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Report on the City Carrier Street Time Study

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Table of Contents

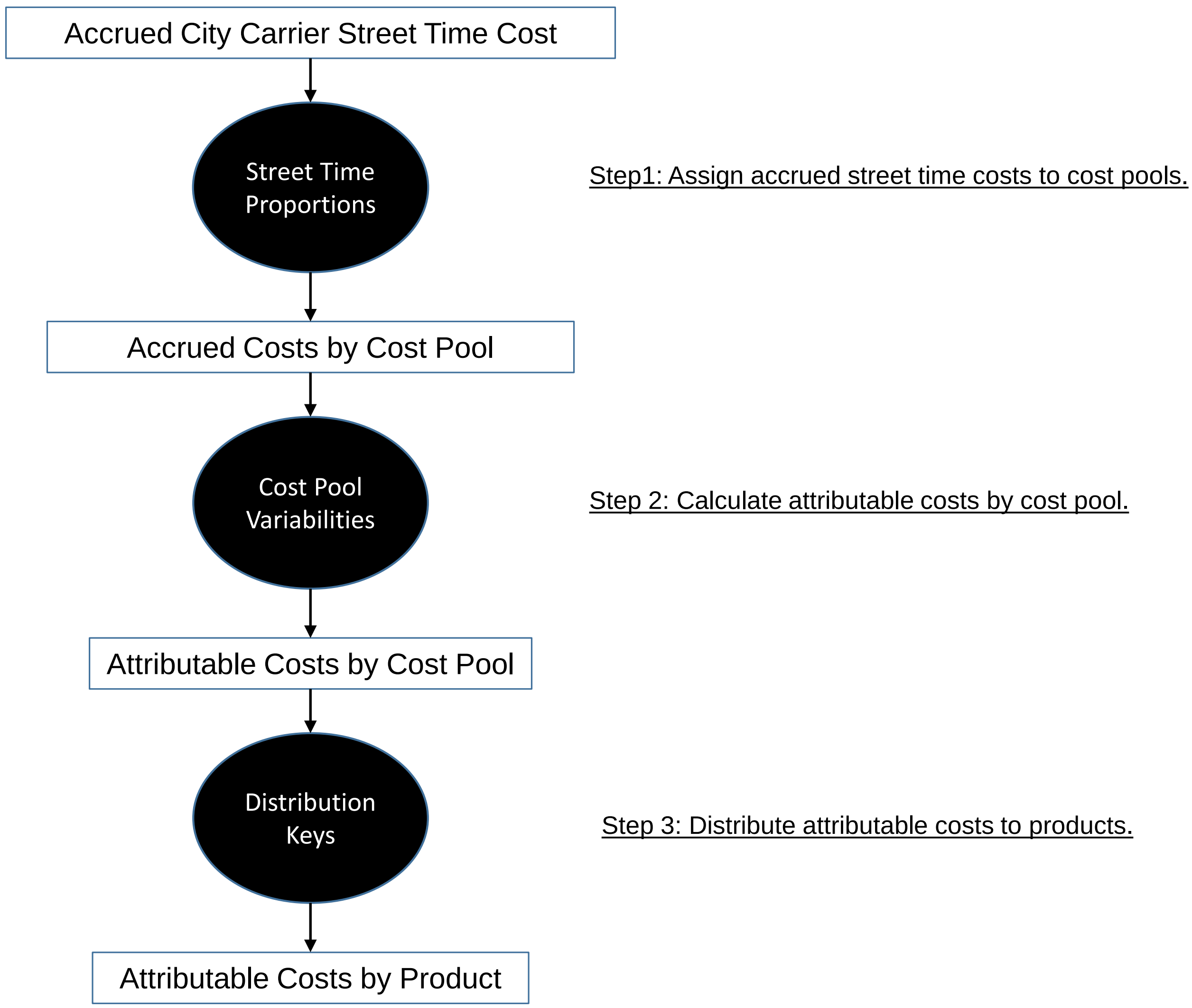
I. INTRODUCTION

The city carrier network is the largest part of the Postal Service's delivery network, incurring a total direct labor cost in Fiscal Year 2013 of almost $16 billion, of which over $12 billion were in street time costs. These city carrier street time costs represented 16.7 percent of total Postal Service costs.

The current development of attributable city carrier street time costs uses a model that was calibrated with data collected in 2002. Since that time there have been a number of important changes to city carrier delivery. These changes include the widespread adoption of the delivery point sequencing (DPS) of letters, dramatic changes in the volumes of mail delivered, restructuring of the city carrier network, and the introduction of the flats sequencing system (FSS). Because of the importance of city carrier street costs and the number of operational changes that have occurred, the Postal Service initiated a comprehensive study of city carrier street time activities and costs. This study has been used to update the existing city carrier street time model and refine the calculation of the resulting attributable costs.

The production of city carrier street time attributable costs has three main steps, which are illustrated in Figure 1. In the first step, the total accrued city carrier street time costs are assigned to cost pools. This step breaks down total costs into the costs associated with the different activities performed on the street, like delivering letter and flats, or driving to and from the route. The relative sizes of the costs pools depend upon the relative amount of time city carriers spend in the various activities.

Figure 1: Calculating Attributable Street Time Costs Has Three Steps



After the first step, the accrued costs are organized by cost pool, or activity. In the next step, the total attributable costs for the various activities are calculated. Attributable costs reflect the causal relationship between variations in mail volume and responses in activity costs. These relationships are measured by estimating the relevant variability or variabilities for each cost pool and then applying them to the cost pool's accrued cost. The last step is distributing the total attributable costs, by cost pool, to the individual products that cause them to arise. This step replies upon distribution keys which measure the proportions of delivered volume for each product within each cost pool.

This study updates and refines the first two steps in the process: determining the cost pools and measuring the variabilities needed to calculate attributable costs. The distribution keys needed to attribute costs to individual product are updated each year with the Carrier Cost System and are not part of this study.

The next section of this report describes the use of operational data to measure the street time proportions required for constructing the cost pools. That is followed by a section then discusses estimating the variabilities for regular delivery. The subsequent section that discusses estimating the variabilities for package and accountable delivery. The last section presents the impact of the study on attributable costs.

II. CONSTRUCTING THE COST POOLS

A. Introduction

As explained above, an important component of the city carrier street time costing process is the formation of cost pools. Cost pools reflect the activities that city carriers perform on the street, such as driving to the route or delivering packages, and capture the costs that are created by the performance of these activities.

The formation of cost pools requires identifying the proportions of city carrier street time that are spent in the various activities. In fact, cost pools are formed by multiplying those street proportions by the relevant accrued street time cost. In the past, the time proportions were derived from expensive special studies that required collection of field data on all carrier activities. The Postal Service proposes replacing those studies with data taken from its city carrier route evaluation system. This approach has several advantages.

First, the route evaluation system covers virtually all city carrier routes in the country, so the data set will be comprehensive. Second, because the data are based upon actual operational practice, the resulting time proportions reflect the operational reality of street time activity. Third, because the data can be extracted from an ongoing data system, its production does not require an expensive special study, and the street time proportions can be updated on a timely basis. Fourth, because they can be updated regularly, time proportions based upon the route evaluation data automatically reflect network and operational changes.

The balance of this section of the report describes the calculation of the time proportions required for constructing the cost pools. First it presents a description of the route evaluation system from which the data were drawn for updating the cost pools. That discussion is followed by an explanation of how the route evaluation data relate to the street time model. Next is a discussion of the actual data set used in the calculations and the section ends with presentation of the new street time proportions.

B. The Route Evaluation Data System

The route evaluation data system consists of one observation for each city carrier route in the country. The data come from when the route is evaluated. A route evaluation is a process in which the Postal Service collects data on the times the carrier spends in the various office and street activities on a route. Although the data are currently collected on an electronic data collection device, the structure of the street time data obtained follows the format of Postal Service Form 3999.[1] Thus, the street time portion of route evaluation data is often called "Form 3999 data."

In order to form cost pools, a Form 3999 database was extracted from the Postal Service's operational data systems in the spring of 2013, to match the period of time when other data were drawn for estimating the regular delivery variabilities, as discussed below. The Form 3999 data set used for this study includes route evaluations for 140,457 city carrier routes. For each route, the most recent evaluation in was used. These evaluations occurred primarily over the period from 2010 through mid- 2013, as 99.5 percent of the evaluations in the database occurred over that three-and- a-half year span. In addition, 96 percent of the evaluations occurred in the final two-and-a-half years, from 2011 through mid- 2013. The evaluations therefore reflect the relevant operating environment which incorporates the introduction of FSS, the widespread deployment of DPS, and the Postal Service's efforts to rationalize its city carrier network in the face of changes to mail volume and mail mix.

The route evaluation process includes recording the times that the carrier is engaged in the various office and street activities, and a mail count conducted by the delivery unit manager or designee. This process includes unannounced selective checks on all of the routes being inspected to verify the accuracy of the mail count. In addition, a route examiner makes a physical inspection of the route and then accompanies the carrier for the full tour on the day of the inspection.

[1] Prior to the use of the data collection devices, the street time portion of route evaluation data were collected manually on Form 3999.

C. Linking the Route Evaluation Data to the Street Time Cost Model

The operations "view" of street activities is similar to, but not identical to the street time cost model "view" of street activities. This means that a concordance between the two views must be made to ensure accurate incorporation of the route evaluation data into the cost model.

There are seven different activity cost pools in the street time cost model, listed in Table 1.[2]

Table 1: Street Time Cost Model
Cost Pools

Regular Delivery
Package and Accountable Delivery
General Collections
Express Mail Collections
Network Travel
Travel To and From the Route
Relay

Six of the cost pools have a single time proportion that determines its size. Package and accountable delivery has two proportions: the package and accountable delivery time, per se, and the deviation travel time required for making package and accountable deliveries.

[2] For a complete description of the street time cost model and its associated cost pools, see, "Summary Description of USPS Development of Costs by Segments and Components, Fiscal Year FY2012," Cost Segment 7, City Delivery Carriers, Street Time at page 7-1.

The listing of the operationally-defined activities that underlie the route evaluation process is more detailed, but rolls up into the cost pool structure listed in Table 1. There are sixteen different activities for which time is recorded in the route evaluation process. These activities can be usefully classified in three ways. First, some of the activities are directly attributable. This means they have individual time proportions in the city carrier street time model and have a variabilities applied to them to find the resulting attributable cost.[3]

Second, some of the activities are indirectly attributable. This means that they do not have separate cost pools and/or variabilities. Instead, they take on the average variability associated with the set of directly attributable activities. Finally, vehicle loading and unloading are currently considered to be office time in the city carrier cost model, and thus are not part of street time proportions. Figure 2 presents the route evaluation activities and their classifications in the city carrier street time cost model.

[3] These activities correspond to the cost pools listed in Table 1.

Figure 2: Route Evaluation Activities and Their Cost Model Classifications

Route Evaluation Activities	Cost Model Classification
Sector Segment Relay Travel to Route Travel From Route Travel Within Accountable Delivery Parcel Delivery Collection from SLB	Directly Attributable
Break Deadhead Personal Needs Customer Contact Gas Vehicle Non Recurring	Indirectly Attributable
Vehicle Load Vehicle Unload	Office Time

The directly attributable route evaluation activities match closely to the time proportions used to form the city carrier cost model cost pools. In most cases, there is a one-to-one correspondence between the route evaluation category and the street time cost model time proportion. The concordance between the two is provided in Figure 3, below:

Figure 3: Linking Route Evaluation Activities and Cost Pools

Route Evaluation Activity	**Cost Model Time Proportion**
Sector Segment	Regular Delivery
Relay	Relay
Travel To Travel From	Travel To/From Route
Travel Within	Network Travel
Acct. Delivery Parcel Delivery	Parcel/Accountable Delivery
Collection	Collections from Street Letter Boxes

D. Description of the Form 3999 Data Set

The Form 3999 data set used to calculate the cost pools includes route evaluations for 140,457 city carrier routes. The history of when those evaluations were performed is presented in Table 2. Note that there are only 82 routes for which data were captured prior to 2009. Because these routes represent only about one-twentieth of one percent of the data, they will be dropped from the subsequent analysis. That leaves a working data set with 140,375 routes.

Table 2: History of Route Evaluations in the Form 3999 Data Base

	Route Evaluations	Proportions
2008 & Before	82	0.06%
2009	864	0.6%
2010	5,344	3.8%
2011	20,772	14.8%
2012	62,658	44.6%
2013	50,737	36.1%
Total	140,457	100.0%

The next step is to examine the data to account for a set of small issues. For example, 116 of the route evaluations reported data that were captured on Sunday. This should not have occurred, and these evaluations are dropped. Also, 313 route evaluations report a negative value for at least one of the directly attributable street time activities. Obviously, this cannot occur, and must be due to a data entry error. These evaluations are also dropped. Finally, 37 route evaluations report gross street time of over 12 hours, and another 42 route evaluations report negative gross street time. Because neither of these outcomes is possible, these route evaluations are also dropped. In sum, eliminating these route evaluations because of data entry errors reduces the data set by just 508 observations, leaving a total of 139,867 useful route evaluations. The resulting analysis data set ends up using 99.6 percent of the raw data.

Gross street hours are defined as total street hours minus lunch. The average value for gross street hours from the analysis data set is 6.14 hours. The relationship between the route evaluation data and the required time proportions for forming cost pools is illustrated through the use of the concordance described in Figure 1, above. That concordance is used to divide gross street hours into the city carrier cost model proportions.

Table 3: Form 3999 Average Daily Hours Broken Out by Carrier Cost Model Definitions

	Hours	**Proportion**
Directly Attributable Street Hours	5.37	87.4%
Indirectly Attributable Street Hours	0.46	7.5%
Vehicle Load/Unload	0.31	5.1%
Gross Street Hours	6.14	100.0%

Cost pools need to be formed for the directly attributable street hours. This requires taking the 5.37 hours from Table 3 and breaking them out into their component parts. This, in turn, requires making use of the concordance presented in Figure 2 to translate the route evaluation activities into the needed cost model activities, and then calculating the proportion of time for each activity. This is done twice. First, it is done for all of the route evaluations in the analysis dataset. Next, it is done for just the most recent route evaluations, from 2012 and the first half of 2013, to determine if the proportions of time spent in each activity are different when based upon only the most recent evaluations. The results of those calculations are presented in Table 4, which shows the proportions for all route evaluations and the proportions for the 2012-2013 evaluations are very close to one another.

Table 4: Street Time Proportions Based upon Form 3999 Data

	2012-2013 Route Evaluations	All Route Evaluations
Regular Delivery	83.38%	83.20%
Package/Accountable Delivery	4.63%	4.59%
Collections From SLB	0.20%	0.19%
Travel To/From Route	5.03%	5.03%
Network Travel	2.93%	3.01%
Relay	3.82%	3.94%
Number of Observations	112,972	139,867

When considering the use of Form 3999 data to calculate the street time proportions, two questions arise. First, a route evaluation may come about because the Postal Service is considering reconfiguring the routes in the ZIP Code. This means that the data extracted from the route evaluation system could have been recorded before the route was adjusted. If so, there is a concern that the Form 3999 data may not be accurately representing the current route system. To assess the importance of this concern, one can investigate how many route evaluations came before route adjustment and how many came after route adjustment. Table 5 shows that a very high percentage came after the route was adjusted, with 76.7 percent of all route evaluations coming after the latest route adjustment and 82.9 percent of route evaluations in the 2012-2013 period coming after the latest route adjustment. These high percentages mitigate the concern that the Form 3999 data do not reflect the current network.

Table 5: Measuring the Proportion of Route Evaluations Coming After Route Adjustment

	All Route Evaluations	2012-2013 Route Evaluations
Routes With Data Captured After Adjustment	107,335	93,610
Total Routes	139,867	112,972
Proportion of Routes With Data Captured After Adjustment	76.7%	82.9%

The second question is how much the street time proportions change on a year-by-year basis. The answer to this question addresses the issue of the utility of older observations. In addition, looking at proportions of activities through time can help gauge whether using some pre-adjustment route evaluation data is an issue of concern. If route reconfigurations lead to material instability in the overall street time proportions, then using pre-adjustment route evolution data could be a problem. On the other hand, if the proportions are stable across years, then the reconfiguration of routes has not affected the overall proportions of time and using pre-adjustment route evaluation data is not a problem.

Table 6 presents the street time proportions by year. It shows that the street time proportions are very stable through time. In addition, the table shows an increasing proportion of time dedicated to package and accountable delivery which is consistent with the growth in package volume relative to letter and flat volume during this time.

Table 6: Cost Pool Proportions Through Time

	2009	2010	2011	2012	2013
Regular Delivery	82.8%	83.0%	82.5%	83.1%	83.7%
Parcel & Accountable Delivery	3.7%	4.1%	4.6%	4.5%	4.9%
Relay	4.2%	4.3%	4.5%	4.1%	3.5%
Travel To/From Route	5.4%	5.0%	5.0%	5.0%	5.1%
Network Travel	3.7%	3.5%	3.3%	3.1%	2.7%
Collections From SLB	0.1%	0.1%	0.2%	0.2%	0.2%
# of Observations	860	5,326	20,709	62,424	50,548

E. Calculating the Time Proportions for Cost Pool Formation

The Form 3999 data extracted from the Postal Service's route evaluation system are of sufficient quantity and quality to serve as the basis for calculating the street time proportions needed for cost pool formation. The stability of the street proportions presented in Table 6 demonstrates that it would be acceptable to use the data from all of the evaluations taken from 2009 through mid-2013. However, because the Form 3999 data set is so large and stable, it is also acceptable to use just the most current route evaluations, those from 2012 and 2013 in forming the time proportions. While this does mean excluding some observations from the calculations, it still provides 112,972 individual routes for finding the time proportions. In addition, it provides the most recent observations which, by definition, are more likely to reflect the current state of the network. Thus, although both the 2009-2013 proportions and the 2012-2013 proportions are acceptable (and quite similar), the more recent set of proportions will be used in constructing the cost pools.

One final adjustment had to be made before the final time proportions could be calculated. The route evaluation process is designed to produce information that is used to configure carriers' routes. To that end, it separately measures the time associated with those packages that cause the carrier to deviate from the normal process of delivery, because such packages are particularly important in calculating the time requirement for the route. In contrast, the time for packages that fit in the mail receptacle is included in regular delivery time, as their delivery is considered to be part of the regular delivery process.

While this approach is entirely appropriate for a route configuration analysis, it does not meet the needs of an attributable costing analysis. An attributable costing analysis requires capturing the time for both deviation packages and those packages that fit in the receptacle. This need is emphasized by the fact that there are more in-receptacle packages than there are deviation packages. Consequently, the time proportions based upon the Form 3999 data must be adjusted to account for the fact that some of the time that the route evaluation process records for regular delivery is actually time associated with delivery of in-receptacle packages.

The adjustment will be made with data collected in the package and accountable field study described in Section IV, below. As part of that study, city carriers recorded the amount of time they spent delivering in-receptacle packages, deviation packages, and accountables. This total delivery time was compared to the total street time (for the same carriers on the same days) to calculate the proportion of total street time dedicated to package and accountable delivery.[4]

Note that the data from the package and accountable field study provided the package and accountable times as a proportion of <u>total</u> street time. But, as explained above, to calculate cost pools one needs the package and accountable delivery time proportions of <u>directly attributable</u> street time, which is a subset of total street time. To find the correct proportions, an adjustment must be applied to the original total street time proportions. The adjustment takes the following form: Suppose that one can directly calculate the proportion that x_1 is of a group of x's, ranging from x_1 through x_p:

$$\rho_1 = \frac{x_1}{\sum_{i=1}^{p} x_i}.$$

However, further suppose that what is needed is x_1 as a proportion of a subset of the x's, namely x_1 through x_q, where by definition, $q < p$:

$$\zeta_1 = \frac{x_1}{\sum_{i=1}^{q} x_i}.$$

[4] Note that total package and accountable delivery time incudes time for delivering both in receptacle and deviation packages. Also, the deviation time proportion needed for cost pool formation is deviation package <u>and</u> accountable delivery. The combined cost pool is required because a deviation delivery that requires a vehicle movement can involve the simultaneous delivery of both a deviation package and an accountable. Although the Form 3999 deviation package and accountable proportion (4.1%) is close to the corresponding field study proportion (4.7%), the package and accountable field study time for both deviation packages and (deviation) accountables will be used to ensure consistency.

To obtain the desired proportion one need only take the originally calculated proportion and multiply it by the ratio of the sums:

$$\zeta_1 = \left(\frac{\sum_{i=1}^{p} x_i}{\sum_{i=1}^{q} x_i}\right)\rho_1.$$

In our case, the ratio of the sums is just the ratio of total street hours (6.14) to directly attributable street hours (5.37). With this adjustment factor, the package and accountable field study proportions of total street time can be converted to the corresponding proportions of directly attributable street time. The two sets of proportions, for both in-receptacle and deviation delivery are presented in Table 7. Because directly attributable street time is smaller than total street time, recorded package and accountable delivery time will be a higher proportion of directly attributable time than of street time.

Table 7: Time Proportions Derived from the Package and Accountable Field Study

Type of Delivery	**Percentage of Street Time**	**Ratio of Total Street Time to Attributable Street Time**	**Percentage of Directly Attributable Street Time**
In Receptacle	3.84%	1.14	4.40%
Deviation	4.71%	1.14	5.39%
Both	8.55%	1.14	9.79%

The package and accountable delivery time proportions can now be used to modify the street time proportions used to construct the cost pools. Because the route evaluation process incorporates in-receptacle package delivery time into regular delivery time, the regular delivery time proportion is overstated for attributable costing purposes. Accuracy requires using the independently measured in-receptacle package delivery time proportion to reduce the route evaluation delivery time proportion. This calculation is done in Table 8.

Table 8: Adjusting Time Proportions To Capture Total Package Delivery

Type of Delivery	**Form 3999 Only**	**Including PA Study Proportions**
Regular Delivery	83.38%	78.23%
Package and Accountable Delivery	4.63%	9.79%
Total	88.01%	88.01%

With this adjustment of the regular delivery time proportion in place, the last step is to incorporate the new regular delivery and package and accountable delivery into the full set of street time proportions. The set of proportions used to calculate the cost pools is presented in Table 9.

Table 9 Street Time Proportions Used to Calculate Cost Pools

Street Activity	Time Proportion
Regular Delivery	78.23%
In-Receptacle Package Delivery	4.40%
Deviation Delivery	5.39%
Collection from Street Letter Boxes	0.20%
Travel To and From	5.03%
Relay	3.82%
Network Travel	2.93%
Total	100.0%

III. ESTIMATING THE REGULAR DELIVERY EQUATION AND CALCULATING THE ASSOCIATED VARIABILITIES

A. Introduction

Regular delivery time makes up the bulk of a city carrier's street time and is the largest cost pool in the street time cost model. It includes primary delivery activities like driving along the route within delivery sections, accessing stops (whether on foot or in a vehicle), putting letters and flats into customers' mail receptacles, and retrieving collection mail from those receptacles.

As discussed above, the use of operational data to define the street time cost pools required adopting an operations set of characterizations of street activities. The operations definition of regular delivery time is a bit more expansive than the definition historically used in the street time cost model.[5] This fact, by itself, suggests that a new set of regular delivery time variabilities should be estimated in order to better align with the regular delivery time obtained from the Form 3999 data set. In addition, there have been a number of operational changes in delivery since the last time regular delivery variabilities were estimated. These include the widespread use of delivery point sequencing (DPS) of letters, the decline in delivered volumes and subsequent route reconfigurations, and the deployment of flat sequencing systems (FSS) in many ZIP Codes. FSS equipment sorts automation flat mail into delivery point sequence.

Taken together, these changes necessitate estimating new regular delivery variabilities that are consistent with operations definitions of street activities and reflect the current cost-causing characteristics of city carrier regular delivery. Estimating these variabilities requires specifying a model of regular delivery, constructing the relevant analysis data set, econometrically estimating the specified model with the analysis data set, and then reviewing and evaluating the results.

The next subsection discusses the issues associated with model specification and variable selection. Normally that would be followed by a subsection on constructing the analysis data set, but because a special field study was required for obtaining volumes of mail collected, the next subsection will be devoted to describing that study. After that description, the expected subsection on constructing the analysis data set is presented. The last subsection describes the estimation of the model and discusses the results of that estimation.

[5] In operations parlance, regular delivery time is often “sector segment” time.

B. Specifying the Regular Delivery Equation to Be Estimated

A logical way to start the specification of the regular delivery equation is by identifying the cost drivers of regular delivery time. In other words, this step involves identifying the variables that determine regular delivery time and should thus be included as explanatory variables in a regular delivery econometric equation. Regular delivery time is caused both by the volumes that are delivered and by the need to cover the network of delivery points. Consequently, the cost drivers of regular delivery time[6] are the volumes, delivered and collected, and the number of delivery points in the network.[7] In addition, regular delivery time could be influenced by the technology of delivery and certain characteristics of the delivery area. In sum, the regular delivery equation should include the relevant volume cost drivers, the number of delivery points to be covered, and variables capturing the characteristics of the delivery technology and the delivery area.

The volume cost drivers should reflect the way the mail is handled on the street. In city carrier delivery, mail is handled in separate bundles on walking routes and in separate containers on driving routes. Mail is selected from these bundles or containers for placement in the mail receptacle. In other words, these bundles or containers define how mail is handled on the street and these handlings generate regular delivery time.

[6] Regular delivery time includes the collection of mail from customers' receptacles. It does not include the collection of mail from street letter boxes. That time is included in another cost pool. In this section, the terms "collection volume" or "volume collected" always refers to mail volume collected from customers' receptacles and not from street letter boxes.

[7] The delivery points in the network are sometimes described as “possible” deliveries because they represent the possible delivery points that carriers must be prepared to cover. On any given day, not all possible delivery points will receive mail.

The appropriate volume cost drivers should reflect this bundle structure and include all city carrier delivered letters and flats. There are volume bundles for DPS mail, cased mail, sequenced mail, FSS mail, and mail collected from customers and these five types of mail are the volume cost drivers. Note that cased mail includes both letters and flats, which are cased together and pulled down into one bundle or container. In addition, there are some pieces which may be classified as packages by the DMM, but are handled as flats by city carriers. These pieces are included in cased mail.[8]

The other main driver of regular delivery cost is the need to cover the delivery network. Some regular delivery costs arise because carriers traverse certain parts of their routes on a daily basis. This time does not vary with small variations in volume but does vary with the size of the network to be covered. This network structure implies that the primary cost-causing characteristic of the network is the number of delivery points to which the mail is delivered, and thus another cost driver included in the regular delivery equation is the number of delivery points to be covered.

The Postal Service manages its city carrier network by ZIP Code. The total hours required for a ZIP Code's delivery function are caused by the ZIP Code's volumes and the number of delivery points included in the ZIP Code. While carrier routes are an important organizing structure for the Postal Service, management decisions are made at the ZIP Code level. This is highlighted by the widespread use of pivoting routes. Pivoting takes place when a route's delivery responsibilities are not handled by its assigned carrier, but rather by other carriers in the ZIP Code. Throughout a week,

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[8] Recall that the time required for the delivery of packages (both in receptacle and deviation) is included in a separate cost pool.

different routes may be pivoted on different days, reflecting the fluidity of the route structure. Thus, to accurately capture the relationship between delivery time and volume, the model should be estimated on ZIP Code level data.

The last set of variables included in the model are designed to capture variations in the delivery environment that could cause differences in the amount of delivery time required to deliver a given amount of volume to a set number of delivery points. These variables are included in the equation to improve its ability to explain regular delivery time and to ensure that the estimated coefficients on the volume variables do not include any non-volume effects.

There are three main characteristics that describe the delivery environment: (1) the primary delivery technology used in the ZIP Code, (2) the proportion of business deliveries in the ZIP Code and the (3) geographical density of delivery points in the ZIP Code. Each of these variables are introduced and explained below.

First, delivery technology is measured for a ZIP Code by examining the delivery technology of the routes within that ZIP Code. Routes are classified as being one of five types: curbline, dismount, foot, park and loop or other. [9]

When identifying delivery technologies for costing purposes, the important distinction is the one between those routes which primarily involve walking (Foot, Park and Loop, and Other) and those routes which primarily involve driving (Curbline and Dismount). Because walking is generally slower than driving, for a given amount of mail,

[9] The delivery mode 'other' are for the extremely small number of routes that do not fit into one of the other four categories. Route on which a carrier uses a Segway or uses public transportation are examples of routes that have a delivery mode of 'other'.

delivery points, and geographical area, ZIP Codes made up of walking routes typically have a greater amount of delivery time.

As such, a technology indicator can be constructed to capture whether a ZIP Code is primarily a walking ZIP Code or driving ZIP Code. To construct this indicator, each route in a ZIP Code is assigned a value of zero if it is a curbline or dismount route (driving route) and a value of one if it is a foot, park and loop, or other route (walking route). The technology indicator is then calculated as the percentage of walking routes in the ZIP Code and has a range from zero through one. If a ZIP Code has all driving routes, the indicator variable takes a value of zero. In contrast, if a ZIP Code has all walking routes, the indicator variable takes a value of one. As the value of the indicator variable goes up, ceteris paribus, regular delivery time should increase.

The next characteristic variable is included in the regular delivery equation to control for the possibility that the time for delivering a given amount of mail to business delivery points is different from the time needed for delivering the same amount of mail to residential delivery points. In other words, this variable is included to allow the econometric model to account for the possibility that ZIP Codes with many business delivery points would have less delivery time for the same amount of delivered volume and delivery points than similar ZIP Codes with few business deliveries. The characteristic variable to capture this effect is calculated as the percentage of business delivery points in the ZIP Code.

The last characteristic variable included in the equation is a measure of the geographic density of the delivery area. The larger the geographic area included in the ZIP Code, for a given number of delivery points, the more time is required to cover those delivery points.[10] A measure of delivery density can be constructed from the land area, in square miles, of each ZIP Code in the data set.[11]

The next step in preparing for estimation is choosing a functional form. If there is technological or other knowledge about the underlying cost-generating process, it can be used to guide functional form selection. If not, there are advantages to selecting a flexible functional form when attempting to measure the responsiveness of cost to volume changes. Finally, one can review previous work to identify functional form selections for similar modeling efforts.

In the area of city carrier delivery, previous work has shown the quadratic functional form to be useful.[12] It has been used by both the Postal Service and the Postal Regulatory Commission (Commission) to specify a number of different models of delivery time. The quadratic functional form also has the advantage of being a flexible functional form in the sense that it places no restrictions on the first and second order derivatives. Thus it is agnostic, *a priori,* about the absence or presence of scale or network economies that cause the variabilities to be less than one hundred percent.

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[10] For a discussion of the impact of density on delivery costs, see, Bernard, Stephane, Cohen, Robert, Robinson, Matthew, Roy, Bernard, Toledano, Joelle, Waller, John and Xenakis, Spyros, "Delivery Cost Heterogeneity and Vulnerability to Entry," in <u>Postal and Delivery Services: Delivering on Competition</u>, Michael Crew and Paul Kleindorfer (eds.), Kluwer, 2002

[11] Square miles of land area for all ZIP Codes were extracted from the 2010 Census.

[12] For example, <u>see</u> Bradley, Michael D, Colvin, Jeff and Mary K. Perkins, "Measuring Scale and Scope Economies with A Structural Model of Postal Delivery," in <u>Liberalization of the Postal and Delivery Sector</u>, Advances in Regulatory Economics Series, Edward Elgar, 2007, or "Testimony of Michael D. Bradley on Behalf of the United States Postal Service," USPS-T-14, Docket No. R2005-1

The primary alternative flexible functional form is the translog. However, because of repeated instances in which one or more of the volume measures has a zero value, a traditional translog cannot be used, as the log of zero is not defined. The Box-Cox transformation can permit the estimation of logarithmic function but, given the previous work employing the quadratic function, it is unnecessary to introduce this nonlinear method of estimation.

Application of the quadratic functional form to the explanatory variables described above yields the following model to be estimated:

$$
\begin{aligned}
DT_{it} \;=\; & \beta_0 + \beta_1\, DPS_{it} + \beta_{11} DPS_{it}^2 + \beta_2\, CM_{it} + \beta_{21} CM_{it}^2 + \beta_3\, SEQ_{it} + \beta_{31} SEQ_{it}^2 + \beta_4\, FSS_{it} \\
& + \beta_{41} FSS_{it}^2 + \beta_5\, CV_{it} + \beta_{51} CV_{it}^2 + \beta_6\, DP_{it} + \beta_{61} DP_{it}^2 + \beta_{12}\, DPS_{it} * CM_{it} \\
& + \beta_{13}\, DPS_{it} * SEQ_{it} + \beta_{14}\, DPS_{it} * FSS_{it} + \beta_{15}\, DPS_{it} * CV_{it} + \beta_{16}\, DPS_{it} * DP_{it} \\
& + \beta_{23}\, CM_{it} * SEQ_{it} + \beta_{24}\, CM_{it} * FSS_{it} + \beta_{25}\, CM_{it} * CV_{it} + \beta_{26}\, CM_{it} * DP_{it} \\
& + \beta_{34}\, SEQ_{it} * FSS_{it} + \beta_{35}\, SEQ_{it} * CV_{it} + \beta_{36}\, SEQ_{it} * DP_{it} + \beta_{45}\, FSS_{it} * CV_{it} \\
& + \beta_{46}\, FSS_{it} * DP_{it} + \beta_5\, CV_{it} * DP_{it} + \beta_7\, DM_{it} + \beta_{71} DM_{it}^2 + \beta_8\, MPDP_{it} \\
& + \beta_{81} MPDP_{it}^2 + \beta_9\, BR_{it} + \beta_{91} BR_{it}^2 + \varepsilon_{it}
\end{aligned}
$$

Where:

DT = Regular Delivery Time
DPS = Delivery Point Sequenced Letters
CM = Cased Mail
SEQ = Sequenced Mail
FSS = FSS Flats
CV = Collection Volume
DP = Delivery Points
DM = Delivery Mode Indicator
MPDP = Miles per Delivery Point
BR = Proportion of Business Deliveries

C. The Collection Volume Study

Once an econometric equation is specified, the normal next step is to construct the analysis data with which the equation's coefficients will be estimated. However, the Postal Service's carrier data systems do not include counts of volumes collected from customers by city carriers, so a special study was required to complete the analysis data set. This subsection describes that special study.

Regular delivery time is simultaneously influenced by both the letter and flat mail delivered to customers' receptacles and the mail collected from those receptacles. The analysis data set used to estimate the regular delivery equation should thus include both delivered and collected volumes for a single set of addresses. The Postal Service performed a field study to obtain collection volumes that were subsequently matched with delivery volumes. The collection and delivery volumes were both from the same ZIP Codes, routes and days, and combining them produced the complete set of volume measures required for estimating the regular delivery equation.

The field study that obtained the collection volumes was carried out with the following steps:

1. The sample was developed.
2. The study process was designed.
3. A beta test of the study was performed and the study process was refined.
4. The full data collection effort was launched.
5. The collected data were analyzed.
6. The collection volumes were combined with delivery volumes.

Each of these steps is discussed in the following subsections.

1. Developing the sample

A sample size of 300 ZIP Codes was determined to be the largest sample consistent with Postal Service budgetary and management resources. This is approximately double the sample sizes of previous city carrier studies and, when combined with the delivery data, provided a substantially larger analysis dataset than was available in past work on carrier costs. To increase the efficiency of the sampling, the collection volume study utilized a stratified systematic sample from a frame of 10,720 ZIP Codes that contain city carrier routes.

Two variables, which are highly correlated with a ZIP Code's street time, were used to stratify the data into six subdivisions. Those two variables are number of routes in the ZIP Code and its overall delivery mode, as either a "driving" ZIP Code or a "walking" ZIP Code. A driving ZIP Code has mostly curbline or dismount routes and a walking ZIP Code has mostly foot or park and loop routes. Details about the development of the sample are included in USPS-RM2015-7/1 but the six subdivisions and their stratum proportions a presented in Table 10.

Table 10
The Stratum Proportions

Stratum	Definition	# of ZIPs	Stratum Proportion of Time
Small Driving	Driving ZIP x < 6 routes	1,209	2%
Small Walking	Walking ZIP x < 6 routes	2,087	4%
Medium Driving	Driving ZIP 5 < x < 21 routes	2,254	20%
Medium Walking	Driving ZIP 5 < x < 21 routes	2,787	24%
Large Driving	Driving ZIP x > 20 routes	882	18%
Large Walking	Walking ZIP x > 20 routes	1,501	32%

2. Designing the study process

The study's goal was to obtain a set of ZIP Code collection mail volumes that corresponded to those ZIP Code's delivered volumes, as reported in Postal Service's Delivery Operations Information System (DOIS) over a two-week period. The field study thus had city carriers record collection volumes, by source and shape, for twelve consecutive delivery days.[13] To ensure accurate data collection, operations experts were integrated into the study process, in terms of both designing and implementing the study. This greatly increased field participation.

Because of the large number of ZIP Codes included in the study, a decentralized study team structure was employed. Headquarters coordinators worked with area coordinators who facilitated the study by identifying and working with local coordinators. The local coordinators supervised the carriers participating in the study and were responsible for ensuring their ZIP Code's data were correctly recorded and entered. Training was conducted prior to implementation to ensure consistent and accurate data collection. Prior to beginning the study, headquarters coordinators trained both the area and local coordinators. Local coordinators then trained individual carriers. The training materials are included in USPS-RM2015-7/1.

There are three possible sources of collection mail for letter carriers: (1) mail received directly from customer receptacles, (2) mail received in collection points (like mail chutes), and (3) containerized mail received from businesses. To guarantee complete coverage of collection volumes, the study required carriers to measure their mail collected from all three sources. Discussions with operations experts lead to the determination that the study would provide the most accurate results if collection mail volume for letters and flats were recorded in linear measurements, using quarter inch increments, and piece counts were to be used for packages. While letter and flat mail can be collected from any of the three sources, packages are not collected in

[13] Because regular delivery time is incurred only by city carriers with regular letter routes, the sample does not include volumes collected by special purpose route (SPR) carriers. The time required for collecting that mail is included in a separate cost pool that is not part of this study.

containers from businesses. As a result, carriers were required to record volumes by eight different combinations of shape and source.

3. Performing a beta test

To ensure that the study process produced accurate data, the Postal Service performed a beta test at a small number of ZIP Codes in March, 2013. The beta test was used to evaluate the study forms, instructions, and procedures. This evaluation was done to allow, if necessary, refinement of the procedures for the full study In addition, examination of the data from the beta test served as a "proof of concept" of the study process before launching the full study.

The beta test took place at five ZIP Codes, including 116 city carrier routes. Collection volumes were measured for six days on each route. This means there was a potential data set of 696 route days of volume. The Postal Service was able to collect data for 695 of the 696 route days, missing only one route day.

The beta test revealed that training and instructions were generally understandable and that the study was not overly burdensome for the field personnel. Yet, the beta test did lead to some revisions of the input forms and study processes that improved the accuracy of the data collection. In addition, the beta test revealed that using email to transfer the data from the local sites to Postal Service headquarters would likely be difficult for a number of ZIP Codes. As a result, the Postal Service constructed a webtool that was used for centralized data submission in the full study.

Examination of the data collected in the beta test demonstrated that the measured collection volumes could be successfully matched to the DOIS delivery volume. In addition, volumes from the beta test were used to construct data screens that supported review and verification of the data collected in the main study.

4. Launching the data collection effort

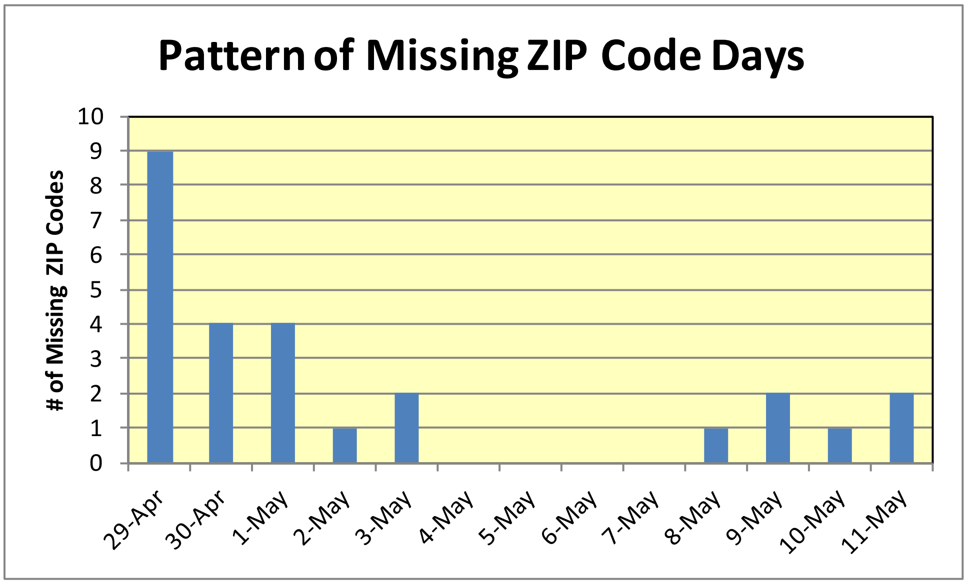
Collection volumes were obtained for 12 delivery days from Monday, April 29 through Saturday, May 11, 2013. 297 of the 300 sample ZIP Codes participated in the study and reported data.[14] Those ZIP Codes included 6,100 routes and there were 73,195 possible route days for which data could have been collected.[15]

The study captured data for 72,178 of those route days. This means that the study captured data for 98.6 percent of the possible route days. A large portion of the missing route days occurred because a few ZIP Codes started the data collection process a day or two late. Fortunately, attrition was very low at the end of the study. During the last four days of the study there were only six ZIP Code days missing out of possible total of 1,188.

[14] Three ZIP Codes did not participate because of route evaluations or other administrative conflicts during the study period.

[15] One ZIP Code added a new route during the study period, going from 25 routes to 26 routes. This increased the total routes studied from 6,099 to 6,100 on May 4. This is why the possible number of route days of data is slightly smaller than 73,200 (6100* 12).

Figure 4: The Pattern of Missing ZIP Code Days



The regular delivery time model is estimated at the ZIP Code level, so it is important to assess what impact the missing <u>route</u> days will have on the number of complete <u>ZIP Code</u> days available to estimate the model.[16] This allows determination if any action needed to be taken to legitimately increase the number of complete ZIP Code days. Of course, the ability to do so depended upon the pattern of missing route days

At one extreme, if a ZIP Code failed to report any data for a given day, then all of the included route days would be missing for that day. At the other extreme, a <u>single</u> missing route day renders the data for the ZIP Code day incomplete. This means that it was important to look at the distribution of missing route days across ZIP Codes.

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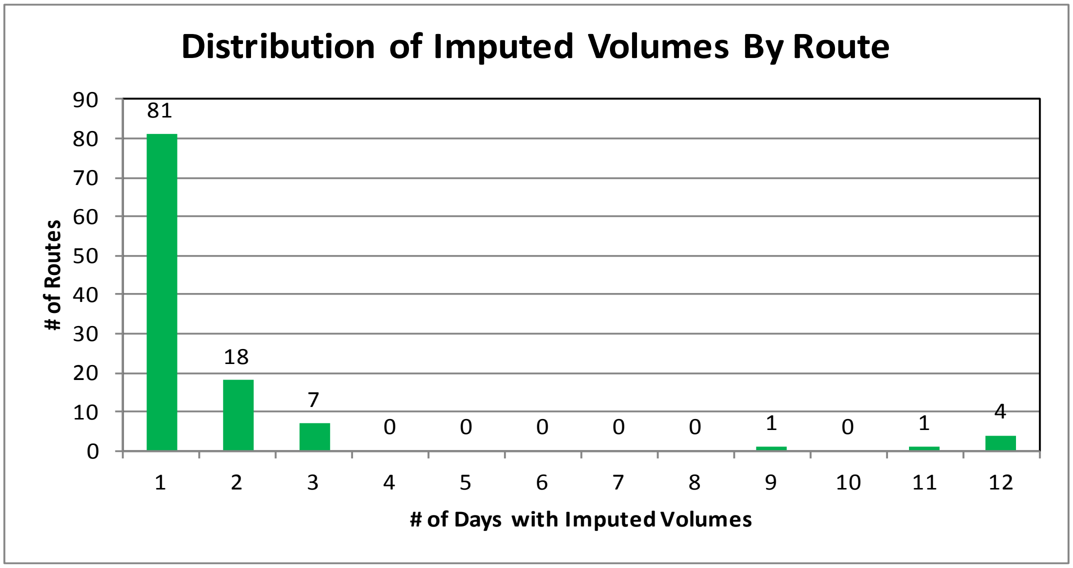
[16] Recall that the regular delivery equation is estimated at the ZIP Code level because Postal Service management decisions are made at that level. In addition, the widespread use of pivoting reduces the reliability of route level data.

59.5 percent of the missing route days occurred in ZIP Codes for which no data were reported for any routes. Nothing could be done to recover data from the missing routes for these ZIP Code days, and they were excluded from the analysis dataset. The remaining 40.5 percent of missing route days occurred on ZIP Code days in which some of the routes in the affected ZIP codes were reporting data. The key issue is how many of the routes within the ZIP Code were reporting data. If the non-reporting routes in a ZIP Code were a small percentage of the total routes, then it may be possible to preserve the ZIP Code day's data by imputing collection volumes for the missing routes. But if too many routes were missing data, then caution was appropriate, to be sure that the collection volumes for the entire ZIP Code day did not reflect just a few of its routes. Prudence dictated that imputation was considered only for ZIP Code days for which at least 80 percent of the routes reported volume.

In addition, imputation for a route was done only when there were many valid days of data reported for that route. As the following chart shows, imputation was rarely repeated for a route, with the overwhelming majority of routes needing imputation for just one day. However, there were six routes which apparently required many, if not all, days of imputation. Investigation revealed that for the six routes with high numbers of imputations, all the imputed values were zero. This is because all six routes were "vacant" routes which had neither hours nor volume and so they actually had zero collection volume.

For all routes that required positive-valued imputations, there were a sufficient number of reported collection volume days so that it was legitimate to use mean values over the days for which the route reported volume as the imputed values.

Figure 5: Distribution of Imputed Volumes



Among the ZIP Code days with at least one route missing data, some had no data reported for any routes, and were thus unusable. Other ZIP Code days had less than 80 percent of its routes reporting data, so they were dropped from the dataset.

One ZIP Code had missing route data for each of the 12 days of the study. Because of this persistent pattern of non-reporting, all days for this ZIP Code were dropped from the data set, despite the fact that half of them had at least eighty percent of routes reporting. In total, there were 125 ZIP Code days recovered through the use of imputed volumes. Table 11 shows the structure of the collection dataset.

Table 11
Use of ZIP Code days in the Analysis Data Set

	Total Possible Observations	Included Observations	Dropped or Missing Observations	% Missing
ZIP Code Days	3,564	3,513	51	1.4%

Because ZIP Codes with partially missing routes either had imputed values for those missing routes or were dropped from analysis data set, “route coverage” is not an issue. All ZIP Code days in the analysis dataset have complete coverage, in the sense that data from all of routes were included in the ZIP Code data. In other words, all ZIP Code days were complete.

5. Analyzing the collected data

While the regular delivery equation was estimated with ZIP Code day volumes, it was reasonable to initially review the route day collection statistics, as they were more familiar. The next table provides sample statistics for the individual collection volume measures. The sample statistics suggest that carrier collection is primarily a letter phenomenon. The median value for letters collected from customer receptacles was 76 per route per day, while the median values for flats and packages collected were both zero. In addition, nearly all collection volume obtained by regular letter carriers (as opposed to special purpose route carriers who sweep street letter boxes) came from customer receptacles.

Table 12
Route Day Statistics for Collection Volume Measures

	Mean	Median	Mode	C.V.
Customer Letter	139.4	76	57	1.67
Customer Flat	12.6	0	0	3.11
Customer Package	2.9	0	0	4.23
Collection Point Letter	12.0	0	0	8.62
Collection Point Flat	1.1	0	0	14.66
Collection Point Package	0.4	0	0	18.48
Container Letter	2.8	0	0	12.28
Container Flat	1.2	0	0	19.33

The distribution of collection volumes across all routes includes a relatively large number of zero observations for flats and packages in the low end of the distribution, and a relatively small number of extremely high-volume observations at the other end of the distribution. In other words, many routes got very little collection mail, but a few routes got a lot. In fact, there were a small number of routes that reported extraordinarily high collection volumes. There were 30 route days with more than 4,000 pieces of collection mail. Those route days occur on 19 different routes in 15 ZIP Codes.

These volumes were generally verified during the data collection process, but because of their unusual nature they deserved another examination, as potential outliers. To that end, the highest collection volume route days, both in terms of total collection volume, and by shape, were individually examined. The investigation into the outliers involved contacting the local site coordinators to verify the counts entered. On several occasions the local coordinator verified the entered count with the carrier who collected the mail. The potential outlier was retained only if the local coordinator verified the accuracy of the entry. If the entry could not be verified the data point was dropped from the analysis dataset.

A number of interesting points arose through the examination process. Most high collection volume routes were business or mixed routes. None of them were foot routes. High collection volume days tended to occur on the same routes throughout the sample period and they are typically created by a small number of business delivery points. For example, a route in Indiana reported over 1,900 letters collected. This turned out to be a business route with a few high-volume businesses. A route in Kentucky with high daily collected package volumes counts included a lawn parts service business that regularly sends out large numbers of packages. A route in North Carolina with high daily flats counts included a custom fabric and gift wrap business that regularly sends a high number of flats to customers. Because they are valid, these high-volume observations were retained in the data set.

There was also a wide dispersion in the amount of daily collection mail volume across ZIP Codes. The mean number of pieces collected per day per ZIP Code was 3,520. The range in collected volume was from no pieces to over 20,000 pieces. There were three ZIP Code days with zero collection volume.

Table 13
Daily ZIP Code Collection Volume

Quantile	Estimate
100% Max	21,634.6
99%	14,690.3
95%	9,972.6
90%	7,749.3
75% Q3	4,862.5
50% Median	2,587.0
25% Q1	1,237.4
10%	380.0
5%	209.0
1%	43.7
0% Min	0.0

To pursue an external validation of the collection volumes produced by the field study, one can compare the means and medians from the City Carrier Cost System in FY2012 with the same statistics for the data collected from the field study. Table 14 indicates that there is a correspondence between the two estimates of collection volume.

Table 14
Comparing Measures of Central Tendency For Two Different Sets of Collection Data

Source	Mean	Median
Collection Volume Study	173.6	94.6
FY2012 City CCS	181.4	95.0

6. Combining Collection Volumes with Delivery Volumes.

Because of good route number hygiene, collection volumes by route and ZIP Code matched their associated DOIS delivery volumes, by route and ZIP Code for all route days included in the study. This lead to construction of a complete volume cost driver data set for all 3,513 ZIP Code days. The next table compares measures of central tendency for collection and delivery volumes. Average daily delivery volume was more than 10 times average daily collection volume.

Table 15

Sample Statistics for ZIP Code Volumes		
	Mean	**Median**
Collected Letters	3,193.5	2,340.9
Collected Flats	293.4	162.9
Collected Parcels	67.4	38.0
Cased Letters	2,180.2	1,656.0
Cased Flats	7,276.0	5,631.0
Parcels	423.2	318.0
DPS	30,636.9	27,717.0
FSS	2,121.4	0.0
Sequenced	4,923.6	122.0

The SAS programs used to obtain the final analysis dataset of 3,513 observations are contained in USPS-RM2015-7/1.

D. Creation of the Analysis Data Set

Along with delivery volumes, DOIS provides daily observations on total street time hours for all of the routes in a ZIP Code. Recall, however, that the dependent variable in the regular delivery equation is regular delivery hours, not total street hours. Constructing that exact dependent variable thus requires turning DOIS street hours into regular delivery hours. In other words, the regular delivery time equation requires data reflecting only regular delivery time, not the complete street time, so it is necessary to subtract out the time for other activities to develop a "pure" regular delivery time.

The calculation starts with recognition that total daily DOIS street time is the sum of daily regular delivery time and daily allied street time. Allied street time includes activities that carriers perform other than the regular delivery of letters and flats. Table 16 presents the breakout of average daily allied street time, as provided by the route evaluation (Form 3999) data.

Table 16

Average Daily Allied Street Times

	Hours	Proportion of Allied Time
Relay	0.21	12.6%
Travel To	0.13	7.7%
Travel From	0.14	8.6%
Vehicle Load	0.22	13.0%
Vehicle Unload	0.1	5.7%
Travel Within	0.16	9.6%
Accountable Time	0.08	5.0%
Parcel Time	0.16	9.7%
Collect SLB	0.01	0.6%
Non Recurring	0.12	7.1%
Break	0.23	13.8%
Deadhead	0.01	0.7%
Personal	0.08	4.9%
Customer	0.01	0.4%
Gas Vehicle	0.01	0.6%
Total Allied	1.68	100.0%

Note that the allied activities do not directly depend upon the delivered letter and flat or collection volumes on individual routes.[17] This means that the allied activities are not determined by the daily volumes used in estimating the delivery time equation. Consequently, each route's regular delivery time can be calculated by taking its total street time and subtracting its allied street time. This calculation can be made with the

[17] Recall that the collection volumes in the regular delivery activity are the volumes city letter route carriers collect from customer receptacles. The time for collections from street letter boxes is in a separate cost pool and depends upon separately measured volumes. In other words, the allied activity "Collect from Street Letter Boxes" does not directly depend upon the volumes measured in the collection volume study.

total street time data from the DOIS database and the allied time data from the route evaluation (Form 3999) database.

Subtracting this route evaluation measure of allied street time from the total street time produces daily regular delivery time. But the route evaluation measure of allied time is just a single measure for each route, and does not vary from day-to-day, whereas the DOIS data provides daily street time. Because this measure of allied time does not vary from day-to-day, it is important to investigate the econometric implications of subtracting a route-specific allied time from each route-day's total street time.

The investigation starts with defining the mathematical relationship between total street time, regular delivery time, and allied time. Note that in the following equation, "t" indexes the days over which data were collected and "i' indexes the routes for which data were collected. Define “ST” to be total street time, “DT” to be regular delivery time and “AT” to be allied street time. The first step is to express the relationship among these measures of street time as:

$$ST_{it} = DT_{it} + AT_{it}$$

Rearranging this equation provides an expression for regular delivery time:

$$DT_{it} = ST_{it} - AT_{it}$$

As explained above, the route evaluation data does not contain measures of allied street time by day. Rather, it measures the systematic allied time for each route, which is defined as: $\widetilde{AT}_{it}$. On any given day, the actual allied time may differ from the systematic allied time because of random factors, such as more or less traffic on the route, or a variation in a carrier's personal needs time. This means an expression for daily allied time can be thus written as:

$$AT_{it} = \widetilde{AT}_{it} + \mu_{it}$$

Note that μ_{it} is the unobserved day-to-day variation in allied time on a route. Substituting this formulation for allied time into the regular delivery time definition provides an expression for regular delivery time as a function of what is observed (total street time and systematic allied time) and what is not observed (random daily variations in allied time):

$$DT_{it} = ST_{it} - \left(\widetilde{AT}_{it} + \mu_{it} \right)$$

This formulation permits investigation of the econometric implications of using the constructed measure of delivery time for estimating the regular delivery time equation. The regular delivery time equation specifies that delivery time is a function of the cost drivers (X_j) and characteristic variables (θ_i):

$$DT_{it} = \alpha_0 + \sum_{j=1}^{n} \beta_j X_{jit} + \sum_{k=1}^{m} \gamma_k \theta_{kit} + \varepsilon_{it}$$

Substituting the expression for regular delivery time yields:

$$ST_{it} - \left(\widetilde{AT}_{it} + \mu_{it} \right) = \alpha_0 + \sum_{j=1}^{n} \beta_j X_{jit} + \sum_{k=1}^{m} \gamma_k \theta_{kit} + \varepsilon_{it}$$

or:

$$\widehat{DT}_{it} = \alpha_0 + \sum_{j=1}^{n} \beta_j X_{jit} + \sum_{k=1}^{m} \gamma_k \theta_{kit} + \eta_{it}$$

where:

$$\widehat{DT}_{it} = ST_{it} - \widetilde{AT}_{it}$$

$$\eta_{it} = \varepsilon_{it} + \mu_{it}$$

This specification reveals that the estimated coefficients for the cost drivers and characteristic variables are unbiased and consistent. The "true" dependent variable already has a stochastic term (ε_{it}) associated with it and adding another one does not affect the relationship between the dependent variable and the independent variables. To see this, observe that the expected value of the composite stochastic term is just the sum of the expected values of the individual stochastic terms:

$$E(\eta_{it}) = E(\varepsilon_{it} + \mu_{it}) = E(\varepsilon_{it}) + E(\mu_{it}) = 0.$$

In addition, the composite stochastic term is not correlated with the right-hand-side variables in the regression:

$$E\left(\eta_{it,}X_{jit}\right) = E(\varepsilon_{it} X_{jit} + \mu_{it} X_{jit}) = E(\varepsilon_{it} X_{jit}) + E\left(\mu_{it} X_{jit}\right) = 0.$$

On the other hand, the estimated coefficients are likely to be inefficient. The size of the estimated equation's stochastic term is likely to be larger with the constructed measure of delivery time and a larger stochastic term leads to a larger variance for the estimated coefficients. In the true model:

$$V(\hat{\beta}_i) = \frac{\sigma_\varepsilon^2}{(\sum X_i - \bar{X})^2}$$

In the constructed dependent variable case:

$$V(\hat{\beta}_i) = \frac{\sigma_\eta^2}{(\sum X_i - \bar{X})^2} = \frac{\sigma_\varepsilon^2 + \sigma_\mu^2}{(\sum X_i - \bar{X})^2}$$

Inefficiency means that the standard errors for the estimated coefficients will be larger than they would be without the construction. Theoretically, larger standard errors could affect inference and make it more difficult to perform statistical tests on the coefficients. Such an inefficiency problem can be solved by having a large data set so the standard errors of the estimated coefficients are small to begin with. Then a modest degree of inefficiency does not affect inference. With a large dataset, reliable statistical inference is still possible even with a constructed dependent variable. This is the case for the estimation of the regular delivery equation. The analysis data set includes nearly 3,500 ZIP Code-day observations and is large enough to produce relatively small standard errors. Results from estimation of the equation, presented below, demonstrate that the potential inefficiency associated with a constructed dependent variable did not create a problem in practice and reliable statistical inference could be made.

To construct the regular delivery time variable, the route evaluation data (the Form 3999 data set) that includes allied time must be merged with the DOIS/CV data set which includes street time, volumes, and delivery points. The Form 3999 data set has over 140,000 route observations as it has one observation for each route in the country. The DOIS/CV data set has 71,933 route day observations covering the 6,066 individual routes in the study. Merger of the two data sets thus requires matching the allied time from the route evaluation data set to each of the corresponding routes in the DOIS/CV data set.

Initial efforts at matching the two data sets revealed that there were just 21 of the 6,066 routes (in 10 different ZIP Codes) that could not be matched. The failure to match occurred because the route evaluation data set did not include a measure of allied time for those routes. If this situation cannot be remedied, it will lead to 120 ZIP Code days (10 ZIP Codes times 12 days) with incomplete data. However, investigation of the ZIP Codes with missing Form 3999 data shows that it is usually just one route in each ZIP with missing data.

The next table presents the ZIP Codes that have routes in the DOIS/CV data set without a corresponding value for allied time in the route evaluation data. It also presents the number of non-match routes in each ZIP Code along with the total number of routes in those ZIP Codes.

Table 17
Identifying the ZIP Codes with Missing Form 3999 Data

Masked ZIP Code	Routes with Missing Allied Time	Total Number of Routes	% Missing Routes
85918	1	16	6.3%
32732	1	6	16.7%
60966	1	8	12.5%
35323	2	39	5.1%
15092	1	31	3.2%
94118	5	25	20.0%
60333	1	23	4.3%
98915	7	34	20.6%
64921	1	23	4.3%
20340	1	31	3.2%

Seven of the ten affected ZIP Codes have just one route with missing allied time data and eight of the ten affected ZIP Codes have less than twenty percent of their routes with missing data. In those ZIP Codes in which there are only one or two routes with missing allied time, the missing allied time can be imputed by using the average allied time over the remaining routes in that ZIP Code, that do have a measure of allied time. The imputed values for the missing routes are given in Table 18.

Table 18

Imputed Allied Times in Selected ZIP Codes

Masked ZIP Code	Route	Imputed Allied Time
85918	C071	2.31
32732	C016	1.16
60966	C032	1.91
35323	C049	2.02
35323	C050	2.02
15092	C095	1.67
60333	C080	1.63
64921	C076	2.88
20340	C051	2.49

By imputing allied time for these 9 routes, an additional 96 ZIP Code days were recovered. This means that there just two (masked) ZIP Codes, 94118 and 98915 with incomplete data. Because of the number of missing routes, these ZIP Codes were dropped from the analysis data set. The analysis data set thus contains 3,489 out of 3,513 possible complete ZIP Code days. This represents 99.3 percent of the possible ZIP Code days. It important to note that the included ZIP Code observations are complete, in the sense that there are no missing routes on any of the ZIP Code days.

The last step in building the analysis data set is to construct the relevant values for the characteristic variables. As explained above, there are three characteristic variables included in the econometric equation, a delivery technology indicator, the proportion of business addresses and the square miles per delivery point in the ZIP Code.

The delivery technology indicator is based upon the delivery technology used on the routes within the ZIP Code. The following table presents the distribution of the 6,066 routes in the sample across these five types.

Table 19
Distribution of Routes by Delivery Technology

	Frequency	**Proportion**
Curbline	1,392	23.0%
Dismount	1,181	19.5%
Foot	347	5.7%
Park and Loop	3,138	51.7%
Other	8	0.1%

Recall that the delivery mode indicator is assigned a value of zero if it is a curbline or dismount route (driving route) and a value of one if it is a foot, park and loop, or other route (walking route). The technology indicator is the percentage of walking routes in the ZIP Code and has a range from zero through one. The average value for this technology indicator is 0.56.

One could consider defining a ZIP Code's delivery technology through using delivery point data as opposed to route type data. For example, one could consider door delivery points and perhaps central delivery points as "walking" delivery points and curbline and perhaps CBU delivery points as “driving” delivery points. However, such an approach is less likely to provide a clear demarcation of delivery technology. This is because individual types of delivery points can be served with either a driving technology or a walking technology. Door delivery points are served by walking on foot or park and loop routes, but they are also served by driving on curbline and dismount routes. Similarly CBU delivery points are served by both walking and driving depending upon the route on which they occur.

This heterogeneity is highlighted in the Table 20, which presents a distribution of the sampled delivery points, by type, across route types.

Table 20
Distribution of Delivery Points by Route Type

Delivery Point Type	Route Type: Curbline	Dismount	Foot	Park and Loop	Other
Door	11.5%	29.9%	34.1%	66.2%	42.4%
Curb	62.2%	12.2%	0.0%	6.6%	1.5%
CBU	15.0%	24.1%	2.6%	7.4%	9.9%
Central	11.2%	33.8%	63.4%	19.8%	46.2%

The next characteristic variable to controls for the possibility that business delivery points may require a different amount of time than residential delivery points for the same amount of volume. This variable is calculated as the percentage of business delivery points in the ZIP Code. The next table presents the average and range for the ZIP Code proportion of business delivery points.

Table 21
Distribution of Business Delivery
Point Proportion

Average	9.1%
Minimum	1.6%
Maximum	75.3%

Finally, delivery density is measured by dividing a ZIP Code's square miles of land area by its number of delivery points. The mean square miles per delivery point is 0.0092. This is equal to 5.9 acres per delivery point. This mean is sharply skewed by some very sparsely populated ZIP Codes. The median square miles per delivery points is just 0.00095, or just over half an acre per delivery point.

Table 22
Distribution of Zip Code Land Area per Delivery Point

	Quantile	**Square Miles Per Delivery**	**Acres Per Delivery**
Max	100%	0.50375	322.40
	99%	0.12297	78.70
	95%	0.04485	28.70
	90%	0.01922	12.30
Q3	75%	0.00293	1.87
Median	50%	0.00095	0.61
Q1	25%	0.00043	0.27
	10%	0.00024	0.16
	5%	0.00014	0.09
	1%	0.00003	0.02
Min	0%	0.00002	0.01

The next table presents the sample statistics, by ZIP Code day for variables included in the econometric equation.

Table 23
Sample Statistics for Included Variables

Variable	Mean	Std. Deviation	Minimum	Maximum
Regular Delivery Hours	94.2	50.1	0.5	304.7
DPS	30,600	19,980	0	168,931
Cased Mail	9,443	7,040	155	57,363
Sequenced	4,898	7,507	0	58,255
FSS	2,138	4,576	0	35,785
Collection	3,547	3,262	0	21,216
Delivery Points	12,298	6,425	531	30,367
Delivery Mode	0.56	0.37	0	1.00
Miles per DP	0.01	0.03	0.00002	0.50
Ratio of Business DPs	0.09	0.07	0.02	0.75

E. Estimation of the Model and Discussion of the Results

The functional form of the delivery equation is quadratic. It has cross products among the cost drivers, but not the characteristic variables. This means it has 34 estimated coefficients, including the intercept. Note that there are three sets of coefficients to review. The first set consists of the linear and quadratic terms for the cost drivers - the volume variables and delivery points. These variables are primarily responsible for causing delivery time and are the most important in determining the estimated variabilities. The second set represents the cross products among the cost drivers. These variables account for the fact that delivery time is different for a group of products than it is if those products are delivered individually. For example, under economies of scope, it take less time to deliver two products at the same time than it does to deliver both of the products individually. The third set includes the coefficients for the characteristic variables which measure the impact of the delivery environment on delivery time.

The complete estimation results are provided in USPS-RM2015-7/1. A summary of the results is provided in the next table. Before reviewing of the results, it is important to acknowledge two potential econometric problems. The estimation of an econometric equation relies upon a set of assumptions that underlie important qualities of the estimated coefficients. When these assumptions are violated, the possibility of spurious inference arises, so it makes sense to check if the model and data match up well with the assumptions. Two assumptions that are often violated are the assumptions of homoscedastic disturbance terms and orthogonal right-hand-side variables. When those assumptions do not hold, the econometric equation may be subject to heteroscedasticity and/or multicollinearity.

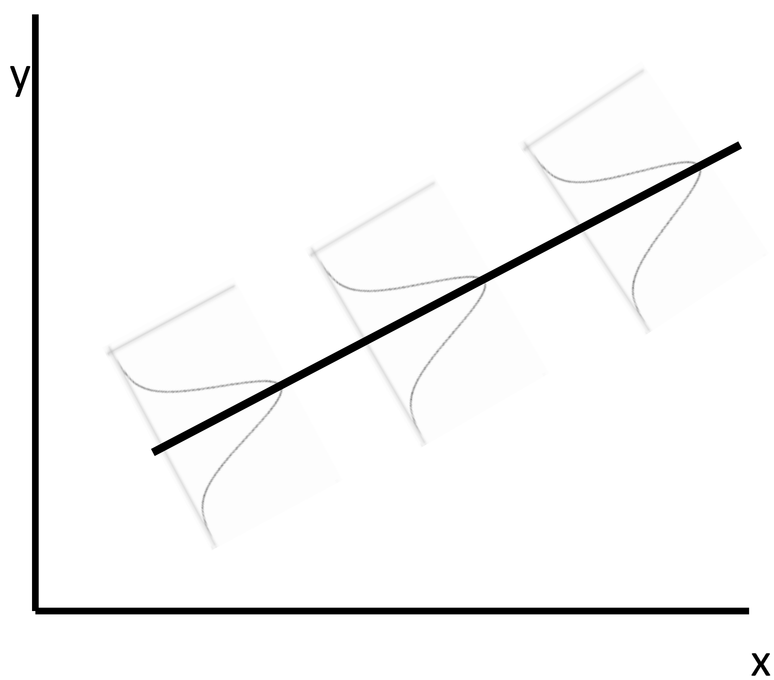
Because these problems had been detected in previously-estimated regular delivery equations, it is prudent to investigate them this time. Such an investigation includes understanding how the problems arise, determining how they can be detected, and, if necessary, addressing how they can be corrected. Heteroscedasticity will be investigated before the initial results are presented and, if appears to be present, multicollinearity will be investigated afterward.

One underlying assumption of the regression model is that the variance of the stochastic terms is constant around the regression line. Consider the following regression equation in which y is the dependent variable, x is the independent variable, and ε is the stochastic, or disturbance, term:

$$y_i = \alpha + \beta x_i + \varepsilon_i .$$

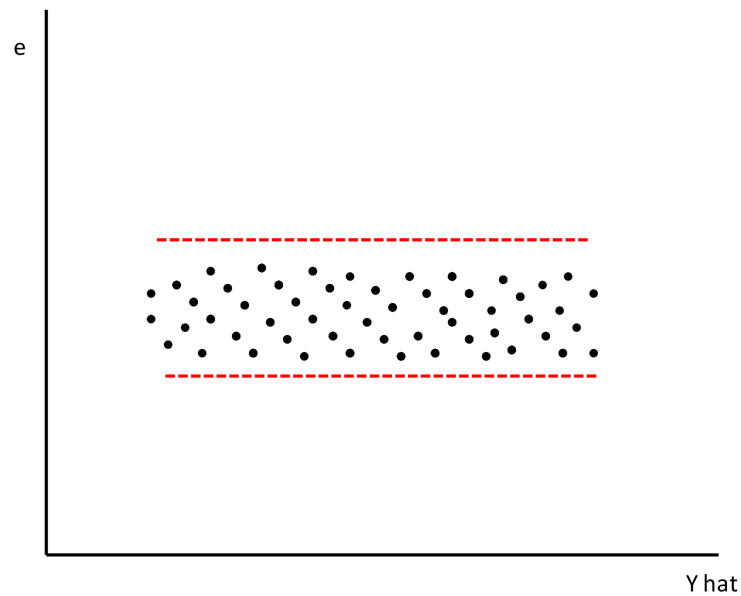
If the variance of the disturbance terms is constant around the regression line, then the distribution of the ε_i around the regression will be the same, regardless of the position on the regression line. This is illustrated in the Figure X which shows the distribution of the disturbance at various points on the regression line.

Figure 6: Distribution of Disturbances around a Regression Equation



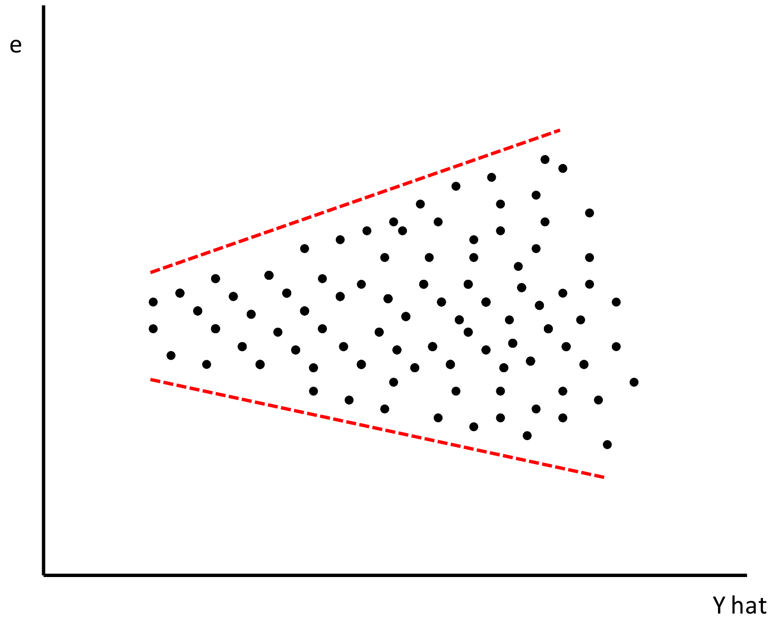
Moreover, if the variance is constant around the regression line, then a plot of the residuals against the predict values (which are on the regression line) should show the same spread at all predicted values for the dependent variable This can be investigated by plotting the residuals (e) against the predicted values (y hat). The residuals in the following plot are homoscedastic:

Figure 7: Homoscedastic Residuals



If the residuals show a pattern of increasing or decreasing at different places along regression line, then it is likely that the variance of the stochastic term is heteroscedastic. The most common form of heteroscedasticity comes from increasing variance as the size of the dependent variable increases. The following plot shows an example of a heteroscedastic disturbance term.

Figure 8: Heteroscedastic Residuals



Because it relates just to the variance of the error terms, heteroscedasticity has no impact on the estimated coefficients.[18] The ordinary least squares coefficients remain unbiased estimators of the true regression coefficients.

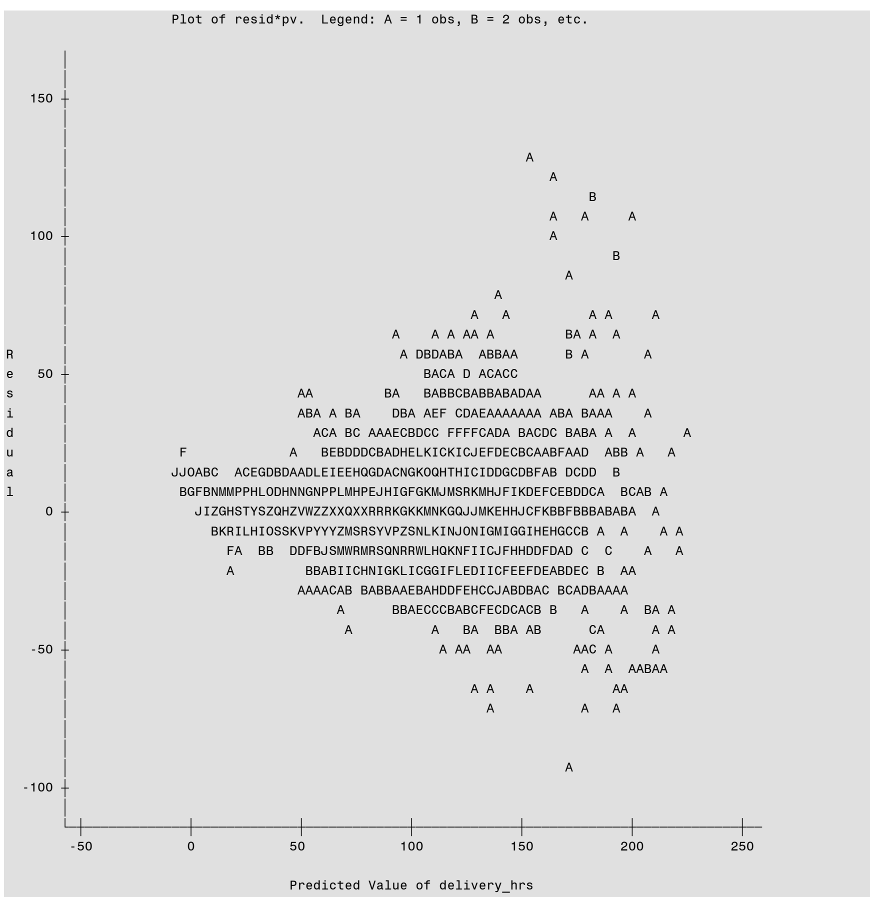
On the other hand, the estimated standard errors of those coefficients are generally biased downward. This means that standard hypothesis tests are not valid. The downward bias comes from the fact that the least squares procedure minimizes the sum of the squared residuals. Under heteroscedasticity, the least squares procedure puts more weight on the observations with large variances. But those observations

[18] The appearance of severe heteroscedasticity could be the reflection of a more serious problem with the model, such as a miss-specified model. If so, the underlying problem could be affecting the estimated coefficients even though the heteroscedasticity is not. This should be kept in mind when investigating heteroscedasticity.

should actually have the smallest weights because they contain the least real information about the model compared to their amount of "noise." As a result, the estimated standard errors are smaller than the actual ones.

There are a number of methods of detecting heteroscedasticity. The first is "ocular inspection," looking at the residuals. A plot of the residuals against the predicted values from a regression may reflect a pattern in variance. Below is the plot of the residuals against the predicted values from the regular delivery equation. The plot suggests that the variance of the residuals increases as the regular delivery time of the ZIP Code days increase.

Figure 9: Residuals Plotted Against Predicted Values from Regular Delivery Equation



However, the plot is not definitive, so it is useful to have some empirical tests for heteroscedasticity. A first test is called the Breusch-Pagan (BP) test. This test is based upon the idea that if the residuals have constant variance, then the variance should not vary with any of the right-hand-side variables. The BP test is based upon an auxiliary regression in which the squared residuals are regressed upon the model's right-hand-side variables:

$$\hat{\varepsilon}_i^2 = \gamma_0 + \sum_{j=1}^{k} \gamma_k x_{ji} + \upsilon_i \,.$$

Under the null hypothesis of homoscedasticity, the γ_k will all equal zero and the equation will have not have any explanatory power. The null hypothesis is tested by constructing the following test statistic, nR^2, which has a chi-square distribution with k degrees of freedom. In the case of the regular delivery equation, the chi-square critical value from the auxiliary regression has 26 degrees of freedom:

$$nR^2 \sim \chi^2_{26,.05}$$

The White test is similar to the BP test, except that it uses not only the right-hand-side variables but also their squares and cross products. In the case of the regular delivery equation, the White test has 305 degrees of freedom. It has the same calculated test statistic, nR^2, and also has a chi-squared distribution.

As the following table shows, both tests indicate rejection of the null hypothesis of homoscedasticity in favor of the alternative hypothesis of heteroscedasticity.

Table 24
Testing for Heteroscedasticity

Test	Bruesch-Pagan	White
Degrees of Freedom	26	305
Test Statistic	869.9	1865
Critical Value	38.85	124.34
Result	Reject H_0	Reject H_0

Given that the two tests indicate the presence of heteroscedasticity, the issue now becomes what to do about it. Because the estimated coefficients are unbiased, heteroscedasticity can be ignored if one is not concerned with hypothesis testing.[19] That is not the case for the regular delivery equation, as it is important to test the significance of the regression coefficients that will be used to calculate the variabilities. Thus, it is important to correct for heteroscedasticity.

There are two primary ways of correcting for heteroscedasticity: using weighted least squares and using robust standard errors. Both were considered for correcting the regular delivery equation. Suppose that the form of the heteroscedasticity is known. In this situation, start again with the simple model:

$$y_i = \alpha + \beta x_i + \varepsilon_i .$$

[19] It is at this point one also assesses the model to investigate whether heteroscedasticity is reflecting a larger problem. To do so, one asks if the appropriate right-hand-side variables are included in the equation, if the overall fit of the equation is acceptable, and if there is an understandable reason why heteroscedastic disturbances could arise. The answers to these questions for the regular delivery equation are all affirmative and indicate that heteroscedasticity is not reflecting a deeper problem.

The heteroscedasticity is assumed to be of the following form:

$$V(\varepsilon_i) = \sigma^2 x_i^2.$$

In other words the variance of the stochastic term increases with the right-hand-side variable. Given this form, the original model can be divided by x_i:[20]

$$\frac{y_i}{x_i} = \frac{\alpha}{x_i} + \beta + \frac{\varepsilon_i}{x_i}.$$

The variance of the transformed error term is homoscedastic:

$$V\left(\frac{\varepsilon_i}{x_i}\right) = \frac{\sigma^2 x_i^2}{x_i^2} = \sigma^2.$$

The problem with this approach is that it requires knowing the form of heteroscedasticity, which is not known for the regular delivery equation. This means that the model's coefficient estimates could be biased by using the wrong variable for the transformation. When the form of the heteroscedasticity is not known, it is appropriate to use the other method of correction: robust standard errors.

Robust standard errors can be applied when the variance structure is unknown. In this approach, ordinary least squares are used to estimate the coefficients, but new standard errors that allow for heteroscedasticity are calculated. Under heteroscedasticity, the OLS standard errors are given by:

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[20] This is called "weighted" least squares because it is the same as multiplying each observation by a weight of $\frac{1}{x_i}$.

$$V(\beta) = \frac{\sum_{i=1}^{N}[(x_i - \bar{x})^2 \sigma_i^2]}{[\sum_{i=1}^{N}(x_i - \bar{x})^2]^2}.$$

This formula depends upon the values for the heteroscedastic errors, the σ_i^2. However, they are unknown, and are replaced with consistent estimates, the squared residuals:

$$V(\beta)_{robust} = \frac{\sum_{i=1}^{N}[(x_i - \bar{x})^2 e_i^2] \;/\; (N-K)}{[\sum_{i=1}^{N}(x_i - \bar{x})^2]^2 \;/\; N}.$$

Table 25 presents the full set of OLS and heteroscedasticity-consistent (robust) standard errors for the full regular delivery model. The table shows the reduction in standard errors and t-tests that arises due to heteroscedasticity. In most cases, the t-tests are sufficiently large, even under OLS, to reject the null hypothesis of a zero coefficient. This reflects the underlying strength of the model and suggests that heteroscedasticity is not a severe problem.

Table 25
Comparing OLS and HC Standard Errors & T-tests

	Ordinary Least Squares		Heteroscedasticity Consistent	
Variable	**Standard Error**	**t Value**	**Standard Error**	**t Value**
INTERCEPT	1.694	-10.21	1.39726	-12.38
DPS	1.01E-04	4.87	1.23E-04	4.01
DPS2	1.16E-09	-6.85	1.84E-09	-4.30
CM	2.36E-04	3.28	3.28E-04	2.36
CM2	5.66E-09	-3.48	6.82E-09	-2.89
SEQ	1.53E-04	5.49	1.69E-04	4.98
SEQ2	3.74E-09	-6.77	4.01E-09	-6.30
FSS	3.02E-04	9.99	3.26E-04	9.25
FSS2	1.11E-08	-2.51	1.30E-08	-2.14
CV	4.31E-04	2.73	5.16E-04	2.29
CV2	2.04E-08	-3.56	2.56E-08	-2.85
DP	2.90E-04	23.56	2.91E-04	23.50
DP2	1.41E-08	-9.29	1.64E-08	-8.00
DPS*CM	4.34E-09	5.07	7.62E-09	2.89
DPS*SEQ	3.41E-09	1.21	5.06E-09	0.81
DPS*FSS	5.60E-09	1.97	7.73E-09	1.43
DPS*CV	8.73E-09	-7.36	1.31E-08	-4.90
DPS*DP	6.90E-09	6.41	1.02E-08	4.35
CM*SEQ	7.98E-09	0.13	1.12E-08	0.09
CM*FSS	1.54E-08	-1.48	2.06E-08	-1.11
CM*CV	1.85E-08	6.01	2.86E-08	3.88
CM*DP	1.51E-08	-3.72	2.17E-08	-2.59
SEQ*FSS	9.98E-09	1.15	1.25E-08	0.92
SEQ*CV	1.33E-08	-2.24	1.78E-08	-1.67
SEQ*DP	9.61E-09	0.62	1.14E-08	0.52
FSS*CV	2.47E-08	4.79	3.15E-08	3.76
FSS*PD	1.81E-08	-6.81	2.37E-08	-5.21
CV*DP	2.64E-08	5.36	3.62E-08	3.91
DM	3.508	12.80	3.095	14.51
DM2	3.401	-7.90	3.187	-8.42
MPDP	22.768	3.11	11.826	5.99
MPDP2	50.699	-2.38	20.132	-5.98
BR	11.901	-3.48	10.31	-4.01
BR2	20.021	2.34	15.39	3.05

An example of why it can be important to correct for heteroscedasticity is given by the coefficient on the cross product between sequenced mail and collection mail. The OLS t-statistic for that cross product is -2.24 and the HCSE is -1.67. Thus, under OLS it would be considered statistically significant when it is not. In addition, the fact that so many estimated coefficients are statistically significant indicates that potential concerns about inefficiency arising from constructing the dependent variable are not material in practice. Table 26 presents a summary of the results of estimating the regular delivery equation.

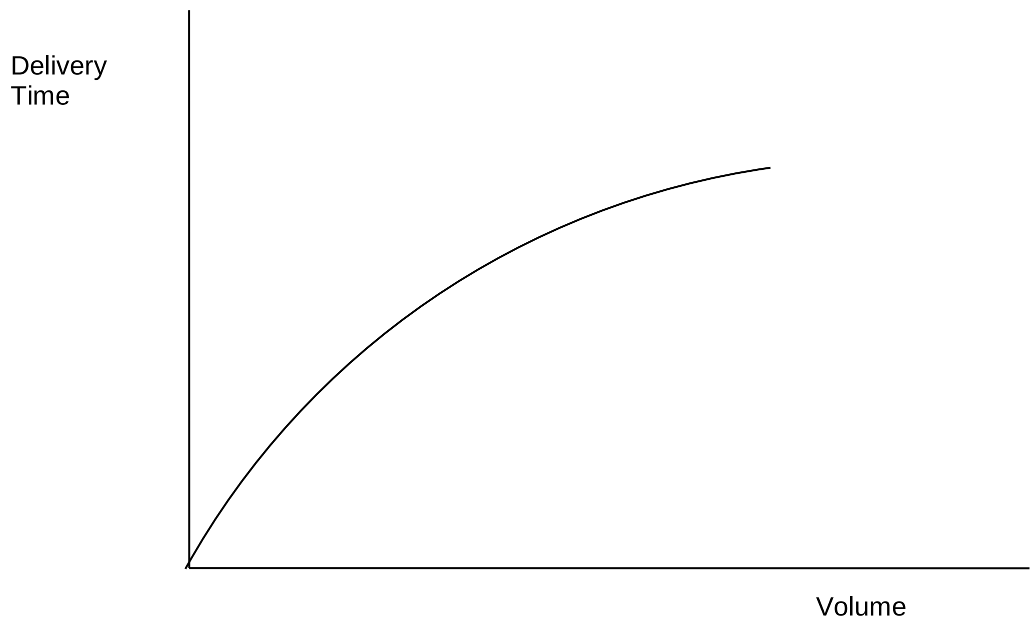
Table 26
Initial Estimation of the Regular Delivery Time Equation

Variable	Estimated Coefficient	H.C. t statistic
INTERCEPT	-17.30	-12.38
DPS	1.77	4.01
DPS2	-0.00003	-4.30
CM	2.78	2.36
CM2	-0.00007	-2.89
SEQ	3.02	4.98
SEQ2	-0.00009	-6.30
FSS	10.84	9.25
FSS2	-0.00010	-2.14
CV	4.25	2.29
CV2	-0.00026	-2.85
DP	24.62	23.50
DP2	-0.00047	-8.00
DPS*CM	0.00008	2.89
DPS*SEQ	0.00001	0.81
DPS*FSS	0.00004	1.43
DPS*CV	-0.00023	-4.90
DPS*DP	0.00016	4.35
CM*SEQ	0.00000	0.09
CM*FSS	-0.00008	-1.11
CM*CV	0.00040	3.88
CM*DP	-0.00020	-2.59
SEQ*FSS	0.00004	0.92
SEQ*CV	-0.00011	-1.67
SEQ*DP	0.00002	0.52
FSS*CV	0.00043	3.76
FSS*PD	-0.00044	-5.21
CV*DP	0.00051	3.91
DM	44.91	14.51
DM2	-26.85	-8.42
MPDP	70.82	5.99
MPDP2	-120.47	-5.98
BR	-41.38	-4.01
BR2	46.87	3.05
R2	0.8576	
# of Obs.	3485	

Cost driver coefficients are in seconds; characteristic variable coefficients are in hours.

In general, the model fits well, with a high R^2 and most coefficients being statistically significant. All of the cost driver coefficients have the expected signs. The first-order terms are positive and the second order terms are negative. The relationship between delivery time and the cost drivers is illustrated in Figure 10.

Figure 10: Delivery Time Function under Economies of Density



The figure shows that delivery time per piece falls as the number of pieces delivered rises, but that effect tapers off as volume gets large. This is consistent with economies of density in delivery.

The signs on the estimated coefficients for the characteristic variables are all as expected. As a ZIP Code becomes a more "walking" ZIP Code, keeping volume and number of delivery points constant, delivery time rises. Similarly, as the miles per delivery point increase, so does delivery time. As the percentage of business delivery points rises, delivery time falls. In addition, in all three cases, the second order term is of the opposite sign, meaning that the effect of the characteristic flattens out as it gets larger. Finally, no variables have to be dropped to get sensible results.

The variabilities implied by this regular delivery equation can be derived directly from the estimated coefficients according to the following formula:

$$\lambda_{DT,V_i} = \frac{\partial DT}{\partial V_i}\frac{\overline{V}_i}{DT(\overline{V})},$$

where $DT(\overline{V})$ is the predicted value for delivery time at the mean values for the volumes, delivery points and density. The variabilities and marginal times for regular delivery are given in the next table. There are two factors that go into the variability: the marginal time per piece and the amount of volume in the cost driver. If two shapes have the same marginal time but one has twice the volume of the other, then the larger-volume shape will have a variability twice the size of the smaller-volume shape. This is why the DPS variability is so high and why the cased mail variability is double the sequenced variability. The overall variability with respect to all volume is just the sum of the individual variabilities. In this instance, the overall variability is 36.1 percent.

Table 27
Variabilities and Marginal Times Produced by the Regular Delivery Equation

Cost Driver	**Variability**	**Marginal Time**
DPS	16.7%	2.07
Cased Mail	6.6%	2.64
Sequenced	3.4%	2.59
FSS	4.0%	7.12
Collection	5.4%	5.72

All but seven of the 34 estimated coefficients are statistically significant at the 95% level, even accounting for heteroscedasticity. This is an important result because a major symptom of multicollinearity is inflated standard errors and thus, low t-statistics. For example, the full model in Docket No. R2005-1 had low t-statistics for 18 of 35 coefficients.[21] The fact that so many of the estimated coefficients are statistically significant in the current work is a result of nearly doubling the size of the data set used to estimate the equation.[22]

Multicollinearity (which is sometimes just called collinearity) is a problem that arises when the right-hand-side variables in a regression are correlated with one another. When this occurs, it may be difficult to accurately identify the separate effects of each of the individual variables in the model.

Multicollinearity is a data problem, not a statistical problem. However, it can lead to statistical problems and that is why it should be evaluated. Multicollinearity leads to additional noise in the estimation of a model's parameters. If a parameter does not start out with a large ratio of useful information to statistical noise,[23] then the additional noise created by multicollinearity could lead to the mis-estimation of the parameter.

Because it is a problem that exists among the right-hand-side variables, multicollinearity does not affect the overall ability of the model to capture the relationship

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[21] See, "Testimony of Michael D. Bradley on Behalf of the United States Postal Service," USPS-T-14, Docket No. R2005-1.

[22] When the regular delivery equation was previously estimated, the data set included 1,545 ZIP Code days. The current data set has 3,485 observations. See, "Testimony of Michael D. Bradley on Behalf of the United States Postal Service," USPS-T-14, Docket No. R2005-1.

[23] This could occur if there is not much variation in the values for a right-hand-side variable in a data set. Then it may be difficult to infer the true relationship between that variable and the dependent variable.

between the dependent and independent variables. This is why a model can have an outstanding overall goodness of fit even though many individual estimated coefficients are not statistically differentiable from zero.

The primary symptom of multicollinearity is inflated standard errors, leading to imprecisely estimated coefficients accompanied by a high R^2 value. In extreme cases, multicollinearity can lead to parameter instability in the sense that relatively modest changes in model specification can lead to major changes in the values of the estimated coefficients; they can even switch sign.

Multicollinearity is very much a problem of degree. It can exist and reduce, to a certain extent, the accuracy of coefficient estimation without causing any specific harm to the estimation of the model. For example, if the relationship between the dependent variable and the independent variable is robust in the data set being used, then the additional noise added by multicollinearity may be insufficient to materially or statistically affect the individual estimated coefficients. On the other hand, strong collinearity could render a relatively weak model might be completely useless for identifying any individual effects. It is important to not only identify the existence of multicollinearity but also to assess the extent to which it affects the estimated parameters.

Detection of multicollinearity starts with examination of the overall goodness of fit for the equation and the statistical significance of the estimated coefficients. In the case of the regular delivery equation, this review indicates that there is only modest impact of multicollinearity. Just 7 of the 34 estimated coefficients are statistically insignificant at a 95% confidence level. This can be compared with the regular delivery equation based upon the 2002 data in which 18 of the 35 estimated coefficients were statistically insignificant. This improved performance reflects doubling of the size of the 2002 data set and confirms the point that an increase in the amount of data is an outstanding solution to multicollinearity.

A more systematic approach to investigating multicollinearity is provided by the calculation of each estimated coefficient's Variance Inflation Factor (VIF). The VIF measures the degree to which multicollinearity is increasing a coefficient's estimated standard error. This is demonstrated by the following formula:

$$\sigma^2_{\beta_i} = \frac{\sigma^2}{x_i' x_i} VIF_i \, .$$

The VIF also reflects the correlation between any right-hand-side variable and all of the other right-hand-side variables. Its computational formula is given by:

$$VIF_i = \frac{1}{1 - R_i^2}.$$

The R_i^2 term is the multiple correlation coefficient of x_i with the remaining right-hand-side variables. As that correlation rises, so does the VIF. Unfortunately, the VIF does not have a critical value or "cutoff" value for determining when multicollinearity is a problem. A value of 10 is sometimes suggested because that is associated with an R^2 value of 90 percent in the auxiliary regression of a given variable on the other variables in the equation. However, given that many of right-hand-variables in the regular delivery time equation are squared terms or cross-product terms, one should expect that they will be correlated with other variables in the equation.

As the next table indicates, there are quite a few VIFs that are large, reflecting the high degree of correlation among the right-hand-side variables.

Table 27

Variance Inflation Factors for the Coefficients in the Intial Regular Delivery Time Model			
Variable	**VIF**	**Variable**	**VIF**
DPS	39.73	Cased*Sequenced	9.50
DPS2	44.44	Cased*FSS	9.49
Cased	26.79	Cased*Collection	13.81
Cased2	16.67	Cased*Possible Dels.	54.92
Sequenced	12.83	Sequenced*FSS	3.57
Sequenced2	6.30	Sequenced*Collection	4.84
FSS	18.58	Sequenced*Possible Dels.	21.75
FSS2	9.22	FSS*Colleciton	5.67
Collection	19.30	FSS*Possible Dels.	21.01
Collection2	8.45	Collection*Possible Dels.	26.89
Possible Dels.	33.89	Delivery Type	16.12
Possible Dels.2	64.91	Delivery Type2	16.63
DPS*Cased	45.06	Miles Per Delivery Point	6.01
DPS*Sequenced	18.12	Miles Per Delivery Point2	4.74
DPS*FSS	27.93	Business Stop Ratio	6.09
DPS*Collection	27.20	Business Stop Ratio2	5.75
DPS*Possible Dels.	106.56		

These values suggest that further investigation into the degree of effect of multicollinearity is warranted. To do so, a measure called the “Condition Index” can be investigated. If the matrix of right-hand-side variables is collinear, then the matrix is close having a linear dependency. This means that some of the "eigenvalues" will be close to zero.[24] This is important, because "pure" multicollinearity arises when there is

[24] The eigenvalues, λ (also known as the characteristic roots), of a matrix A, solve the following problem: det(A-λI) =0.

a perfect linear dependency, there is an zero eigenvalue, and the matrix is singular.[25] A small eigenvalue can be taken as a sign of potentially serious multicollinearity because it may indicate a strong linear dependency. However, there still is a problem in determining how small is "small." It is possible for a particular set of data to have small eigenvalues, not because of a strong linear dependence, but because of the values of the data.

To solve this problem Belsley, Kuh. and Welsch, suggest calculating all of the eigenvalues for the matrix and then forming the ratio of the largest eigenvalue to the current eigenvalue.[26] Thus, for row "i" of the matrix, the Condition Index is given by:

$$Condition\ Index\ = \frac{u_{Max}}{u_i}.$$

The Condition Index is calculated for all eigenvalues, starts at a value of one, and increases from there. Belsley, Kuh and Welsch indicate that a Condition Index greater than 30 indicates moderate dependencies among the right-hand-side variables and a value approaching 100 indicates strong dependencies. The next table shows that the largest Condition Index indicates the existence of moderate multicollinearity that may need to be addressed.

[25] A perfect linear dependency occurs when one variable is a linear transformation of another one. For example a perfect linear dependency is given by z = 2 * x. In this situation, z does not provide any information for the model not already contained in x.

[26] See, Belsley, David, Kuh, Edwin, and Welsch, Roy, Regression Diagnostics: Identifying Influential Data and Sources of Collinearity, John Wiley and Sons, 2004.

Table 28

Condition Indexes for the Initial Regular Delivery Time Equation			
Eigenvalue	**Condition Index**	**Eigenvalue**	**Condition Index**
11.8837	1.00	0.0969	11.08
4.7797	1.58	0.0955	11.15
3.7433	1.78	0.0800	12.19
2.9184	2.02	0.0668	13.34
2.2229	2.31	0.0639	13.64
1.6965	2.65	0.0501	15.41
1.5384	2.78	0.0415	16.92
1.1752	3.18	0.0368	17.98
0.7088	4.09	0.0338	18.75
0.4333	5.24	0.0310	19.57
0.2649	6.70	0.0289	20.26
0.2309	7.17	0.0219	23.30
0.1967	7.77	0.0181	25.63
0.1539	8.79	0.0145	28.61
0.1318	9.49	0.0089	36.51
0.1284	9.62	0.0054	47.13
0.0996	10.93		

A primary method for dealing with moderate multicollinearity in a model with many higher order terms, including cross products, is to investigate removal of some of those higher order terms. This approach preserves the model's ability to capture the effects of all right-hand-side variables on the dependent variable while continuing to produce unbiased estimates. Following this approach, suggested previously by the Commission, lead to removing those terms that are not statistically significant. This reduces the model to 26 right-hand-side variables. The results of estimating the re-specified model are presented in Table 29.

Table 29
Estimation of the Reduced Regular Delivery Time Equation

Variable	Estimated Coefficient	H.C. t statistic
INTERCEPT	-17.25	-12.29
DPS	1.85	4.14
DPS2	-0.00002	-5.32
CM	2.66364	2.17
CM2	-0.00007	-2.95
SEQ	3.35484	8.96
SEQ2	-0.00007	-5.92
FSS	10.72800	9.57
FSS2	-0.00008	-2.07
CV	4.21200	2.23
CV2	-0.00030	-3.28
DP	24.37200	23.74
DP2	-0.00047	-8.35
DPS*CM	0.00007	3.08
DPS*CV	-0.00022	-4.89
DPS*DP	0.00015	4.22
CM*CV	0.00038	3.99
CM*DP	-0.00018	-2.37
FSS*CV	0.00044	4.27
FSS*PD	-0.00038	-4.66
CV*DP	0.00049	3.85
DM	45.40	14.67
DM2	-27.40	-8.59
MPDP	71.52	6.01
MPDP2	-122.07	-6.03
BR	-41.38	-3.97
BR2	48.03	3.06
R2	0.8574	
# of Obs.	3485	

Cost driver coefficients are in seconds; characteristic variable coefficients are in hours.

Three results of this re-estimation are important. First, all of the remaining terms are statistically significant, indicating that multicollinearity is no longer causing difficulty in separating out the individual effects. Second, the Condition Indexes are reduced substantially, indicating that removing the terms has removed terms that were contributing to the linear dependence. The two largest values for the Condition Index are now are 29.6 and 39.4.

Third, the empirical results are very stable across the removal of the terms. Recall that multicollinearity is a problem when modest changes in specification lead to dramatic changes in results. Removal of the insignificant higher order terms causes almost no change in the variabilities, reflecting the stability in the estimated coefficients. The following table provides the results of the two models.

Table 30
Estimated Variabilities for the Full and Reduced Models

Cost Driver	Full Model Variability	Reduced Model Variability
DPS	16.7%	16.8%
Cased Mail	6.6%	6.5%
Sequenced	3.4%	3.4%
FSS	4.0%	4.1%
Collection	5.4%	5.5%

The results suggest that elimination of a small number of cross-product terms effectively controlled for multicollinearity.

Another issue that bears investigation is the relatively high marginal time for FSS mail. While operations experts recognize that adding the additional FSS bundle to the carrier workload can increase street time, the difference between the FSS marginal time and the other marginal times is striking. This difference raises the possiblity that FSS ZIP Codes are different from non-FSS ZIP Codes for reasons other than the presence of FSS mail. If so, then the coefficients on the FSS variables could be picking up something other than its pure cost-causing effect and its marginal time could be overstated.

The normal way to proceed with this investigation would be to separately estimate the regular delivery equation for FSS and non-FSS ZIP Code days. However, there is a problem with this approach because of the relatively small number of FSS ZIP Code days. With just 967 observations for FSS zones, multicolinearity becomes a serious problem. Even with the reduced-variable model, twelve of twenty-seven estimated coefficients have low t-statistics in an FSS-only model.

This suggests that infernences drawn on this model would be inaccurate and/or that a different (and simpler) model would have to be estimated for FSS zones because of multicollinearity. Neither of these inferences are appealing.

An alternative approach is to include a "categorical" or "dummy" variable for FSS zones. This variable takes the form:

$$\delta = \begin{cases} 1 \; if \; FSS > 0 \\ 0 \; if \; FSS = 0 \end{cases}$$

This variable will capture any effects associated with FSS zones that are not caused by the FSS volumes in those zones. It also can be estimated on all 3,485 observations so multicollinearity should not be a problem.

Estimation of the model including the FSS dummy variable yields significant coefficients for all but one variable. The only coefficient with a low t-statistic is the second order term on FSS volume. That variable is dropped and the model is re-estimated. The resulting re-estimated model is presented in the next table.

This model is very similar to the previous one; the estimated coefficients on the volume and network cost drivers, except for the FSS bundle, are quite close to the previously-estimated coefficients. The one noticable change is the reduction in the FSS coefficient. This change suggests that the FSS variable may have been picking up an underlying, non-volume difference for FSS zones.

Table 32

Estimation of the Reduced Regular Delivery Time Equation
Including a Dummy Variable For FSS Zones

Variable	Estimated Coefficient	H.C. t statistic
INTERCEPT	-18.22	-12.47
FSS Dummy	3.86	2.87
DPS	1.81	4.06
DPS2	-0.00002	-5.35
CM	2.96266	2.39
CM2	-0.00007	-3.12
SEQ	3.32597	8.80
SEQ2	-0.00007	-5.71
FSS	8.38800	6.00
CV	4.06800	2.15
CV2	-0.00029	-3.26
DP	24.55200	23.78
DP2	-0.00047	-8.45
DPS*CM	0.00007	3.04
DPS*CV	-0.00022	-4.91
DPS*DP	0.00015	4.33
CM*CV	0.00038	4.00
CM*DP	-0.00018	-2.39
FSS*CV	0.00045	4.31
FSS*PD	-0.00039	-5.07
CV*DP	0.00049	3.88
DM	45.46	14.68
DM2	-27.38	-8.59
MPDP	79.43	6.54
MPDP2	-135.88	-6.60
BR	-39.82	-3.80
BR2	46.23	2.94
R2	0.8574	
# of Obs.	3485	

Cost driver coefficients are in seconds; characteristic variable coefficients are in hours.

An examination of the resulting varibilities provides a guage for evaluating the impact of this specifcation change. They are presented in the next table:

Table 33

Excluding FSS Dummy

Cost Driver	Variability	Marginal Time
DPS	16.8%	2.08
Cased Mail	6.5%	2.62
Sequenced	3.4%	2.63
FSS	4.1%	7.27
Collection	5.5%	5.82

Including FSS Dummy

Cost Driver	Variability	Marginal Time
DPS	16.8%	2.07
Cased Mail	7.0%	2.79
Sequenced	3.4%	2.61
FSS	3.0%	5.21
Collection	5.4%	5.75

Difference

Cost Driver	Variability	Marginal Time
DPS	-0.1%	-0.02
Cased Mail	0.5%	0.17
Sequenced	0.0%	-0.02
FSS	-1.2%	-2.06
Collection	0.0%	-0.07

The variabillites and marginal times for DPS volume, sequenced volume, and collection volume are not affected. The variability and marginal time for cased mail are slightly increased. The variability for FSS mail falls by over one percent and the marginal time falls by two seconds. This change puts the FSS marginal time more in line with the other estimated marginal times from the model.

A final issue to be investigated is the possibility of a small number of atypical observations having an undue impact on the estimated regression equation. To identify potentially troublesome observations, one must identify those observations which are both far from the regression line and have the potential to influence the estimated coefficients.[27] To investigate this possibility, the individual observations are examined to see which are both far from the regression line and potentially influential.

“Studentized Residuals" can be used to identify outliers. The Studentized Residual measures the distance to the observation from the regression line. To calculate the measure, one divides the value for the ith residual by the standard error of the residuals with the ith residual removed:[28]

$$e_{si} = \frac{e_i}{\hat{\sigma}(e_i)}.$$

This statistic gives a scaled, and thus comparable, measure of distance for each observation from the regression line. In large samples, the cutoff value for potential

[27] For a detailed discussion of outliers and their potential effect on the regression equation, see “Report on Updating the Cost-to-Capacity Variabilities for Purchased Highway Transportation,’ USPS-RM2014-6/1, Docket No. RM2004-1.

[28] The residual in a regression equation is equal to the difference between the actual value for the dependent variable for a given observation and its predicted value.

outliers is typically 2.5, but based upon the t-distribution, a more conservative cutoff value is 2.0 which is applied here.

"Leverage" can be used to identify potentially influential observations as it measures how "far" a given observation on the right-hand-side variables is from the centroid of the right-hand-side variables. The leverage for a given observation is:

$$h_i = \frac{1}{n} + x_i (X'X)^{-1} x'_{i.}$$

Note that x_i is the row of the matrix of right-hand-side variables (X) that contains the ith observation. The cutoff for observations with high leverage is given by 2*(p/n), where "p" is the number of right-hand-side variables and "n" is the number of observations. For the regular delivery equation the cut off value is 2 *(27/3485) = 0.0155.

There are 44 observations that are both outliers and have high leverage. This is the set of potentially influential observations that could unduly affect the estimated coefficients used to calculate the delivery time variabilities. A complete list of the observations is provided in USPS-RM2015-7/1, but important characteristics of these observations are discussed below.[29]

First, note that there is a tendency for these of observations to occur more than once in a ZIP Code. The 44 observations are clustered in just 18 ZIP Codes. ZIP

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[29] This discussion is responsive to the Commission's order that the "Postal Service should describe the nature of excluded observations when it uses this method as it did in the case of excluded inter-Cluster tractor trailer observations." See, Postal Regulatory Commission, "Order No. 2180 on Analytical Principles Used In Periodic Reporting," Docket No. RM 2014-6 (Sept. 10, 2014) at 15.

Code 10456, in the Bronx, has six of these outlier observations; ZIP Code 60634, in Chicago has seven of these outlier observations; and ZIP Code 77573, outside Houston, has five of these outlier observations.

Table 35

Sources of Potentially Influential Observations

Masked Zip Code	# of Potential Influential Obs.
68555	1
83226	2
26979	1
49047	2
42765	4
55433	**6**
15092	1
97116	1
68245	1
31736	**7**
44113	4
57737	1
48719	**5**
76688	2
84931	2
49771	1
59701	1
83077	2

Second, note that nearly half of the observations occur on Mondays, suggesting that the potentially influential observations may be associated with high volume days.

Table 36
Distribution of Potentially Influential Observations By Day of Week

Day of Week	Date	# of Potential Influential Obs.
Monday	**29-Apr-13**	**9**
Tuesday	30-Apr-13	4
Wednesday	1-May-13	2
Thursday	2-May-13	2
Friday	3-May-13	1
Saturday	4-May-13	2
Monday	**6-May-13**	**12**
Tuesday	7-May-13	4
Wednesday	8-May-13	2
Thursday	9-May-13	2
Friday	10-May-13	2
Saturday	11-May-13	2

Examination of the characteristics of the 44 potentially influential observations shows that they have high leverage because they are in large ZIP Codes. The values for the right-hand-side variables are often more than twice the average size, so they tend to be high-volume, high-delivery-point ZIP Codes.

Table 37
Comparison of Overall Means and Outlier Means

Variable	Overall Mean	Outliers Mean
Delivery Hours	94.2	179.0
DPS Volume	30,599.6	70,591.5
Cased Volume	9,442.8	24,296.5
Sequenced Volume	4,897.7	11,655.5
FSS Volume	2,138.4	4,137.0
Collection Volume	3,546.9	4,845.2
Delivery Points	12,298.4	24,604.1

The ultimate test of potential influence is given by re-estimating the equation with the outlier(s) omitted and comparing the resulting coefficients with the original coefficients. To do this, the regular delivery time equation was re-estimated after dropping the 44 potentially influential observations. The complete results are given in USPS-RM2015-7/1, but in summary, dropping the observations had surprisingly little impact on the estimation. All of the coefficients remain statistically significant and none switch signs. More importantly, as the following table shows, eliminating these 44 outliers does not materially affect the estimated variabilities.

Table 38
Delivery Time Variabilities from the Regular Delivery Equation

	All Observations	Dropping 44 Outliers	Difference
DPS Volume	0.1676	0.1594	-0.0083
Cased Volume	0.0699	0.0763	0.0064
Sequenced Volume	0.0338	0.0344	0.0006
FSS Volume	0.0295	0.0303	0.0008
Collection Volume	0.0541	0.0569	0.0029
Delivery Points	0.5491	0.5522	0.0030

Review of the data for the 44 observations reveals nothing to suggest that the observations contain data errors or do not come from valid ZIP Codes that perform standard city carrier delivery operations. Rather they are made up of high volume days in large ZIP Codes. Given that these observations do not seem particularly unusual and that they do not exhibit undue influence on the estimated coefficients, it is preferred to leave them in the data set when estimating the regression.

IV. ESTIMATING THE PACKAGE AND ACCOUNTABLE DELIVERY EQUATIONS AND CALCULATING THE ASSOCIATED VARIABILITIES

A. Introduction

Regular delivery time covers the delivery of letters and flats throughout the Postal Service's network of city carrier letter routes. It does not include the time required for delivering packages and accountables.[30] Moreover, finding the street time costs for packages and accountable can be a challenge, for several reasons.

First, the volume of packages delivered is very small relative to the volumes of letters and flats delivered. A typical city route, on an average day, delivers about 2,300 letters and flats to about 600 delivery points. But that same typical route will deliver only 30 to 40 packages. This means that fewer than 5 percent of delivery points get a package on a typical day, and that packages represent under 2 percent of total delivered volume. Consequently, the delivery time for packages is an order of magnitude smaller than the delivery time for letters and flats, and the impact of package delivery on total delivery time can be overwhelmed by the impact of letter and flat delivery. This makes it extremely difficult to estimate a package variability jointly with letter and flat variabilities.

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[30] The one exception is for small packages (according to their DMM definition) that are handled like flats in the office and cased along with residual letters and flat. From the perspective of street time costs, these pieces are handled just like the other pieces of cased mail and thus are included in the cased mail bundle in the regular delivery equation.

The volume of accountables is even smaller than the volume of packages, with a typical route delivering just a handful per day. Despite the fact that accountable delivery is time consuming, on a per-piece basis, it accounts for a tiny amount of total street time. Finally, packages are handled in different ways in delivery, depending upon their size, and this complicates the task of measuring a street time variability for packages. For these reasons, it is logical to pursue a separate analysis to measure the attributable costs of packages and accountables.

Investigation of Postal Service data systems revealed that its carrier databases do not include complete data on package and accountable delivery times and volumes. Therefore, a special field study was required to collect the data needed for estimating package and accountable attributable costs.

Estimating package and accountable variabilities takes the same general steps as estimating the variabilities for letters and flats. It requires specifying models of package and accountable delivery, collecting the data, constructing the relevant analysis data set, econometrically estimating the specified models with the analysis data set and then reviewing and evaluating the results. Each of these steps is described, in turn, in this section.

B. Specifying the Package and Accountable Models to be Estimated

There are three separate delivery activities included in total package and accountable delivery time: the delivery of packages which fit into the mail receptacle, the delivery of packages that require a carrier deviation or change in the regular delivery procedures, and the delivery of accountables which require a signature or customer contact.[31] As with regular delivery, the cost drivers of package and accountable delivery are the volumes delivered and the number of delivery points to be covered.

Package and accountable delivery is also affected by the environment in which delivery takes place, but the relevant characteristic variables are somewhat different from those describing the letter and flat delivery environment. For regular delivery, the three characteristic variables are: (1) the primary delivery technology used in the ZIP Code, (2) the proportion of business deliveries in the ZIP Code, and the (3) geographical density of delivery points in the ZIP Code. Each of these can be reviewed for its applicability to package and accountable delivery.

While package and accountable delivery is affected by the delivery technology, it is not affected by the overall delivery technology of the route, but rather the delivery technology of package and accountable deliveries made. Because there are so few package and accountable deliveries made on a route, it could well be that the route's overall delivery type does not reflect the delivery technology for its package and accountable delivery.

For example, it could be that on a given day, all of a route's packages are delivered to a cluster box, even though the route is predominantly park and loop. To accurately capture the nature of package and accountable delivery, the package delivery time equations will include the proportions of the package and accountable deliveries made by mode. In other words, to control for different delivery environments,

[31] Packages that are also accountables are treated as accountables.

the package delivery time equations will include the proportions of door, curb, cluster box, dismount, and central package and accountable deliveries.

Because regular delivery time includes much of the time that carriers spend traversing their routes, a measure of geographic density was included in the regular delivery equation to control for variations in time associated with different geographic distances. But package and accountable delivery time occurs when the carrier is at the stop and does not depend upon the distance between stops. Accordingly, the package and accountable equations will not include a measure of miles per delivery point. On the other hand, package and accountable delivery time, like regular delivery time, could be affected by the presence of business deliveries, so the package and accountable equations will include the proportion of business delivery points.

In-receptacle packages are delivered in the same receptacle as letters and flats, and are delivered in the course of the carrier's regular line of travel, using regular delivery procedures. The actions required to deliver in-receptacle packages are not, consequently, related to the actions required to deliver deviation packages and accountables. It is appropriate, therefore, to specify a separate equation for in-receptacle package delivery. A ZIP Code's volume of in-receptacle packages and its delivery points are the cost drivers for an in-receptacle package delivery time equation. The characteristic variables included to control for variations in the delivery environment are the proportions of in-receptacle deliveries, by mode, and the proportion of business deliveries.[32]

[32] The five different mode of delivery proportions sum to one and thus, along with the intercept, they form a linear combination. Consequently, only four of the five proportions can be included in the equation.

The in-receptacle package delivery time equation has a quadratic form:

$$IRPDT_{it} = \lambda_0 + \lambda_1 IRP_{it} + \lambda_{11} IRP_{it}^2 + \lambda_2 DP_{it} + \lambda_{22} DP_{it}^2 + \lambda_{12} IRP_{it} * DP_{it} + \lambda_3 \rho DR_{it}$$
$$+ \lambda_4 \rho CR_{it} + \lambda_5 \rho DM_{it} + \lambda_6 \rho CEN_{it} + \lambda_7 BR_{it} + \nu_{it}$$

Where:

IRPDT	=	In-Receptacle Package Delivery Time
IRP	=	In-Receptacle Package Volume
DP	=	Delivery Points
ρDR	=	Proportion of Door In-Receptacle Deliveries
ρCR	=	Proportion of Curb In-Receptacle Deliveries
ρDM	=	Proportion of Dismount In-Receptacle Deliveries
ρCEN	=	Proportion of Central In-Receptacle Deliveries
BR	=	Proportion of Business Deliveries

Both deviation package and accountable deliveries require the carrier to deviate from the regular delivery procedures and either make customer contact or make the delivery in a place other than the customer's regular receptacle. This means that deviation packages and accountables can be and are delivered together. In addition, on driving routes, a deviation delivery for a deviation package, an accountable, or both, may require a "move vehicle" delivery. When there are both deviation packages and accountables being delivered in this type of delivery, the move vehicle time is jointly caused by the two products. For these reasons, it is appropriate to estimate a joint equation for deviation packages and accountables.[33] The dependent variable will be deviation delivery time, which is the sum of deviation package delivery time,

[33] This specification was proposed by the Postal Service and accepted by the Commission in Docket No. R2005-1.

accountable delivery time, and move vehicle time. The deviation delivery equation also has a quadratic specification.

$$
\begin{aligned}
DEVDT_{it} \; = \; & \psi_0 + \psi_1 DEVP_{it} + \psi_{11} DEVP_{it}^2 + \psi_2\, ACT_{it} + \psi_{22} ACT_{it}^2 + \psi_3\, DP_{it} + \psi_{33} DP_{it}^2 \\
& + \psi_{12}\, DEVP_{it} * ACT_{it} \; + \psi_{12}\, DEV_{it} * DP_{it} + \psi_{23}\, ACT_{it} * DP_{it} + \psi_4\, \rho CBU_{it} \\
& + \psi_5\, \rho CR_{it} + \psi_6\, \rho DM_{it} + \psi_7\, \rho CEN_{it} + \psi_8\, BR_{it} + \xi_{it}
\end{aligned}
$$

Where:

DEVDT = Deviation Delivery Time
DEVP = Deviation Package Volume
ACT = Accountable Volume
DP = Delivery Points
ρCBU = Proportion of Cluster Box In-Receptacle Deliveries
ρCR = Proportion of Curb In-Receptacle Deliveries
ρDM = Proportion of Dismount In-Receptacle Deliveries
ρCEN = Proportion of Central In-Receptacle Deliveries
BR = Proportion of Business Deliveries

The data required to estimate these equations is not currently collected within the Postal Service’s carrier data systems, so a field study was required to collect the requisite data. That study is described in the next subsection.

C. The Package and Accountable Field Study

The package and accountable field study was designed to record both volumes and delivery times for five package/accountable activities:

- Delivery of in-receptacle packages.
- Delivery of deviation packages.
- Delivery of accountables.
- Deliveries of packages or accountables that require an extra vehicle movement.
- Collection of prescheduled Package Pickups.

The sample for the field study was the same 300 ZIP Codes that were included in the collection volume study, and were thus used to estimate the regular delivery equation. The package and accountable field study was carried out with the following steps:

1. The study process was designed.
2. A beta test of the study was performed and the study process was refined.
3. The full data collection effort was launched.
4. The collected data were analyzed.

Each of these steps is discussed in the following subsections.

1. Designing the study process

Delivery times for the various activities were developed by having carriers self-record the time they spent in each activity. The times were recorded by carriers using their hand-held scanners, which they now use on a daily basis, to scan a limited number of special barcodes, indicating that a particular activity was starting or finishing. The elapsed time for the activity was measured as the difference between the initial scan (indicating the activity was starting) and the terminal scan (indicating the activity was finished). Volumes were counted and collected through a webtool similar to the one used in the collection volume study.

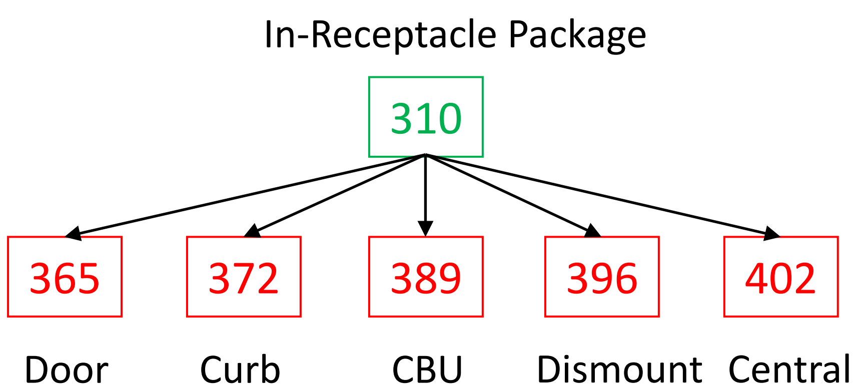
2. Performing a beta test

A beta test of the package and accountable field study was performed at seven ZIP Codes over the six delivery day period from January 27 through February 1, 2014. The beta test provided an opportunity to see if the instructions and training were sufficient to allow the carriers to accurately record their package and accountable delivery times and to accurately count and record their package and accountable volumes.

The beta test successfully provided a proof of concept that carriers were able to understand the study process and complete the required scans. It also showed that the carriers were able to successfully record their delivered volumes of in-receptacle packages, deviation packages, and accountables. In addition, an important refinement resulted from the beta test. The beta test caused the study team to recognize that the scan sequence could be simplified from a three-scan process: scan Begin Delivery barcode → scan End Delivery barcode → scan Mode barcode, to just a two-scan process: scan Begin Delivery barcode → scan Mode barcode. The simplified scanning system provided the same information as the three-scan process and allowed all activity time to be recorded with just ten different bar codes, reducing the complexity of the process and reducing the potential for errors while providing the necessary information about delivery mode and the end delivery time simultaneously.

For example, suppose bar code 310 was for recording the beginning of an in-receptacle package delivery. Under the two-scan method, a carrier would use the hand held scanner to scan barcode 310 when he or she was just beginning an in-receptacle package delivery. When the delivery was finished, the carrier would then scan one of five mode scans, depending upon the type of delivery. As well as recording the mode of delivery, scanning the mode barcode indicated when the in-receptacle delivery was over. The elapsed time for that delivery would be the difference between the recorded time for the in-receptacle package scan and the recorded time for the mode scan. The two barcode process is highlighted in the following figure.

Figure 11: Barcode Pairs for In-Receptacle Package Delivery



3. Launching the data collection effort

Prior to launching the study, extensive training was provided, including the use of both video materials and written training documents. Following training, the main study was carried out for a two-week period from March 25 through April 7, 2014. Of the 300 ZIP Codes in the original sample, 289 were able to participate in the package and accountable study.

Not all ZIP Codes were able to provide both scan and volume data for all twelve days of the study, and a few ZIP Codes were able to provide only a few days of data. To ensure reliability, a ZIP Code's data were included in the study data set only if the ZIP Code was able to provide at least one full week's worth of data. This leads to a total of 282 ZIP Codes being included in the study's data set. As Table 39 shows, most of the included ZIP Codes were able to provide both scan and volume data for all twelve days the study.

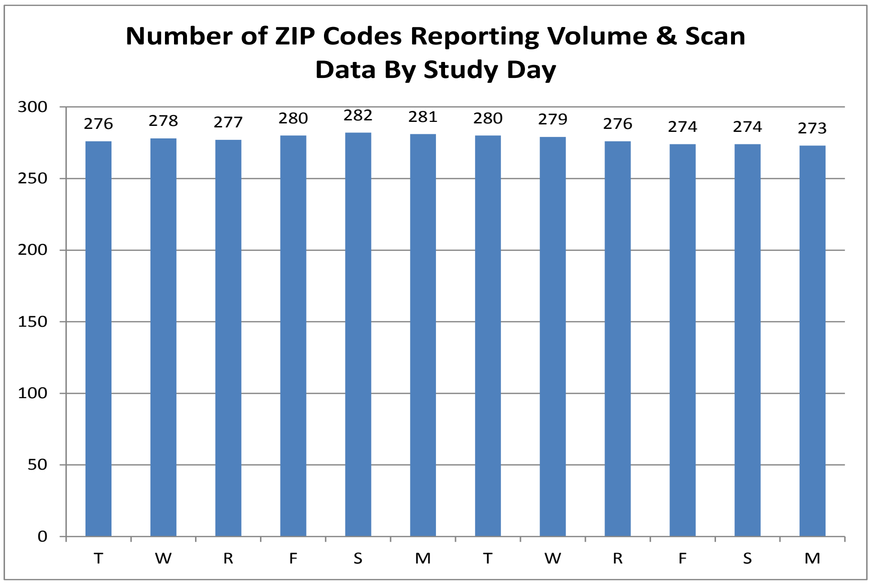
Table 39

Pattern of ZIP Codes' Reporting Days

# of Days Reporting Both Volume & Scan Data	ZIP Codes With That Number of Reported Days
6	2
7	0
8	2
9	5
10	5
11	9
12	259

While a few ZIP Codes were late starting their participation in the study, the primary reason that a ZIP Code did not provide all twelve days of data is that it stopped participating before the end of the study. There are a total of 54 ZIP Code days missing from a possible total of 3,384 ZIP Code days (12 days times 292 ZIP Codes). This is a loss of 1.6 percent of the possible ZIP Code days. The next figure visually shows the pattern of ZIP Code day attrition. As expected, there are more ZIP Code days lost at the end of the study period as a few participating ZIP Codes stopped participating in the study.

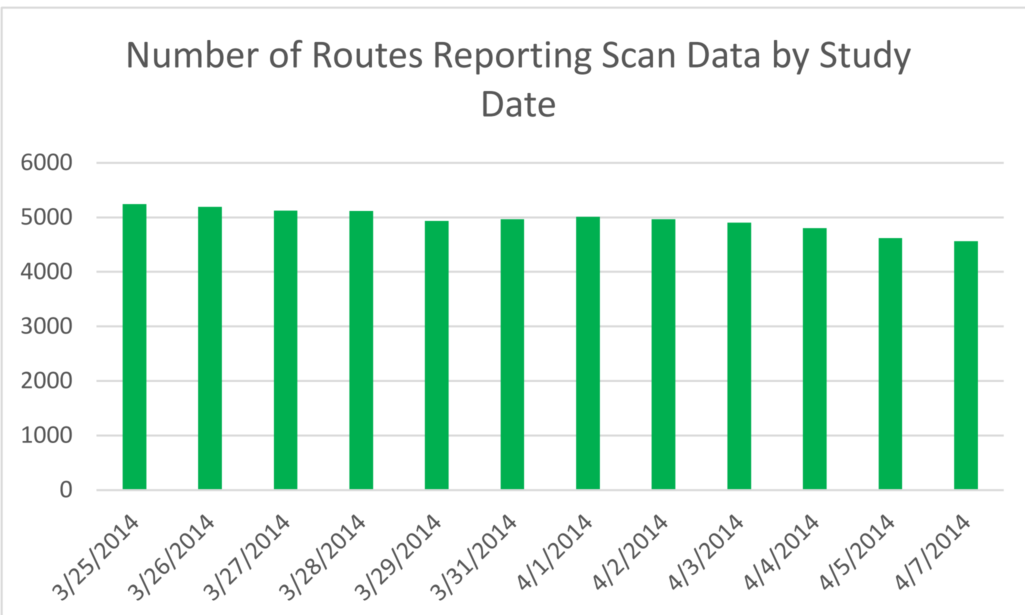
Figure 12: ZIP Code Data Reporting Pattern



In addition to losing entire ZIP Code days, it is typical in a field study to lose some individual routes within the participating ZIP Codes. This might happen for a number of reasons. For example, a carrier trained in the study protocol may be out sick or on annual leave and the replacement carrier may not participate in the study. More likely, the carrier's route is handled through pivoting, in which portions of its workload are assigned to other carriers working that day. In the case of pivoting, the delivery times are included in the data recorded on other routes. When this occurs, the entire ZIP Code's delivery time is recorded even though not all of its routes recorded scan data. In other words, even though a route did not report separately, its data are still included in the overall ZIP Code values. Finally, it is possible that a carrier may have suffered from “study fatigue,” meaning they simply stopped participating before the end of the study period.

While all three reasons likely occurred during the package and accountable study, there is some evidence, as shown in the next figure, of modest study fatigue. The number of routes reporting scan data fell in the second week of the study, particularly the last few days.

Figure 13: Routes Reporting Scan Data by Date



This pattern of attrition was anticipated when the study was designed and was part of the motivation for selecting a two-week period rather than a one-week period. In addition, possible attrition was part of the reason that a large number of ZIP Codes were included in the sample. Most importantly, subsequent analysis showed that neither ZIP

Code nor route attrition materially affected the estimated variabilities. Experiments of re-estimating the models with just the first week of data or with dropping just the last couple of days of data produced variabilities quite close to those estimated on the full data set.[34]

The next table provides some basic route-day statistics from the sample. During the study period, there were, on average, 41 packages delivered per route per day. About 60 percent of those packages were delivered in-receptacle. The average number of accountables delivered per route per day was just 2.8. In addition, neither prescheduled package pickups nor on-demand pickups were large enough to merit further investigation. The median pickup volume for all categories was zero and approximately 90 percent of routes had no package pickup or on-demand volumes over the two-week period.

[34] For example, the in-receptacle package variability, estimated on the full data set was 48.8 percent. Re-estimating the in-receptacle package equation dropping the last day, the last two days, the last three days and the last four days of data yielded variabilities of 49.2 percent, 49.4 percent and 49.5 and 49.1 percent, respectively. Estimating the model on just the first week of data yielded a variability of 47.5 percent.

Table 40

Average Daily Volumes Per Route

	Average	Median	Inter Quartile Range	Minimum	Maximum
IN RECEPTACLE PACKAGES	24.5	23.0	13-33	0	1,000
DEVIATION PACKAGES	16.6	15.0	8-22	0	718
ACCOUNTABLES	2.8	2.0	0-4	0	432
PP EXPRESS COLLECTED	0.3	0.0	0-0	0	127
PP PRIORITY COLLECTED	0.0	0.0	0-0	0	80
PP FIRST CLASS COLLECTED	0.9	0.0	0-0	0	1,393
PP OTHER COLLECTED	1.2	0.0	0-0	0	1,811
OD EXPRESS COLLECTED	0.2	0.0	0-0	0	220
OD PRIORITY COLLECTED	0.0	0.0	0-0	0	116
OD FIRST CLASS COLLECTED	0.0	0.0	0-0	0	151
OD OTHER COLLECTED	0.0	0.0	0-0	0	87

4. Analyzing the collected data

There were two data issues that needed to be addressed before the analysis data set could be constructed. First, the sequence of actions used to record the barcodes during the study caused the recorded delivery times to be inflated by the time it took for scanning the mode barcode. Recall that the scanning sequence for each activity started with a begin activity scan and ended with the mode scan. For example, an in-receptacle package delivery at a cluster box would start with the carrier scanning the “Begin In-Receptacle Package Delivery” barcode and would end with the carrier scanning the “NDCBU Delivery” barcode. The activity time was then computed as the elapsed time between the time stamp for the begin activity scan and the time stamp for the mode scan.

The study instructions required the carrier to scan the "Begin In-Receptacle Package Delivery" barcode before beginning the in-receptacle package delivery, so the time to scan that barcode was not included in the elapsed time. But, by the nature of the process, the "NDCBU Delivery" barcode could not be scanned until after the in-receptacle package delivery was completed. This means that the recorded elapsed time included both the time it took to deliver the package and the time it took to scan the mode barcode.

To account for this extra time, participating ZIP Codes were asked to keep track of the additional daily street time that was required to complete the study scans. Dividing this additional time by the number of barcode scans taken produced the average time per study scan of 12 seconds. Consequently, to adjust for the inclusion of study scanning time, the elapsed time for each activity pair was reduced by 12 seconds.

The second data issue to be examined also related to the scanning process. To fully record each barcode, a carrier was required to perform three actions: read the barcode with the scanner, press the "enter" key to record the activity, and then press the "A" key to record the time stamp. Thus, to accurately record the elapsed time for an activity, the carrier needed to undertake six physical actions: To record the time when the activity started required scanning the barcode, then hitting the "Enter" key and then hitting the "A" key. To record the time when the activity finished required scanning the barcode, then hitting the "Enter" key and then hitting the "A" key.

If the carrier failed to hit the "A" key for the begin activity scan, then the time stamp was not recorded for the beginning of the activity and both the begin activity scan and the mode scan were associated with the same time stamp, the one for the mode scan. Consequently, the recorded elapsed time for that activity was zero seconds.

A review of the scan data set revealed that there were a substantial number of barcode pairs with zero recorded elapsed time due this problem.[35] As a result, if no adjustment were to be made, the recorded delivery time for any route for which this mistake occurred would be understated. To account for this possibility, the following adjustment was applied to each route:[36]

$$\begin{matrix}Adjusted\\ Time\end{matrix} = \sum_{i=1}^{m} \left.\begin{matrix}Net\\ Delivery\\ Time\end{matrix}\right|_{Time>0} + \left(\left.\begin{matrix}Avg.Net\\ Delivery\ Time\end{matrix}\right|_{Time>0}\right) * \begin{matrix}\#\ of\ Deliveries\\ With\ Zero\ Time\end{matrix}$$

In this equation "net" delivery time refers to the adjustment that was previously made to account for the time required for study scans:

$$\begin{matrix}Net\\ Delivery\\ Time\end{matrix} = \begin{matrix}Gross\\ Delivery\\ Time\end{matrix} - \begin{matrix}Avg.\\ Study\ Scan\\ Time\end{matrix}$$

Note that the adjustment is completely neutral for any route that avoids the zero elapsed time problem.

[35] 3.8 percent of deviation package deliveries had zero elapsed time. 3.2 percent of accountable deliveries and 5.1 percent of in-receptacle package deliveries also had zero elapsed time.

[36] The computational version of the equation is:

$$\begin{matrix}Adjusted\\ Time\end{matrix} = \sum_{i=1}^{m} \left.\begin{matrix}Net\\ Delivery\\ Time\end{matrix}\right|_{Time>0} * \frac{(Total\ \#\ of\ Deliveries)}{\left(\begin{matrix}\#\ of\ Deliveries\\ With\ Positive\ Time\end{matrix}\right)}$$

D. Constructing the Analysis Dataset

The analysis data set was constructed by merging the scan data set with the volume data set. There were 3,332 ZIP Code days in the volume data set and 3,369 ZIP Code days in the scan data set. Matching the two data sets constructed an analysis data set with 3,330 ZIP Code days. There were 2 ZIP Code days in the volume data set for which there were no matching scan data and 39 ZIP Code days in the scan data set for which there were no matching volume data. The analysis data set thus contains 3,330 of the possible 3,384 ZIP Code days or 98.4 percent of possible observations.

The package and accountable scan data were self-reported by carriers and thus were potentially subject to data reporting errors. This possibility was investigated after the scan and volume data were combined by looking at ZIP Codes with unreasonably high or low productivities as measured by delivered time per piece. Discussion with operations experts lead to the establishment of possible high and low productivity cutoffs, beyond which the ZIP Code data may reflect infeasible operations.

Table 41

Potential High and Low Productivity Filters

Shape	High End Value	Low End Value
In Receptacle Package	3 minutes	10 seconds
Deviation Package	5 minutes	10 seconds
Accountable	10 minutes	20 seconds

Application of the high-end cutoff is relatively straightforward, but economies of density in delivery makes it more difficult to establish a low-end cutoff. It is important to exclude only truly infeasible data, and if a ZIP Code had very high in-receptacle volumes, it may be possible for it to average very low average delivery times per piece because of economies of density. If so, the ZIP Code data are valid and should be included. The goal is to develop an algorithm to identify just those ZIP Code days with infeasible data. For example, if a ZIP Code experienced a shortage of routes reporting scan time on a given day but complete reporting of volume, then it will have apparently low delivery times per piece. But, the observed low delivery times per piece were artificial, and that ZIP Code day's data should be dropped from the analysis data set.

To accommodate these different reasons for low average delivery times per piece, the low-end cutoff was modified in two ways. First, if a ZIP Code day averaged more than two pieces per delivery point for in-receptacle delivery, then its data were preserved, even if it had very low average times per piece. This captures the impact of economies of density on average delivery times. In contrast, to identify artificially low average delivery times, an indicator of under reporting, called the "route gap", was constructed. The route gap was designed to identify the percentage of routes within a ZIP Code not reporting scan data on a given day.[37] The route gap indictor is given by:

$$Route\ Gap\ = \frac{(\#of\ Reporting\ Volume\ Routes - \#of\ Reporting\ Scan\ Routes)}{\#of\ Reporting\ Volume\ Routes}$$

[37] Because of pivoting, it is quite possible that a ZIP Code could accurately have fewer routes reporting scan data than volume data. The volume would be counted in the office and assigned to a pivoted route, but the scan would be recorded on the routes that picked up the portions of the pivoted route.

If a particular ZIP Code day had 10 routes reporting volume data and 8 routes reporting scan data, then its route gap would be (10-8)/10 = 20 percent. To allow for valid pivoting, but to capture under-reporting, low delivery time per piece ZIP Code days with a route gap of more than 25 percent were dropped as it is unlikely that more that 25 percent of a ZIP Code's routes were pivoted.

One additional complication occurred for deviation deliveries. Productivity estimates for deviation package delivery time per piece or accountable time per piece necessarily exclude "move vehicle" time from the calculation. This is because "move vehicle" time is not associated with either individual volume and can occur for both. Thus, it is possible for a ZIP Code day to have reasonable actual average delivery times for both deviation packages and accountables (including valid move delivery time) but still show very low recorded individual deviation package delivery time per piece and/or low individual accountable time per piece. This can happen if a substantial proportion of the deviation packages and accountables were delivered in "move vehicle" deliveries and that valid time does not show up in the individual average time calculations.

To control for this possibility, an indicator, called the move vehicle ratio was calculated. This indicator simply measures the percentage of deviation delivery time, (which is the sum of deviation package delivery time, accountable delivery time and move vehicle delivery time) made up of move vehicle time:

$$Move\ Vehicle\ Ratio\ = \frac{Move\ Vehicle\ Time}{Deviation\ Delivery\ Time}$$

If a ZIP Code day had 40 minutes of deviation package delivery time, 35 minutes of accountable delivery time and 25 minutes of move vehicle time, then its move vehicle ratio would be (25/(40+35+25)) or 25 percent. This indicator was used to identify high move vehicle ZIP Codes. Thus, if a ZIP Code day had a move vehicle ratio of greater than 25 percent, then its data were retained even if it had low deviation package or accountable delivery times per piece.[38]

E. Estimating the Econometric Models and Discussion of Results

After the analysis data set was constructed, it was reviewed. That review revealed the fact that there are some ZIP Code days with very large package and accountable delivery time. For example, the median in-receptacle package delivery time is 2.97 hours per ZIP Code day but there are a number of ZIP Code days with over 8 hours of in-receptacle package delivery time.

Further investigation of these large ZIP Code days suggested that their cost generating process may be different from the rest of the ZIP Code days. This difference is highlighted by a comparison of the cross plots between in-receptacle package time and in-receptacle package volume for those ZIP Code days with more than 8 hours of in-receptacle package time, and for those ZIP Code days with less than 8 hours of in-receptacle package delivery time. These cross-plots are presented in Figure 14.

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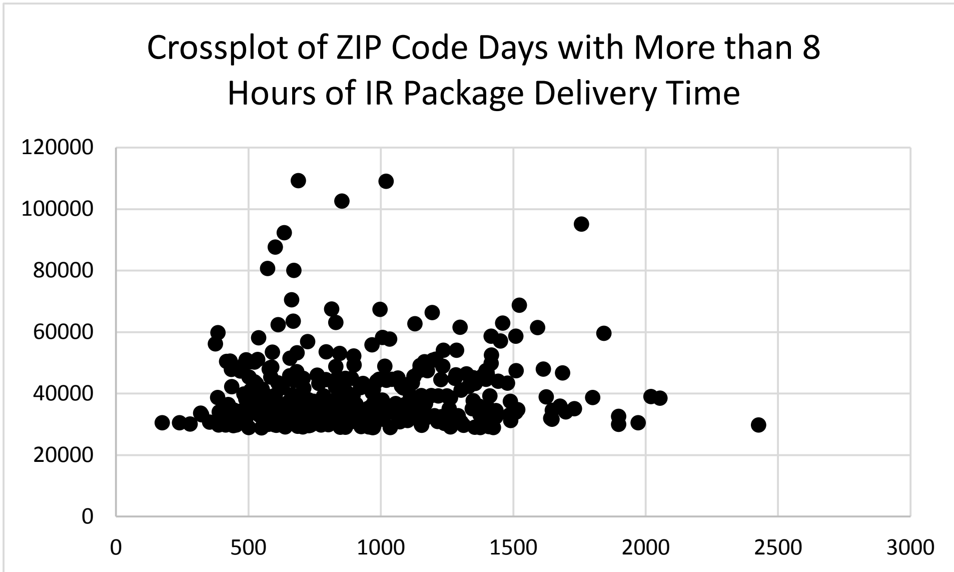
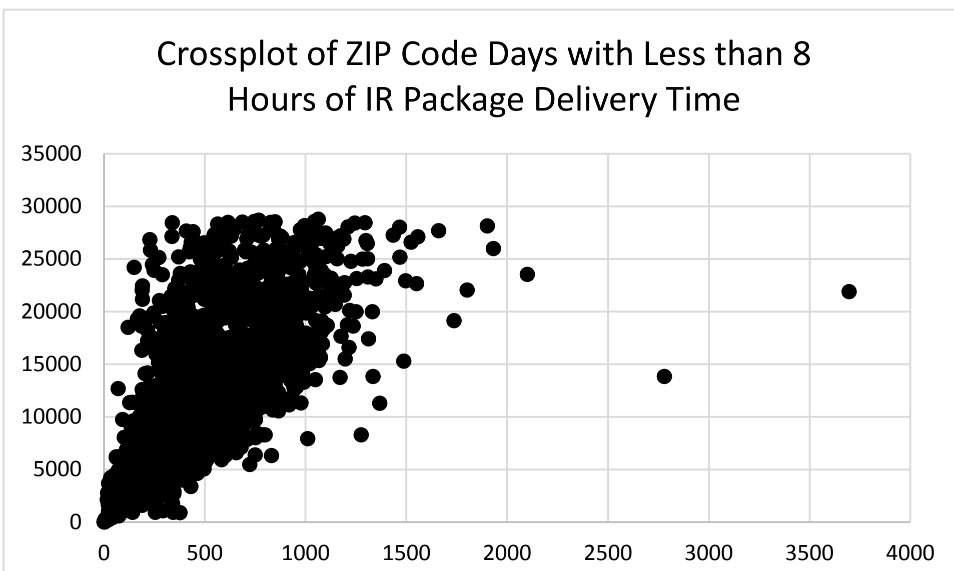
[38] The median move vehicle ratio is 12.3 percent, so 25 percent is approximately twice the median value. Only 19 percent of ZIP Code days had a move vehicle ratio higher than 25 percent. Among that group, however, the average move vehicle ratio was 37.2 percent.

Figure 14: Cross Plots of In-Receptacle Delivery Time and In-Receptacle Volume by Type of ZIP Code Day





These plots show a very different relationship between delivery time and volume in the two data subsets. Because of this difference, an investigation was undertaken to evaluate the characteristics of the ZIP Codes with large delivery times in an attempt to identify any operating characteristics that could cause them to be different. The analysis was not particularly fruitful. These large ZIP Code days were in more concentrated areas and tended to have higher proportions of central and cluster box deliveries than most ZIP Codes, but the observed differences were not sufficient to be causing the difference in the underlying cost-generating process. In addition, there was no clear way to find the dividing line between the two sets of ZIP Code days.

In this circumstance, an alternative approach to this "switching" problem is to estimate a threshold model.[39] In a threshold model, one set of coefficients governs behavior until the threshold variable reaches a key level. Then another set of coefficients takes over. Consider a situation in which the dependent variable, y, is determined by two underlying models, both with the same independent variable, x, but with different coefficients for the two models. Moreover, the switch between the two models takes place when y exceeds a certain threshold value, given by γ:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \varepsilon_i \qquad if \quad y_i \leq \gamma$$

$$y_i = \alpha_0 + \alpha_1 x_i + \alpha_2 x_i^2 + \varepsilon_i \qquad if \quad y_i > \gamma$$

[39] See, Hansen, Bruce E., "Sample Splitting and Threshold Estimation," Econometrica, Vol. 68, No.3 (May 2000), 575-603.

There are two main problems with attempting to estimate this model. First, one of the subgroups may have a relatively small number of observations.[40] If so, it may be infeasible to separately estimate the econometric model for the subgroup. Second, there may be no basis for determining the exact value for the threshold parameter, γ. That can make it extremely difficult to accurately identify the two subgroups. Under these conditions, which apply here, estimation of the model is facilitated by rewriting the two-regime model as a single equation:

$$y_i \quad = \quad \beta_0 + \beta_1 \, x_i + \beta_2 \, x_i^2 + \delta_0 d_i + \delta_1 \, x_i(\gamma) + \delta_2 \, x_i^2(\gamma) + \varepsilon_i$$

where: $x_i(\gamma) = \; x_i \; d_i(\gamma)$ and d_i is a dummy variable whose value depends upon the threshold variable:

$$d_i \quad = \quad \begin{cases} 0 \quad if \quad y_i \quad \leq \quad \gamma \\ \\ 1 \quad if \quad y_i \quad > \quad \gamma \end{cases}$$

The parameters to be estimated are (β, δ, γ) and can be estimated with least squares through minimizing the sum of squared error function. But the practical problem is that there are too many possible values for γ over which to apply a continuous search. However, the estimated values for the β and δ parameters are linear, conditional on γ. This property means that the optimal value of γ can be found through a grid search. A grid search proceeds through the following steps:

[40] For example, there are only 378 Zip Code days with over 8 hours of in-receptacle package delivery time.

Step 1: Estimate the model for a wide range of values to identify which one minimizes the root means squared error of the equation:

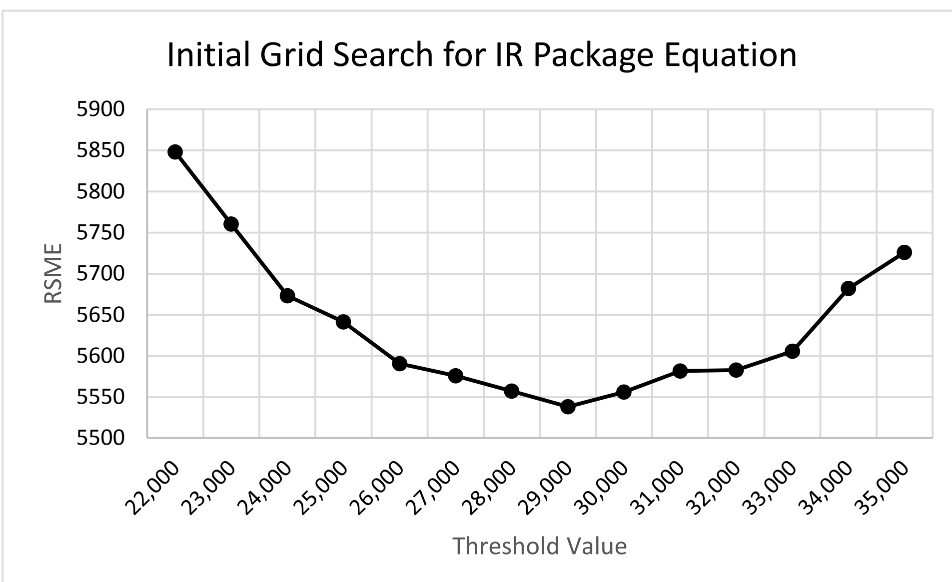
$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$$

Step 2: Select a finer grid for the area around the initial value for γ and repeat the grid search to find the next most precise value for γ.

Step 3: Repeat the procedure until the overall optimum value of γ is found.

The threshold model was first estimated for the in-receptacle package delivery equation. The grid search started with a range of values from 22,000 seconds (6.11 hours) through 35,000 seconds (9.72 hours) in increments of 1,000 seconds. As the next figure shows, an initial threshold value of 29,000 seconds minimized the RMSE.

Figure 15: Grid Search Results for the In-Receptacle Package Equation



The next, finer, grid search was centered on 29,000 seconds and examined increments of 100 seconds. That search produced an intermediate threshold value of 29,300 seconds. The final grid search centered on 29,300 seconds and examined increments of 25 seconds. That last search confirmed the threshold value of 29,300. The model was estimated around this threshold. The results are presented in Table 42.[41]

[41] As with the regular delivery equation, heteroscedasticity is dealt with through estimation of heteroscedastic standard errors. See Section III, above, for a discussion of heteroscedasticity.

Table 42

IR Package Delivery Time Model

Variable	Parameter Estimate	Heteroscedasticity Consistent Standard Error	t Value
Intercept	-5,059.92	587.35	-8.61
IR Package	25.63	1.25	20.56
IR Package2	-0.0044800	0.0009881	-4.54
Delivery Points	0.24	0.06016	3.99
Delivery Points2	0.0000069	0.0000034	2.01
IR Package*Del. Pts.	-0.0003379	0.0001064	-3.18
% IR Door Dels.	4,902.14	565.00	8.68
% IR Curb Dels.	1,270.38	623.64	2.04
% IR Dismount Dels.	10,674.00	1,003.66	10.64
% IR Central Dels.	4,414.07	1,252.95	3.52
Business Ratio	5,638.84	1,265.80	4.45
d_1	51,370.00	11,211.00	4.58
d1*IR Package	-31.25	9.47	-3.30
d1*IR Package2	0.0011000	0.0027300	0.40
d1*Delivery Points	-0.8876700	0.8611000	-1.03
d1*Delivery Points2	-0.0000003	0.0000235	-0.01
d1*IR Package*Del. Pts.	0.00093638	0.00039739	2.36
d1*% IR Door Dels.	1,769.70	6,111.05	0.29
d1*% IR Curb Dels.	-730.99	7,465.00	-0.10
d1*% IR Dismount Dels.	-21,284.00	8,043.82	-2.65
d1*% IR Central Dels.	-16,994.00	8,992.02	-1.89
d1*Business Ratio	-10,773.00	11,631.00	-0.93
# of Obs	3,161		
R2	0.7931		
Theshold Value	29,300		

All of the primary coefficients are statistically significant. The linear term for in-receptacle package volume is positive and the quadratic term is negative indicating the presence of economies of density in in-receptacle package delivery. Both the intercept dummy and the dummy variable term for in-receptacle package volume are statistically significant and a test of the significance of all of the dummy variable coefficients rejects the null hypothesis that they are jointly equal to zero. This confirms estimation of the threshold model.

Table 43
Test of Threshold Coefficients using Heteroscedasticity Consistent Covariance Estimates

Chi-Square Statistic	P Value
549.65	<.0001

After estimating the model, the residuals were inspected, using the procedures described in Section III, above, to identify potentially influential observations. Calculation of Cook's D statistic identified four observations with a value for Cook's D above the threshold of 0.10.[42] As the following table shows, the four observations are extremely large relative to the average ZIP Code day and have either very high or very low delivery times per piece.

Table 44
Characteristics of Outliers From IR Package Equation

	IR Package Delivery Time (Seconds)	IR Package Volume	Ratio
Obs. 1	109,222.7	689	158.5
Obs. 2	108,992.9	1,020	106.9
Obs. 3	95,090.5	1,758	54.1
Obs. 4	21,895.0	3,696	5.9
Average	14,067.8	493.9	28.5

[42] The Commission has determined that "The Postal Service's method of setting the Cook's D threshold for removing an observation equal to 0.1 is reasonable." See, Postal Regulatory Commission, "Order No. 2180 on Analytical Principles Used In Periodic Reporting," Docket No. RM 2014-6 (Sept. 10, 2014) at 15.

These four observations were dropped from the analysis data set, and the in-receptacle package model was re-estimated. The results are presented in Table 45

Table 45

IR Package Delivery Time Model With Outliers Removed

Variable	Parameter Estimate	Heteroscedasticity Consistent Standard Error	t Value
Intercept	-5,100.44	587.39	-8.68
IR Package	27.10	1.13	24.01
IR Package2	-0.0064400	0.0007475	-8.62
Delivery Points	0.19566	0.05811	3.37
Delivery Points2	0.0000072	0.0000033	2.22
IR Package*Del. Pts.	-0.0002758	0.0000953	-2.89
% IR Door Dels.	4,901.15	561.63	8.73
% IR Curb Dels.	1,243.10	621.61	2.00
% IR Dismount Dels.	10,668.00	1,005.05	10.61
% IR Central Dels.	4,313.94	1,254.06	3.44
Business Ratio	5,679.84	1,270.17	4.47
d_1	46,595.00	8,537.73	5.46
d1*IR Package	-28.38	7.81	-3.63
d1*IR Package2	0.0036600	0.0025000	1.46
d1*Delivery Points	-0.6455000	0.7611400	-0.85
d1*Delivery Points2	0.0000010	0.0000221	0.04
d1*IR Package*Del. Pts.	0.00058267	0.00032607	1.79
d1*% IR Door Dels.	1,686.22	5,414.13	0.31
d1*% IR Curb Dels.	-1,613.10	6,359.38	-0.25
d1*% IR Dismount Dels.	-16,340.00	7,173.14	-2.28
d1*% IR Central Dels.	-10,775.00	8,067.70	-1.34
d1*Business Ratio	-11,001.00	10,682.00	-1.03
# of Obs	3,157		
R2	0.809		
Theshold Value	29,300		

Estimation of the deviation delivery time equation followed the same procedures used to estimate the in-receptacle delivery time equation. The grid search procedure started with examining threshold values for daily time per deviation package from 10.000 seconds (2.78 hours) through 24,000 seconds (6.67 hours). The first grid search produced a minimum RMSE threshold of 14,000 seconds. Subsequent grid searches refined the investigation until an optimal threshold value of 14,080 seconds was identified.

The initial estimation of the deviation delivery time model is presented in Table 46. The model fits well, with a high R^2 and nearly all of the main coefficients being statistically significant. The first order terms on both types of volume are positive and the second order terms are negative, signaling the existence of economies of density in deviation delivery. The cross-product term between accountables and deviation packages is negative but not statistically significant, indicating possibly weak economies of scope between the two products.

Table 46
Deviation Delivery Time Model

Variable	Parameter Estimate	Heteroscedasticity Consistent Standard Error	t Value
Intercept	-936.53	428.31	-2.19
Dev. Package	31.09	3.28	9.48
Dev. Package2	-0.0063800	0.0117700	-0.54
Accountable	100.21	13.66	7.33
Accountable2	-0.0976700	0.0355400	-2.75
Delivery Points	0.7649300	0.0737700	10.37
Delivery Points2	-0.0000221	0.0000038	-5.79
Dev. Pack.* Acct	-0.0739900	0.0536900	-1.38
Dev. Pack*Del Pts.	-0.0002193	0.0002883	-0.76
Accountable*Del.Pts.	-0.0004041	0.0011100	-0.36
% Dev NDBU Dels.	2,999.66	963.31	3.11
% Dev Curb Dels.	2,990.42	832.84	3.59
% Dev Dismount Dels.	1,102.42	435.70	2.53
% Dev Central Dels.	-2,726.55	1,214.42	-2.25
Business Ratio	-4,190.41	1,615.98	-2.59
d_1	10,539.00	2,978.33	3.54
d1*Dev. Package	2.56	7.11	0.36
d1*Dev. Package2	-0.0024500	0.0135800	-0.18
d1*Accountable	-30.32	28.51	-1.06
d1*Accountable2	0.01	0.07	0.19
d1*Delivery Points	-0.4071600	0.3299800	-1.23
d1*Delivery Points2	0.0000207	0.0000131	1.58
d1*Dev. Pack.* Acct	0.1038600	0.0652300	1.59
d1*Dev. Pack*Del Pts.	0.0002391	0.0005393	0.44
d1*Accountable*Del.Pts.	0.0002195	0.0018200	0.12
d1*% Dev NDCBU Dels.	-9,506.42	2,542.48	-3.74
d1*% Dev Curb Dels.	-6,009.71	2,056.01	-2.92
d1*% Dev Dismount Dels.	4,515.71	2,565.86	1.76
d1*% Dev Central Dels.	-1,903.06	4,431.46	-0.43
d1*Business Ratio	-5,109.05	7,605.05	-0.67
# of Obs	3,066		
R2	0.8168		
Theshold Value	14,080		

A number of the dummy variable coefficients have low t-statistics, so it is important to test the null hypothesis that the dummy variable coefficients are jointly equal to zero. The calculated chi-square statistic easily rejects the hypothesis.

Table 47

Test of Threshold Coefficients using
Heteroscedasticity Consistent
Covariance Estimates

Chi-Square Statistic	P Value
159.52	<.0001

The residuals were inspected to identify potentially influential observations. Calculation of Cook's D statistic identified five observations with a value for Cook's D above the threshold of 0.10. Examination of the five observations shows that they all have extremely large deviation package or extremely large accountable volumes relative to the average ZIP Code day. This is demonstrated in Table 48.

Table 48

Characteristics of Outliers From Deviation Equation

	Deviation Package Volume	Ratio to Average	Accountable Volume	Ratio to Average
Obs. 1	913	2.7	49	0.9
Obs. 2	440	1.3	430	7.8
Obs. 3	1,343	4.0	288	5.2
Obs. 4	308	0.9	490	8.9
Obs. 5	2,138	6.4	170	3.1
Average	333.9	1.0	54.9	1.0

These five observations were dropped and the deviation delivery equation was re-estimated. The results are presented in Table 49.

Table 49
Deviation Delivery Time Model With Outliers Removed

Variable	Parameter Estimate	Heteroscedasticity Consistent Standard Error	t Value
Intercept	-1,090.18	427.34	-2.55
Dev. Package	31.82	2.97	10.70
Dev. Package2	-0.0199000	0.0089100	-2.23
Accountable	92.06	13.10	7.03
Accountable2	-0.1895300	0.0342100	-5.54
Delivery Points	0.7845400	0.0749700	10.47
Delivery Points2	-0.0000215	0.0000038	-5.63
Dev. Pack.* Acct	0.0481000	0.0447200	1.08
Dev. Pack*Del Pts.	-0.0001247	0.0002685	-0.46
Accountable*Del.Pts.	-0.0016400	0.0011200	-1.46
% Dev NDBU Dels.	2,760.26	957.09	2.88
% Dev Curb Dels.	3,220.21	802.04	4.02
% Dev Dismount Dels.	1,192.03	431.61	2.76
% Dev Central Dels.	-1,948.68	1,218.76	-1.60
Business Ratio	-3,123.58	1,615.53	-1.93
d_1	12,108.00	2,816.35	4.30
d1*Dev. Package	-7.20	6.93	-1.04
d1*Dev. Package2	0.0228700	0.0127900	1.79
d1*Accountable	-13.00	28.34	-0.46
d1*Accountable2	0.03	0.10	0.31
d1*Delivery Points	-0.3590900	0.3212200	-1.12
d1*Delivery Points2	0.0000192	0.0000131	1.46
d1*Dev. Pack.* Acct	-0.0357800	0.0602900	-0.59
d1*Dev. Pack*Del Pts.	-0.0000433	0.0005687	-0.08
d1*Accountable*Del.Pts.	0.0022500	0.0018400	1.22
d1*% Dev NDCBU Dels.	-9,118.96	2,547.87	-3.58
d1*% Dev Curb Dels.	-6,362.11	2,024.03	-3.14
d1*% Dev Dismount Dels.	3,960.36	2,486.86	1.59
d1*% Dev Central Dels.	-2,833.15	4,445.31	-0.64
d1*Business Ratio	-5,020.48	7,519.96	-0.67
# of Obs	3,061		
R2	0.8193		
Theshold Value	14,080		

The estimated in-receptacle and deviation delivery time models can be used to calculate the in-receptacle package, deviation package and accountable variabilities. The variability calculation must take into account the threshold characteristic of the model and the required formula is a slight variation on the traditional variability formula.

Consider a delivery time threshold model with one volume cost driver. For algebraic convenience, the analysis will employ a delivery time equation with just one volume cost driver (V_i) and one characteristic variable (Z_i). The threshold model in this case is given by:

$$\begin{aligned} DT_i = \beta_0 &+ \beta_1 V_i + \beta_{11} V_i^2 + \beta_2 DP_i + \beta_{22} DP_i^2 + \beta_{12} V_i DP_i + \beta_3 Z_i \\ &+ \delta_0 d_i + \delta_1 V_i(\gamma) + \delta_{11} V_i^2(\gamma) + \delta_2 D_i(\gamma) + \delta_{22} D_i^2(\gamma) \\ &+ \delta_{12} V_i D_i(\gamma) + \delta_3 Z_i(\gamma) + \varepsilon_i. \end{aligned}$$

As with a standard delivery time equation, the elasticity of delivery time with respect to volume is based upon the partial derivative of DT with respect to the product's volume, evaluated at the mean values for the independent variables. Applying that approach to the threshold equation yields the following formula for the variability:

$$\eta_{DT,V} = \frac{(\beta_1 + \delta_1 \bar{d}_i)\bar{V}_i + (\beta_{11} + \delta_{11}\bar{d}_i)\bar{V}_i^2 + (\beta_{12} + \delta_{12}\bar{d}_i)\,\overline{DP}_i}{DT(\bar{V}_i, \overline{DP}_i, \bar{Z}_i)}$$

Note that $DT(\bar{V}_i, \overline{DP}_i, \bar{Z}_i)$ is the value for delivery time calculated by evaluating the estimated equation at the mean values for the right-hand-side variables. Applying this formula to the estimated in-receptacle package and deviation delivery equations yields the required variabilities.

Table 50

Calculated Package and Accountable Variabilities

Shape	Variability
In Receptacle Package	48.8%
Deviation Package	31.1%
Accountable	18.0%

V. ASSESSING THE IMPACT OF THE STUDY

To assess the impact of the new study, the new cost pools and variabilities were embedded in the FY 2013 city carrier street time model as constructed in the Cost Segment 6 and 7 (CS06&7) spreadsheets. The volume variable costs were then recalculated and compared with the volume variable cost produced by the original model.

At the highest level of aggregation, total Cost Segment 7 volume variable costs can be compared. Table 51 shows that the combined impact of the study is a modest decline in overall volume variable costs. The average variability for the cost segment falls slightly from 48.5 percent to 47.3 percent.

Table 51

Impact of the New Study on Cost Segment 7 Volume Variable Costs

Category	FY 2013 With New Study	FY2013 CRA	Difference
Total Volume Variable Costs	$7,396,300	$7,585,485	($189,185)
Other Costs	$8,237,378	$8,048,193	$189,185
Accrued Costs	$15,633,678	$15,633,678	$0
Average Variability	47.3%	48.5%	-1.2%

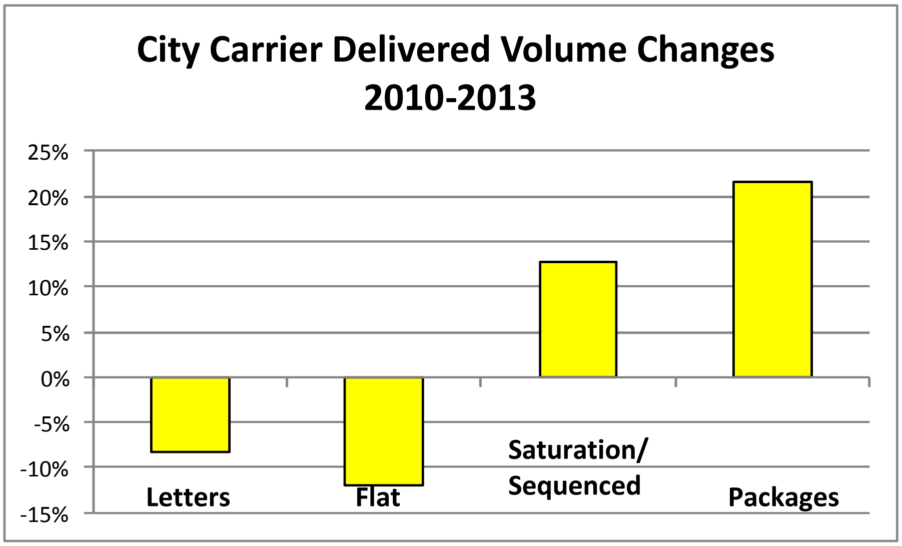
While the study did not lead to much change in overall volume variable costs, id did lead to changes in attributable costs across products. As Table 52 shows, volume variable First-Class Mail street time costs fell, as a result of the updated data and study, whereas Standard Mail and package street time costs rose.

Table 52
Changes in Volume Variable Street Time Costs by Product

	FY 2013 CRA With New Study	FY 2013 CRA	Difference
FIRST-CLASS MAIL			
SINGLE-PIECE LETTERS	$1,274,692	$1,539,729	($265,037)
SINGLE-PIECE CARDS	$71,987	$84,929	($12,942)
PRESORT LETTERS	$1,053,440	$1,126,093	($72,653)
PRESORT CARDS	$51,451	$54,670	($3,219)
SINGLE PIECE FLATS	$149,609	$165,937	($16,328)
PRESORT FLATS	$89,062	$89,277	($215)
PARCELS	$51,575	$44,015	$7,560
STANDARD MAIL			
HIGH DENSITY & SATURATION LETTERS	$145,675	$131,999	$13,676
HIGH DENSITY & SATURATION FLATS & PARCELS	$462,102	$280,815	$181,286
EVERY DOOR DIRECT MAIL - RETAIL	$36,805	$23,446	$13,359
CARRIER ROUTE	$651,512	$588,339	$63,173
LETTERS	$1,280,824	$1,381,078	($100,254)
FLATS	$562,062	$529,267	$32,795
PARCELS	$18,519	$15,114	$3,405
PERIODICALS			
IN COUNTY	$30,553	$27,787	$2,766
OUTSIDE COUNTY	$421,632	$395,317	$26,315
PACKAGE SERVICES			
BOUND PRINTED MATTER FLATS	$19,272	$19,568	($295)
BOUND PRINTED MATTER PARCELS	$47,277	$43,698	$3,579
MEDIA AND LIBRARY MAIL	$22,697	$20,756	$1,941
Ancillary Services			
CERTIFIED	$93,244	$117,738	($24,494)
COD	$427	$523	($96)
INSURANCE	$4,351	$6,191	($1,840)
REGISTRY	$1,150	$1,326	($176)
Competitive Products			
Total Competitive Products	$679,641	$598,167	$81,474

These changes are entirely consistent with a decline in First-Class Mail relative to Standard Mail, and increases in both sequenced mail volume and package volume.

Figure 16: Percentage Changes in Delivered Volumes by Shape



Lastly, the impact of the changes in street time volume variable cost on individual product costs can be assessed by recalculating the overall FY2013 attributable costs per piece using the new study. Those new costs, along with the FY 2013 costs are provided in Table 53.

Table 53
Changes In Costs Per RPW Piece

	FY 2013 CRA With New Study	FY 2013 CRA	Difference
FIRST-CLASS MAIL			
SINGLE-PIECE LETTERS	$0.259	$0.275	-$0.016
SINGLE-PIECE CARDS	$0.261	$0.278	-$0.016
PRESORT LETTERS	$0.116	$0.119	-$0.002
PRESORT CARDS	$0.079	$0.081	-$0.002
FLATS	$0.878	$0.890	-$0.011
PARCELS	$2.400	$2.361	$0.040
STANDARD MAIL			
HIGH DENSITY & SATURATION LETTERS	$0.063	$0.060	$0.003
HIGH DENSITY & SATURATION FLATS & PARCELS	$0.095	$0.074	$0.021
EVERY DOOR DIRECT MAIL - RETAIL	$0.058	$0.039	$0.018
CARRIER ROUTE	$0.196	$0.187	$0.009
LETTERS	$0.102	$0.105	-$0.003
FLATS	$0.459	$0.452	$0.008
PARCELS	$1.586	$1.524	$0.062
PERIODICALS			
IN COUNTY	$0.150	$0.144	$0.006
OUTSIDE COUNTY	$0.369	$0.363	$0.006
PACKAGE SERVICES			
BOUND PRINTED MATTER FLATS	$0.566	$0.568	-$0.002
BOUND PRINTED MATTER PARCELS	$1.238	$1.216	$0.022
MEDIA AND LIBRARY MAIL	$3.967	$3.940	$0.027
Ancillary Services			
CERTIFIED	$2.149	$2.288	-$0.138
COD	$7.348	$7.609	-$0.261
INSURANCE	$2.612	$2.699	-$0.086
REGISTRY	$12.395	$12.500	-$0.105