	0.273%	0.274%	0.284%	0.275%	0.276%
Automation 3-Digit Letters	48.085%	48.076%	48.057%	48.045%	48.006%	48.119%	48.143%	48.133%	48.103%	48.097%	48.083%	48.074%	48.045%	48.042%
Automation 5-Digit Letters	29.410%	29.561%	29.704%	29.741%	29.954%	30.121%	30.237%	30.261%	30.403%	30.474%	30.537%	30.548%	30.641%	30.682%
Automation 3/5-Digit Flats	1.066%	1.070%	1.067%	1.056%	1.053%	1.114%	1.132%	1.120%	1.115%	1.119%	1.115%	1.103%	1.099%	1.103%
Automation Carrier-Route Letters	1.964%	2.109%	2.041%	1.963%	1.784%	1.873%	1.788%	1.714%	1.545%	1.688%	1.630%	1.563%	1.410%	1.556%
Private First-Class Cards														
Single-Piece	47.540%	48.003%	43.153%	47.884%	47.086%	48.914%	45.369%	49.277%	48.488%	48.859%	45.156%	48.785%	48.049%	48.435%
Presort Nonautomation	8.665%	9.200%	10.159%	8.319%	7.739%	5.516%	5.347%	4.013%	3.638%	4.005%	4.731%	3.481%	3.192%	3.540%
Automation Basic	9.097%	8.986%	9.173%	9.215%	9.204%	9.243%	9.343%	9.357%	9.352%	9.322%	9.371%	9.381%	9.376%	9.352%
Automation 3-Digit	19.836%	19.336%	21.111%	20.147%	20.705%	21.265%	23.109%	22.283%	22.735%	22.331%	23.717%	22.919%	23.321%	22.901%
Automation 5-Digit	13.621%	13.286%	14.548%	13.424%	14.223%	14.068%	15.210%	14.236%	14.927%	14.664%	15.628%	14.749%	15.349%	15.090%
Automation Carrier Route	1.241%	1.189%	1.856%	1.011%	1.041%	0.994%	1.622%	0.833%	0.860%	0.818%	1.397%	0.685%	0.713%	0.683%
Standard Regular														
Letters														
Basic														
Nonautomation	22.727%	22.709%	22.452%	22.455%	22.259%	22.252%	22.126%	22.127%	22.031%	22.027%	21.967%	21.971%	21.925%	21.928%
Automation	77.273%	77.291%	77.548%	77.545%	77.741%	77.748%	77.874%	77.873%	77.969%	77.973%	78.033%	78.029%	78.075%	78.072%
Presort														
Nonautomation	3.172%	3.852%	2.946%	3.509%	2.885%	3.210%	2.355%	3.025%	2.449%	3.266%	2.532%	3.231%	2.582%	3.426%
Automation 3-Digit	52.907%	52.196%	52.483%	51.702%	52.064%	51.645%	52.156%	51.372%	51.817%	50.993%	51.558%	50.804%	51.390%	50.556%
Automation 5-Digit	43.922%	43.952%	44.572%	44.789%	45.051%	45.145%	45.489%	45.603%	45.733%	45.741%	45.910%	45.965%	46.028%	46.018%
Nonletters														
Basic														
Nonautomation	67.458%	67.048%	66.669%	66.322%	66.003%	65.712%	65.444%	65.199%	64.976%	64.772%	64.595%	64.442%	64.309%	64.194%
Automation	32.542%	32.952%	33.331%	33.678%	33.997%	34.288%	34.556%	34.801%	35.024%	35.228%	35.405%	35.558%	35.691%	35.806%
Presort														
Nonautomation	11.247%	11.563%	11.112%	10.926%	10.489%	10.714%	10.395%	10.264%	9.957%	10.115%	9.896%	9.813%	9.606%	9.739%
Automation	88.753%	88.437%	88.888%	89.074%	89.511%	89.286%	89.605%	89.736%	90.043%	89.885%	90.104%	90.187%	90.394%	90.261%

	2001Q4	2002Q1	2002Q2	2002Q3	2002Q4	2003Q1	2003Q2	2003Q3	2003Q4	2004Q1	2004Q2	2004Q3	2004Q4	2005Q1
Standard Nonprofit														
Letters														
Basic														
Nonautomation	34.309%	33.917%	33.932%	33.266%	32.998%	32.763%	32.773%	32.375%	32.216%	32.076%	32.088%	31.862%	31.780%	31.711%
Automation	65.691%	66.083%	66.068%	66.734%	67.002%	67.237%	67.227%	67.625%	67.784%	67.924%	67.912%	68.138%	68.220%	68.289%
Presort														
Nonautomation	20.944%	17.446%	18.664%	18.740%	18.022%	14.671%	15.843%	15.921%	15.240%	12.075%	13.208%	13.350%	12.808%	9.966%
Automation 3-Digit	48.706%	48.504%	48.875%	49.093%	49.218%	49.051%	49.381%	49.582%	49.700%	49.572%	49.859%	50.030%	50.125%	50.005%
Automation 5-Digit	30.350%	34.050%	32.461%	32.167%	32.760%	36.277%	34.776%	34.497%	35.060%	38.353%	36.933%	36.619%	37.067%	40.029%
Nonletters														
Basic														
Nonautomation	63.849%	62.171%	63.449%	58.619%	57.054%	55.338%	56.644%	51.774%	50.232%	48.561%	49.915%	45.396%	44.182%	42.930%
Automation	36.151%	37.829%	36.551%	41.381%	42.946%	44.662%	43.356%	48.226%	49.768%	51.439%	50.085%	54.604%	55.818%	57.070%
Presort														
Nonautomation	15.499%	15.401%	15.174%	13.330%	11.442%	11.370%	11.197%	9.756%	8.296%	8.241%	8.140%	7.093%	6.055%	6.122%
Automation	84.501%	84.599%	84.826%	86.670%	88.558%	88.630%	88.803%	90.244%	91.704%	91.759%	91.860%	92.907%	93.945%	93.878%
Parcel Post														
Non-Destination Entry														
Inter-BMC	14.375%	12.794%	13.212%	12.667%	12.146%	10.828%	11.174%	10.722%	10.293%	9.214%	9.496%	9.128%	8.779%	7.908%
Intra-BMC	9.252%	8.235%	8.503%	8.153%	7.817%	6.969%	7.192%	6.901%	6.625%	5.930%	6.112%	5.875%	5.650%	5.090%
Destination Entry														
DBMC	53.088%	52.444%	52.894%	52.976%	53.160%	53.831%	53.761%	54.144%	54.563%	55.729%	55.463%	55.925%	56.386%	57.582%
DSCF	1.838%	2.171%	2.027%	2.102%	2.165%	2.325%	2.260%	2.295%	2.323%	2.390%	2.363%	2.378%	2.389%	2.416%
DDU	21.447%	24.357%	23.364%	24.102%	24.712%	26.047%	25.613%	25.937%	26.196%	26.737%	26.566%	26.694%	26.796%	27.004%